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Gilberto Montibeller

Decision Making for Enhanced Health Security

Managing Emerging Health Threats, Making Reasoned Choices, and Allocating Scarce Resources

Foreword by Detlof von Winterfeldt



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To my parents, Gilberto and Ione, who have taught me the importance of scientific reasoning and the value of human lives.

Foreword

To demonstrate how timely and important this book by Gilberto Montibeller is, let me start with an example of a health policy problem that I am facing in real time as I write this foreword.

In March of 2020, my university, the University of Southern California (USC), stopped teaching classes in person due to the then-emerging COVID-19 pandemic. When the pandemic appeared to subside in the summer of 2021, USC opened its campus for the Fall semester classes with the following strict COVID-19 policies: all students, faculty, and staff must be vaccinated against COVID and the flu; all students have to be tested at least once a week; before coming to campus, a health test questionnaire has to be completed every day by students, faculty, and staff; and masks are required in all indoor spaces and seating is arranged to accommodate 6 ft. distancing.

Over 98% of USC students and employees have been vaccinated since Fall classes started in August 2021. USC publishes the results of testing every week. During the last week of October 2021, 29,728 tests were performed with 37 positive cases (0.1% of those tested) among the 45,900 students and 3 positive cases among the 21,320 faculty and staff (0.3% of those tested). It appears that the vaccination mandate was very successful, but, given the extremely low positivity rate, students now question whether the added weekly testing is still necessary, especially since tests take about one hour and may lead to false positives. Similarly, is indoor masking still necessary, considering the discomfort of wearing masks and the increased difficulty in communicating with masks?

To paraphrase Bernoulli's statement in the Prologue of this book: Using data and a little analysis would go a long way to resolve these policy issues. This book helps the reader to approach them with an analytical mindset using the best data and science, but also addressing conflicting values and concerns of those affected by health policies and decisions, under conditions of high uncertainty.

Gilberto Montibeller's book comes at the right time to address health security problems, whether they originate in pandemics, climate change, or bioterrorism. Gilberto is an internationally known decision and risk analyst who builds on his vast

knowledge and experience to present a systematic approach to health policy and decision making in this book.

I first met Gilberto in 2010 when I was appointed Centennial Professor in the Department of Management at the London School of Economics. He was a full-time faculty member at the LSE, part of a strong LSE Decision Sciences team, and Program Director of the Masters in Decision Sciences, which was also my home as a visiting professor. From that time, we have developed a fruitful joint research agenda on the intersection of Decision Analysis and Behavioral Decision Research, specifically developing research on cognitive and motivational biases relevant for Decision and Risk Analysis.

Our research collaboration further developed in 2011, when he was appointed as a visiting scholar to the International Institute for Applied Systems Analysis (IIASA) in Austria, during my tenure as director of IIASA from 2009 to 2012. Gilberto also started collaborating with the Center for Risk and Economic Analysis of Threats and Emergencies (CREATE) team at the University of Southern California, which I led before becoming the IIASA director, by using Decision Analysis to support decision making in security problems.

As CREATE expanded from its original focus on terrorism risk to other security threats and emergencies, it was clear that Decision and Risk Analysis can make important contributions to addressing health security problems. Gilberto brought to CREATE his extensive experience in supporting health security decisions for many national and international organizations, including the World Health Organization (WHO), the Food and Agriculture Organization of the United Nations (FAO), the United States Agency for International Development (USAID), the Pan-American Health Organization (PAHO), the UK Department of Health and Social Care, and the UK Department for Environment, Food and Rural Affairs (DEFRA), among others.

His experience in leading large-scale applied research projects in health security, working with multidisciplinary teams of health experts, health policymakers, and health economists, coupled with his very solid academic background and research publications in this field, makes him one of the top international experts in Decision and Risk Analysis applied to health security decisions. The importance of strengthening health systems preparedness and for the need of reasoned public decision making in health security situations is now, due to the COVID-19 pandemic, self-evident.

The sheer complexities of making these decisions in a reasoned and systematic way are also now obvious: serious health, social, and economic impacts that may be caused by epidemics and pandemics; huge uncertainties caused by emerging health threats; limited budgets for health preparedness; and difficulties in identifying suitable actions to enhance health security.

In many ways, the current research on health security decision making is at the same stage as homeland security decision making was when we set up CREATE in the early 2000s: lacking a clear conceptual framework for how decisions should be made and missing clear connections between systems analysis (e.g., disease

transmission models or assessments of preparedness of health systems) and decision making.

These knowledge gaps highlight the relevance of this book for health security decision making. The book provides a logically sound conceptual framework for how decision should be made in the health security context, so public health leaders can maximize the societal value of choices with very scarce resources. Importantly, the book also suggests how public health leaders can make clear connections between evidence and predictive transmission models that better inform their decision making.

Readers will learn how to improve the main phases of health security decision problems, from problem framing to the definition of decision objectives and key uncertainties, which can help the development and choice of health security actions with high societal value. The book provides an excellent coverage of Decision Analysis for this important category of problems. It is written without relying heavily on mathematics and formulas while being strongly rooted in Decision Sciences, which makes it both accessible and rigorous. In addition, the focus of this book on reasoned decision making and sound decision processes highlights the importance of Behavioral Decision Research in making sure that decision models are of high quality and decision processes are efficient and fair.

There are several innovative treatments of Decision Analysis in this book, which makes it highly relevant not only to health security decisions but also to the design of public policies and the support of public choices as a whole, thus significantly enriching the literature of Decision Analysis for public decision making. Specifically, the book provides:

- An integrated Decision Sciences perspective, with close ties among Decision Analysis, Risk Analysis, and Behavioral Decision Research.
- Insightful recommendations on how to minimize behavioral, motivational, and group judgment biases in public decision processes.
- Clear advice on how to adequately represent conflicting decision objectives and multiple impacts in decision models that support public decision processes.
- A strong focus on the design of superior public policies, geared toward the maximization of societal value.
- A simple (but not simplistic) treatment of uncertainty in the assessment of impacts of health security actions and health threats.
- An important emphasis on planning for action and on systematic learning during public decision processes.

I am delighted that the original initiatives that we developed at IIASA and CREATE, in bridging Systems Analysis, Risk Analysis, and Decision Analysis to improve security decisions, have now been extended by this book to health security decisions, which so far have often lacked sound logic and systematic decision processes.

Gilberto Montibeller has made a significant academic and practical contribution to this book. From a practical perspective, it is the first book focused on health security decision making and has laid the ground for the use of the rigorous concepts and approaches from Decision and Risk Analysis in this context. From an academic

perspective, the book's innovative coverage of Decision and Risk Analysis and Behavioral Decision Research provides significant advances for the literature on how this methodology can better support public decision making.

I hope that this book helps health leaders and experts to improve their decision processes and to enhance planning and preparedness of our health security systems. I also hope that the book encourages more colleagues from Decision Sciences to further engage with this important category of societal problems.

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Detlof von Winterfeldt

Preface

The topic of health security continues to be important and pertinent, particularly given the recent occurrences in world events. Emerging health threats create vast challenges that must be confronted by public health leaders and policymakers, as these threats pose a significant danger to societal well-being, the results of which have been illustrated by the COVID-19 pandemic that started in 2020, the Ebola outbreak in Western Africa in 2014–2015, the emergence of HIV during the 1980s, and the many other episodes of disease outbreaks that have been recorded throughout history.

The developments that come about as a result of health threats have potentially transformative impacts upon human health, economies, and societies. Consequently, enhancing health security requires that actions be taken in such a way as to better manage health threats and improve the preparedness and the resilience of health systems, and requires that policymakers consider and negotiate the plethora of available scientific knowledge and perspectives while acknowledging and having a clear understanding as to the consequences, priorities, and risks that are involved when striving to enhance health security.

Reasoned and evidence-based decision making is at the core of adequately planning, effectively implementing, and comprehensively responding to emerging and re-emerging health threats. In this context, there arise many critical decisions to be made. We must assert as to which potential health threats should be more closely monitored, which capabilities a given health system should seek to prioritize and which capacities should be strengthened and expanded. Furthermore, it is vital that policymakers determine different ways to increase the robustness and resilience of a health system and render a health system more responsive to disease outbreaks. Public health leaders that are responsible for health security shall always be confronted by these difficult choices. When responding to emerging health threats, these leaders must take into account the multiple impacts, populational needs, and conflicting societal priorities, alongside considering the risks associated with failing to respond to a novel threat.

Perhaps there exists no better contemporary example of the need for reasoned decision making than the events that have come about as a result of the different

national responses to the COVID-19 pandemic at the time of its emergence in early 2020. While some countries had imposed timely and efficient risk measures and have seen a lower death toll as a result, other nations had experienced protracted actions, which had taken the form of ambiguous rules regarding social distancing, poor decisions regarding the provision of protective equipment for frontline health professions and convoluted strategies for test production and testing, all of which have resulted in certain countries incurring a higher death toll.

Reasoned and evidence-based decision making remains crucial for effectively managing emerging and re-emerging health threats and for developing enhanced health security. Currently, there exists a gap in the health security literature for public health leaders, policymakers, and health experts that wish to further improve health security decision making in health systems. I shall briefly describe the six overlapping spheres that inform health security in order to delineate the interstice that has formed between them, the existence of which this book seeks to address through adopting a lens that is directly focused on decision making for health security decisions.

First, most obviously, health policymakers and health experts have extensive scientific training in Health Sciences and thus, naturally, turn their attention toward biological and epidemiological evidence. However, these individuals often have a limited grasp of Decision Sciences, which can significantly hinder their decision processes. Second, Health Economics rightly emphasizes the efficient allocation of resources in health systems, but the lens the field adopts mainly focuses on the standard levels of demand for health care resources. However, as with any emergency situation, health threats pose risks and demands that well exceed the steady state of health systems. Third, Medical Decision Making is mainly focused on individual treatment decisions by clinicians, instead of guiding policy choices that must be determined by public health leaders, the latter of whom are responsible for managing health threats and enhancing health security. Fourth, while there exist other comprehensive contributions on decision making that target the field of healthcare, these works have not been designed specifically for decisions that are related to managing health threats and enhancing health security. This book differs from other contributions in that the decision contexts with which the book seeks to grapple with reveal some unique challenges when compared with other types of health-related decisions. Fifth, there also exists an extensive body of literature on transmission models in Epidemiology, but while transmission predictions form an essential facet of evidence-based decision making, these predictions usually prove insufficient for adequately guiding the reasoned selection of the best decision alternatives for risk mitigation and enhanced health security, the process of which I shall detail in this book. Finally, the current literature that addresses Health Security is mainly focused on institutional issues which, although relevant, fails to directly address the decisions that are required to manage health threats and enhance health security.

In this book, I shall present the ways in which public health leaders can use the extensive research available from Decision Sciences to better manage emerging and re-emerging health threats, with a focus on enhancing health security. While these decisions must be informed by the best available evidence, they must also address

competing priorities and key uncertainties and mitigate critical risks, albeit in a cost-effective manner which seeks to maximize societal value. Since most of these health security decisions are taken in groups whose composition is typically formed by a combination of government officials, scientific advisors, and representatives of key stakeholders, my emphasis shall be on group decision making, although we frequently discuss how these processes are also connected to individual and organizational decision processes and the scientific evidence that underpins these two entities.

From an organizational perspective, available risk management plans and selected health security actions can only be successfully implemented if resources have been properly allocated to execute implementation; the efficient and targeted use of resources proves particularly crucial for health security settings, wherein budgets are typically very scarce. Thus, this book also seeks to explore the interstice that exists between risk management, decision making, and resource allocation.

Both the content and the focus of this book are based on my experience, having worked for over a decade with national and international organizations that are responsible for health security, in order to support the improvement of their decision making. These organizations have included the World Health Organization (WHO), the Food and Agriculture Organization of the United Nations (FAO), the UK Department for Environment, Food and Rural Affairs (DEFRA), the UK Department of Health and Social Care, the Pan-American Health Organization (PAHO), and the United States Agency for International Development (USAID)/Malaria Initiative.[1] In those decision aiding interventions, I employed my expertise in Decision Analysis, Risk Analysis, and Behavioral Decision Research to support multidisciplinary teams composed of public health leaders, policymakers, health experts, and health economists who sought to further improve the quality of their decisions and recommendations.

In addition, I have trained hundreds of policymakers and senior managers on how to make better strategic decisions, at the London School of Economics (UK), Warwick Business School (UK), the Hertie School (Germany), IE Business School (Spain), Loughborough University (UK), and the University of Sao Paulo (Brazil). This book reflects both my experience of engaging with senior management and policymakers, and the complexities inherent to making policy and managerial decisions.

My research and publications have also sought to address this interstice that exists between Health Security, Decision Analysis, and Risk Analysis. This book seeks to present these findings and approaches that stem from this translational research agenda in a manner that is more accessible so that a wider audience can engage with these ideas. To do so, I deliberately employ very simple examples to illustrate core decision-making concepts, as in my experience, this proves to be the best way of conveying such concepts to a general readership. However, the book

[1] All the opinions and any eventual mistakes that are contained within this book are exclusively mine and do not represent the views or opinions of any of these client organizations.

also describes some factual projects that I have led, which illustrate the use of the framework in realistic settings.

The book has been written for three main audiences. The first encompasses public health leaders, health policymakers, and managers that are responsible for health security and that are striving to further enhance their health security decision making. The second audience includes decision analysts, risk analysts, and health policy researchers who are interested in conducting research and in developing applications in this important field of decision problems. And the third audience encompasses health scientists, epidemiologists, public health experts, and health policy analysts who wish to adapt and extend their health policy analyses so as to render them more relevant to policymaking and policymakers.

This book is written from a Decision and Risk Analysis perspective as this is my background and expertise, but I have attempted to write the content in such a way as to communicate the details in a manner that is accessible, reducing the amount of mathematics and axiomatization, while maintaining the content rigorous. The references that are included provide sources for those readers that wish to further develop their knowledge on a specific topic. The references from Decision Sciences are drawn from the scientific literature. For those readers without a background in Health Sciences, I have included more accessible references on health threats and health security to better contextualize their respective challenges and decision problems.

Health Decision Analysis can aid in structuring the decision-making process in such a fashion as to selectively adopt, negotiate, adjust, and re-establish information that is contributed by experts and inputs that are imparted by decision makers, in a manner that proves suitable, relevant, and beneficial to health security decisions.

This is a book about *how* decisions on health security can be improved, both in terms of the content that is utilized in a health decision analysis and the decision processes that are employed in reaching a decision. It is not, however, a book that provides specific prescriptions for which specific option a decision maker should select when managing a health threat or when attempting to enhance health security. There exist two main reasons for adopting this process-based perspective over its content-prescriptive counterpart. First, each and every decision that strives to manage health threats or enhance health security emerges from contexts that are extremely specific. Thus, the decisions themselves are contingent on the problem in question, the relevant impacts that are under consideration, the key uncertainties that surround the problem, the critical risks that must be mitigated, and the available options that could be considered. Second, the individuals that are most suited to make these specific choices are those that have the knowledge and/or the responsibility for managing health threats and enhancing health security, that is to say, public health leaders, health experts, health risk managers, and health policymakers. These individuals shall certainly benefit from employing adequate concepts and processes to make more reasoned decisions, the ideas of which shall be presented in this book. However, decision making should not solely be delegated to health policy analysts or consultants.

The book is divided into three themes. The first discusses how decisions concerning health security are typically made and the challenges that are confronted by public health leaders when making such decisions. This first theme also introduces the different streams of Decision Sciences research and positions the book content within this vast literature. The second theme suggests a conceptual framework for making reasoned decisions in this context based on Health Decision Analysis. This framework can help public health leaders to make more evidence-based and reasoned choices, which maximize benefits, control costs, and adequately manage risks. The third theme discusses how we can increase the health preparedness of health systems, the task of which involves improving health capabilities, increasing the robustness of health systems against health threats, and developing health resilience and responsiveness against disease outbreaks.

From a Decision Analysis perspective, this book discusses an extraordinarily important category of decision situation, providing several novel treatments and interpretations of the pre-existing literature. First, a strong emphasis is placed on decision processes and group decision making, in contrast with the more traditional emphasis on decision models. Second, an extensive coverage of the relevant aspects of Behavioral Decision Research of both decision models and of decision processes is contributed, instead of any superficial allusions to biases in decision making. Third, a balanced coverage of both decisions with conflicting objectives and decisions under uncertainty is detailed, instead of a focus on only one of these characteristics. Fourth, the treatment of risk is fully aligned with the concerns and practices of public decision making, avoiding the use of risk preference parameters that, in this decision context, may prove to be rather artificial. Fifth, a significant emphasis is also placed on systematic learning and shifting from the planning to the implementation of the selected health security actions, in contrast to the assumption of linear decision processes and the straightforward execution of implementation.

It is my hope that the content and the concepts that are presented in this book can help to further improve the quality of decisions that address health security. Health threats pose significant dangers to humankind and form a major source of human suffering and sorrow. Responsible leadership and reasoned decision making can significantly improve the arenas that are affected by health threats, through establishing a better allocation of very scarce resources for building health capabilities and for increasing health preparedness, responsiveness, and resilience.

London & Loughborough, UK Gilberto Montibeller

Prologue: The Very First Health Decision Analysis

Around 250 years ago, the first-ever decision analysis that was conducted on a health security decision was published by Daniel Bernoulli,[1] who was one of the greatest scientists of the eighteenth century. While the figure of Bernoulli and his early conceptualization of marginal utility as a precursor of Economics and Decision Analysis[2] is well-known, his pioneering contribution to Health Decision Analysis, however, has been neglected thus far. Instead, the only aspects from his analysis that have been highlighted discuss the pioneering epidemiological components.[3] In adopting the lens of Decision Sciences, this prologue hopes to retell this story so as to underscore the notion that important decisions, which affect human health and the well-being of humankind, should be based on the sound and logical bases of scientific reasoning.

Smallpox was a serious infectious disease caused by the variola virus, claiming the lives of, on average, 30% of those that were infected, and leaving disfiguring scars on the bodies and faces of those that survived. Smallpox was an ancient disease, with evidence demonstrating that the disease had already affected the Egyptian empire around the third century BCE and had appeared in China in the fourth century CE, spreading to Asia Minor subsequently. The Arab invasion of Portugal and Spain in the seventh century, and the Crusades in the Middle East in the eleventh century spread smallpox across Western Europe.[4] A particularly virulent strain emerged in the early seventeenth century and by the eighteenth century the disease was endemic in Western Europe and was responsible for 10% of deaths in this

[1] Bernoulli, Daniel. 'Essai d'une Nouvelle Analyse de La Mortalite Causee Par La Petite Verole'. In *Mem. Math. Phy.* Paris: Acad. Roy. Sci., 1766.

[2] Winterfeldt, Detlof von, and W. Edwards. *Decision Analysis and Behavioral Research*. New York, NY: Cambridge University Press, 1986.

[3] Dietz, Klaus, and J. A. P. Heesterbeek. 'Daniel Bernoulli's Epidemiological Model Revisited'. *Mathematical Biosciences* 180, no. 1 (1 November 2002): 1–21.

[4] US Centers for Disease Control. 'History of Smallpox'. At: https://www.cdc.gov/smallpox/history/history.html

region,[5] with epidemics occurring periodically, particularly in large cities such as London and Paris.

The smallpox inoculation, called variolation, consisted of transferring infectious material from a suffering case into the skin, or on the membranes of the nose, of a susceptible individual, the process of which caused a mild infection and could produce lifelong immunity. There were, however, some risks, including a small number of deaths and complications and the inoculated person could still transmit the disease. This practice of variolation was already well established in Asia and the Middle East, but in Western Europe variolation was not known until late the seventeenth century.

In England, the Royal Society started investigating variolation overseas after smallpox caused the deaths of Queen Mary in 1694 and Prince William, the Duke of Gloucester, in 1700. However, variolation was only introduced to England in 1721 by Lady Mary Wortley Montagu, who herself had been disfigured by the disease in 1715. The husband of the aristocrat was an ambassador to the Ottoman Empire and Lady Mary witnessed the practice of variolation in Constantinople. Later, the couple decided to inoculate their son and, after returning to England, her daughter was also inoculated in 1721. This was the first time the practice of "artificial smallpox" had been performed in Britain, and the event was witnessed by several preeminent physicians. Their favorable report stimulated other British aristocrats to follow the same treatment against "natural smallpox," despite the deaths of some children after the inoculation, as the procedure was not totally without risk.

Even after these early successes in England, the practice of variolation generated some fierce debates, particularly in Continental Europe, as there existed doubts concerning the efficacy and the safety of the treatment. During this same period, the Royal Academy of Science in France promoted variolation, but the Catholic Church and some conservative medical authorities in the country opposed the procedure. Specifically, critics argued that:[6] (i) variolation was risky because "artificial smallpox" could cause deaths; and (ii) inoculation programs could increase the transmission of the disease (since inoculated individuals could still transmit smallpox).

Bernoulli decided that the best manner to evaluate the public health consequences of variolation was to employ scientific reasoning. The *decision problem* that Bernoulli sought to address was whether variolation was beneficial to mankind and society: "my intention is simply to make a comparison between the condition of mankind as it is without inoculation and what it would be if this salutary operation were either generally admitted or simply followed with certain rules."[7] There were,

[5] Harrison, Mark. *Disease and the Modern World: 1500 to the Present Day*. Themes in History (Polity Press). Cambridge ; Malden, MA: Polity, 2004.

[6] Bernoulli, Daniel, and Sally Blower. 'An Attempt at a New Analysis of the Mortality Caused by Smallpox and of the Advantages of Inoculation to Prevent It'. *Reviews in Medical Virology* 14, no. 5 (September 2004): 275–88.

[7] Bernoulli, Daniel. 'Essai d'une Nouvelle Analyse de La Mortalite Causee Par La Petite Verole'. In *Mem. Math. Phy.* Paris: Acad. Roy. Sci., 1766. English translation by Bradley, Lesley in

therefore, *two decision alternatives*: the *variolation* option or no variolation option (the *status quo* option).

In his analysis, published in 1766, Bernoulli considered the scenario of 1300 children over a 25-year period. He employed data collected in England by Edmond Halley (the famous astronomer) to construct a life expectancy table that displayed the survival rate for a smallpox infection, which Halley had recorded, from 0 to 24 years of age (the average life expectancy during this period in England and France was around 30 years).

Bernoulli considered two main *consequences* when comparing the two decision alternatives, associated with the following *fundamental objectives*: the *increase in the number of survivors per year* (population benefit) and the *increase in average life expectancy* (individual benefit). Wisely, he recognized the fragmented nature of the information pertaining to inoculation available at the time while understanding the importance of the (decision) analysis, stating: "It is still true that we lack adequate information to answer this question precisely, but it seemed to me that we have enough information to throw some new light on a subject whose great importance we are beginning to realize."

He also considered the *risks* in this decision problem: the risk of an individual being infected by smallpox every year (rate of infection), the risk of death were an individual to be infected by the virus (rate of mortality), and the risks associated with the variolation procedure (rate of mortality after inoculation). Moreover, Bernoulli recognized the difficult *trade-off* involved in this decision: "What would be the state of the human race if, at the price of a certain number of victims, we could procure for it freedom from natural smallpox?"

In sequence, he derived equations to determine the number of individuals that would survive per year, from the 1300 newborns, both with and without the liability of being infected by smallpox, and presented the results in a table (reproduced in Table 1). The second column of this table indicates the number of individuals that remain alive per year without variolation (the *status quo* option) and, in the third column, the number of individuals that remain alive per year with variolation (the *variolation* option). In his analysis, the benefits of variolation, against no inoculation, demonstrated an increase from 565 to 644 individuals reaching the age of 25 (population benefit), as the last column of the same table shows. Bernoulli also estimated that the life expectancy would increase from 26 years 7 months (with no variolation) to 29 years 9 years with variolation (individual benefit).

Bernoulli conducted an extensive *sensitivity analysis* in his study, given the judgments that he had used to establish the rates in the model in the absence of complete evidence and also in order to challenge the two main points raised by inoculation critics. In order to challenge the first criticism that variolation was risky because the "artificial smallpox" (*variolation* option) could cause deaths, Bernoulli repeated his calculations including the assumption that 1 out of every 200 inoculated patients

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Smallpox Inoculation: An Eighteenth Century Mathematical Controversy (Adult Education Department, Nottingham, 1971).

would die from the "artificial smallpox." This adjustment reduced his estimate of gain in life expectancy by only one month. To challenge the second criticism that inoculation programs could increase the transmission of the disease, Bernoulli estimated that "artificial smallpox" to be 13 times less severe and 4 times less transmissible than "natural smallpox." In this case, he concluded that infection of individuals with "natural smallpox" (*status quo* option) was 32 times as great as infection with "artificial smallpox" if the variolation decision alternative were adopted.[8]

Variolation became widespread in Britain after the second half of the eighteenth century, but it was only adopted during this period by the aristocracy in France and other European countries. A more effective and safer solution than variolation was found by Edward Jenner in 1796, with the invention of a vaccine against smallpox using cowpox, a disease that affects cattle. There were extensive vaccination campaigns in the twentieth century that were led by the World Health Organization. Smallpox was finally eradicated from the world in the 1970s. The eradication of this dreadful disease is considered to be the biggest achievement in the international public health security ever achieved.

If we return to the public policy debate about variolation in the eighteenth century, it remains unclear as to how persuasive the analysis that was conducted by Bernoulli truly was influencing the inoculation policy of France and Continental Europe. Nevertheless, this landmark study is the first published mathematical analysis that was used to try to attempt to influence public health policy.

Like Bernoulli's analysis, this book draws on long traditions and recent developments. The book is a study that is underpinned by Enlightenment thought, in that the notion that humans should seek to cultivate knowledge about factors that affect humanity and transform this knowledge in such a way as to improve our condition forms the very foundation of all the concepts that are presented. It is also a study that contributes a new perspective, by re-interpreting, elaborating upon, and contributing to the pre-existing literature to fill an interstice that had been formed, the presence of which had, in some ways, highlighted the absence of answers that directly addressed how to improve decisions that are required to manage health threats that are emerging. It is from this paradox between the traditional and the novel that this book emerges, and I hope that my contribution serves to broaden our knowledge by closing this interstice.

[8] Bernoulli, Daniel, and Sally Blower. 'An Attempt at a New Analysis of the Mortality Caused by Smallpox and of the Advantages of Inoculation to Prevent It'. *Reviews in Medical Virology* 14, no. 5 (September 2004): 275–88.

Table 1 Bernoulli's comparison of the two decision alternatives, variolation vs no inoculation[a]

Ages by years	Natural state with smallpox	State without smallpox	Difference or gain
0	1,300	1,300.0	0.0
1	1,000	1017.1	17.1
2	855	881.8	26.8
3	798	833.3	35.3
4	760	802.0	42.0
5	732	779.8	47.8
6	710	762.8	52.8
7	692	749.1	57.2
8	680	740.9	60.9
9	670	734.4	64.4
10	661	728.4	67.4
11	653	722.9	69.9
12	646	718.2	72.2
13	640	714.1	74.1
14	634	709.7	75.7
15	628	705.0	77.0
16	622	700.1	78.1
17	616	695.0	79.0
18	610	689.6	79.6
19	604	684.0	80.0
20	598	678.2	80.2
21	592	672.3	80.3
22	586	666.3	80.3
23	579	659.0	80.0
24	572	651.7	79.7
25	565	644.3	79.3

This table enables us to see at a glance how many out of 1300 children, supposed born at the same time, would remain alive from year to year up to the age of 25, supposing them liable to smallpox; and how many would remain if they were all free from this disease; with the comparison and the difference of the two states.

[a]Source: Bernoulli, Daniel. 'Essai d'une Nouvelle Analyse de La Mortalite Causee Par La Petite Verole'. In *Mem. Math. Phy.* Paris: Acad. Roy. Sci., 1766. English translation by Bradley, Lesley in *Smallpox Inoculation: An Eighteenth Century Mathematical Controversy* (Adult Education Department, Nottingham, 1971)



I simply wish that, in a matter which so closely concerns the wellbeing of the human race, no decision shall be made without all the knowledge which a little analysis and calculation can provide.

Daniel Bernoulli, 1760.

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Chapter 1
Making Health Security Decisions: Challenges and Complexities



Public health leaders are experienced decision makers, who are accustomed to making difficult choices through negotiating competing needs, often under strained budgets. However, in contrast to healthcare decisions, health security decisions pose additional challenges and complexities against endemic diseases and chronic conditions. In this first chapter, we discuss the main challenges and complexities in making health security decisions and highlight the importance of reasoned decision making in coping with health threats.

We start this chapter by conceptualizing the category of health threats that we shall focus on, that is to say: emerging health threats from infectious diseases. We then discuss the challenging environment surrounding health security decisions and the biases that decision makers may suffer in improving health preparedness. We also analyze the complexities confronted by both health policymakers (who oversee health security), and by health professionals (who are responsible for managing health threats and improving health security), when making decisions within this domain.

While experienced public health leaders may have already faced these challenges and complexities, and dealt often with them in practice, the aim of this chapter is to provide a systematic analysis. A clear understanding of these challenges and complexities may aid the reader to better appreciate why taking health security decisions is a challenging process. Moreover, understanding the challenges and complexities involved in decision making may also highlight the benefits of using more systematic decision processes and reasoned approaches when making health security decisions.

We also examine how health security decisions are typically analyzed in practice. Attempts to inform these decisions range from ad hoc assessments of health security decision alternatives to score-and-weight procedures that are used to prioritize emerging health threats. We discuss the shortcomings intrinsic to these commonly employed assessment methods. The complexities involved in making health

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security decisions, combined with these rather inadequate assessment methods that often underpin said decisions, establish the basis for the need to improve the quality of health security decisions and to apply Health Decision Analysis.

1.1 Improving Health Security and Preparedness Against Emerging Health Threats

In this section, we start to delineate the scope of this book. As detailed next, we focus on emerging health threats, as these constitute some of the most challenging health issues confronting health systems, which are dramatically illustrated by the COVID-19 global pandemic that started in 2020 (WHO, 2021a). The section also highlights the multiple trends for an increasing number of emerging health threats and defines the conceptualization of health security that we adopt. Subsequently, we discuss the challenges that public health leaders face when making decisions required to improve the preparedness against emerging health threats. The fundamental nature of these adverse events poses decision-related challenges that go well beyond obstacles that are traditionally present in standard healthcare decisions or in the management of endemic diseases.

1.1.1 Emerging Health Threats and Health Security Decisions

This book is focused on emerging health threats from infectious diseases, which are among the many other threats that we humans are exposed to, such as air pollution, noncommunicable diseases, antimicrobial resistance, in addition to others (WHO, 2020d). There are several sources of such emerging health threats, including pathogens of pandemic potential, zoonoses with spillover potential, dual-use research of concern, and bioterrorism.

Human history is beset by occurrences of pandemic and epidemic outbreaks of such infectious diseases, often leading to devastating consequences (Harrison, 2004). Epidemic malaria has severely affected humans for thousands of years (Arrow et al., 2004) and the medieval era was troubled by recurrent outbreaks of bubonic plague. Likewise, the modern era has been plagued by recurrent outbreaks of cholera, smallpox, and yellow fever. In the early part of the previous century, the 1918 Spanish influenza killed more than 50 million individuals, and, in the latter part of the previous century, HIV has caused more than 30 million fatalities since the start of the pandemic in the 1980s. More chronologically proximate outbreaks, such as the global COVID-19 pandemic that started in 2020, or the Ebola epidemic in West Africa in 2014–2016, highlight the social and economic costs that health threats can bring about (Montibeller et al., 2020a).

Recent and rapid changes to ways of life have exacerbated the risks of emerging health threats and future pandemics (Koblentz, 2010; Montibeller et al., 2020a; Scheidel, 2017). First, the extensive migration of the global population has led to the development of megacities and high-density urban areas. Many of these large urban areas are in developing countries, where health systems are more precarious, housing is often insalubrious, and thus, the population is more vulnerable to disease. Second, we find that the deforestation of natural habitats often places humans in close contact with other plant and animal species, which can act as potential vectors of new diseases. Indeed, zoonoses are a major source of health threats, stemming from possible pathogen spillovers from animals to humans, are often highly contagious and associated with high fatality rates (Kelly et al., 2020). Third, the mutation of existing pathogens into more deadly or transmissible strains, both from human-to-human and animal-to-human transmissions. Fourth, these societal and technological changes have triggered a rapid flow of travelers around the globe, increasing the speed of any disease outbreak; these changes have also opened up new trading routes and demands for fresh and live commodities, which themselves can be vectors of diseases. Globalization has also created long and complex supply chains for food production, which have increased the pathways to food contamination. Fifth, the permanent risk of bioterrorism or the misuse of biotechnologies, threatens to spread vectors of known diseases or to potentially create new health threats.

The World Health Organization (WHO) defines (global) health security as: "activities required, both proactive and reactive, to minimize the danger and impact of acute public health events that endanger people's health across geographical regions and international boundaries." (WHO, 2020a).

We focus on health security from emerging infectious diseases, while recognizing that other types of health threats are also relevant. There are three main reasons for focusing on this category of health threats to health security (Benson & Glasgow, 2018). First, emerging infectious diseases are often of a large scale, with potentially high levels of morbidity and mortality, and therefore constitute a security threat to organizations and societies. Second, such diseases can be targets for containment or eradication, in an analogous way to other security threats confronted by organizations or countries. Third, emerging infectious diseases are a serious threat at present in many areas of the globe, and, in an increasingly interconnected world, these diseases have the ability to pose devastating consequences in the future for mankind. Fourth, the *emerging* nature of these diseases inherently makes their assessment more difficult, given the limited hard evidence available when preparedness and response decisions must be made.

Despite our focus on emerging health threats, as these prove the most difficult to manage, the framework and concepts that we present here can be also employed for making reasoned choices when managing any health threat caused by infectious diseases that threaten to cause local and national outbreaks, epidemics and pandemics. In contrast to emerging health threats, there typically exists greater bodies of evidence and knowledge about well-known diseases (such as rabies, malaria, and so on), which may reduce the difficulties of estimating the impacts of these health threats and of implementing health security actions against these threats. However,

all the other challenges encountered when making reasoned health security decisions persist for non-emerging health threats and must be adequately addressed, the solutions of which shall be proposed in this book.

There exists a plethora of decisions that can be considered for enhancing health security, Obviously, prior to considering the available decisions, public health leaders must decide how serious each of the health threats is. Fortunately, we are able to identify two major types of health security decisions.

Assessment of Health Threats *How serious are the emerging health threats?* In this first type of decision, public health leaders typically *categorize* or *prioritize* health threats. A common practice undertaken involves defining the risk level of these health threats. For instance, these leaders may wish to rank a set of possible zoonoses in terms of their expected impacts if animal-to-human infection were to take place and lead to subsequent outbreaks within the human population. This is a crucial first step for any subsequent health security decision, as this step indicates the possible impacts that may be triggered by the threat and, thus, how serious this threat is likely to be.

Selection of Health Security Decision Alternatives *What are the best actions to enhance health security against the health threats?* In this second type of decision, public health leaders may decide to *select* or *rank* actions to improve health security against one or more emerging health threats. For instance, these leaders may consider either investing in a post-exposure treatment *versus* buying stocks of a vaccine against a health threat, if resources are limited and both actions cannot be provided to the community. Other decisions may be required against this specific health threat, ranging from devising vaccination campaigns, increasing hospital surge capacity, stockpiling emergency medicines, imposing social distancing rules during outbreaks, delivering treatments to infected patients, among many others.

These categorizations shall help us to generalize the advice and recommendations contained in the book. These categories are later utilized in this chapter, to discuss how health security decisions are typically made. Such categories are also employed in the subsequent chapters, to illustrate how the evaluation of threats can be improved and health security decisions can be enhanced.

We focus on decisions wherein the health security team has sufficient amount of time (at least a few hours), to decide and engage in a health decision analysis. There are two reasons for this focus. First, it encompasses a large number of health security decisions, from choosing a set of health security actions against an emerging threat to considering a portfolio of initiatives that can significantly improve preparedness and enhance health security. Second, there is a large body of Decision Sciences research and methods that can inform these decision processes, as detailed in the second chapter. This research ranges from evidence about biases and pitfalls in unstructured decision making,[1] to learning how to develop systematic decision

[1] We define *unstructured decision making* as those decision processes that lack both a clear framework to represent the main components of the decision and eschew the sound rules on how decision alternatives should be chosen to maximize societal value. In practice, they typically involve

processes and implement a clear conceptual decision framework in supported decision making.

Decisions that have an emergency nature, whereby actions must be taken immediately without time for deliberation, have a different nature than the ones we consider in this book. There is a niche body of behavioral decision research that investigates decisions under such circumstances, involving the study of plane pilots and firefighters faced with emergency situations (Klein, 2017). The findings of this body of research indicate that extensive simulation and experience in dealing with similar events and receiving reliable feedback regarding performance is the best way of preparing decision makers to deal effectively with these emergencies. Unfortunately, that is hardly the case for emerging health threats, given their novelty and uniqueness, the extended time lags to receive feedback, and their multiple possible impacts (Kahneman & Klein, 2009). In such cases, our recommendation is to institute health leaders that have extensive experience in dealing with emerging health threats and in implementing emergency actions.

Improving health security necessarily involves adequately managing emerging health threats, from enhancing the levels of preparedness against possible threats to being efficient in responses against outbreaks. This requires reasoned and evidence-based decisions from public health leaders. Indeed, there is unanimity in public health fora about the need for evidence-based actions and a tacit acceptance of the importance of reasoned decision-making. However, preparedness levels are often below what they should be, caused by important health capacities missing and relevant health capabilities lacking. What are the causes of insufficient preparedness even in wealthy countries with sophisticated health systems? We discuss some possible barriers to adequate health preparedness against emerging health threat next.

1.1.2 Improving Preparedness Against Emerging Health Threats

We conceptualize health preparedness following the definition provided by Nelson et al. (2007): "(…) the capability of the public health and health care systems, communities, and individuals, to prevent, protect against, quickly respond to, and recover from health emergencies, particularly those whose scale, timing, or unpredictability threatens to overwhelm routine capabilities. Preparedness involves a coordinated and continuous process of planning and implementation that relies on measuring performance and taking corrective action." We selected this definition of preparedness as it encompasses improving prevention, enhancing resilience, and increasing responsiveness of public health systems.

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an informal discussion regarding which choices to make, which is focused on an ad hoc appraisal of the benefits and drawbacks of each decision alternative.

There are many complex issues involved in improving the preparedness of public health systems (WHO, 2021b). Indeed, the COVID-19 pandemic has stimulated a welcome discussion on how to improve these systems against pandemics, emphasizing the importance of strengthening national-level systems (Khor & Heymann, 2021), international regulations, and health governance structures (Duff et al., 2021). We fully recognize the relevance of these issues and applaud the health policy experts that are championing these mobilization efforts. The scope of this book is more specific, focusing on health security decisions for enhancing preparedness against emerging health threats.

We believe that this targeted focus on decision making provides a pragmatic way of linking high aspirations for better (global) health preparedness, providing tangible actions on improving health capacities and deploying health capabilities that are able to be implemented at both regional and national levels. It is vital to stress the central role of decision making involved in any health preparedness initiative. Given that resources are necessarily limited, difficult choices must be made regarding which health capacities should be improved (e.g. health equipment, health personnel, medicines) and which health capabilities should be developed and deployed (e.g. surveillance, surge capacity for health care services, risk communication) (Stoto & Nelson, 2012).

Additionally, no matter how detailed and robust the preparedness planning is, the actual response of the health systems will depend on the measures that were actually implemented and how responsive the system is when dealing with an actual disease outbreak. These requirements call for effective implementation, key factors of which are a well-designed decision process and agile yet reasoned decision making in emergency situations.

Indeed, the World Health Organization (WHO) and the Interational Health Regulations stress the relevance of decision making for public health leaders, and the importance of adequately intertwining science with policy in said decisions (see also von Winterfeldt (2013) for a detailed discussion on a decision focus for global systems analysis). Notably, in a comprehensive WHO framework that has been developed for health systems to enhance health security, this *leadership* requirement is listed as the first core capability for achieving health security: "Leadership: From the highest level of governments and along the chain of command, mechanisms and tools to *facilitate decision making*, linking science to policies" (WHO, 2021b, p. 9, italics added).

However, why is adequate preparedness a more challenging element to achieve against emerging health threats in comparison to other health needs (such as chronic conditions and endemic diseases)? A core characteristic of emerging health threats is that they are low-probability but high-impact adverse events (Camerer & Kunreuther, 1989).

There is a relevant body of behavioral decision research that studies how preparedness decisions are affected by this characteristic which was originally developed to better understand natural hazard events, such as hurricanes, earthquakes and flooding (see Meyer & Kunreuther (2017) for an accessible introduction). Here, we discuss how preparedness against emerging health threats may be affected by the

nature of these threats: rare adverse events with potential for severe health and socioeconomic impacts.

The relative rarity of emerging health threats imposes a wicked learning environment (Soyer & Hogarth, 2020) for public health leaders. There are few opportunities in this environment to assess outcomes by direct observation. Additionally, the uniqueness of each health threat makes it difficult to extrapolate experiences from one event that has already occurred to possible future events (Stoto & Nelson, 2012).

Additionally, there exists a lack of timely and reliable feedback about preparedness actions and responses of the health system, which may prevent consistent learning about effective and ineffective initiatives (Kahneman & Klein, 2009; Klein, 2017). The lack of counterfactuals (Roese, 1999) in risk management compounds this issue. That is, decision makers necessarily lack an understanding of the consequences that would have occurred if risk mitigation actions (which may have prevented a disaster) were not implemented. Equally, had an alternative set of risk mitigating actions been implemented in place of the actions that were selected, the consequences of implementing the former would remain uknown (Woo, 2016).

Wicked learning environments provide patchy and messy data that may be random, incomplete, unrepresentative, inconsistent and ambiguous (Soyer & Hogarth, 2020). Nonetheless, public security leaders must make timely and informed decisions anyway, given the huge potential impacts of health threats. Unfortunately, such decisions are often affected by some relevant biases, which systematically affect judgments and decisions (Gilovich et al., 2002; Kahneman & Tversky, 2000).

These biases might have a cognitive nature, stemming from faulty reasoning processes, or a motivational nature, whereby the external motivations distort reasoning processes (see Montibeller & von Winterfeldt (2015) and the next chapter for details). In addition, group judgment biases may also affect decisions taken by health security teams (Montibeller & von Winterfeldt, 2018). The biases that may affect preparedness in health security decisions, and their possible impact on the quality of these choices, are briefly discussed below (see also Meyer & Kunreuther (2017)).

Myopia Bias Decision makers often suffer from myopic decision making, wherein short term consequences are more heavily weighted than long term ones (Frederick et al., 2002). This may explain why preparedness investments might be perceived as being too expensive against long-term health and social benefits. This bias also helps to explain why decision makers often procrastinate when making health preparedness decisions. Procrastinators are averse to spending resources now but consider it wise to be spending them tomorrow, since the future expenditure is perceived as cheaper than present-day investment. Unfortunately, when tomorrow arrives, this same attitude resumes, and once again future investment is perceived as better than investing now.

Amnesia Bias Decision makers tend to focus on salient and recent events (Tversky & Kahneman, 1973; Wänke et al., 1995). They may also quickly forget the hedonic impacts of previous losses, i.e. the sense of tragedy that an outbreak has brought to micro and macro communities. However, preparedness decisions require long-term

memories of previous adverse events. These decisions also require decision makers to appreciate the societal value in costly health security actions, which necessarily involve assessing the human suffering and societal disruption that a health threat could provoke.

Optimism Bias Decision makers may suffer from optimism bias, the tendency to believe that they are more immune than others to bad outcomes (Krizan & Windschitl, 2007; Weinstein, 1980). Research has shown that even if subjects consider that a hazard is likely to occur, they believe that said hazard will afflict others but not themselves. If extrapolated to communities, this tendency helps to explain why decision makers may take no action to improve health security, in the optimistic belief that their community will be spared from disease outbreak. Additionally, optimistic decision makers tend to construct a scenario that they hope will happen, instead of preparing for realistic scenarios in which their community may be also affected by the adverse event.

Inertia Bias The tendency to stay with the status quo option is a pervasive bias in decision making (Kahneman et al., 1991; Samuelson & Zeckhauser, 1988). Confronted with uncertain consequences of a rare adverse event, decision makers may decide to do nothing rather than invest heavily into health security actions which could significantly improve preparedness. Additionally, organizational inertia is a widespread phenomenon (Kelly & Amburgey, 1991). If budgets have been traditionally allocated to a set of health investments for clear, tangible health needs, the later re-directing of those resources becomes very difficult when preparing against possible health threats that may not occur in the near future or, indeed, at all.

Simplification Bias The oversimplification of decision problems (Legrenzi et al., 1993; Legrezni & Girotto, 1996) may lead to decision makers disregarding or ignoring available information related to risks and adverse consequences. Indeed there is strong evidence that subjects often ignore probability information when making decisions under uncertainty (Huber et al., 1997, 2001). The inherent vagueness of small probabilities of outbreaks from emerging health threats compounds this problem, as it is often difficult to relate to small numbers. Additionally, decision makers may believe that the probability is so low that the event should be ignored completely, neglecting the huge impacts that an outbreak could cause were the event to take place. Another relevant over-simplification is to consider a single health security action, disregarding the need for multiple actions that are typically required for significantly improving health preparedness.

Herding Bias Decision makers may decide to follow the actions of other decision makers, who are responsible for similar health systems, instead of critically appraising what the best course of action is for their specific health system. This behavior may be a consequence of risk aversion, since decision makers could be punished for doing something different to their peers if these actions were to have negative consequences (Mazzocco et al., 2004). Herding bias may also stem from social conformity (Asch, 1956; Kerr & Tindale, 2004), wherein decision makers are afraid of challenging the majority of opinions in their peers' group. The consequences of this

bias are that health security actions that may be inappropriate or inadequate for a particular situation are nevertheless implemented.

In summary, there is strong behavioral evidence that health security decisions for improving health preparedness against emerging health threats are frequently biased. This may be the case even for experienced, engaged, and committed public health leaders, as these biases are systematic in human judgments and decisions, particularly under wicked learning environments (Kahneman & Klein, 2009; Soyer & Hogarth, 2020). This behavioral evidence provides, we hope, compelling arguments for more systematic and reasoned decision processes. Furthermore, the second line of argument which stresses the need for such enhanced decision processes is underpinned by the sheer complexity of health security decisions. The dimensions of complexity in health security decisions are the topic of the next section.

1.2 Coping with Complexities in Health Security Decisions

In this section, we discuss the main complexities involved in making health security decisions against emerging health threats (see also Keeney (1982) and Hickson et al. (1986) for analyses of complexities in decision making). We classify these complexities into two large categories. First, there are those complexities inherently associated with the *decision context*, arising from the complex nature of the decision problem and of the decision settings. Second, there are complexities related to health security *decision processes*, due to the involvement of multiple stakeholders, decision makers and experts, as well as high stakes and politicized environments.

1.2.1 Coping with Complexities in the Decision Context

We now consider the main challenges in making health security decisions. The first set of challenges in making decisions for health security is that the decision context itself is complex, with unclear decision contexts, many relevant consequences, several key uncertainties, and some possible solutions that are difficult to choose from. The main sources of decision context complexity are described below.

Varied Perspectives There are almost invariably many lenses through which issues should be viewed to answer which problems should be addressed when wanting to enhance health security. This plethora of perspectives naturally arises from the many extensive potential impacts and consequences that health threats may cause (see also Mingers & Rosenhead (2001) for the relevance of multiple perspectives in complex policy problems). These multiple perspectives trigger several crucial questions. What are the core perspectives that relate to the decision situation? What is the exact decision problem that must be tackled? What are the ways in which we can enrich our understanding of these central issues?

Many Relevant Consequences Health threats have potentially extensive and severe consequences on human health, economies, and societies. Some of these consequences are tangible, such as the number of fatalities caused by a disease outbreak, the economic consequences of a pandemic, the social costs of risk mitigation actions such as quarantines and lockdowns, among others. Decisions makers must consider these multiple consequences and to which degree each health security alternative may work to reduce each one of these impacts. Which consequences are the most crucial to consider in a specific health security setting? How effective will a health security action actually be in mitigating those consequences? How should the relevant consequences be characterized?

Intangible Consequences For emerging diseases, both the tangible and the perceived consequences are of great importance, for these diseases have the potential to cause dreadful and unknown health consequences (Del Rio Vilas et al., 2013; Slovic, 1987), like those caused by the Ebola virus. These intangible impacts might exert great influence on human behavior, such as cultivating prejudices against communities seen as "causing" the disease, as was reported in the medieval period during the plague epidemics (Cohn, 2016). Therefore, intangible consequences must be considered in health security decisions even if the consequences are challenging to appraise. How should intangible consequences be adequately measured? How should they be considered in health security decisions? How should data regarding these "soft" issues be gathered?

Unclear Decision Context Associated with varied perspectives and coupled with the many consequences that health threats may cause, policymakers often struggle to clearly identify the decision context (see Keeney (1992) for a full discussion on the importance of defining clearly the decision context and Barcus & Montibeller (2008) for a process-focused perspective). What, then, should be *included* in a health security decision and equally, what exactly should be *excluded*? What are the time frames that should be applied when assessing potential impacts? What are the fundamental objectives to be pursued by policymakers in charge of managing the health threat? How narrow or wide should the scope be when searching for adequate solutions?

Numerous Possible Scenarios A major complexity encountered when planning how to increase the preparedness of health systems against health threats, or how to improve responsiveness once an outbreak starts, is the presence of numerous possible scenarios. There exists a very large number of pathogens and, among them, several have been identified as posing great risks to public health, due to their epidemic potential and/or the limited countermeasures available (WHO, 2020c). Although both variables are hard to estimate, the number of cases and the scope of the outbreak must be considered in these scenarios, as they are necessary in identifying the required resources and health capabilities. Consequently, which scenarios should be considered when planning against a health threat? How should these scenarios be defined? How should these scenarios inform the evaluation of health security actions?

Uncertainties Concerning Impacts One of the most difficult aspects of managing health threats and making health security decisions is the widespread presence of uncertainty (see also Morgan (2014) and Morgan (2017) regarding the role of uncertainty in policymaking). For instance, let us consider a pandemic scenario in the future caused by a virus. There exists uncertainties concerning the number of infected individuals, and of these infected individuals, one must consider how many will require intensive care and how many will perish. There also exists uncertainties regarding the social and economic impacts if a large proportion of the population becomes critically ill. Indeed the economic costs associated with preventive actions and palliative treatments is ultimately undetermined. Furthermore, uncertainties also relate to how long a potential outbreak will last. These uncertainties create inherent difficulties for health policy leaders to consider and weigh-in, as they must act in the present-day without knowing the exact circumstances of the future. Which uncertainties should be considered in preparedness and response decisions? How should the impacts from both threats and health security actions be considered in health security decisions? How should decisions be made under uncertainty in a way that maximizes the societal value of health security actions?

Limited Evidence Public health leaders and health experts may have limited high-quality evidence concerning these relevant consequences related to emerging health threats but nevertheless, are tasked with making immediate decisions. The high-quality evidence from systematic reviews of primary studies, the hallmarks of evidence-based medicine (Hunink & Weinstein, 2014) and evidence-based health policy (Cairney & Oliver, 2017), is significantly harder to be achieved when dealing with emerging health threats. Typically, the early evidence employed in these cases involves findings from initial studies, expert assessments based on surveillance data, and other "soft" sources of information. Which sources should be employed? How can the reliability of expert assessments be increased? How can expert judgments be debiased? Where should health leaders allocate efforts to improve the quality of data?

Dynamics of Impacts Many of the impacts caused by health threats have a dynamic behavior. We see this characterized by the number of cases in a given population (Brauer et al., 2019) or the ripple economic effects after a pandemic (see Meltzer et al. (1999)'s predictive model for an example). These dynamics make the parametrization of predictive models a scientific challenge and thus require careful consideration in a reasoned decision process. How should dynamic impacts be considered in a health security decision? For the impacts identified, how, then, can the assessment of relevant consequences be improved? Which are the best health security decision alternatives in the presence of dynamic impacts?

Critical Risks Many health threats pose critical risks to human life and health, such as potential deaths, or severe consequences and long-term sequelae (see Fischhoff et al. (1993) on the link between threats and risk). These risks must be properly mitigated, either by focusing on the ways that impacts caused by health threats can be reduced, or ways to reduce the probability of these threats occuring. How should

critical risks be defined in these decisions? How should critical risks be considered in a health security decision? How can we prevent or mitigate critical risks?

Long-Term Horizons Compounding the issues brought by multiple and severe potential consequences, most of them difficult to appraise precisely due to high levels of uncertainty, are the long-term horizons associated with possible outbreaks and health security actions (Osterholm & Olshaker, 2017). Many variables may have long horizons, particularly in large-scale pandemics: the duration of the outbreak itself (months or years), the duration of the consequences stemming from said outbreak (years or decades), the duration of measures implemented to better manage the outbreak (months or years), and the duration of policies to prevent or mitigate the reoccurrence of a similar event (years or decades). What, then, is the time horizon for the decision? How should the long-term impacts of both health threats and health security actions be considered? How should the benefits and costs of short-term versus long-term health security initiatives be appraised?

Limited Resources While health expenditure is relatively high for developed countries (on average US$4600/year per capita in 2009 (Plewes & Kinsella, 2012)), the share allocated to health security is necessarily limited, given the large commitments for regular health care expenditure on the one hand, and the potential direct and indirect costs associated with preparedness improvements on the other hand. Less developed countries are often faced with a very limited health budget (on average US$25/year per capita in 2009 (Plewes & Kinsella, 2012)), even when budgets are supplemented by international donations. For rich countries, the budgets against emerging health threats are constrained when compared with counter-terrorism and military preparedness (for example, since 2010 the USA has been spending on average US$180 billion/year on counter-terrorism efforts but only US$2 billion/year on pandemic and emerging infectious-disease programs; the budget in 2019 for the Pentagon was US$685 billion against US$7 billion for the Center for Disease Control (Power, 2020)). The constrained budgets stress the crucial concept that resources should be spent efficiently on the actions and programs that provide the highest value-for-money for enhanced health security. Which health security actions should be prioritized? How should the available resources be efficiently allocated? What shall be the consequences of supplementing or of downscaling a budget on the portfolio of available health security actions?

Difficulty in Identifying Good Alternatives The complexities described above pose a challenge in the identification of good decision alternatives to improve health security. Indeed, there is ample evidence that decision makers often consider a limited number of alternatives when dealing with strategic or complex problems (Das & Teng, 1999). Even harder than identifying good alternatives is the challenge of designing new and better options than the ones currently on the table, given the limited amount of time typically available to act when confronted with a health threat (see Keeney (1992) and Keeney (2013) on the relevance of creating better alternatives). Which health security actions should be considered in a decision? How can better decision alternatives be designed? How can the societal value of the decision be increased?

Table 1.1 Complexities in the decision context

Complexity in the decision context	Definition
Varied perspectives	Health security decisions bring about varied perspectives regarding which issues should be considered and which problems should be tackled all of which must be taken into account.
Many relevant consequences	Health threats have potentially huge and severe impacts which must be adequately considered. Additionally, the consequences of health security actions must be realistically assessed.
Intangible consequences	Health threats may trigger some relevant intangible consequences such as the dreadfulness and fear caused by emerging diseases. Despite the challenges faced when measuring intangible consequences, they should be considered in health security decisions.
Unclear decision context	Health security decisions often have an unclear context, which must be clarified to allow for reasoned decision making.
Numerous possible scenarios	There exists a possibility of numerous outbreak-related scenarios that may be caused by emerging health threats. Such scenarios must be adequately identified, detailed and considered when making health security decisions.
Uncertainties concerning impacts	Health threats trigger widespread uncertainties regarding their potential impacts and any health security decision is bounded by uncertainty. Reasoned health security decision making should consider these impacts in preparedness and response actions.
Limited evidence	Public health leaders and health experts may have limited high-quality evidence related to the relevant consequences of emerging health threats. The best evidence available should be gathered and, whenever necessary, reliable and debiased expert-based estimates may be included.
Dynamics of impacts	Health threats cause impacts that have dynamic behavior, such as the number of cases during an outbreak, which must be adequately considered in health security decisions.
Critical risks	Health threats typically cause critical risks to life and health that must be mitigated.
Long term horizons	Health threats may cause long term impacts and health security actions can have long term horizons. Health security decisions must adequately consider impacts and consequences that involve time dimensions.
Limited resources	Health threats must be adequately managed, and health security must be enhanced, with an optimal allocation of limited resources.
Difficulty in identifying good decision alternatives	Public health leaders should allocate maximum effort into the identification and development of high-value health security alternatives that increase health preparedness.

The complexities related to the decision context, summarized in Table 1.1, impose severe difficulties for making reasoned health security decisions without an appropriate decision making framework. This framework can inform the development of decision models that adequately represent the main components of a decision and support a health decision analysis (Howard, 1968; Keeney, 1982; Raiffa, 1968). In addition to the decision context complexities, decision processes also give rise to their own set of complexities, which shall be discussed next.

1.2.2 Coping with Complexities in the Decision Process

Organizational or multi-organizational decision making is essentially a process that involves public health leaders, health experts, and government officials. In such decision processes, stakeholders interact, discuss solutions, negotiate positions and, all being well, reach a conclusion concerning the best solution. The complexities involved in health security decision processes are as challenging as the processes belonging to the decision context itself, which were discussed above. The main sources of decision process complexity are discussed next.

Multiple Stakeholders There are always multiple stakeholders affected by and/or involved in health security decisions. Citizens, businesses, health organizations, health policymakers, scientists, advisors, and government representatives are all relevant stakeholders (see also the list of stakeholders in the context of the One Health approach that Mazet et al. (2014) compiled). Each stakeholder will have a very different role and perspective concerning the issues at stake, as well as influence and power, and must be properly managed (Ackermann & Eden, 2011). Some critical choices about stakeholders precede any decision on how to manage health threats and improve health security. Who should be involved in or excluded from the decision process? Which experts should be consulted? Which organizations should be considered as being appropriate participants?

Several Decision Makers Decision makers are those individuals whose role it is to sit at the decision table and whose shared responsibility it is to make decisions. Decisions are usually taken at a group level (Eden & Ackermann, 2001) by a health security team, which is typically composed of health leaders and government representatives although advisors and scientists may also be involved. A larger group encompassing a wide variety of perspectives results in a broader understanding of the issues at stake. On the other hand, groups may suffer from dysfunctional behavior and there exists a possibility of large groups becoming quite inefficient at making decisions under time pressure (see also Kerr & Tindale (2004)). Who, then, should sit at the decision table and who should be excluded? What are the responsibilities of each member of the health security team? How can the possibility of dysfunctional group dynamics be minimized? How can the decision efficiency of the health security team be maximized?

Power and Political Dynamics Power and politics play a crucial role in any important organizational decision process, including in health security decisions (see Pfeffer (2010) on power and their impact on decision making and Child et al. (2009) on the political aspects of decision making). Decision makers represent different stakeholder groups, with varying levels of power and influence. Therefore, there exists a power structure among the health security team, with a single individual (expectedly) being the ultimate decider. External organizations, such as other departments within a government, scientific bodies, lobby groups and businesses may all attempt to exert their influence. Political dynamics may play a detrimental role if not properly managed, impacting the quality of the decision, reducing the

commitment to implementation, delaying the decision process, and making the process itself more expensive and convoluted than need be. Thus, political dynamics must be properly managed. How, then, should power in health security decisions be effectively managed? How should power struggles be addressed? How can political behavior that may be detrimental to the decision process be managed?

Difficult Trade-Offs A challenging task for health policymakers and those responsible for health security is to make difficult trade-offs among conflicting objectives (see Keeney (1992, 2002) on trade-offs in decision making and Oliu-Barton et al. (2021) for a health security context). One frequent trade-off is balancing between short term investments in health preparedness with long term health gains. Another relevant trade-off is choosing between the efficiency of delivering preventive health initiatives, such as vaccination programmes against an emerging disease, versus equity in society. An example where the latter was prioritized over the former is well illustrated by the sheer cost and effort undertaken by the Brazilian army when vaccinating the population living in native Brazilian settlements (which are scattered around the Amazon forest) during nationwide vaccination campaigns in the previous century. Many other trade-offs are required in health security decisions, with costs being weighed against benefits. As these trade-offs are politically sensitive (Tetlock et al., 2000), often they are implicitly made in opaque decision processes, which may lead to poor allocation of resources. Which trade-offs should be made in a given health security decision? Which individuals should be responsible for making these trade-offs? How should decision makers approach and consider trade-offs and express their priorities?

Sensitive Risk Limits Public health leaders must adequately define risk limits, as they restrict the acceptable impacts and delimit the set of feasible decision alternatives. Different societies and organizations have distinctive risk limits, and these function to define how many critical cases can be incurred when considering policies for risk mitigation against a health threat (see Fischhoff et al. (1993) on the concept of acceptable risks in policy analysis). Once again, these parameters are politically sensitive (Tetlock et al., 2000) and are characterized by an element of uncertainty in public decisions. Opaque decision processes, which consider risk limits only implicitly, may lead to inadequate assessment and decisions that are inadvertently too risky or, instead, with unrealistic targets of zero risk. How should risk limits be defined? Which individuals should be responsible for setting risk limits? What is the impact of setting up an unrealistic risk limit?

Varied Expertise One of the most ubiquitous characteristics of issues related to health security is its interdisciplinary nature. Indeed, the One Health approach rightly emphasizes this multidisciplinary nature, which stems not only from the consideration of both animal and human health, but also from the various areas of expertise required to deal with health threats (WHO, 2020b). A sound analysis of the problem would require: (i) epidemiologists to provide knowledge about population-level health, (ii) physiologists and biomedical scientists to understand individual health, (iii) economists to assess the economic impacts and financial

costs, (iv) psychologists to inform about psychological aspects and impacts, (v) sociologists to understand impacts on micro and macro communities, (vi) risk analysts to model uncertainties, and (vii) decision analysts to represent the decision and support group decision making. When should each expert be deployed? What information should each expert provide? How can we debias expert opinion?

Expert Judgment Expert judgment is required whenever reliable predictive models are not available (such as when predicting transmission patterns in the early stages of a potential outbreak) or the scientific evidence is incomplete or inadequate (for example on the health impacts caused by an emerging disease). However, there is ample behavioral evidence that expert judgment may be biased by either cognitive or motivational biases (Gilovich et al., 2002; Kahneman & Tversky, 2000; Montibeller & von Winterfeldt, 2015). Therefore, it is important to adequately use the opinions and judgments of experts in health security decisions. How should information from experts be elicited? Which biases are more pervasive in expert judgments? Which debiasing tools should be employed in expert elicitation?

Imprecision in Estimates Estimates are always needed in any health security decision, given the uncertainties regarding the future (Morgan, 2017; Morgan & Henrion, 1992), the use of expert judgment (Morgan, 2014), and the need to prioritize objectives (Keeney, 2013). The adequate use of both future estimates and valuation judgments is key for reasoned decision making. However, the choice of the best health security actions may be sensitive to these estimates and judgments (Morgan & Henrion, 1992; Rios-Insua, 1990). Therefore, there exists a danger that biased or distorted estimates misrepresent the actual impacts of health security actions or prioritize health security objectives in an inadequate manner. Without a clear understanding of the sensitivity of the results on the input estimates, decision makers risk selecting an alternative that is not robust. How should the sensitivity of results to imprecision in estimates be analyzed? How robust are the solutions against such imprecisions? Which are the most relevant imprecisions that should be reduced?

Organizational Culture The organizational culture can promote reasoned decision making (Spetzler et al., 2016) or, instead, hinder it with opaque decision processes that are authoritarian, dysfunctional, inefficient, or protracted (Kerr & Tindale, 2004). A culture of transparency and accountability can aid in increasing the quality of health security decision processes, although this may require adequate governance structures and external oversight. How can transparency be promoted in decision processes? What should decision makers be held accountable for? Which behaviors should be incentivized, and which ones should be curbed, in decision making processes?

Implementation of Health Security Actions The successful implementation of health security actions is paramount to any successful health security initiative. Indeed, if the chosen alternatives are not implemented after the decision is made, it becomes truly irrelevant as to how well understood the decision context was, how well-designed and well-organized the decision process had been, and how carefully

chosen the alternatives were. The majority of the texts on decision making disregard this crucial aspect, whereby there exists an assumption that once a high-value option has been chosen, its implementation should be straightforward. However, implementation barriers are common, and many organizations struggle to move from *planning* to *acting* (Spetzler et al., 2016). How should implementation concerns inform decision making processes? How can barriers to implementation be alleviated? How can health security teams more rapidly transition from the planning stages to tangible implementation?

Systematic Learning Organizational learning is one of the most neglected aspects of the decision-making literature (Roy, 1993), but essential for both promoting high-quality decisions (Spetzler et al., 2016), and for improving upon previous decision successes and mistakes (Gregory et al., 1993). It is very difficult to learn at all from poorly designed decision processes due to haphazard flows of information, discussions, and choices. Furthermore, a lack of a clear conceptual framework can render decision makers unable to understand the main components involved in a decision, thus preventing the possibility to improve upon available choices. Decision makers may also struggle to learn about previous successes and mistakes (Soyer & Hogarth, 2020) without a transparent and clear decision process, which, if deployed, can effectively record agreed upon decisions and the reasons for selecting a decision alternative against the other options under consideration. How can decision learning be promoted? How should systematic learning be pursued? How can health security teams recursively learn during a decision process? How can decision makers learn from past successes and mistakes to improve subsequent decisions?

In Table 1.2 the complexities of health security decision processes are summarized. Taken as a whole, these complexities convey that it is very difficult to make sound decisions without a clear and well-planned decision process. Such a process should ensure that valuable inputs and perspectives from various stakeholders are properly considered. The process must also ensure that the participation of decision makers and experts is carefully managed, in a way that their inputs serve to benefit the quality of the decision making. In addition, the decision process should minimize the dysfunctional behavior of groups and stakeholders, while adapting to the organizational culture and promoting reasoned decision-making practices (Montibeller et al., 2020a).

This section presents several complexities that may exert severe influence on health security decisions. There exists several technical issues, such as multiple and uncertain impacts caused by health threats, which must be properly considered, utilizing the correct decision modeling tools. There also exists social elements, such as an extensive range of stakeholders and a group of decision makers, which equally must be suitably managed using adequate decision processes. Overall, health security decisions have high *socio-technical complexity* (see Mumford (2006) for an overview) which must be properly dealt with and wisely managed.

How are health threats evaluated in practice? How are health decision actions assessed on the ground? The next section describes how evaluations that inform health security decisions are typically made and discusses the benefits and shortcomings of each mode usually employed.

Table 1.2 Complexities in the decision process

Complexity in the decision process	Definition
Multiple stakeholders	Health security decisions are always related to multiple stakeholders, who have the ability to influence and/or be affected by such issues. These stakeholders must be properly managed during decisions processes.
Several decision makers	Health security decisions are typically taken by a group of decision makers, who may suffer from dysfunctional behavior. Health security teams should work efficiently and have dysfunctional behaviors minimized.
Power and political dynamics	Power and politics are present in any health security decision. Power should be adequately managed, and potentially detrimental political behavior minimized.
Difficult trade-offs	Trade-offs are inevitably required to identify priorities among conflicting health security objectives. Trade-offs should be carefully considered and clearly defined in health security decisions.
Sensitive risk limits	Risk limits must be adequately defined in health security decisions, as they limit the acceptable impacts and delimit the set of feasible decision alternatives.
Varied expertise	Health security decisions, given their multidisciplinary nature, necessarily require different types of expertise, which must be adequately employed.
Expert judgment	Expert judgment may be required in health security decisions in situations where reliable predictive models are unavailable, or, where the scientific evidence is incomplete or inadequate. Expert judgment should be reliable and unbiased in health security decisions.
Imprecision in estimates	Estimates, which may be imprecise, are typically needed in health security decision, both for current judgments and future estimates. The robustness of the solutions under consideration against these imprecise estimates should be assessed and considered.
Organizational culture	The organizational culture influences how health security decisions are made and therefore may hinder reasoned decision making. A culture of transparency and accountability can aid in increasing the quality of health security decision processes and should be promoted.
Implementation of health security actions	Barriers may prevent the implementation of health security actions chosen during reasoned decision processes. These implementation barriers should be minimized, so that actions can be implemented effectively.
Systematic learning	Organizational learning in health security decisions is challenging but crucial and should be promoted. Understanding the main components that constitute the decision can improve the choices. Systematically learning from previous successes and errors can improve subsequent decisions.

1.3 Evaluating Health Threats and Health Security Actions in Practice

Health leaders typically employ evaluation procedures to cope with the challenges and complexities involved in making health security decisions. Within the context of health security, this is a wise strategy, as even the most basic evaluation procedure allows for the possibility of responsible decision making that would otherwise be rendered impossible.(Johnson & Payne, 1985; Payne et al., 1993). And, thus, these assessments typically play a major role in informing health security decisions.

This section analyzes how both types of health security decisions: *How serious are emerging health threats?* and *what are the best actions to enhance health security?* are typically supported by evaluation procedures.

As previously mentioned, in the first type of decision, policymakers may wish to *categorize or prioritize* health threats, for example, a common practice is to define them as *low risk* or *high risk*. In the second type of decision, health risk managers may wish to *select* or *rank* actions to improve health security against an emerging health threat. For example, decision makers may wish to identify which is the best available vaccine against an infectious disease, therefore requiring the evaluation of the various vaccines in terms of their value-for-money. All the vaccines under consideration are classed as decision alternatives, while, the vaccine that maximizes value-for-money (the best decision alternative), should be chosen.

We suggest that there are three levels of assessment that are typically employed in practice. These assessments are archetypical modes, as many variations can be observed in practice from what is described here. The understanding of different assessment modes shall highlight why a health decision analysis may be helpful in increasing the quality of health security decision processes. Each mode is subsequently described, with a brief discussion on their advantages and shortcomings from a Decision Sciences perspective.

1.3.1 Level 1: Ad Hoc Assessments

In this level of assessment, evaluations are made in an ad hoc and informal manner, without a clear decision structure or decision framework underpinning the evaluations (Montibeller et al., 2020a). If the decision task is to *evaluate health threats*, policymakers informally gather extensive information and data in relation to the emerging health threats and informally assess the severity of the threat. If the decision task is to *select health security decision alternatives*, decision makers informally consider the advantages and disadvantages of each alternative, subsequently choosing the most suitable option(s).

While ad hoc assessments are a simple and rapid way of making decisions, the central issue that arises when employing this assessment mode is that it typically encourages low-quality decision processes. There is extensive evidence from

Behavioral Decision Research demonstrating that when confronted with a complex choice (Cowan, 2015; Larichev & Moshkovich, 1997; Miller, 1956), decision makers who are not supported by a clear decision framework resort to simplified and sub-optimal decision rules (mental short cuts) that hinder the quality of their decisions (Payne et al., 1993). For instance, decision makers may focus on a small subset of salient impacts while disregarding many other relevant ones (Tversky & Kahneman, 1973; Wänke et al., 1995). Decision makers may also struggle to consider all the relevant trade-offs that are required when making those choices (Keeney, 2002). Furthermore, there is a worrying possibility that crucial uncertainties and risks involved in the decision may be neglected (Jargowsky, 2005).

The behavioral evidence is clear that ad hoc decision assessments can lead to poor choices, due to both the over-simplification of the decision task (Payne et al., 1993), and the cognitive biases that affect the judgments required for choices under uncertainty in an unstructured decision processes (Gilovich et al., 2002; Kahneman & Tversky, 2000). These finding demonstrate that ad hoc assessments are unsuitable when making decisions as important as those concerning health security.

In addition to the deficiencies pertaining to ad hoc assessments, the lack of transparency during these decision processes renders decision makers unable to systematically learn from previous decisions, and as such, prevents the opportunity for improving upon decisions (Russo & Schoemaker, 2002). This opacity may also allow for health policymakers to be left unaccountable for their choices (Lerner & Tetlock, 1999). This evaluation mode is commonly employed in organizations and countries whose health security structures are less developed, and where the level of accountability is often low.

1.3.2 Level 2: Holistic Assessments

The second level of decision assessment encompasses those organizations and policymakers that make a holistic assessment (Arkes et al., 2009) of health threats and health security actions. If the decision task is to *evaluate health threats*, then policymakers would holistically consider all the possible impacts that these threats may trigger and classify each threat, such as "this threat is *high risk* while that threat is *low risk*". If the decision task is to *select health security decision alternatives*, then decision makers would typically holistically rank available options (usually from a smaller set) and select the leading option(s).

Once again, this is a simple and rapid method of making decisions. This is an improvement upon **Level 1** in that there exists a minimal element of formalism in the assessment. This method therefore allows for the comparison of both the health threats (*high risk* vs *low risk*) and the health security decision alternatives ("this option A_3 is better than other four available options").

In addition, there exists a foundational level of transparency, particularly concerning the prioritization of health threats ("we took some action concerning this health threat because it was assessed as being *high risk*"). To some extent, this can

also apply to health security decision alternatives ("we considered five different options, compared them and opted for option A_3").

However, it is important to consider that the available evidence from Behavioral Decision Research is also quite negative about this mode of assessment. Let us consider the practice of qualitatively labelling health threats. First, there exists ample evidence demonstrating that these labels are highly ambiguous in that what may be considered as a *high risk* option by one health expert may otherwise be considered as being *low risk* by another (Budescu & Wallsten, 1985; Wallsten et al., 1986). Second, it remains unclear as to whether the same type of impact is being considered to assess possible health threats when utilising this mode of assessment (if the number of casualties is a relevant consequence, is this impact being estimated when assessing each potential threat?). Consequently, the evaluation may not be sufficiently consistent and systematic (Keeney, 2014). Third, it is not clear whether the assessment is based on impacts or on the probability of an outbreak occuring (is the threat classified as *low risk* because the impacts are low or because the probability of the threat occurring is low?).

Similar issues that were identified in the discussion of **Level 1** also afflict these second types of evaluations. These issues involve the selection of health security decision alternatives, which are holistically ranked and the top option(s) selected. First, it remains unclear as to which impact has been considered and whether all available options have been assessed against the same set of criteria (Keeney, 2014). Second, the complexity in the assessment allows for the very likely possibility that sub-optimal mental decision rules are employed for the selection of the best option(s) (Payne et al., 1993). These decision rules may ignore certain relevant impacts, neglect important trade-offs, and disregard key uncertainties and risks.

Finally, for both categories of decision problems, *evaluate health threats* and *select health security decision alternatives*, this level of assessment promotes low levels of transparency and accountability. The behavioral evidence, as previously mentioned, is that holistic assessments may lead to low-quality decision processes and therefore poor choices. Unfortunately, this assessment mode is frequently used by countries and health security organizations that are managing health threats and making health security decisions.

1.3.3 Level 3: Simple Scoring Assessments

In this level of assessment, health threats and health security decision alternatives are assessed using scales (e.g. scores range from 1 to 5) and these scores are then somehow aggregated to provide an overall ranking.

Let us consider initially the first category of decisions, the *assessment of health threats*. Risk matrices are widely employed for risk management and this includes when conducting health threat assessments. This method typically consists of assessing each threat on two dimensions using a 1-to-5 scale: *severity* of the outbreak and *likelihood* of occurrence. These two scores are then multiplied to provide

an "expected severity" for each threat, enabling each threat to be ranked and prioritized.

One major benefit of risk matrices is the decomposition of assessments, into severity and likelihood, which has been shown by Behavioral Decision Research to produce more reliable estimates than holistic ones (Arkes et al., 2006). In addition, risk matrices allow for a ranking of threats that provides more granularity than the approach outlined in **Level 2**, as the joint scale (*severity* × *likelihood*) has 25 possible scores, instead of a few qualitative labels. Finally, risk matrices enable a greater level of transparency to be maintained than the approaches outlined in **Level 1** and **Level 2**.

However, there are some important conceptual problems associated with risk matrices (Cox, Jr., 2008; Thomas et al., 2014). First, the scale used is rather arbitrary – What exactly does a score of 1 mean in terms of *impact*? What does a score of 5 actually represent? The same is true for the *likelihood* scale; these scores are arbitrary. In some risk matrices, there are qualitative labels associated with these score points, but once again the labels themselves are vague (for example "5 = *high impact*", but what does exactly *high* mean?).

The second, and more technical issue associated with risk matrices, is that their scores should be considered as an ordinal scale, given how these impact levels are defined. Hence, the *impact* scores indicate magnitudes of impact, but do not necessarily convey information concerning the relative strength between two scores (see Krantz et al. (1971) on measuring scales). For instance, a score of 2 indicates a greater impact than a score of 1, but the score does not indicate how much greater the former impact measures against the latter one. A similar critique holds true regarding the *likelihood* scale. Importantly, ordinal scales should not be summated nor multiplied, but multiplications are performed in risk matrices.

The third problem that exists regarding risk matrices is that the multiplication of *impact* and *likelihood* scores may produce unhelpful results. For instance, consider a threat T_1, with a *likelihood* score of 5 and an *impact* score of 1 ($5 = 5 \times 1$). This threat would be ranked as having the same expected impact as another threat, T_2, that scores only 1 on *likelihood* but 5 on *impact* ($5 = 1 \times 5$). However, we can see that their underlying impacts may be quite distinct, while the risk matrix assessment gives the impression that both threats are equally significant.

Let us scrutinize the last issue with an example. We shall posit that threat T_1 is an outbreak of a cold, which triggers 100 potential deaths nationwide (*impact* score of 1) and the probability of event occurrence is that of 80% (*likelihood* score of 5); and that threat T_2 is an outbreak of meningitis, triggering 10,000 potential deaths nationwide (*impact* score of 5) and the probability of event occurrence is that of 10% (*likelihood* score as 1). In this example, the risk matrix would therefore be misleading, as the latter threat has a much greater expected impact than the former,[2] despite both threats having an equal 5-point score produced by the risk matrix.

[2] The expected impact of T_1 is $0.8 \times 100 = 80$ expected deaths and the expected impact of T_2 is $0.1 \times 10{,}000 = 1{,}000$ expected deaths. The second chapter introduces the concept of expected value, which is detailed in the ninth chapter.

For the second decision category, *select health security decision alternatives*, this level of evaluation consists of a score-and-weight procedure. The evaluation typically comprises three phases. First, relevant consequences are listed as evaluation criteria. Second, the performance of each alternative on a given consequence is evaluated using a 1-to-5 scale. Third, the scores for each alternative are summated for all given consequences and the alternative with the highest overall score is chosen. A more sophisticated version of this procedure weighs the criteria, rather arbitrarily, and then summates the weighted scores of each alternative.

We have observed many attempts to conduct these score-and-weight procedures and have researched the evaluations accordingly (Montibeller et al., 2020b). These evaluations have a similar level of advantages as the risk matrices when applied to this type of decision problem, in that the procedures promote a formal assessment of the decision alternatives on a set of criteria, enable decomposed assessments of the performance of each decision alternative on the criteria, and consider aggregation of performances into a single, overall score for each alternative. In this sense, score-and-weight procedures are much less ambiguous and more transparent than those assessments discussed in **Level 1** and **Level 2**.

Nevertheless, there are some intrinsic weaknesses associated with score-and-weight procedures. First, the 1-to-5 scores are arbitrary and lack clear anchors (what exactly does a score of 5, or a score of 1, for a given consequence, represent?). Second, these scores should be considered as being measured on an ordinal scale, which would therefore prevent summating differently scored impacts (*i.e.* a 1 score on economic impact should not be summated with a 1 score on health impact). Third, summating the scores assumes that all criteria have the same relative importance, which is often not the case. Even if one were to attach weights to the criteria, these are almost invariably arbitrarily defined and therefore lack any clear meaning with regards to trade-offs (Keeney, 2002).

These simple scoring evaluations are perhaps the most common way of informing health decisions in countries and health security organizations that have advanced protocols and procedures for health security evaluations. Scoring evaluations present a marked improvement from **Level 1** and **Level 2**. However, they lack any conceptual basis built upon Decision Sciences and, as discussed in the specialized literature, can provide illogical or inadequate recommendations to health policy leaders and health security teams (Budescu & Wallsten, 1985; Montibeller et al., 2020b; Wallsten et al., 1986).

A summary of these three levels of assessment formulated for the two categories of decision problems is presented in Table 1.3, which describes their evaluation process and presents the benefits and shortcomings pertaining to the assessments. Overall, each evaluation protocol has serious conceptual problems and may provide misleading results, potentially having a detrimental effect on health security decision processes that employ these protocols as input. These shortcomings can be fully addressed with the development of a health decision analysis as shall be detailed in this book.

Table 1.3 Assessment levels of health threats and health security actions

Assessment level	Type of decision problem	Evaluation process	Benefits	Shortcomings
Level 1: Ad hoc assessments	*Assessment of health threats*	Policymakers informally gather extensive information and data regarding the emerging health threats and informally assess how serious they are.	Simple and fast method of informing decisions.	Low-quality evaluation which over-simplifies the complexities of the decision problem. Ample behavioral evidence that it may lead to poor choices. Opaque choices that lack transparency and accountability.
	Selection of health security decision alternatives	Decision makers informally consider the advantages and disadvantages of decision alternatives and then select the best option(s).		
Level 2: Holistic assessments	*Assessment of health threats*	Policymakers holistically consider all the possible impacts that emerging health threats may cause and attach a label to each impact, such as "this threat is *high risk*".	Simple and fast way of informing decisions. There is minimal formalism involved in the assessment.	Simplistic assessments, which are likely to lead to poor recommendations and choices due to conceptually ambiguous and holistic evaluations. Low transparency and accountability.
	Selection of health security decision alternatives	Decision makers holistically rank the decision alternatives, considering informally their advantages and disadvantages, and select the top alternative(s).		
Level 3: Simple scoring assessments	*Assessment of health threats*	Risk matrices that assess each emerging health threat on two dimensions using a 1-to-5 scale: *severity* and *likelihood*.	Simple and fast way of informing a decision with an element of formalism within the assessment. There is a basic level of transparency and accountability.	Simplistic assessments, which are likely to lead to poor recommendations and choices due to conceptual weaknesses.
	Selection of health security decision alternatives	Score-and-weight assessments whereby each decision alternative is evaluated on a set of criteria using a 1-to-5 scale; scores are summated to provide an overall score for each alternative.		

1.4 Conclusions: Making Health Security Decisions – Challenges and Complexities

Emerging health threats pose complex challenges to public health leaders. In this chapter, we have explored the key challenges that these threats give rise to and analyzed the main complexities involved in health security decisions.

We have focused specifically on emerging health threats, as they are one of the most difficult categories of health threats to deal with, as they are characterized as being low-probability but high-impacts adverse events. Managing emerging health threats in an effective manner is critical to enhance health security.

We have argued in this chapter that decision making provides a key element in combining high aspirations to strengthen health security with the effective implementation of health security actions. Hence, this book is focused on health security decision making.

Despite the plethora of decisions that are required within the health security realm, we are able to classify these decisions as belonging to one of two major categories: the assessment of health threats, which leads to the decision of how serious each health threat is; and the evaluation and selection of health security decision alternatives that maximize societal value. In the chapters that follow, the book systematically covers these two categories.

The available Decision Sciences literature on decision making preparedness provides worrying evidence with regards to the potential low quality of decisions concerning emerging threats, particularly given their low-probability yet high-impact nature. As we have mentioned in this chapter, such decisions are frequently affected by a series of cognitive, motivational, and group judgment biases, which may inhibit adequate preparation against emerging health threats.

Public health leaders are also confronted with many complexities when making health security decisions. These complexities have been classified into two groups. The first encompasses complexities concerning the decision context which involve health security decisions. The second group of complexities consists of those related to the health security decision process.

These challenges and complexities indicate the need for an adequate decision framework and well-designed decision processes, particularly given the behavioral evidence related to the inherent cognitive limitations of decision makers and the prevalence of dysfunctional group decision making. Decision context complexities can be managed using a robust decision framework that allows for a full representation and responsible decision analysis of the situation. Decision process complexities can be tackled by well-planned decision processes, which are able to provide adequate levels of participation and varied perspectives, while still being efficient and focused on enhancing health security.

This chapter has also discussed common modes of evaluation utilized in health security decisions. The majority of the assessments employed to inform these decisions in practice, from ad hoc assessments to simple scoring tools, lack a firm scientific underpinning by Decision Sciences and may therefore lead to poor

conclusions and inadequate recommendations. These assessments are tools that are far too simplistic in nature to be deployed in such complex situations and thus, should be avoided.

Experienced health leaders are likely to have previous first-hand experience approaching the challenges and dealing with the complexities that have been discussed in this chapter. We anticipate that this systematic analyses, presented in this chapter, has helped to firmly establish the importance of further improving health security decision making.

Health security decisions require assessments that are able to adequately deal with and respond to the complexities inherent to decision making processes, and while these assessments should be made simple, they should not be simplistic. When making reasoned decisions, health leaders require a framework that is conceptually robust and based on the extensive developments from the field of Decision Sciences. This decision framework is introduced in the next chapter.

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Chapter 2
Making Reasoned Health Security Decisions: Key Concepts and Main Benefits



In the first chapter we have discussed the challenges and complexities involved when making health security decisions. In these decision situations, we must deal with multiple possible scenarios and their consequences, including the tangible and intangible impacts that any action (or inaction) may cause, the uncertainties concerning evidence and impacts, the trade-offs among competing priorities, and the risk limits on detrimental impacts. Moreover, the process of making such decisions is inherently complex, involving multiple stakeholders, experts, policymakers, and political actors.

We have also argued in the previous chapter that unstructured decision making processes should be avoided, given the sheer complexities of making such decisions and the inherent cognitive limitations of human beings. Simplistic assessments must also be avoided, as they may provide illogical or low-quality recommendations. We can better cope with these challenges and complexities if we implement a conceptually robust framework for making health security decisions. This chapter introduces said framework for reasoned decision making, which is aimed at enhancing health security.

We start the chapter by positioning this decision making framework within Decision Sciences. This scientific basis is important, as it provides an adequate conceptual background for understanding how decisions can be represented, analyzed, and improved. This conceptual positioning is followed by the important distinction between *decision processes* and *decision outcomes,* which stresses the relevance of improving the former when seeking to achieve the latter.

Subsequently, we briefly describe the main stages required for making reasoned health security decisions, which forms an overview of the chapters that follow. We also highlight the potential benefits of using a rigorous and Decision Sciences-based framework for making health security decisions.

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2.1 Researching Decision Making – Approaches in Decision Sciences

A large body of research studies decision making, under the *Decision Sciences* umbrella. One useful manner to classify this scientific field is to identify the three approaches that constitute the field (Bell et al., 1988; Dyer & Smith, 2020): *how decisions should be made*, *how decisions are actually made*, and *how decisions could be better made*. These approaches are underpinned by three distinct disciplines, respectively: Decision Theory, Behavioral Decision Research, and Decision Analysis.

This distinction of different approaches in decision making research is important for two reasons. First, when considering how to improve health security decision making, we must follow a robust conceptual foundation to establish recommendations for making reasoned choices. Second, this distinction of different approaches allows us to appropriately employ both theory and evidence from Decision Sciences without committing any conceptual errors. Unfortunately, such errors are frequently observed in both popular science literature and in some bodies of decision research, which therefore produce inadequate advice and misguided recommendations on decision making. Perhaps the most common conceptual error stems from the transforming of an *observation* concerning how a decision is made into a *recommendation* on how the decision should be made. While a given health security option may be frequently chosen in practice by public health personnel, the option itself does not necessarily mean that it is the best choice for the decision situation under consideration, and therefore the option should not always be prescribed to similar situations.

2.1.1 Understanding How Decisions Should Be Made: Decision Theory

The first approach to decision making, based on Decision Theory, establishes how rational decision makers should decide when considering a set of decision alternatives so as to maximize the value of their choices under uncertainty (see French (1989) for an overview). It is assumed that these rational decision makers have clear decision objectives they wish to pursue, stable and well-formed preferences, and an unlimited capacity of gathering and processing relevant information concerning the decision context.

Rational choices are *coherent*, as they follow a logical set of rules (axioms) regarding the evaluation, comparison and selection of decision alternatives. Rational decision makers *should* employ these logical axioms to identify the option with the maximum expected value according to their decision objectives and preferences, given the uncertainties within the decision context. Let us discuss the consequences of this conceptualization of rationality and present the axioms that rational decision makers should follow.

Substantive Rationality The definition of rational decision making that is stated above is, of course, an idealization; yet nevertheless, this idealization remains a useful concept, as it provides the golden standards for how we should decide. The definition employs the concept of *substantive rationality*, which is also adopted in Economics, whereby rationality is conceptualized in terms of the choices that the decision reasoning produces. Importantly, the concept enables us to predict choices that a rational decision maker should make if their decision objectives and preferences have been pre-established, and, if they have full knowledge of their decision situation (Simon, 1986).

Notice that, contrary to the lay usage of the word, *rational* here does not denote a *homo economicus*, who merely wishes to maximize profit or minimize costs, or who is devoid of preferences or values. Instead, rational decision makers can have multiple objectives and may consider risk preferences and trade-offs. However, these decision makers must be able to define reliable estimates regarding future events and should also have clear and stable preferences, without hesitancies or shifting opinions (Fischhoff, 1991; Slovic, 1995).

Axioms of Rational Decision Making The rational decision maker, as mentioned above, should follow a set of logical rules when making decisions. These rules guarantee coherence and the maximization of expected value when choosing a decision alternative (Keeney, 1982). These logical rules, formalized as axioms, shall be illustrated by this case:

> A public health leader is considering possible treatments against a given emerging health threat. There exist three treatments under consideration (Treatment A, Treatment B, and Treatment C), all of which incur identical implementation costs, socio-economic impacts, risks and benefits; the only exception being the possible number of lives saved, which therefore allow us to distinguish between these decision alternatives.
> In this decision problem, the decision maker wishes to *maximize the expected total number of lives saved* during a localized outbreak of this health threat, which has affected a given region over a well-defined time period.

If this public health leader were a *rational* decision maker, they should fulfill the following axioms (Keeney, 1982):

Axiom 2.1a *The decision alternatives can be specified and there are at least two alternatives.*

In this case, we know that there exist three available treatments: Treatment A, Treatment B, and Treatment C. Therefore, we can confirm that this axiom is indeed valid for this decision problem.

Axiom 2.1b *The consequences of each decision alternative can be specified.*

In this case, the consequence of concern (the overall number of lives saved during the outbreak) could be reliably assessed as:

Treatment A – which could save 10,000 lives;
Treatment B – which could save 12,000 lives;
Treatment C – which could save 5,000 lives.

Therefore, we can again assert that this axiom is valid for the decision problem.

Axiom 2.2 *The relative likelihood (probability) of each outcome can be estimated.*

In this case, the probability of the success of each treatment could be reliably estimated, as follows:

Treatment A – with a probability of 70% of success;
Treatment B – with a probability of 50% of success;
Treatment C – with a probability of 90% of success.

Hence, this axiom is valid for the decision problem.

Axiom 2.3 *The relative desirability for all the possible consequences of each alternative can be specified.*

In this same case, when we multiply the *probability of treatment success* by *the number of lives saved* we obtain the *expected* number of lives saved[1]:

Treatment A could provide 0.70 × 10,000 lives saved = 7,000 expected lives saved;
Treatment B could provide 0.50 × 12,000 lives saved = 6,000 expected lives saved;
Treatment C could provide 0.90 × 5,000 lives saved = 4,500 expected lives saved.

If the decision maker is willing to use this indicator to rank the treatments, the axiom is valid.

Axiom 2.4a *If two alternatives bring about the same consequences, the alternative yielding the higher probability of the preferred consequence must be preferable.*

Let us posit that a new Treatment D is discovered, which could also save 10,000 lives but whose likelihood of success is only 50%. In this case, if the decision maker still prefers Treatment A to Treatment D, since the former could save an equal number of lives whilst having a higher probability of success than the latter, then this axiom remains valid.

Axiom 2.4b *The preferences should be transitive, i.e., if an alternative is preferred to a second available alternative, and this second alternative is preferred to a third alternative, then the first alternative should also be preferred to the third alternative.*

Let us posit a new situation utilizing the same case wherein the decision maker considers Treatment A (7,000 expected lives saved) preferable to Treatment B (6,000 expected lives saved), and that Treatment B is also preferable to Treatment C (4,500 expected lives saved). Moreover, if the decision maker also prefers Treatment A to Treatment C, their preferences are therefore transitive, and the axiom is valid.

Axiom 2.4c *If an alternative is modified by replacing one of its consequences by a new set of consequences and associated probabilities (with the modified consequences being indifferent to their original counterparts), then the original and modified alternatives should be of equal value.*

[1] This book will focus on the concept of expected value for reasons that will be detailed in the ninth chapter.

Let us postulate that Treatment A has undergone a modification and now there exists a Treatment A′, which could save 7,000 lives and whose likelihood of success is 100%. The expected value of this modified treatment is thus calculated as:

Treatment A′ could provide 1.00 × 7,000 = 7,000 expected lives saved;

If the decision maker is indifferent toward treatments A and A′ this axiom is valid.

The need for Axioms 2.1 through to 2.3 is clear when conceptualizing decisions: we require decision alternatives (Axiom 2.1a), estimations of consequences for each available alternative (Axiom 2.1b), likelihoods for each outcome (Axiom 2.2), and a metric that allows for the comparison of the value of each alternative (Axiom 2.3). Axiom 2.4a is required to indicate how the alternatives should be compared. Axiom 2.4b allows for the comparison of more than two alternatives. Finally, Axiom 2.4c enables for the simplification of alternatives.

Note that a rational decision maker, as an idealized entity, *should* observe these four axioms. If all axioms are valid, then the decision alternatives can be compared by a single metric (in this book the alternatives are compared by their expected value), which will subsequently guide the choice of the decision maker.

In the same case, if the axioms hold, the expected value v(.) of each alternative can be computed as:

v(Treatment A) = 0.70 × 10,000 lives saved = 7,000 expected lives saved;
v(Treatment B) = 0.50 × 12,000 lives saved = 6,000 expected lives saved;
v(Treatment C) = 0.90 × 5,000 lives saved = 4,500 expected lives saved.

Therefore, we are able to compare and rank the alternatives, in terms of their expected value, and select the option that provides the highest expected performance, i.e., Treatment A:

v(Treatment A) > v(Treatment B) > v(Treatment C)

Here, the decision maker is making a *reasoned choice*. Said choice maximizes the expected value of the objective that they are pursuing (to *maximize the number of lives saved*) and is coherent in the way that the choice considers evidence regarding the performance of each treatment (*number of lives saved*) and aggregates information (*probability of success* times number of lives saved).

Additionally, beyond the function of exemplifying what constitutes a reasoned decision, the presentation of these axioms aids to illustrate that each axiom functions to formalize common sense. Since these axioms formalize logical and sensible rules for comparing decision alternatives, if the axioms themselves are not observed, the decision maker may not select the best decision alternative.

Let us consider the fundamental principle of transitivity of preferences (Axiom 2.4b), which functions to underpin coherent choices, to illustrate what happens when an axiom is not followed. If our hypothetical decision maker is taken as being intransitive, then they prefer Treatment A to B, and B to C, but then revert and prefer Treatment C to A. This intransitivity renders the decision maker more prone to exploitation when offered to exchange treatments for a fee, in that the decision maker becomes a "money pump" for an infinite number of exchanges (see Cubitt & Sugden, 2001).

As this example about intransitivity highlights, not observing an axiom may lead to illogical choices. Despite the logical appeal of these axioms, do individuals actually follow these axioms when making decisions? This is the research question that the subsequent Decision Sciences approach seeks to answer.

2.1.2 Understanding How Decisions Are Made: Behavioral Decision Research

The second approach to decision making is championed by Behavioral Decision Research, and studies how decision makers decide during unstructured decision processes. This area of inquiry is a branch of Cognitive Psychology that seeks to understand individual reasoning processes, judgments, and choices. Behavioral Decision Research has contributed to important findings since its inception as a result of the seminal papers written by Edwards (1954, 1961) (see Kahneman (2011) for an introduction and Fischhoff and Broomell (2020) for a detailed review). The field began with the empirical study of individual choices under uncertainty (see Kahneman and Tversky (2000) and Gilovich et al. (2002)). This line of research was subsequently extended and applied to decisions with conflicting objectives (e.g. Weber and Borcherding (1993) and Borcherding and von Winterfeldt (1988)). More recently, Behavioral Decision Research has shed light on how decision makers adapt their reasoning to the complexity of decision problems (Payne et al., 1992, 1993).

In parallel to these scientific developments, group judgments and group decision making have been extensively studied since the pioneering studies conducted by Asch (1956). These studies stem from the field of Social Psychology which, in this context, is preoccupied with the role of group dynamics and the influence of social pressure on judgments and choices (see Kerr and Tindale (2004) and Kerr et al. (1996) for details).

The overall conclusion of these behavioral decision studies demonstrates the existence of a boundedly rational decision maker (Simon, 1982), which is in direct contrast to the fully rational decision maker idealized by Decision Theory. By considering the existence of a boundedly rational decision maker, this Decision Sciences approach gives rise to major findings, three of which prove highly relevant to this book (see also Montibeller (2018) for details). First, these studies have identified a great number of biases intrinsic to judgments and decision making. Second, we are able to recognize that, among these many biases, some are particularly relevant for quantitative decision models. Third, by taking into account the inherent cognitive limitations that affect decision makers, we can determine the impacts these limitations have on choice processes. Let us briefly review each of these findings.

Cognitive and Motivational Biases A considerable number of systematic cognitive biases in judgment and decision making have been identified since the 1960s (Gilovich et al., 2002). Judgments and choices are considered as being biased when they diverge from the normative responses established by Decision Theory concerning future estimates and preference judgments.

The standard experimental design of behavioral studies (Leary, 2016) when observing judgment biases is to develop hypothetical judgment tasks and compare the response of each subject with the axioms of rationality. Accordingly, the studies compare the actual choices made by each subject to the choices that *should* have been made by the subjects were they to be rational decision makers. Beyond the setting of behavioral laboratories, there exists evidence that experts and decision makers also suffer from these biases in real-life situations (Koehler et al., 2002). A few of these cognitive biases have been mentioned beforehand in the first chapter, which discusses their propensity to act as hinderances against effective health preparedness, such as the availability bias (Tversky & Kahneman, 1973) that causes decision making amnesia.

Motivational biases are also significant in that they affect expert judgment and decision making. Motivated reasoning occurs when experts and decision makers (Kunda, 1990) selectively gather positive information pertaining to a decision alternative while neglecting its innately negative aspects (Seybert & Bloomfield, 2009). Similarly, decision makers may selectively gather data pertaining to the negative consequences of an alternative that is initially disliked (Dolinski et al., 1987).The optimism bias that was mentioned in the first chapter is an example of a motivational bias, in that the bias prevents adequate health preparedness. There also exists ample evidence regarding the dysfunctional behaviors that arise when a group of individuals makes decisions (Kerr et al., 1996; Kerr & Tindale, 2004). These behaviors have a detrimental impact on group motivation and productivity, and may generate group judgment biases (Jones & Roelofsma, 2000; Kerr & Tindale, 2011; Montibeller & von Winterfeldt, 2018).

We shall posit a case wherein a health expert has been requested to estimate the possible number of cases of an Ebola outbreak within an African country that shall occur within the next year, assuming the hypothetical scenario wherein an infected but asymptomatic person arrives from abroad in that country. To make this judgment in a reliable and unbiased manner, following the rationality standards, this expert should consider all the available information concerning previous outbreaks in Africa, and adjust their estimate to the specific country wherein the outbreak would occur. However, we know that this judgment may be biased. The judgement produced by our expert, if anchored to an irrelevant factor, may suffer from the anchoring bias (Furnham & Boo, 2011). Were the judgement to be excessively focused on recent evidence from other countries, which may not reflect the situation in the decision context wherein the health threat is situated, the judgement may be affected by the availability bias (Tversky & Kahneman, 1973; Wänke et al., 1995). Both anchoring and availability are cognitive biases caused by faulty reasoning. The expert may also suffer from optimism bias, if they were to consider the problem as being unlikely to occur in their country (Krizan & Windschitl, 2007). This is a motivational bias, stemming from motivated reasoning that does not wish to contemplate the possibility of the adverse event occurring. On the other hand, if a group composed of health experts were to discuss and agree on this estimate, their group estimate may become polarized in that the estimate may be too extreme in comparison to the original individual estimates (Lamm, 1988). Group polarization is an example of a group judgment bias.

These biases are systematically observed as affecting judgments and choices and as a result, a considerable number of biases has been identified. Which biases are considered as being the most relevant and, therefore, should be debiased in health security decisions? The subsequent categorization may help with this identification.

Relevant Cognitive and Motivational Biases We are able to classify cognitive and motivational biases into three categories, in terms of their relevance for quantitative decision modeling and strategies for debiasing judgments (Montibeller & von Winterfeldt, 2015).

First, there exist biases that occur in unstructured decision making, whereby experts and decision makers are not fully aware about biases and their negative consequences to decision making quality. One relevant example in this category is the hindsight bias (Blank et al., 2007; Roese & Vohs, 2012), which occurs when there appears new, relevant information that was not previously available when the decision was originally made. Decision makers may be tempted to re-evaluate the quality of their decision utilizing this new information, which constitutes an irrational assessment. An awareness concerning these biases should be enough to avoid them occurring.

Let us consider the swine flu pandemic in 2009. The World Health Organization (WHO) decided to categorize the emerging health threat as a pandemic, a judgement which was predicated on the evidence available at that time and the potential risk of serious illness and spread of the virus. The outbreak itself led to a relatively small number of fatalities, which triggered severe criticism of the WHO for "overreacting" (Mackenzie, 2020). This criticism, in our view, can be explained by hindsight bias. The decision to denominate the outbreak as a pandemic was evaluated a posteriori, once all the data and evidence related to the relatively limited impact of the outbreak could be gathered and analyzed. However, this information was understandably not available to WHO at the time when the decision to denominate the outbreak as a pandemic was made.

Second, there exist biases that can be corrected with some logic and reasoning. For example, the behavioral research on transitivity which was conducted in behavioral laboratories, has found that subjects may violate this axiom. As we mentioned previously, if we apply this violation to our choice of treatment case (particularly the discussion of Axiom 2.4b), we see that intransitivity would lead to a decision maker preferring Treatment A to B, then B to C, but reverting and preferring treatment C to A (see Cubitt and Sugden (2001) for a detailed discussion on this bias).

In practice, intransitivity usually occurs when the decision setting is not well-defined. This ill-defined decision setting can occur when decision makers are considering a different temporal dimension when comparing options, or when comparing other consequences that were not explicitly listed. The solution for this form of faulty thought process is one which seeks to clarify the decision setting and demonstrate the logic behind the bias (Montibeller & von Winterfeldt, 2015). For instance, the issue of intransitivity can typically be resolved by *clarifying* and *specifying* the precise nature of the decision context and the decision alternatives. A logical explanation should be enough to avoid this type of bias.

Third, there exist biases that heavily impact the quality of judgments which are required by the normative axioms (Montibeller & von Winterfeldt, 2015). Let us consider three of these axioms and continue with our choice of treatment case from the previous section: Axiom 2.1a, Axiom 2.1b, and Axiom 2.2.

The normative Axiom 2.1a requires that all relevant decision alternatives be specified. However, there exists ample evidence that decision makers suffer from the omitted variable bias (Jargowsky, 2005), and thus, may neglect important options during their decision making (Butler & Scherer, 1997; Pitz et al., 1980). In the context of this book, this is a relevant bias, as this cognitive bias heavily impacts the quality of a health decision analysis (Montibeller & von Winterfeldt, 2015).

The normative Axiom 2.1b requires that the consequences of implementing each alternative be estimated in a reliable manner. However, there exist motivational biases that may affect these estimates. This occurs at times due to wishful thinking (Seybert & Bloomfield, 2009; Vosgerau, 2010), which is a type of desirability or a positive outcome bias (Krizan & Windschitl, 2007; Tichy, 2004), and may lead experts to overestimate the benefits related to one of these treatments.

The normative Axiom 2.2 necessitates that the probabilities of outcomes be estimated. In practice, there often exists insufficient or unreliable data that can be employed when making reliable predictions, particularly concerning relatively rare events, including emerging health threats. In situations such as these, we must rely on expert judgment (Morgan, 2014). If we relate this scenario to our case, the health expert could be asked to provide the likelihood of success for each treatment. However, these judgments may be distorted by a series of cognitive biases, such as the anchoring bias or the availability bias.

While the entire body of research focused on biases is highly relevant for understanding how humans make decisions, the category of biases described above proves the most relevant category in the context of this book. These are biases that affect the validity of the axioms for rational decision making or distort judgments against rationality standards. Consequently, these biases have a tangible impact on the quality of any decision analysis and therefore, we must debias these judgements (Montibeller & von Winterfeldt, 2015, 2018). We detail these biases throughout the chapters of this book. Notably, we underscore the presence of a bias whenever a judgment is required for a health decision analysis, and discuss how these judgements can be debiased in practice.

What are the causes of these biases? Cognitive and motivational biases stem from three sources of errors pertaining to their psychological origins (Arkes, 1991). Strategy-based errors occur when decision makers employ a suboptimal cognitive strategy to make a judgment, such as intransitive preferences. Association-based errors are a consequence of faulty automatic mental associations, which may lead to biases such as the omitted variable bias, the availability bias, or desirability of a positive consequence bias. Finally, psychophysically-based errors result from the incorrect mapping between the evidence and the judgment, which causes errors such as the anchoring bias (see Montibeller and von Winterfeldt (2015) for details).

Cognitive Limitations in Decision Making Humans have inherent cognitive limitations concerning the holding and processing of multiple pieces of information, particularly with regards to short-term memory, as indicated by the classical studies conducted by Miller in the 1950s (Cowan, 2015; Miller, 1956). These cognitive limitations present two relevant issues that affect decision makers responding to complex decision problems.

First, important components that constitute decision problems were found to be omitted in choice processes (see Montibeller and von Winterfeldt (2015) for details). For instance, decision makers often ignore relevant future scenarios when making decisions under uncertainty (Thomas et al., 2008). Decision makers are also known to frequently consider only one or a few decision alternatives (Butler & Scherer, 1997; Nutt, 1998). Even more remarkably, decision makers may disregard relevant decision objectives in their choices (Bond et al., 2008).

Second, decision makers greatly simplify their mental representations of a given situation when decision problems become more complex (Legrezni & Girotto, 1996). This simplification process often eliminates relevant decision objectives and decision alternatives. Additionally, decision makers may employ sub-optimal cognitive strategies (decision rules) for their choices (Payne et al., 1992, 1993).

These simplifications stem from the highly adaptive human reasoning that takes place during unstructured decision processes (Payne et al., 1992, 1993), which are focused on negotiating the two cognitive goals of accuracy and effort. Generally, the more cognitively complex the choice (i.e. a greater number of decision alternatives, consequences and uncertainties), the further the cognitive strategy drifts from the rationality standards defined by Decision Theory. In these complex choices, simple cognitive heuristics typically replace the axioms.

While some specific heuristics may be successful in guiding particular choices (Gigerenzer & Gaissmaier, 2011), these heuristics may cause a deterioration in decision quality which allows for sup-optimal choices (Spetzler et al., 2016). This deterioration is particularly concerning in the context of high-stakes choices under uncertainty, whose decision objectives are at times conflicting, such as the situations involved in health security decisions.

For instance, one cognitive simplifying strategy (a heuristic) involves the removal of decision alternatives that are above or below a certain threshold, which has the effect of reducing the complexity of the choice. If we apply this heuristic to our previous case, wherein the health expert must select one treatment among the three available options, the boundedly rational decision maker is able to simplify the choice by disregarding treatments that save fewer than 5,000 expected lives. This heuristic would eliminate Treatment C (4,500 expected lives saved), thus reducing the choice to a binary selection between Treatments A (7,000 expected lives saved) or Treatment B (6,000 expected lives saved). We can see that this heuristic would still provide a solution whose outcome is identical to that which a rational decision maker would have produced (Treatment A).

However, let us posit another heuristic: the disregard of probabilistic information concerning the treatments, which therefore ignores the uncertainty in the decision problem. This heuristic would lead to our boundedly rational decision maker to

select Treatment B (12,000 lives saved). In actuality we can see that the choice of Treatment B (6,000 expected lives saved) would lead to 1,000 fewer expected lives saved than Treatment A (7,000 expected lives saved). Evidently, this choice is not identical to that which a rational decision maker would select (Treatment A) and therefore, Treatment B is of poor decision quality. This heuristic contradicts the rational decision rule we should employ when deciding under uncertainty, which entails defining probabilities of scenarios and maximizing expected value.

Two approaches to decision making have been presented thus far. The first approach formalizes how a rational decision maker (who is pursuing decisions objectives, has clear preferences, and is confronted by uncertainty) should coherently decide among decision alternatives to maximize expected value. The second approach assesses that humans are at times significantly removed from these rationality standards of decision making, and identifies biases and over-simplifications that may occur during unstructured decision processes. How, then, can we make reasoned decisions despite our inherent cognitive limitations and potential biases? It is this question that the third approach in Decision Sciences seeks to address, and shall be detailed in the subsequent section.

2.1.3 Understanding How Decisions Could Be Better Made: Decision Analysis

The third approach to decision making is championed by Decision Analysis, and consists of developing methods that are able to support decision makers to make better decisions and promote *reasoned choices*. There exists a large body of literature that is focused on this field, see von Winterfeldt and Edwards (1986) for an excellent exploration that is also tied to Behavioral Decision Research, Eisenführ et al. (2010) for an accessible text book, and Hunink and Weinstein (2014) for a focus on healthcare decisions. For literature that focuses on Risk Analysis (a sister field to Decision Analysis which is also relevant for decisions under uncertainty), see Morgan and Henrion (1992) for a comprehensive coverage and Morgan (2017) for literature that is also linked to policy analysis.

Decision Analysis has been extensively, and successfully, employed to support better decision making in a variety of fields, and there exist some excellent books concerning the application of methodology to specific categories of problems. Facility location problems (Keeney, 2014), environmental decisions (Gregory et al., 2012), corporate applications such as new investments (McNamee & Celona, 2005), homeland security (Abbas et al., 2017), and health care decisions (Hunink & Weinstein, 2014) are all specific categories of problems that have been explored by Decision Analysis.

While health security decisions share many of the complexities that are also intrinsic to other categories of decision problems, specific elements related to health security decisions create their own specific challenges. These challenges are generated due to dynamic impacts triggered by health threats, the low-probability high-consequences nature of health threats, and the central role of risks in this type of

societal decision. Additionally, in comparison to typical healthcare decisions, there exists a high level of uncertainty and many other impacts to be considered beyond the consequences to individual health. On the other hand, the current literature on health security (e.g. Rushton & Youde, 2018; Masys et al., 2020) is mainly centered around institutional issues, and therefore not focused on the support to enhanced health security decision making.

Decision Analysis provides an effective methodology to tackle the challenges and complexities intrinsic to health security situations through providing a strong conceptual framework for making reasoned health security decisions. Decision Analysis employs suitable external representations concerning the decision problems (Eisenführ et al., 2010; Howard & Abbas, 2016), defines adequate methods to elicit and aggregate information (Dias et al., 2018), and provides support to identify the best decision alternatives that maximize societal value (Keeney, 1982, 1992).

Decision Analysis employs the axioms of rational decision making, while considering the behavioral aspects involved when decision makers and experts exert judgments and make decisions. This decision making methodology can allow for decision processes to become more coherent and comprehensive (Phillips, 2007), and, simultaneously, enables for the biases in judgments to be reduced and for the dysfunctionalities in group behavior to be minimized (Montibeller, 2018; Montibeller & von Winterfeldt, 2015, 2018).

Let us return to a previously described case, wherein a health expert has been tasked with estimating the number of potential Ebola cases in an African country during a hypothetical outbreak scenario. Prescriptively, we wish to ensure that the judgments of our health expert are debiased and accurate. This requires several carefully defined steps within the analysis: (i) defining the scenario from which the estimate is derived in a precise manner (the manner in which the asymptomatic case arrives, the persons that this individual comes into contact with, and so on); (ii) elucidating all the assumptions that shall be used to make the estimate; (iii) and employing debiasing tools to minimize the possible biases in this estimate (e.g. removing anchors and minimizing the excessive focus on evidence or information that has recently become available).

If a group of experts were to be involved in this estimate of Ebola cases, additional care should be taken to avoid group polarization (Lamm, 1988). To minimize this bias, experts may be individually tasked with producing their initial estimates, and then disclosing and justifying these estimates to the other members of the group. Outliers derived from the estimates are therefore able to be further scrutinized, as individual members may have employed different assumptions, which could therefore produce valuable information. Through employing this expert elicitation protocol, an estimate which has been agreed upon by the group can be defined.

The principal objectives of Decision Analysis are to guide reasoned choices (Hammond et al., 1999) and to support systematic learning in decision processes (Roy, 1993). These goals are accomplished through a clear understanding of the decision problem, a better appraisal of the possible consequences that stem from implementing different decision alternatives, a more comprehensive assessment of the key uncertainties and risks, and a transparent perspective concerning the required trade-offs that each choice encompasses.

This book follows the third approach from Decision Sciences: how decision could be better made. The content of this book aims to assist public health leaders, health security teams, and health experts in making reasoned health security decisions. This aim is accomplished by representing decision problems utilizing Health Decision Analysis and structuring decision processes in such a way that they function to underpin high-quality decision making.

However, important decision insights are also derived from both Decision Theory and Behavioral Decision Research, after all, these three approaches of Decision Sciences provide research triangulation on decision making. Consequently, we shall mention these approaches throughout the text whenever they prove useful or relevant. Among these insights, a key component is the distinction between decision processes and decision outcomes, which shall be discussed next.

2.2 Distinguishing Between Decision Processes and Decision Outcomes

In decisions under uncertainty, decision makers are unable to establish a priori the precise performances of their decision alternatives, as key uncertainties affect said performances. In the previous chapter, we established that every important health security decision necessarily involves uncertainties. Hence, we must recognize that choices may not bring about the benefits that were originally intended, or reduce negative impacts as was originally planned. This is because uncontrollable factors influence these consequences.

Let us posit a carefully planned quarantine which has been established to prevent the spread of an emerging contagious disease, however, there exists the risk that the quarantine may fail if citizens do not abide by quarantine rules. This risk constitutes an uncontrollable factor, that health policy makers may not be able to fully assess. In this case, the uncertainty as to whether people would obey the quarantine mandate or not impacts the effectiveness of the quarantine policy.

As such, due to the intrinsic factor of uncertainty in health security decisions, we should *not* evaluate the quality of a decision based on its outcome (Howard, 1988). Furthermore, we should not, necessarily, reward decision makers that were responsible for a decision that produced successful outcomes. Likewise, we should *not*, automatically, penalize decision makers that were responsible for a decision that led to unsuccessful outcomes.

Consider two health policy makers that are working in different countries while managing the same emerging health threat, and find themselves confronted with the option to implement a quarantine mandate. The policy maker in the first country carefully considers the advantages and disadvantages of establishing a quarantine and decides to impose it. However, the country has few social sanctions to condemn the breaking of imposed rules, and as a result, the quarantine is widely violated triggering a great of number of infections. The policy maker in the second country is impulsive and takes the decision to impose a quarantine, although there was a minimal deliberation of its consequences. However, the citizens in this second

country regularly engage in social sanctioning to enforce legal compliance, and the decision aids in minimizing the number of infections. Which decision maker should we consider as being better?

If a society rewards positive outcomes, decision makers that have a stroke of luck may be favored (in the quarantine case described above, the decision maker that lives in a law-abiding society). On the other hand, if a society penalizes the unsuccessful outcome, this penalization may be damaging toward high quality human resources, particularly if competent public health leaders whose decisions have been affected by external, uncontrollable, factors were to be dismissed (in the same quarantine case, subjects that disregard newly imposed social norms and legislation). This phenomenon is termed as an outcome bias (Mazzocco et al., 2004), which is a well-known phenomenon that occurs during unstructured decision making processes, and is a highly detrimental bias that should be avoided.

Additionally, many of the uncertainties in policy making are irreducible (Hammond, 1996). This type of uncertainty cannot be reduced or eliminated merely by increasing or gathering more evidence, nor can the uncertainty be eliminated by allocating more time to make the decision. In our experience, this element of irreducibility of some uncertainties is at times frustrating for scientists in charge of making policy recommendations, as they wish to have gathered all the evidence before issuing a policy recommendation. Policy makers, on the other hand, typically recognize that they must often decide with only partial evidence, and that delaying the implementation of a policy is not always a sensible option.

How, then, should we improve decision making, if outcomes are not fully under our control and policy choices have irreducible uncertainties? The only factors that decision makers are able to fully control is the ability to carefully plan, design, and execute decision processes that underpins a choice (Spetzler et al., 2016). These processes encompass many meta-choices concerning the decision process, which all work in tandem to heavily influence the choice itself: which stakeholders should be considered? Who should sit at the decision table and who should be excluded? Which decision problem should be analyzed? Which scenarios should be considered? Which consequences should be taken into account when assessing the different health security actions? Which key uncertainties should be included? Which decision alternatives should be appraised? Which experts should be consulted and what shall they contribute? Who should define the trade-offs required when multiple consequences must be considered? Who should establish risk limits that identify acceptable and unacceptable risks? How should these trade-offs and risk limits be defined? How should we plan the implementation of the choice? How should we systematically learn during and from decision processes?

Hence, the design of an efficient and reasoned decision process ultimately forms a foundation on which public health leaders are able to improve upon the quality of health security decision making. In this book we demonstrate the manner in which we can improve the quality of these decision processes for enhanced health security, an overview of this framework is presented in the subsequent section.

2.3 Making Reasoned Health Security Decisions

There exist seven main stages for making reasoned decisions for health security, which are represented by Fig. 2.1. The figure indicates the main complexities pertaining to each decision stage, which were discussed in the previous chapter. These are the complexities that we must confront during the decision stage and shall be greatly alleviated by the use of the decision-making framework described in this book. Additionally, the figure indicates the main input(s) into a decision stage, as well as the output(s) from a decision stage. For example, the decision stage *specifying relevant objectives and consequences*, has as inputs: the *problem definitio*n and the *consequences* of decision alternatives (in-arrows to this stage). The same decision stage has as an output: relevant *consequences* associated with the related objectives (out-arrows from this stage).

Three main components constitute this decision making framework. The *modeling the decision problems* component is based on Decision Analysis (Howard, 1968; Raiffa, 1968) and its extension to decisions with conflicting objectives (Keeney & Raiffa, 1993). The *sequence of decision stages* is based on the best practices for Decision Analysis interventions for complex decision problems (Keeney, 1982; Spetzler et al., 2016). The *behavioral and organizational insights* are drawn from the extensive literature on Behavioral Decision Research and Organizational Decision Making studies that are relevant for Health Decision Analysis (Montibeller et al., 2020a; Montibeller & von Winterfeldt, 2015, 2018).

This section provides a brief overview of each decision stage, which shall be expanded upon in the subsequent chapters of this book. Through our experience in supporting complex health security decisions, we have observed that this decision making framework has benefits both for decision making content and decision making processes. First, if adequately employed, the framework has tangible impacts on the quality of decisions that are made. Second, a systematic decision process enables policy makers and health experts to employ their time more efficiently, engaging in a more effective and productive manner. Third, Health Decision Analysis allows for more reasoned, justified, and evidence-based decisions that maximize societal value.

2.3.1 Framing Health Security Decisions

The first, and perhaps the most important stage when making reasoned health security decisions is the framing of the decision problem. During this stage, it is essential to specify and delineate the exact problem that must be tackled or the decision situation that must be addressed. We should also identify the exact decisions that must be made in order to solve a health security problem, or the available choices that must be implemented to enhance health security. These decision situations are typically ambiguous and consequently, the decision problem must be adequately framed if we wish to reveal a new field of successful solutions.

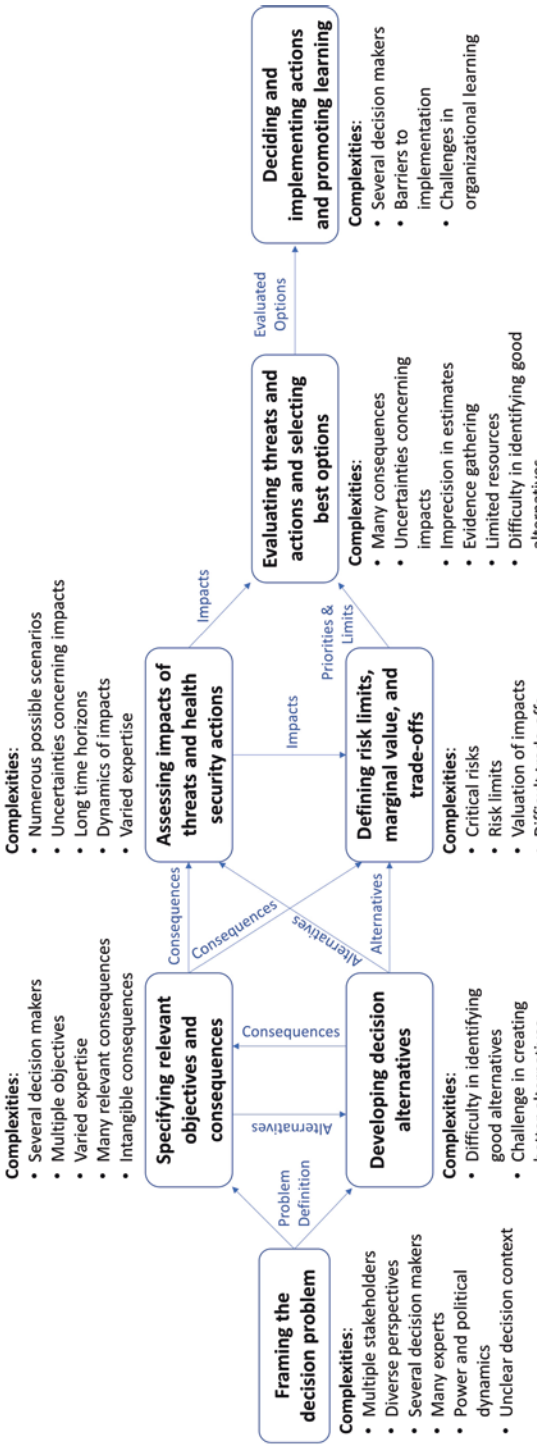

Fig. 2.1 Making reasoned decisions for enhanced health security

An excellent illustration on the importance of problem framing is demonstrated by the early policies implemented by different countries in response to the COVID-19 global pandemic in 2020. East Asian countries that were successful in managing the initial outbreak (such as South Korea) framed the problem as a SARS-like pandemic. On the other hand, some Western countries framed the outbreak as an Influenza-like pandemic (Horton, 2020), which is typically less deadly than SARS pandemics. The full initial responses of each country was consequently bound by this early problem framing, and therefore some time was taken before said Western countries adjusted their initial assessment regarding the nature of the problem (Calvert & Arbuthnott, 2021).

In health security settings, the decision making group is often composed of health experts, health policy makers, and other advisors. There exists ample evidence from social psychology that varied groups increase the quality of decision making, as these groups can bring different perspectives, expertise, and experiences. Therefore, the participation and engagement of key stakeholders must be properly planned. However, this process of engagement and participation should also be carefully managed, to reduce dysfunctional group behaviors and minimize group judgment biases (Kerr et al., 1996; Kerr & Tindale, 2004; Montibeller & von Winterfeldt, 2018).

Hence, it is critical to identify which individuals should be involved and how each individual should contribute to the decision process. As in any strategic decision, power and political dynamics play a crucial role in these decision processes and must therefore be carefully managed (Child et al., 2009; Pfeffer, 2010).

The third chapter discusses in detail how we can improve problem framing in health security situations. This stage involves taking into account different perspectives, managing the participation of decision makers and health experts, and managing power and political dynamics. Managing this decision stage allows for the clarification of the decision context regarding situations which are intrinsically complex and challenging. Importantly, this decision stage forms a foundation on which we are able to make reasoned health security decisions.

2.3.2 Specifying Relevant Objectives and Consequences for Health Security Decisions

With every health threat, there emerges a potentiality of multiple tangible and intangible impacts that constitute a threat to individual health, societies and economies (Montibeller et al., 2020b). Therefore, multiple objectives must be established to prevent or mitigate these potential impacts, and policy makers and public health leaders must consider: reducing or avoiding damage to individual health, minimizing health impacts at a population level, controlling economic losses, avoiding or minimizing social disruption, and reducing the costs associated with the implementation of risk mitigating actions. A clear understanding of these decision objectives and their related consequences is therefore crucial to reasoned health security decisions (Keeney, 1992, 2013).

Quarantine mandates epitomize long-established measures that are implemented in the event of a potential health threat. We shall now turn to and discuss decision objectives that were pursued to manage outbreaks that occurred during the nineteenth century, among which were quarantines. This was an epoch characterized by the first wave of globalization (Harrison, 2004), and as such, a complex network of structures formed specific conditions, producing an arena of possibilities for the spread of diseases. The specific historical situation of a growing maritime trade therefore enhanced the potential for disease to spread across developed countries (particularly cholera and yellow fever from the tropics, and bubonic plague from West Asia).

Quarantines were considered by the governments as a means of avoiding infection and deaths (health objectives), despite there existing scientific uncertainties concerning the manner in which these diseases were transmitted. However, stakeholders whose interests pertained to the freedom of commerce frequently objected to quarantines, on the grounds that they not only reduced trade (an economic objective) but also caused unemployment and poverty (socio-economic objectives).

Historically, during these nineteenth century pandemics, different countries would favor health or socio-economic arguments, depending on their previous experiences with a disease, the influence of health experts that drove the policy, and the relative power of their different stakeholders. In our current era, the COVID-19 global pandemic which started in 2020 is a stark reminder of how these societal priorities have driven different policies that have been deployed to either eliminate or mitigate the threat, and therefore we have witnessed dramatically different health and economic consequences (Oliu-Barton et al., 2021).

The fourth chapter describes how we can better specify the decision objectives when making health security decisions. This precise definition of objectives during this decision stage can help us to clearly identify the multiple consequences that are relevant in such decisions. These consequences are either tangible (such as the number of severe cases that a health security action may prevent), or intangible (such as the risk perception caused by a health threat). Moreover, a clear understanding of decision objectives is a crucial for increasing the societal value achieved by health security decisions.

2.3.3 Assessing Impacts of Threats and Health Security Actions

From a decision making perspective, as described in the previous chapter, we are confronted with two categories of decisions in health security situations. The first decision category evaluates how serious an emerging health threat is. The second decision category selects the best decision alternatives to enhance health security. In both cases, impacts that may be triggered by both health threats and health security actions must be properly assessed on the relevant consequences (Keeney & Gregory, 2005).

The first category of decision requires an assessment that estimates the impact of each health threat under consideration. Similarly, the second category of decision

requires an assessment that estimates the performance of health security actions. Both tangible and intangible impacts are of importance when making health security decisions, and thus must be adequately assessed to inform decision making.

For decisions whose central focus concerns the selection of decision alternatives to better manage health threats, we typically wish to minimize the detrimental impacts that threats may trigger (reduce the number of casualties, decrease the number of serious cases, control economic disturbances, lessen social impacts, and so on) while simultaneously minimizing risk management costs.

One pervasive characteristic of managing health threats involves the high level of uncertainty regarding their impacts (Morgan & Henrion, 1992). There exist three dimensions that are always relevant when assessing impacts of health threats. First, what is the extent of the impact (e.g., the total number of cases from an outbreak)? Second, what is the time horizon of the impact (e.g., the duration in months)? Third, what is the dynamic pattern of some impacts (e.g., cases per day over the time horizon under consideration)? These dimensions must always be considered when the consequences of health security decision alternatives (which have been devised to manage the health threat) are compared.

For decisions whose central focus constitutes selecting decision alternatives to improve health security, we typically wish to maximize the positive impacts of the health security actions (increase population health, generate jobs, etc.) while simultaneously minimizing the costs of implementing these actions. Here, the performance of each decision alternative is usually what gives rise to the uncertainties associated with managing health threats.

The existence of these uncertainties requires that any sound assessment of health threats and health security actions be based on a set of plausible scenarios (Schoemaker, 1993). The adequate definition and characterization of scenarios is critical for successful planning and reasoned decision making. It is important that these scenarios be both realistic, indicating a risk path for infection and a possible outbreak, while simultaneously covering a wider range of possible outcomes. Hence, reasoned health security decisions must adequately assess the impacts of health threats and of health security actions under different scenarios, as is detailed in the fifth chapter.

2.3.4 Defining Risk Limits, Marginal Value, and Trade-Offs in Health Security Decisions

Three types of judgments are relevant when making health security decisions. First, risk limits must be established to identify acceptable and unacceptable impact levels. Second, marginal value over impact levels are often required. Third, trade-offs among the conflicting objectives must be defined . We provide a brief explanation concerning each type of judgment next.

Judgments are required to define risk limits, as often it is unfeasible to reduce a risk to zero (Fischhoff et al., 1993). A risk limit serves to define a quantified threshold, which if exceeded, renders the impact unacceptable. For instance, we could

define a risk limit as constituting 1,000 critical cases that require hospitalization, as this number represents the maximum capacity of the intensive care unit in the region under consideration.

These risk limits function as constraints, allowing for health security decision alternatives to be considered. If we elaborate upon the same case stated above, any health security action devised to cope with a health threat cannot incur more than 1,000 critical cases, as this would render the alternative as being unfeasible and the option would thus be discarded from further consideration. Conversely, any alternatives that incur fewer than 1,000 critical cases (which lies below the risk limit) would be contemplated in the decision.

The risk limits may also function as a quantified threshold that is able to reveal the urgency with which we must manage health threats, due to their potential impacts that have the ability to exceed an acceptable threshold. If we consider our case, a threat that could cause more than 1,000 critical cases emerges as being distinct, and requires more intensive preparedness and preventive actions to be implemented against the threat.

Additionally, many decisions require the appraisal of marginal value over impacts. A classic example involves the decreasing marginal societal value of vaccinating additional proportions of a population for diseases that trigger mild symptoms, once herd immunity levels have been achieved (Brauer et al., 2019). An assessment of marginal value over this metric (proportion of the population vaccinated) would indicate that resources could be more efficiently employed in other health security-related actions, once a herd immunity level has been achieved, as relatively low additional societal value would be obtained by vaccinating additional proportions of a population beyond such level.

Health security decisions invariably require difficult trade-offs, stemming from an inevitable judgment in any decision that is characterized by conflicting objectives (Keeney, 1992, 2002). For instance, when comparing different decision alternatives for risk mitigation against a health threat, we typically negotiate the number of prevented cases with the implementation costs inherent to risk mitigating actions. When managing pandemics, policy makers whose aim it is to eliminate the disease through implementing lockdowns must conciliate trade-offs (Oliu-Barton et al., 2021), such as the one that involves the loss of short term economic gains against the reduction of health losses.

Transparency, an essential facet of high-quality decision processes, should also be applied to these three forms of judgment. As such, macro and micro communities that are affected by these decisions are able to access information regarding the manner in which policies are being devised and selected. Transparency calls for the explicit modeling of trade-offs (Keeney, 2002) and marginal valuation over impacts (Dias et al., 2018), and these parameters provide a clear separation between the evidence available and the judgments that are employed to choose health security decision alternatives. Given the extensive available evidence demonstrating that these judgments can suffer from cognitive and motivational biases, as well as group judgment biases, it is therefore crucial that they are properly debiased prior to being employed in decision making (Montibeller & von Winterfeldt, 2015, 2018).

The presence of multiple decision makers increases the challenges we face when defining these judgments, as these individuals may have different priorities, preferences, and risk tolerances. Consequently, these decision makers must effectively engage, to arrive at a conclusion that accommodates these different perspectives. The organizational culture also plays a major role, for instance in the way that priorities are interpreted and the level of transparency that is required.

In the sixth chapter we detail how to consider and adequately represent risk limits, marginal value, and trade-offs, in health security decisions. Furthermore, to establish parameters that are reliable and consistent, we suggest strategies for minimizing biases when defining these parameters. The individual factors of defining such judgments, as well as the group factors involved in such decision processes, are also discussed in this sixth chapter.

2.3.5 Developing Decision Alternatives for Enhanced Health Security

Decision alternatives constitute actions available to public health leaders responsible for health security decisions. To better illustrate these actions, let us posit a case wherein a national health service is in the process of devising a vaccination campaign aimed at children to manage an emerging health threat. This health service wishes to establish how to vaccinate this segment of the population, therefore, the decision alternatives in this case take the form of the different locations available at which to vaccinate the children (centralized in hospitals, centralized in health clinics, centralized in schools, or decentralized in home visits). If the policy makers are also considering other methods to reduce transmission during this ongoing outbreak, then they may consider alternative policies to implement (such as social distance rules, stay-at home rules, compulsory protective equipment in public spaces, and so on).

The quality of a choice is heavily dependent upon the decision alternatives under consideration (Keeney, 1992; Siebert & Keeney, 2015; Spetzler et al., 2016). If all decision alternatives are deemed as being poor in quality, the alternative that shall be selected will therefore be a low-quality option. Due to the complex processes involved in identifying relevant consequences in health security decisions, identifying good alternatives is not a trivial task. This challenge of identifying good alternatives is compounded by the practical impossibility of designing an 'ideal' option, as every alternative will involve some drawbacks (we typically see that the alternatives that open up the possibility for greater benefits also incur the highest costs.)

In addition, there exist limited resources both for designing and selecting alternatives, as well as for financing the implementation costs. These factors therefore necessitate a more transparent and efficient process that functions to underpin the identification and development of decision alternatives. After all, decision alternatives constitute a crucial component that allow for high-quality choices to be made when improving health security, which is detailed in the seventh chapter.

2.3.6 *Evaluating Health Threats and Actions, and Selecting Best Options*

In the introduction of the decision stages thus far in this section, we have estimated the impacts relating to possible health threats under different scenarios for possible outbreaks, and we have defined clear trade-offs and risk limits. This information now enables us to estimate possible impacts from health threats, evaluate risk mitigating actions against such threats, and assess decision alternatives to enhance health security.

Three chapters of this book shall address this decision stage, which entail a discussion concerning the gathering of evidence, the evaluation of health threats and health security actions, and shall conclude with the identification of potentially good options for the final decision.

If the decision concerns the selection of health security decision alternatives, the information made available by the previous stages of the analysis shall enable an assessment of the societal value of each possible action. This value assessment is predicated on the decision objectives under consideration. Therefore, the assessment considers the extent to which impacts have been reduced, the reduction in the likelihood of occurrence of the impacts, the relative importance allocated to each impact by decision makers, the risk limits that have been established for each impact, and the effectiveness and costs related to the possible interventions.

On the other hand, if we wish to assess the potential impacts of health threats, in order to evaluate the severity of the threat, the assessment should focus on the health threats with the highest societal dis-value. This assessment considers the severity of the impacts triggered by the threat on the multiple relevant consequences, the importance allocated by decision makers to each of these impacts, as well as identifying the risk limits and trade-offs under consideration. These evaluations of decision alternatives on multiple objectives and of health threats on multiple impacts is detailed in the eighth chapter.

As we have previously mentioned, uncertainty is a central component in any health security decision. Impacts of health threats may be difficult to forecast, benefits of risk mitigation action may be hard to estimate, and the performance of health security alternatives may involve variability. The adequate assessment of health threats and actions under uncertainty shall be the focus of the ninth chapter.

The assessment of health threats and health security actions requires data from reliable predictive models, which enables us to determine events such as transmission patterns and estimate the number of cases. This assessment also requires the use of scientific evidence to estimate factors such as the severity of the symptoms triggered by an emerging disease. Often, such assessments may also require expert judgment to estimate these impacts, particularly whenever hard evidence is not available or incomplete (Morgan, 2014). A reasoned assessment of health threats and health security decision alternatives necessarily must be underpinned by high-quality evidence. Whatever the nature of the evidence, the descriptive and predictive models should be reliable and expert opinion must be unbiased. In the tenth chapter we discuss how these different sources of evidence can be adequately employed to support decision making.

There exist several types of decision situation that may necessitate a detailed evaluation. These situations involve the selection of a single option, or the ranking, categorization, and recurrent evaluation of multiple options, or, indeed, the selection of a portfolio of projects to improve health security. Similarly, different types of evaluation may be required for distinctive situations in managing health threats, such as selecting a single threat to target, ranking threats, categorizing threats, or conducting recurrent evaluations of threats. It is important that the evaluation of health security actions and health threats be modeled on and adapted to the type of decision situation, a point which is also discussed in the tenth chapter.

2.3.7 Deciding and Implementing Health Security Actions and Promoting Systematic Learning

A detailed and reasoned evaluation of health threats and health security actions must lead to a selection of options that enhance health security. In the eleventh chapter of this book, the discussion primarily pertains to the social aspects involved in these choice processes. Three main issues arise at this final decision stage, which are discussed in said chapter.

First, the chapter discusses how we can decide in an effective manner and avoid dysfunctional group dynamics during the selection of options phase. Here, the options that had been previously identified, evaluated and valued serve to propel us toward making reasoned choices. We suggest several strategies for improving the choices of health security teams, which range from establishing rules and responsibilities among members of the decision making group to the use of internal or external group facilitators.

Second, we consider the thorny issue of implementation of health security actions. The implementation phase of chosen alternatives is an aspect that is often neglected in the decision making literature. Regardless as to whether a decision has been made in a thorough and reasoned manner, if the choices are not implemented, they shall not aid in improving health security at all. We discuss how we can work to ease barriers that prevent or hinder implementation and, consequently, enable us to increase the likelihood that the selected decision alternatives are successfully implemented.

Third, we emphasize the crucial role of systematic learning in decision making processes. While also often neglected in the decision making literature, systematic learning constitutes another very important topic. This book recommends that systematic decision processes be followed, and Health Decision Analysis employed, so that organizations and public health leaders are able to learn more effectively during and from their decision processes.

This framework for supporting health security decisions has many potential benefits when contrasted with the typically unstructured decision making that we often observe in health security practice. While some of these benefits were alluded to earlier in this section, they are discussed in more depth next.

2.4 Assessing the Quality of Health Security Decision Processes

In this section we describe the properties required for high-quality decision processes (see also Fischhoff et al. (1993), Keeney (2014), and Spetzler et al. (2016)). For each property, we compare Health Decision Analysis against unstructured decision making processes often employed in health security situations.

Comprehensive Process A decision process should adequately involve all the relevant individuals that must be consulted. The process should also consider all the aspects that are relevant and necessary for making a reasoned choice.

> Unstructured decision making struggles to provide a complete picture of the decision problem. This issue stems from the *absence* of a formal representation, and whose *presence* would otherwise enable policy makers and experts to engage in the sharing of relevant elements that compose the decision problem (Franco & Montibeller, 2010). Given the available behavioral evidence concerning unstructured decision processes, we know that decision makers are likely to over-simplify the choice of decision alternatives (Payne et al., 1992, 1993) and may suffer from a narrow problem representation (Legrenzi et al., 1993; Legrezni & Girotto, 1996; Payne et al., 1999).
>
> A health decision analysis, on the other hand, is able to consider all aspects that are relevant to a decision, as the decision analysis forms a structure to organize and combine the decision components in a logical manner (Raiffa, 1968). The use of an external representation (a decision model) enables decision makers to consider a vast amount of complex information, which is often required in health security decisions.

Transparent Process A decision process should be transparent, in that the evidence and information employed to formulate the decision should be indicated, alongside ensuring that the manner in which the evidence influenced the consideration of decision alternatives (and ultimately, a conclusion) be made available. This transparency involves a process that clarifies the assumptions and simplifications made, and defines the extent to which the conclusions are predicated on these assumptions, on the evidence, and on the information employed in the choice.

> Unstructured decision making is a highly opaque act. The process of information gathering is frequently decentralized among different experts, who may employ different assumptions, evidence, and reasoning processes to reach their respective conclusions. Once an expert opinion has been formulated, decision makers often assess the opinion based on the extent to which decision makers are able to trust the expert (this often results in a judgement of expert credentials rather than the quality of the assessment conducted by the expert). Consequently, this lack of a formalized analysis renders the judgement opaque, as there is little information regarding which specific factors were considered and the manner in which a decision was reached.
>
> Conversely, a health decision analysis allows for a high degree of transparency. Decision makers, experts, and external bodies are able to access the information that was employed when alternatives were being compared and selected, and the manner in which this information was being considered during the decision analysis. Assumptions, simplifications and limitations are therefore made clear if a careful decision analysis is undertaken.

Unbiased Choice A decision process should be unbiased in that it uses both reliable evidence and debiased judgments (related to impacts, risks limits, and trade-offs) to identify the best alternatives. The recommendations fostered by the process should not give undue weight to any misdirected interest or any type of unwarranted consideration.

> Unstructured decision making leaves ample space for biases. Experts may provide biased estimates concerning the impacts of possible decision alternatives, decision makers may have favored options that they wish to promote, and policy makers may establish skewed risk limits and distorted trade-offs. Lobbying by some interest groups may strongly influence the information employed in the decision, as well influencing the choice that is made. Unfortunately, as the transparency level remains typically low, an assessment that considers the extent of the biases involved in the decision process is rendered difficult.
>
> On the other hand, a carefully conducted health decision analysis, reveals a space wherein an evidence-based and balanced assessment of decision alternatives can take place, and wherein unbiased judgements, explicit trade-offs and risk limits all come to the foreground. This approach is characterized by its clear separation between evidence and judgment, alongside the ability to conduct a sensitivity analysis that focuses on both the evidence and judgments employed in the selection of the best options to enhance health security.

Justifiable Choice A decision process should lead to a decision that is justifiable to external bodies, making explicit the evidence and information employed in the decision, the manner in which this evidence and information was utilized when the available alternatives were being considered, and how conclusions were reached. The requirement of a justification is particularly important in public decisions (such as those that concern health security) as decision makers have a fiduciary duty to society and, should therefore be open to scrutiny.

> The low level of transparency that is intrinsic to unstructured decision making results in a process that struggles to meet the requirement of justifiability. This opacity stems from the manner in which decisions are made, whereby decision makers become advocates for their chosen options, and deliberately stress the advantages while understating the disadvantages to persuade others (Garvin & Roberto, 2001). The aim of the decision maker consequently becomes one wherein external bodies are persuaded that the chosen alternative was the best option.
>
> On the other hand, a health decision analysis enables the possibility of inquiry. Through the process of exploring the best available options, policy makers and experts are able to select options that adequately negotiate benefits and costs while considering the risk limits that have been established. These decision processes are highly transparent, and, if carefully conducted, are also unbiased. The explicit analysis of decision alternatives can be clearly explained and are justifiable to external bodies.

Conductive to Learning Systematic learning from both successful and unsuccessful decision processes is critical if societies wish to improve their preparedness and resilience against future health threats. Here, learning involves the comparison of the evidence and the information that were employed when estimates were made against the actual consequences of implementation, and the contrast between the assumptions and judgments made when selecting decision alternatives against the case in actuality. One particularly difficult aspect that pertains to learning in risk-related decisions is the absence of counterfactuals (Roese, 1999), which occurs

when a risk is neutralized by successful risk mitigation actions. In such instances, the success of neutralizing the risk constrains the possibility of knowing what would have occurred had these actions not been implemented (Montibeller et al., 2020a; Woo, 2016).

> Unstructured decision making does not typically foster opportunities for learning. The low transparency that characterizes these decision processes restricts the ability to identify any particularities that were employed when making a choice. The absence of a formal process involving evaluations and comparisons of decision alternatives results in decision processes that begin with no pre-established foundation, and as such, employ different ad hoc protocols, informal group interactions, and different manners to reach a conclusion. This lack of a systematic method renders experts and policy makers unable to learn from previous mistakes or successes, and they instead become hindered by this opacity of the analysis and the unstructured decision processes.
>
> Contrastingly, a health decision analysis, provides a foundation that is highly conductive to systematic learning. This high degree of transparency stems from the ability of decision makers to trace the previous modes of information and decision components that were employed in the selection of the decision alternatives. Once a decision is made, and uncertainties resolved, decision makers are able to deduce components that were missing and factors that had proved relevant to the case in actuality. The decision process involves an element of separation between evidence and judgments, and thus we are able to determine whether the evidence was reliable, and how data gathering could be improved in the future. This separation also enables an assessment as to whether the judgments were indeed unbiased, and the manner in which these judgements could be refined for similar future decisions.

Conductive to High Quality Decision Making There exist six dimensions of decision quality (Spetzler et al., 2016) that must be targeted in reasoned decision making. In high quality decision processes, decision makers should: (i) create an adequate problem frame that makes clear what the decision is, (ii) define which consequences are valuable in the decision, (iii) develop a creative set of alternatives, (iv) gather useful information concerning these alternatives, (v) promote sound reasoning when comparing the alternatives, and (vi) establish a commitment to implement the option(s) once the best alternatives have been chosen.

> Unstructured decision making often struggles to achieve high quality decision processes. The problem frame may be too narrow, whereby it only takes into consideration a limited number of consequences and a reduced number of alternatives. The information gathered to compare the alternatives is often limited or incomplete, and fails to fully cover all the consequences under consideration. Judgments may be biased or be taken from too few experts and policy makers, therefore providing an unbalanced comparison of alternatives. This issue is compounded by a low-transparency environment. Finally, given that these are unstructured decision processes, the manner in which alternatives are considered and chosen may render a team less committed to implementing the options that have been selected.
>
> Health decision analysis has been designed to be conductive to high quality decision making. Indeed, the decision steps demonstrated by Fig. 2.1 represent the means by which we can reach such high decision quality. Adequately framing the decision problem can provide the basis on which to construct an adequate problem frame. Indeed, a frame that specifies relevant scenarios and consequences will aid in identifying the dimensions that are valuable in a decision. Identifying decision objectives and relevant consequences allows for the development of a creative set of options. Assessing the impacts for each alternative on the consequences that are most relevant will delineate and direct our efforts to gather useful

information. Defining trade-offs and risk limits should promote sound reasoning when comparing the decision alternatives. And, evaluating the decision alternatives and selecting the best options in a reasoned manner can foster a high commitment to implement the options chosen among all members of a health security team.

In addition to the benefits listed above, there exists strong evidence that decision processes are relevant to organizational decision making. Indeed, an extensive 20 year-long study of 400 important decisions made by private, public, and non-profit organizations has shown that half of these decisions failed due to poor decision-making processes (Nutt, 2002, 2008).

However, there exist a few disadvantages when conducting a health decision analysis. First, a more formalized decision making process requires more time to conduct than its unstructured counterpart. Hence, a health decision analysis is mainly suitable when making important decisions with high stakes. While decisions with high stakes are an intrinsic element of health security decisions, some less complex decisions may employ a simplified version of this framework.

Second, a more transparent decision enables the potentiality of scrutiny, and is therefore not an appropriate process for organizations that wish to remain opaque when making choices. We argue that opacity should be avoided in health security decisions, as opacity allows for actions such as the misuse of scarce resources and the neglect of relevant consequences. Indeed the importance of good governance structures, which should also monitor and scrutinize health security decision processes, is emphasized by the World Health Organization framework on health systems for health security (WHO, 2021). However, striving toward transparency may require challenging organizational barriers if one wishes to implement a more reasoned and transparent method of making health security decisions as is presented in this book.

2.5 Conclusions: Making Reasoned Health Security Decisions – Concepts and Benefits

In this chapter we have firmly anchored the content of this book to Decision Sciences. We have argued for the need to make reasoned health security decisions and discussed the benefits of employing a conceptually robust framework, Health Decision Analysis, to support such decisions.

We have introduced three approaches to decision making which constitute a useful classification when categorizing the vast Decision Sciences literature. The first approach, led by Decision Theory, describes how a rational decision maker should proceed in order to make reasoned decisions and maximize the value of their choices. This idealized perspective is formalized by a set of axioms, and functions to provide the golden standards, on which decisions under uncertainty and conflicting objectives should be made.

The second approach in Decision Sciences, promoted by Behavioral Decision Research, studies how individuals decide in actuality, and compares these judgments and choices against judgements made by a rational decision maker. This body

of research reveals the existence of a boundedly rational decision makers, in contrast with the idealized rational decision maker from Decision Theory.

An important consequence of acknowledging the existence of this bounded rationality is that the approach identifies the cognitive limitations of decision makers when acquiring, processing, and aggregating information during reasoning required for making choices. Furthermore, the approach also identifies the existence of a decision maker that may suffer from both cognitive and motivational biases when making judgments and choices. The consequences highlighted by this approach reveal the need for an adequate decision making framework when dealing with high-stake decisions under high levels of uncertainty, such as those involved in many health security situations.

The third approach in Decision Sciences, promoted by Decision Analysis, investigates how we can make high-quality decisions. The approach draws from the axioms of Decision Theory in order to understand how decision should be made. These axioms inform how decision makers in actuality can be guided in reasoning about choices.

Decision Analysis also draws from Behavioral Decision Research, in order to understand the cognitive limitations that hinder actual decision makers in expressing their judgments, and in making their choices, when reasoning about decision problems. This understanding enables the field to develop adequate representations of decision problems, as well as rigorous protocols for the elicitation and debiasing of judgments. It is the third approach that is followed by this book within a health security context, that is to say: Health Decision Analysis.

This chapter has highlighted the important conceptual drive to improve decision processes, as opposed to the traditional focus on decision outcomes. This focus on decision processes stems from two characteristics pertaining to health security decisions. First, any health security decision involves uncertainties and therefore, outcomes that cannot be fully controlled by the decision makers. Second, some uncertainties are irreducible in policy making, regardless as to how much evidence is gathered. We have argued that the primary way to improve decision processes is through employing Health Decision Analysis and adopting more systematic decision processes in health security situations. Public health leaders *do* have control over decision processes and should fully exert this control to reach high quality decision making.

There exist many benefits to employing Health Decision Analysis to support health security decisions, all of which have been discussed in this chapter. Decision Analysis enables for a more comprehensive understanding of the decision problem and the main components that constitute the problem. The framework provides a transparent structure to compare and select options and aids to develop choices that are unbiased and justifiable to external bodies. Learning from previous successes and failures becomes less complex when employing Decision Analysis, given its transparency and rigor. A Health Decision Analysis enables the possibility to achieve high-quality decisions if each decision stage is successfully accomplished. The following chapters detail each decision stage, starting with decision framing in the subsequent chapter.

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Chapter 3
Framing Health Security Decisions



The first chapter of this book has established that health security problems are invariably characterized by their complex nature. Among those many complexities, there exists an unclear decision context and as a result, it remains ambiguous as to which aspects, among the many existing factors that form complex situations, should be included in and excluded from a health decision analysis.

Health policy decisions contain also an intrinsic element of high stakes, in that these policies have the potentiality to trigger acute and widespread health and socio-economic impacts. Naturally, the extensive possibilities of implementing various policies brings about the involvement of multiple stakeholders. These stakeholders contribute both various perspectives and expertise pertaining to the relevant issues under consideration, as well as distinctive interests and priorities. The complexity inherent to these decisions is compounded by the involvement of multiple decision makers and subject matter experts, which may lead to power dynamics and political struggles.

Prior to any decision being made, the decision problem must be adequately framed, as this constitutes the first, and perhaps the most crucial stage when making reasoned health security decisions. To frame the decision problem, the health security team must define the components that constitute the health security problem, and elucidate the exact decisions that must be made to solve, or considerably alleviate, the problem. The complex dynamics that form the foundation on which the decision problem must be framed amounts to a difficult undertaking.

This chapter suggests how we can adequately frame health security decisions. Decision framing encompasses considering different perspectives, guiding the participation of decision makers and experts, managing the power and political dynamics, and clarifying the decision context in situations that are typically inherently ambiguous and poorly defined.

In the previous chapter we presented a diagram that illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 3.1. The first decision stage, *framing the decision problem*, is now highlighted

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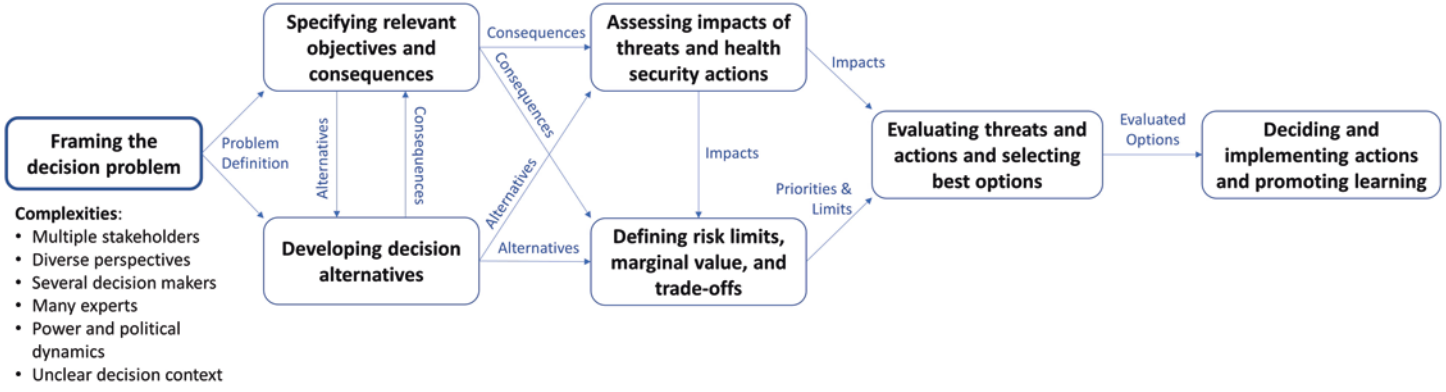

Fig. 3.1 Making reasoned health security decisions: A focus on framing the decision problem

in this modified figure. Decision framing provides the foundation for reasoned health security decisions as we shall discuss in this chapter.

3.1 Identifying Relevant Problems

Emerging health threats give rise to a plethora of data and information that public health leaders must direct their attention toward, while simultaneously managing information regarding endemic infectious diseases. Valuable information concerning the initial stages of emerging diseases, or localized outbreaks of known diseases is shared among the health expert community, utilizing health surveillance systems and communications (Groseclose & Buckeridge, 2017; Morse, 2012). However, the network of communication becomes one which is laden with information, and thus, we must ask the pressing question: Among so many competing issues, what must the conditions that indicate a sufficiently relevant problem be, to necessitate a health decision analysis?

In this book, we shall consider the case where there exists a group of policymakers and health experts, the *health security team*, who are responsible for making health security decisions. Since there exists the distinct possibility that a single decision maker shall employ a narrow perspective through which to view the issues at stake, making a group of individuals responsible for these decisions is an advisable measure. The highly complex nature of these decision problems can be better undertaken by a group, enabling members to contribute distinctive expertise and varied previous experiences, as is the case with any strategic-level decision (Nickerson & Argyres, 2018).

However, even if experts and policy makers were to contribute varied modes of expertise and experience, an absence of responsibility and accountability required for such important decisions may result in the group failing to adequately address the problem. For this reason, a health security team should be varied, in that reliable experts and accountable policy makers are adequately represented, and each member has clear responsibilities and a well-defined role[1] within the group.

The first step in any health security decision entails the health security team identifying the relevance of the health security problems. Although in practice this identification is often conducted in an informal manner, we shall analyze the requirements of this assessment and emphasize the need for judgments, as is discussed next.

3.1.1 Assessing the Relevance of Health Security Problems

There exist four conditions that the health security team must follow when conducting the assessment that establishes the relevance of the health security problem (Landry, 1995). The first condition is the *existence of a past, present, or future*

[1] In the eleventh chapter we discuss in greater depth the importance of establishing clear responsibilities and defining roles for decision making groups responsible for health security decisions.

occurrence that is judged to be negative by a member or members of the team. This condition can be illustrated by a case wherein a health surveillance system has gathered data about a large growth in the number of cases of an emerging infectious disease in a region of a country, and this information is considered by the health security team as an indication of a potentially large outbreak.

Notice that this first condition encompasses both the notion of *crises* and of *opportunities*. Crises are threatening situations with restricted response times (Clearfield & Tilcsik, 2018), such as the circumstances in this surveillance data scenario, which is a scenario that is often confronted by health security teams. Opportunities, on the other hand, involve initiatives that are voluntarily established, and are aimed at improving a situation that had previously been considered to be acceptable (Keeney, 1992). If we posit the example wherein a health budget is increased, this increase allows for the opportunity to expand the intensive care units, and thus improve health security preparedness against health threats.

The second condition entails the *preliminary judgement made by the health security team, as to whether there exists some intervention capability to manage the issues under consideration*. If we apply this condition to our health surveillance case, let us assume that the team had at their disposal some vaccination capability, in the form of a number of vaccine stocks against the disease. These vaccines therefore constitute one possible resource.

This second condition requires that a group be able to exert a minimal level of control over the situation to develop health capabilities (Del Rio Vilas et al., 2013). If there exists a total absence of resources, the team is rendered incapable of intervening or developing the necessary health capabilities that the situation requires, regardless as to whether the team is highly concerned or not. This issue may be observed in practice, occurring in situations wherein health experts are not appointed to positions whose role allows for intervention capabilities to be deployed, despite any concerns they may have related to recent data or trends.

The third condition involves *the expression of interest in undertaking an issue, and the allocation of appropriate resources to deal with said issue* by the health security team. If we apply this third condition to our health surveillance case, this expression of interest and allocation of resources can manifest themselves through the funding and executing of a vaccination campaign in the area afflicted by a surge in infections.

Hence, we see that this third condition requires not only the interest and willingness to undertake the issue under consideration, but also the issue itself must be considered relevant enough if the team is to allocate resources toward managing the issue. Consequently, the specific issue must be viewed within a context wherein this issue is competing against other issues for scarce resources (Bower & Gilbert, 2005), as these resources would otherwise be allocated to address other relevant problems affecting the health system.

The fourth condition entails *a lack of clarity* that besets the health security team, *concerning the specific actions to be implemented and how to execute this implementation in order to effectively manage the issue*. If we illustrate this fourth condition using our health surveillance case, the team could be unsure as to the specific

Table 3.1 Four conditions for a relevant health security problem to be analyzed

Condition	Requirement
1. Unsatisfactory event	The existence of a past, present, or future occurrence that is judged to be negative by at least one member of the health security team.
2. Resource availability	The health security team has some intervention capability to deal with the health security issue.
3. Commitment of resources	The health security team is willing to commit some resources to deal with the health security issue.
4. Lack of clarity	The health security team lacks clarity concerning the appropriate actions to manage the health security issue and how to implement such actions.

manner in which to conduct the vaccination campaign, the adequate levels of immunization required, the appropriate amount of resources needed, and on how to best implement the health security actions. Conversely, situations that are judged to be negative, but have pre-established solutions to manage said situations would fail to fulfill this fourth condition. Similarly, this fourth condition remains unfulfilled for situations wherein a group is able to act without first deliberating the best future actions to implement.

A summary of these conditions is presented in Table 3.1. Notice that *all* four conditions *must* be fulfilled for a health security problem to be considered as sufficiently relevant to necessitate a health decision analysis. This overall requirement would not be fulfilled, for example, in a case where a negative trend is detected by health experts (unsatisfactory event detected, therefore fulfilling condition 1) that have not been appointed to influential positions, as these health experts would be unable to allocate and commit resources to tackle the trend (failing conditions 2 & 3), regardless as to whether there exists a lack of clarity concerning the best future actions to implement (fulfilling condition 4). While a health decision analysis could still be conducted for a case such as this, it is unlikely that the findings of this analysis could ever be implemented.

It is important to note that each condition and its respective assessments (that are elucidated by Table 3.1) require that a *judgment* be conducted by the health security team, or at least some of its members. The first condition requires that the team *judge* the occurrence of an event to be unsatisfactory. Utilizing our health surveillance case, let us consider the scenario wherein an increase in the number of cases of an endemic disease occurs, and that this disease provided immunity for those who were infected but survived. If some health policymakers believe that an increase in infections shall bring about herd immunity at a population level, then these policymakers may not consider this increase to be unsatisfactory, and as a consequence, shall not consider the increase in infections to be a problem that must be managed. On the other hand, other policymakers may consider the increase worrying, given the potential mortality rate at a population level, and therefore, the latter set of policymakers shall view the infection rate to be a problem that must be managed. Hence, a judgment must be made by the group whether the event be negative or not.

The second condition requires that the *judgment* by the health security team confirm the availability of appropriate resources. In our health surveillance case, this

would require an assessment as to whether or not health capabilities are available, or could be mobilized, against the health threat.

The third condition requires the *judgment* that these resources can indeed be allocated to undertake the problem. In our health surveillance case, this would necessitate that group members agree upon the allocation of some resources (e.g. time, money, personnel), to address the problem.

The fourth condition requires that the health security team *judge* the lack of clarity to be sufficiently high and the solution to not be evident, so as to agree to consider different solutions to manage the decision problem. If these four conditions were met, then it is advisable to conduct a health decision analysis, given the benefits discussed in the previous chapter.

The first condition, involving the detection of an unsatisfactory event forms a nexus between the signals produced by health surveillance systems and health security decision making. Thus, we shall scrutinize the first condition and its nexus in greater detail in the subsequent section.

3.1.2 Predicting and Acting: Health Security Threats

The discussion in the previous section highlighted the importance of judgments when deciding as to whether an emerging health threat is relevant. The first condition required the identification of an unsatisfactory event, which forms the starting point for identifying any relevant decision problems. In practice, this judgement is guided by health surveillance systems, which play a central role in providing signals of the potential severity of an emerging disease (Groseclose & Buckeridge, 2017; Morse, 2012). Let us analyze the role of the evidence brought about by these surveillance systems, and the inherent difficulties that public health leaders are confronted with when making this judgment (see also Hammond, 1996).

Let us postulate a health surveillance system that indicates the potential severity of different disease outbreaks on a 0-to-100 scale, as represented by the x-axis of the graph presented in Fig. 3.2a. Assume that the actual severity of each outbreak would also be measured on this same severity scale, and represents the y-axis of the same graph. The predictions provided by the system are imperfect, as indicated by the ellipse in the graph. The ellipse represents the degree to which the system is accurate, and delineates the predicted severity (x-axis) over the actual severity (y-axis). Hence, a highly accurate health surveillance system would be represented by a narrow ellipse as Fig. 3.2b demonstrates, and a poorly accurate system would be represented by a wide ellipse as is shown in Fig. 3.2c.

The vertical line in Fig. 3.2 indicates a threshold, at which point an action is taken by the health security team. In this case, let us assume that the *potential severity* score of 50 marks the quantified threshold, to the right of which indicates high severity and to the left of which indicates low severity. In a similar way, the *actual severity* also has a score of 50, delimiting high severity (above this point) and low severity (below this point). The threshold indicates four different situations, each

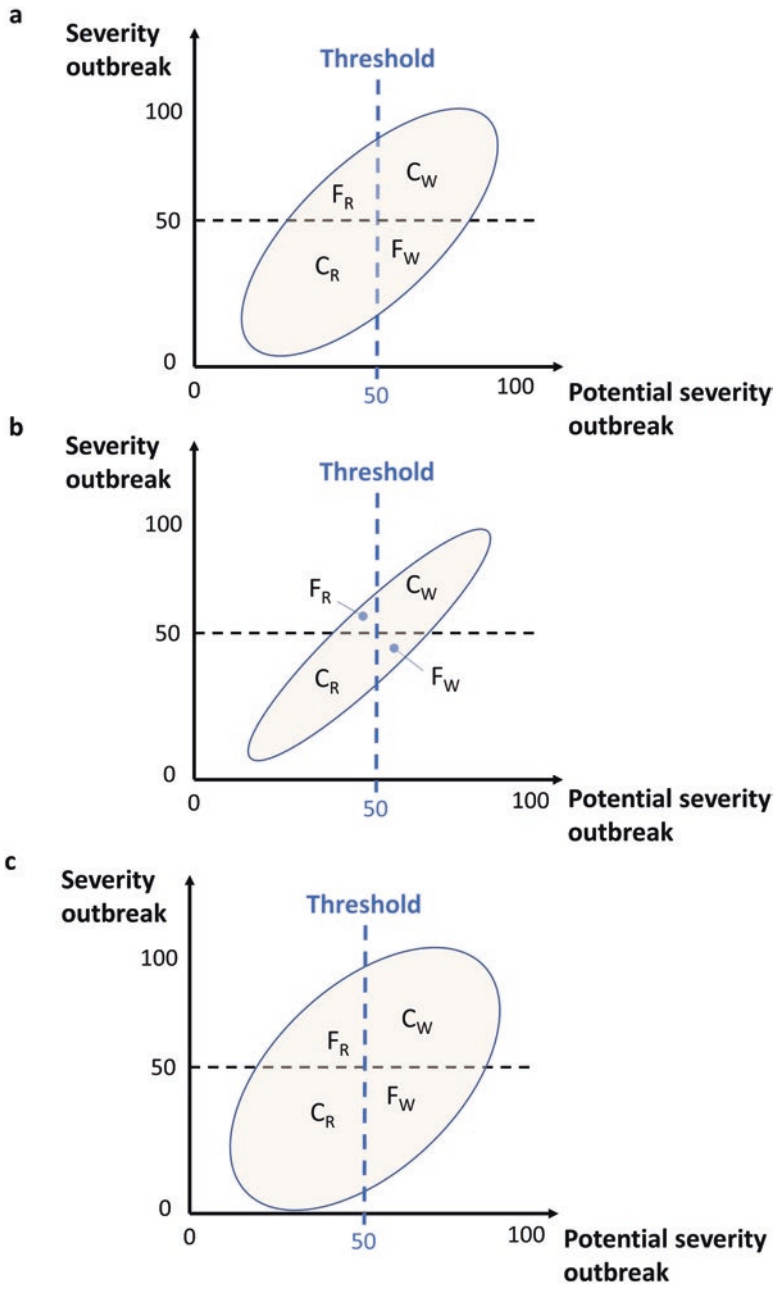

Fig. 3.2 Accuracy of health surveillance systems and predictive power: (**a**) Regular accuracy, (**b**) High accuracy, (**c**) Low accuracy (adapted from Hammond 1996)

represented by an area in the ellipse in the same figure: a correct warnings (C_W), where the *potential severity* was indicated to be *high* and the *actual severity* was *high*; a correct rejections (C_R), where the *potential severity* was signaled to be *low* and the *actual severity* was *low*; a false warnings (F_W), where the potential severity was indicated to be *high* but the *actual severity* was *low*; and a false rejections (F_R), where the *potential severity* was indicated to be *low* but the actual severity was *high*.

In health surveillance systems, the role of accuracy in driving correct actions forms a fundamental concept for this analysis. If the heath surveillance system is very accurate, as represented in Fig. 3.2b, both areas of false warnings (F_W) and false rejections (F_R) shall decrease, leading to a greater number of correct actions. On the other hand, if the system is highly inaccurate, as represented in Fig. 3.2c, both the area of false warnings (F_W) and of false rejections (F_R) shall increase, leading to a greater number of incorrect actions.

Let us consider the situation depicted in Fig. 3.3a, assuming that the accuracy of the health surveillance system cannot be further improved. Importantly, the threshold is determined by the health security team and may be shifted to the left, rendering the assessment more stringent, or to the right, rendering the assessment less stringent.

A false rejection is, evidently, a major concern for any public health leader. One manner of reducing the area of false rejections (F_R) entails moving the threshold to the left from the original threshold position (shown in Fig. 3.3a), for instance, establishing the threshold at 30, as shown in Fig. 3.3b. While this stringent threshold would increase the number of correct warnings (C_W), the new threshold would also result in a decrease in the number of correct rejections (C_R) and an increase in the number of false warnings (F_W) in relation to the original areas (shown in Fig. 3.3a). The latter aspect has a detrimental effect on public health, as false warnings may foster a distrust toward health security systems.

Conversely, there exists a major concern relating to false warnings, as such, health leaders may establish less stringent thresholds (in relation to the original threshold position shown in Fig. 3.3a) to avoid such warnings. For example, they may establish the threshold at 70, as shown in Fig. 3.3c. Indeed, this shift would reduce the number of false warnings (F_W) in relation to the original area, as depicted in the same figure. The less stringent threshold would increase the number of correct rejections (C_R) in relation to the original area (shown in Fig. 3.3a). However, two detrimental consequences of this decision involve the decrease in the number of correct warnings (C_W) and the increase in the number of false rejections (F_R) in relation to the original areas (shown in Fig. 3.3a). The latter aspect may lead to severe outbreaks that trigger extensive impacts.

This analysis concerning the types of potential policy errors illustrates the dilemma faced by both policymakers in general (Hammond, 1996), and public health leaders responsible for health security in particular. There exists a trade-off involved in shifting the threshold to the left or to the right, with regards to the policy errors that are reduced and increased as a consequence of such a shift. Note that the threshold itself forms another relevant *judgment* that health security teams must make during this first decision stage of health security decisions. This judgment

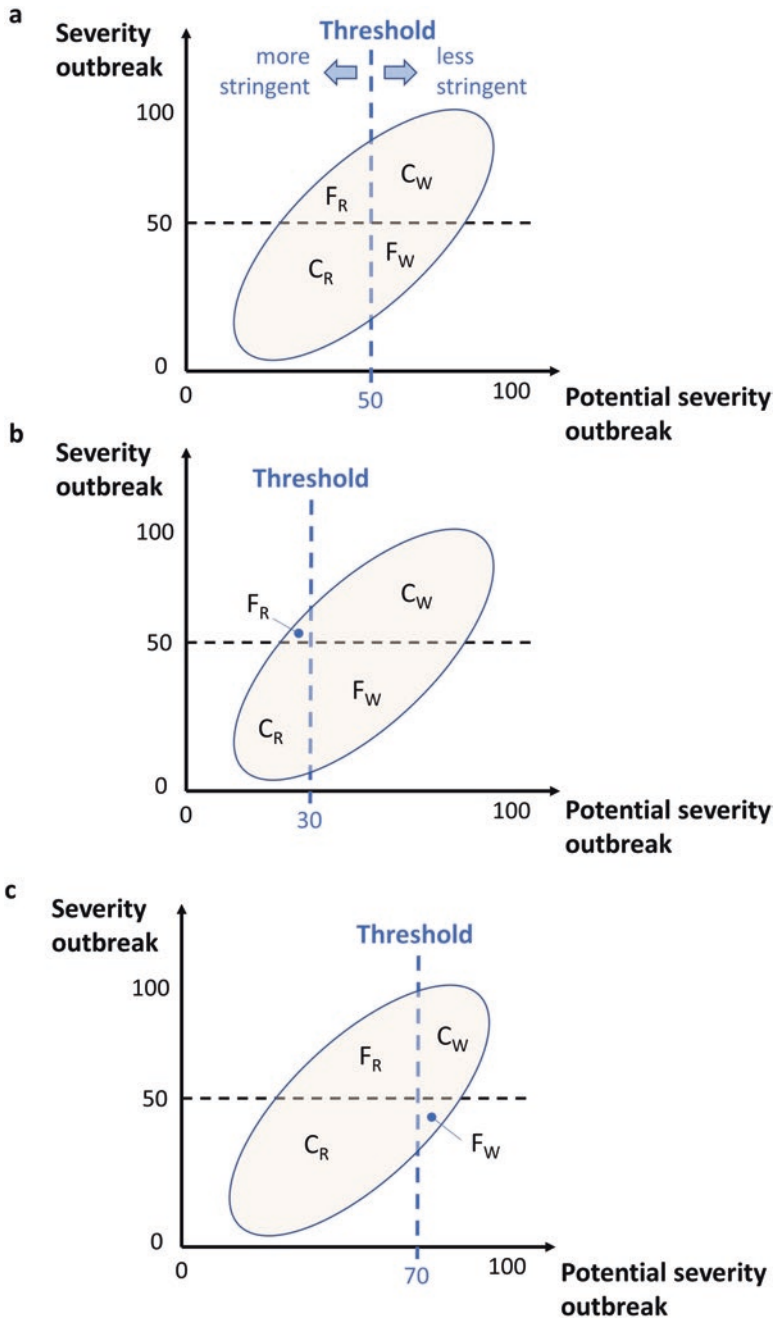

Fig. 3.3 Defining the threshold for health security actions: (**a**) Regular threshold position, (**b**) More stringent threshold position, (**c**) Less stringent threshold position

requires groups to establish a balance, with regards to inevitable types of policy errors that are acceptable and unacceptable and, thus, must be carefully considered.

We shall now assume that a relevant health security decision problem has been identified to be of concern by the health security team. Consequently, this decision stage now demands that the decision problem be adequately defined, the topic of which is covered in detail in the next section.

3.2 Defining the Health Security Decision Problem

The conceptualization of what exactly constitutes a *problem* has vast implications for how a problem should be defined and, subsequently, how this problem can be solved. This conceptualization also has implications for how a decision process should be structured, and which individuals should be consulted in decision making, so that the theoretical discussion be relevant to guide best practices.

The body of research that observes problem solving has given rise to a useful dichotomy, that of the *objectivist* view and the *constructivist* view of problems (Landry, 1995; Roy, 1993). Knowledge plays a central role in the conceptualization of problems, in that problem solving implies an inquiry into the selection and justification of actions. As a result, it is only through producing knowledge that a problem can be solved (Landry, 1988). The manner in which knowledge is produced about the issues under consideration constitutes the factor that brings about this dichotomy of views, and shall be discussed next.

3.2.1 Taking an Objectivist View of Problems

The most traditional conceptualization of problem follows the objectivist view (Eden & Sims, 1979; Landry, 1995), whereby problems are conceptualized to be external objects, that lead an autonomous existence, and are not dependent upon the knowledge of any subject. Viewed through this objectivist lens, the judgment that a problem exists is understood to be an objective assessment, derived from the empirical observation of facts and evidence. Consequently, the objectivist view engenders this common advice that we should solve the "right problem", and avoid solving the "wrong problem" (which would incur in the Type III Error (Mitroff & Featheringham, 1974)).

The objectivist view has a long tradition, based on scientific empiricism, and works satisfactorily for well-defined, technical problems. In this type of conceptualization, the system has a single clear and undisputed purpose, and thus an unsatisfactory event can be objectively identified with ease (Checkland & Scholes, 1999).

Let us consider the design of an artificial cardiac pacemaker. There exist preestablished ranges for the key outputs of this medical device, such as the voltage, current, and frequency of pulses. An objective assessment should use adequate

testing equipment for measuring these outputs. Any variation detected outside the pre-established ranges (from one of the outputs) would indicate a problem that must be corrected. Testing equipment that is more accurate can provide a more objective assessment concerning the performance of the pacemaker, and this test ultimately does not depend upon or require any subjective observations by the testing equipment user. Indeed, one wishes to avoid asking the user for their subjective opinion as to how well the pacemaker is functioning and, instead, prefers to employ a highly accurate testing device.

However, as we have discussed in the first chapter, health security decisions are complex, involving many stakeholders, multiple decision makers, unclear decision contexts, and sources of evidence that are often conflicting. When we take these factors into account, we see that the context is characterized by its inherent ambiguity and thus, it is far from clear as to what the problem to be solved is, or, indeed, if there exists a problem at all. In contrast to the problems that are solely technical, health security problems also have embedded in them an intrinsic element of *socio-technical* complexity (Mumford, 2006).

Let us posit a case wherein there exists recent evidence regarding a small number of cases of pathogen transmission between an animal reservoir to another animal, a bat-to-ferret transmission. This health threat could bring about an emerging disease that may affect humans. Veterinarians responsible for monitoring bio-security threats may become deeply concerned about this event and perceive the event to be a significant health security problem if the pathogen were to spill over to humans. On the other hand, public health officials may consider the event to be irrelevant, as it would fail to directly affect humans, unless a further transmission path from ferrets to humans were to form. Therefore, we see that for these latter officials, this evidence may not constitute a problem.

In this case, one could argue that only future events shall enable us to know which officials were correct or incorrect with regards to their judgements concerning the transmission of this pathogen. Either the veterinarians responsible for monitoring bio-security threats and the identification of a bat-ferret transmission that was classed to be a health security problem, or the public health officials, who did not perceive the same event to be a problem at all, shall be proven correct or incorrect. The occurrence of a future event involving a spillover from ferrets to humans would provide the necessary evidence for this retrospective assessment.

However, this type of hindsight evaluation would suffer from the outcome bias that was described in the second chapter, entailing the evaluation of a judgment (as to whether there exists a problem, condition 1 in Table 3.1) utilizing information that was not available at the time when this judgement was made (Mazzocco et al., 2004). From a Decision Sciences perspective, this evaluation fails to constitute a valid method of assessing judgments as to whether a problem did indeed exist. Certainly, at the time when there was deliberation as to whether to designate this new issue as a problem, it was not possible to objectively identify the correct or incorrect party with regards to the judgement of veterinarians versus public health experts. Instead, we see a process wherein each stakeholder employed their own remit, experience, and scientific knowledge, to judge the available evidence and make a judgment call.

What this case above, hopefully, illustrates is that there exists the need to adopt a different paradigm[2] for health security problems, as a consequence of their socio-technical complexity. When undertaking complex health security decisions, the conceptualization of problems require that we assume a constructivist view, as argued in the subsequent section.

3.2.2 Taking a Constructivist View of Problems

Cognitive Psychology research has discerned that individuals employ a mental frame to acquire, understand, and make sense of events that they observe (McKenzie et al., 2009). While events and evidence are objective, what is perceived and understood by an individual is subjective, in that this perception and understanding is dependent upon responsibilities, experiences, and scientific knowledge that are unique to the subject. The constructivist view of problems (Landry, 1995) understands learning to be the interaction between an object (the external reality) and the subject (the internal reality), and, since meaning is not exogenous, the subject actively creates meaning through this process of interaction with their environment.

From a constructivist perspective, problems are not conceptualized to be external realities but instead, problems are taken to be human constructs, wherein an external reality forms a root from which problems are actively constructed. This constructivist view is in direct contrast to its objectivist counterpart, whose conceptualization of problems involves the *discovery*, as opposed to the construction, of problems. There exist more (and less) beneficial ways of constructing problems, so that the modes of thinking and frameworks employed be more (or less) beneficial, and contribute toward the manner in which a situation is perceived and understood.

This constructivist perspective clarifies as to why individuals whose backgrounds, responsibilities, and concerns vary greatly may perceive and approach the same situation in completely different ways. For instance, a physician may view an infectious disease to be a problem of individual health, while a public health expert may see view the same disease as a problem of population health. However, these are not mutually exclusive problem definitions and, indeed, a joint problem definition from these two professionals may define the disease to be both a problem of individual health *and* population health.

An important consequence brought about by this constructivist perspective is that there exist different conceptualizations of "what the problem is". This multi-conceptualization occurs whenever there is a socio-technical complexity, such as the presence of multiple stakeholders, involvement of many decision makers, and engagement of several experts. Each of these individuals may initially develop a distinctive problem definition, which entails a construction from the same reality.

[2] Paradigm in the strictly scientific sense, as originally formulated by Kuhn (Kuhn & Hacking, 2012).

This multi-conceptualization from different perspectives is illustrated graphically in Fig. 3.4a. The figure depicts the *individual* problem definition (PD) that has been constructed by four different stakeholders who have been confronted by the *same reality*, giving rise to four individual problem definitions: PD_1, PD_2, PD_3 and PD_4. If we were to consider a single problem definition produced by only one stakeholder, in this case, for instance PD_4, the analysis of and solution to the problem would be undertaken in a narrow and distinctive manner, as is unique to this fourth stakeholder, thus ignoring the many aspects that concern the other three stakeholders.

On the other hand, if we were to consider all four perspectives, these different perspectives would work in tandem to produce a more extensive conceptualization. Notice that aspects of the *individual* problem definitions (contributed by a single stakeholder), at times coincide with that of the other stakeholders, such as the coincidence between Stakeholder 2 and 4 (area C_{24} in the Fig. 3.1a) and Stakeholders 1, 2 and 3 (area C_{123} in the same figure), although these joint aspects are rather limited.

Contrary to the popular recommendations that we must "solve the right problem", and "avoid solving the wrong problem", this more contemporary perspective on problem solving emphasizes that problems are defined by people (Eden & Ackermann, 2013; Eden & Sims, 1979). Hence, in a constructivist view, the concept of the "right" or "wrong" problem does not exist, instead, there simply exists the presence or the absence of the problem itself. To understand "what the problem is", it is necessary to have an understanding as to how each stakeholder perceives and conceptualizes the situation, and identify their distinctive perspectives (areas that do not overlap in Fig. 3.4a), as well as their joint perspectives (areas that do overlap in the same figure).

Let us consider the debate surrounding compulsory vaccination against infectious diseases. While the majority of health experts view this policy favorably, the anti-vaccination movement, which has become increasingly popular in recent years, particularly in wealthy Western countries (Osterholm & Olshaker, 2017), is opposed to this policy on the basis of potential risks caused by the vaccines and the argument of freedom of choice. If we were to assume that there indeed exists a "right problem" to be solved, one could neglect the anti-vaccination concerns and impose compulsory immunization. On the other hand, if we were to understand problems as having been defined by subjects, we would try to appreciate the perspective of those that mobilize anti-vaccination campaigns and the sources of their concerns. This understanding could underpin the creation of campaigns that address anti-vaccination concerns and, hopefully, could reduce the hesitancy to being vaccinated (for instance, by developing safer vaccines or funding educational campaigns that promote the benefits against the low risks involved in the use of well-established vaccines).

The strong behavioral evidence demonstrating that decision makers frequently suffer from the myopic problem representation bias further stresses the importance of employing multiple perspectives. When this bias does occur, decision makers adopt an oversimplified problem definition, that is otherwise too simplistic in contrast to the complex reality that decision makers are confronted with (Legrenzi et al., 1993; Legrezni & Girotto, 1996). In this case, the problem is defined too

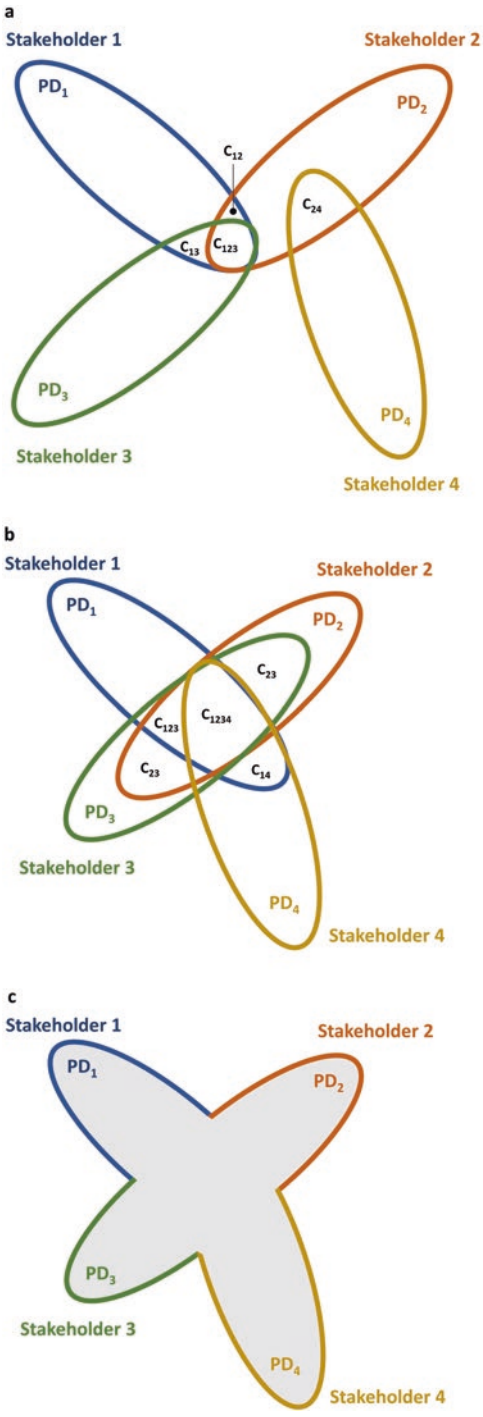

Fig. 3.4 Group problem definition: (**a**) Individual problem definitions. (**b**) Joint problem definitions. (**c**) Negotiated problem definition

narrowly by the subject, and as a result, important aspects that should have been considered are overlooked. This narrow problem definition shall likely lead to the development of solutions that are simplistic and may struggle to be implemented, as our compulsory vaccination case illustrates. Accordingly, how can we ensure that the problem definition is broader and encompasses all the relevant points that must be considered?

This question directs us to another important consequence of adopting a constructivist perspective in relation to problem definition, which can inform us as to how to best conduct the procedure of developing a more comprehensive definition. If problems are taken to be an individual construct, then avoiding a narrow problem definition necessitates the engagement of key stakeholders to develop a shared problem definition (Eden & Ackermann, 2013; Eden et al., 1983; Eden & Sims, 1979).

The process of developing a shared problem definition requires that the health security team share their different individual perspectives (PDs in Fig. 3.4a), identify any areas of commonalities and negotiate a *joint problem definition*. Such a definition shall foster a shared understanding and agreement with regards to the situation among all the members of the decision team (area C_{1234} in Fig. 3.4b), between some of its members (e.g. areas C_{23} or C_{14} in the same figure), while retaining their individual perspectives (areas that do not overlap in Fig. 3.4b). Taken as a whole, the joint problem definition therefore constitutes a *negotiated and agreed definition* of the decision problem that must be solved, as illustrated in Fig. 3.4c.

Notice that merely increasing the number of individuals that comprise the health security team fails to suffice as an action aimed at broadening the problem definition. If all members of the group were to share the same background, have similar responsibilities, experiences, and perspectives, they would likely to develop similar problem definitions (for example they would all develop the problem definition PD_1 in Fig. 3.4a). In addition, teams with low variation in views may suffer from *groupthink* (Janis, 1983), wherein a cohesive and protective group environment prevents other perspectives from being considered and incorporated into the problem definition. Thus, we see that this group bias can bring about narrow problem definitions (Jones & Roelofsma, 2000; Kerr & Tindale, 2011; Nickerson & Argyres, 2018).

To minimize groupthink and broaden the problem definition, a varied set of experts and policymakers that espouse different perspectives should be incorporated into, and form part of the health security team. Additionally, it is important that we foster these different perspectives among team members and support the negotiation of their shared problem definition (Eden & Ackermann, 2013; Eden et al., 1983; Montibeller & von Winterfeldt, 2018). In order to identify the suitable individuals that shall constitute part of the health security team, an understanding of the role of key stakeholders within the decision context is required, as shall be discussed in the subsequent section.

3.3 Identifying Key Stakeholders

The discussion in the previous section has stressed the importance of identifying the key stakeholders involved in every relevant health security decision to develop a suitable problem definition. Any group or individual who has the influence to affect or is affected by the decision is considered to be a stakeholder (Bryson, 2004). This section discusses how we can identify stakeholders, as well as consider the level of engagement that they could have in health security decisions.

3.3.1 Identifying Stakeholders' Interest and Power

When identifying key stakeholders, two factors hold great importance(Ackermann & Eden, 2011). The first factor is the level of *interest* of the stakeholder concerning the issues at stake. The second factor is the level of *influence* that the stakeholder has, or may exert, on the decision-making process.

Neglecting stakeholders that are significantly affected by the decision, while having little influence may lead to the design and selection of policies that neglect societal concerns. The compulsory vaccination campaign against smallpox introduced in Rio de Janeiro in the early part of 1904, epitomizes the risks and consequences that stem from ignoring this category of stakeholders. The compulsory vaccination campaign triggered mass civil unrest, involving looting, barricades, burned trams, and confrontations between deployed troops and civilians. As a result, the vaccination campaign in Rio de Janeiro was abandoned and the city was the locus of several large outbreaks of smallpox in the years that followed (Meade, 1986).

Another problematic act entails neglecting stakeholders that have significant influence over a decision, but are affected to a relatively low extent. With regards to vaccines, pharmaceutical companies had demonstrated little interest in developing novel vaccines during the first two decades of the twenty-first century, despite their financial and intellectual capacity to do so. This behavior may be in part explained by governments providing low financial incentives to these companies (governments constitute a stakeholder that is both influential and heavily affected by this decision), causing negative consequences to public health (Osterholm & Olshaker, 2017).

Stakeholders that are highly influential *and* are heavily affected by the decisions also constitute a crucial facet of health security decisions. This group encompasses, for instance, the health policymakers responsible for health security, health experts and epidemiologists, government officials that are heads of health systems, and health professionals that manage health systems.

Since many health security decisions are multi-organizational, it advisable that the assessment of the influence and interest of each stakeholder be focused on the issues at stake and on the decision process, as opposed to focusing on a single organization or a specific sector of society (Gregory et al., 2020). A clear focus on decision making, and on the specific decision context, can greatly facilitate the identification of key stakeholders (de Gooyert et al., 2017; Keeney, 1992).

There exist a plethora of methods for stakeholder analysis in the context of public decisions (see Bryson (2004) for an overview and Brugha and Varvasovszky (2000) for a review of stakeholder analysis for health policy decisions). The successful identification of key stakeholders involves recognizing those that must be involved in health security decisions. However, not only must we identify these stakeholders, but we must also adequately manage the level of engagement of key stakeholders, as detailed next.

3.3.2 Managing Levels of Engagement with Stakeholders

Once we have located the position that stakeholders retain with regards to their respective levels of interest and influence, and key stakeholders have been identified, there exist three levels pertaining to their engagement in decision making processes (Green & Hunton-Clarke, 2003). These levels are described below.

Informative Participation The first level of engagement is informative participation, wherein the stakeholder is informed about issues related to the decision process. An example of this level of engagement could take the form of a risk communication about a health threat to members of society, through describing modes of transmission, potential severity, and precautions to be taken against infections. Here, the stakeholder is only engaged in passive participation, in that they receive information. However, we can foster informative participation by enabling the possibility for a two-way interaction involving the stakeholder and the health security team, for instance, employing and circulating an opinion survey about the perceived risk of a health threat. Despite implementing measures such as this, the level of stakeholder participation remains limited, with decision makers having a rather superficial understanding of stakeholder perspectives and priorities.

Consultative Participation The second level of engagement is consultative participation, wherein the stakeholder is asked for their views and perspectives on a given issue, so that decision makers may gain a deeper understanding as to the concerns held by the stakeholder than the previous level of participation would otherwise allow. For instance, consultative participation could take the form of engaging health experts, with the aim of eliciting their expert opinion on possible consequences of a health threat. The information from this interaction is then typically used as input by the decision makers responsible for health security decisions.

Decisional Participation The third level of engagement is decisional participation, wherein the stakeholder actively participates in the decision-making process. At this level, engagement assumes the form of the direct involvement of the stakeholder, whose participation influences the problem definition, identification of relevant consequences, definition of decision alternatives, and selection of options. Therefore, the choice of stakeholders with decisional participation is crucial; the

absence of an important stakeholder may delegitimize the decision or neglect an important perspective, and the presence of an inadequate stakeholder may derail or hinder the decision process.

Once key stakeholders have been identified and the level of engagement for each stakeholder has been defined, the composition of a health security team has been determined. The manner in which we can effectively manage these groups shall be the topic of the next section.

3.4 Managing Health Security Teams

When dealing with large scale health security decisions, two groups are usually assembled. One group is composed of decision makers, which encompasses health policy makers, health professionals, and government representatives that are responsible for making the decision. These are stakeholders that are engaged in decisional participation. Often, these decision making groups are supported by an independent decision analyst, whose expertise in Decision Analysis underpins the modeling of the decision problem, and whose presence facilitates group interaction, promoting efficient and effective group decision making processes (Franco & Montibeller, 2010, 2011; Montibeller, 2018). A second group is composed of experts, which may involve epidemiologists and health experts, as well as experts on risk communication and economists. This latter group usually plays an advisory role, and therefore their level of engagement is that of consultative participation.

It is advisable that the size of these groups be monitored, as group size has a significant impact on group dynamics, which may affect how decisions are made and conclusions reached. Smaller groups are easier to facilitate and, where possible, are typically preferred for leading decision making processes (Franco & Montibeller, 2010; Phillips, 2007). On the other hand, large groups usually require specific tools to guide decision making or consultative processes (Shaw et al., 2004). A useful method to manage these larger groups entails organizing breakout rooms, wherein smaller groups analyze specific issues and their conclusions are then relayed to the main group. Accordingly, establishing a balance between stakeholder representation and group size is important, and constitutes a crucial meta-choice[3] in decision making processes.

When focusing on smaller scale health security decisions, often health experts and policy makers shall sit at the decision table, and, in terms of participation level, there exists a more ambiguous delineation. At times, health experts contribute opinions that are decision-focused (decisional participation), while also presenting

[3] Meta-choices drive a decision process and ultimately have a strong influence on the choices that are made, as the meta-choices influence which decision alternatives are considered, which consequences are deemed relevant, which uncertainties are analysed, which evidence and judgments are included, and how options are appraised and chosen (Ferretti & Montibeller, 2016).

evidence and scientific knowledge (consultative participation). Policymakers may also a play a dual role, in that they have considerable expertise, as well as designated decision-making responsibilities. In such case, it is advisable that the roles be more explicitly defined. Therefore, an expert should make clear when they are contributing hard evidence, or, conversely, expressing an opinion or making a judgment. Similarly, a decision maker, when commenting on data, should make explicit their role as an expert, or, when setting up a priority or defining a risk limit, should make explicit their role when performing the function of a policymaker. Once again, decision analysts often support these mixed groups, using Decision Analysis to model the decision, while facilitating group discussions and supporting the team in reaching a conclusion (Franco & Montibeller, 2010; Phillips, 2007).

There exists substantial evidence from Social Psychology that varied groups increase the quality of expert advice and of decision making, if the process of engagement and participation of these groups is carefully managed (Kerr & Tindale, 2004). There exist several benefits to forming teams of policymakers and experts (Kerr & Tindale, 2011; Montibeller & von Winterfeldt, 2018), in addition to providing a richer and broader shared problem definition (Nickerson & Argyres, 2018). First, groups enable the pooling of relevant information from their participants, stemming from the different expertise and knowledge contributed by these participants. In varied and multi-disciplinary groups, this information tends to be highly complementary, therefore providing a more detailed account of the situation. Second, groups allow for the greater possibility to detect errors. When gathering evidence and data, there always exists the possibility of errors, regardless as to the effort exerted when attempting to work in an accurate and precise manner. Members of the group can detect errors in the data or in the interpretation of the data, as well as any inaccurate arguments or simplistic solutions. Third, groups can enhance individual task motivation. Individuals usually increase their level of effort when this effort is deemed to be important in obtaining valued outcomes (which could take the form of robust advice or reasoned decision making). Fourth, working in groups can lead to higher satisfaction rates for group members, in comparison with individual (and consequently, isolated) work. Fifth, for decision making groups, one additional benefit is a sense of common purpose and an agreement on how best to proceed (Phillips, 2007).

However, working as a group also incurs potential disadvantages (Kerr & Tindale, 2011). First, there frequently exists the element of group pressure to conform to the majority view, suppressing minority opinions which may be highly valuable or important for reaching a conclusion. Second, groups may be dominated by a strong leader or influential member. This may lead to a narrow perspective of the issue being considered and, if this influential member is incorrect concerning elements of the decision process but nevertheless dominates the discussion, wrong conclusions may be drawn. Third, groups may demonstrate indifference toward novel information that is only in that moment being communicated. Typically, we see that groups focus on information shared by its members, but disregard information that is novel when it is communicated by a single member. Fourth, groups may suffer from dysfunctional shared representations, which can bring about false

assumptions and thus, misinformed conclusions.[4] Fifth, groups may fail to coordinate effectively, which directly affects their performance. This failure to coordinate stems from group work that lacks structure, which increases the likelihood that the group becomes less coordinated. In addition, as we have previously mentioned, it is a more difficult task to coordinate larger groups in comparison to smaller ones. Sixth, the process of working in a group may prove time-consuming for their participants and costly for their organizational sponsors. Finally, interpersonal conflicts that may arise during group work could prove to have a detrimental effect on group dynamics, as well as on on the commitment on how to proceed.

Therefore, it is crucial that health security teams be well managed, given the typical usage of groups in these health security decision situations and the potential benefits of assembling key stakeholders as a group on one hand, and the element of possible drawbacks involved in group work on the other. Health Decision Analysis can aid in structuring the decision-making process in a way that the information contributed by experts, and the inputs imparted by decision makers, are selectively adopted, negotiated, adjusted and re-established in a manner that is suitable, relevant and beneficial to the situation in actuality. Therefore, such an analysis is essential in identifying not only which individuals should be involved but also how each of these individuals can contribute to the decision process.

Effective group facilitation can also aid in increasing the quality of the health security team performance. In such cases, the group work is supported by a facilitator, whose role it is to promote effective team work while ensuring that dysfunctional group behaviors are minimized (Kerr & Tindale, 2011) and group judgments are debiased (Montibeller & von Winterfeldt, 2018). This facilitation is accomplished either through instating an internal group member as a facilitator (Schwarz, 2002; Weaver & Farrell, 1997; Whichard & Kees, 2006), or through instating an external facilitator that employs Health Decision Analysis to support the health security team (Franco & Montibeller, 2010; Montibeller, 2018). We shall return to the management of group decision making, in more detail, in the eleventh chapter. We turn next to another thorny issue involved in health security decisions, that of managing power dynamics.

3.5 Managing Power Dynamics in Health Security Decisions

Power dynamics plays a central role in health security decisions, both at national and supranational levels, and is an intrinsic element of any strategic decision (Child et al., 2009). These decisions typically affect several stakeholders, many of them influential, while directly involving health experts, policymakers, risk managers,

[4] For example, the notion that providing clean needles for intravenous drug users to prevent the transmission of HIV and hepatitis C would increase drug consumption, could lead to a ban on the distribution of clean needles, and a consequent increase in the risk of transmission among these drug users.

and advisors, all of which have varying degrees of influence and authority. This complex decision setting is often compounded by unclear power structures, involving multiple organizational units within a government and the involvement of private organizations.

In decision processes, we must carefully manage any existing power dynamics among key stakeholders. Indeed, an effective management of power relations is important if we wish to succeed in designing high-quality decision alternatives, deciding as to which are the best options, and implementing the selected options successfully (see Pfeffer (2010) for a detailed discussion on how to manage organizational power).

An effective way to manage power dynamics within decision making groups entails the appointment of an internal or external facilitator (Franco & Nielsen, 2018). A facilitator can assist in fostering healthy discussion concerning any divergence in opinions and perspectives (Garvin & Roberto, 2001) by ensuring that less influential group members are included, and their opinion considered while preventing that more influential members dominate these discussions (Schwarz, 2002; Weaver & Farrell, 1997). Similarly, we can employ tools for digital collaboration wherein members of the team input and link ideas, as utilizing a digital medium may provide an equal opportunity for the exchange of perspectives. A digital medium also enables an initial anonymization of ideas, which can assist members in safely divulging their opinions to other, more influential, members of the groups from a relative distance, and otherwise allows these members to avoid the risk of experiencing social pressure against dissent (Janis, 1983). Data security evidently should be assured if utilizing these digital collaboration tools, to minimize the risks of hacking, tracking, leaking or erasing sensitive information.

Health security decisions are likely to generate political behavior among the influential stakeholders involved or affected by the decision outcomes. Not only do these decisions prove to be complex, triggering significant consequences, and being bounded by uncertainty, as discussed in the first chapter, but often, stakeholders compete for scarce resources that allow for the improvement of health preparedness. This competition for resources could either occur at an intra-organizational level (among divisions of a governmental department), or at an inter-organizational level (among governmental departments).

Specifically, there exist several factors that contribute to the politicization of health security decisions (Child et al., 2009; Hickson et al., 1986). First, the organization responsible for health security decisions is often dependent upon external organizations for resources or approvals. This dependency emplaces the organization in a subordinate position, and may require the organization to lobby external agents for resources, involve influential external agents as advisors or policymakers, or to develop political capital with external agents. Second, in health security decision settings, we often observe that there exists a decentralized power structure, whose inherent qualities tend to increase conflict and power struggles among the stakeholders involved in the decision. Third, conflict and rivalry may arise between highly specialized groups and organizational divisions that are characterized by their own, unique internally cohesive expertise, scientific background, and

organizational culture. Fourth, power dynamics are malleable. Changes often occur when instating contingency-management groups, such as task forces, and the presence of these groups provokes shifts in pre-existing power dynamics. We see this shift take place particularly *after* the acquisition of resources and the implementation of actions that had been required to manage an emergency.

There exist several political tactics that influential stakeholders may use (Elbanna, 2006) when seeking to exert excessive influence on the decision-making process, or affect the decision content in a manner that excessively favors the particular interests of these stakeholders (through the inclusion of factors that they significantly prioritize, or the exclusion of factors that they wish to omit from consideration). These tactics include actions such as: (i) coalition formation to promote narrow or specific interests, (ii) agenda control to distort decision making processes, (iii) opportune actions to exert excessive pressure on decision makers or to avoid full scrutiny concerning the favored solutions, (iv) use of external expert consultants to promote a favored perspective, (v) off-the-table negotiation or bargaining to influence participants or options, (vi) excessive use of power to prioritize specific interests, and (vii) manipulation and control of crucial information to distort a health decision analysis.

Political behavior has the potential to bring about some significant detrimental consequences for health security decisions (Child et al., 2009). This set of behaviors may negatively affect both the quality of the decision process and the implementation of chosen solutions (Elbanna, 2006) on several fronts. First, political tactics may lead to the distortion of information and the deliberate presentation of incomplete information. This mismanagement of information transgresses the requirement that information be shared and discussed openly, which is a vital element of high quality decision making, as detailed in the previous chapter (Schulz-Hardt et al., 2006; Spetzler et al., 2016). Second, a politicized environment typically leads to highly polarized, divisive, protracted, and convoluted decision processes. Instead, a more collaborative and less antagonist decision process (Amason, 1998; Garvin & Roberto, 2001) is likely to prove more productive and effective. Third, some more influential figures may retain a narrow set of objectives that they wish to impose. The motivation to achieve an imposition of a narrow set of objectives could stem from the desire to exclude other feasible alternatives whose consequences, for whatever reason, are deemed to be unfavorable by these influential figures. Similarly, a narrow set of objectives may neglect important consequences and constraints in the decision setting. This action contradicts the advice that has been established to bring about high quality decision making, which stipulates that we must consider all the relevant consequences and conduct a thorough assessment of a varied set of decision alternatives (Keeney, 1992, 2013). Fourth, highly politicized environments are likely to foster a situation that is less cohesive and whose participants are less commitment to the implementation of the chosen solutions. Instead, carefully facilitated decision processes should underpin a shared understanding of a given situation and a full commitment concerning how best to proceed (Phillips, 2007).

Given these negative impacts on the quality of decision processes, it is important that political behavior be detected and minimized to the greatest extent possible in

health security decisions. An example of the role of political behavior in health security decisions is observed in the political interference among different nations and special interest groups that have prevented an objective scientific assessment as to the origins of the SARS-CoV-2 virus which triggered the global pandemic in 2020. Since the beginning of the pandemic there have been appeals made that stress the importance of identifying the animal source of the virus, by the International Health Regulations Emergency Committee of independent experts, (WHO, 2021), however, the highly politicized environment has made such an investigation exceedingly challenging.

If we adopt the perspective required for decision processes, the most appropriate advice entails recognizing that there exists an intrinsic element of power dynamics in health security decisions and that these dynamics must be effectively managed (Pfeffer, 2010). This necessitates that we design decision processes that seize the beneficial potential that also constitutes an inherent facet of making decisions in groups. However, we must also consider that the more negative potentialities intrinsic to making decisions in groups, require the effective management of power dynamics and the minimization of dysfunctional group and political behavior. In addition to these recommendations, from a decision content perspective, the advice is to make clear and precise the details involved in the decision context, as detailed in the following section.

3.6 Clarifying the Decision Context

Key stakeholders will continuously highlight important trends and events that may require action and bring them to the attention of the health security team (Nutt, 1998). For instance, health experts may highlight new cases of a known disease that has begun to re-emerge with concerning mutations, or health surveillance systems may indicate worrying signals concerning an emerging health threat. However, almost invariably, health security decisions have an unclear decision context, which define what should be included and excluded in the decision. Indeed, a crucial advantage brought about through the adequate framing of the decision situation is that this framing provides a clear and comprehensive understanding of the decision context and the exact decision objectives that the team wishes to achieve. Consequently, two important tasks in the structuring of a decision situation are to clearly identify the purpose of the decision, and to delineate the scope of the health decision analysis. These two tasks are detailed in the subsequent sections.

3.6.1 Identifying the Decision Purpose

The decision purpose seeks to clarify the exact nature of the decision itself (Spetzler et al., 2016). Rather than utilizing a broad problem statement, the construction of a more clearly defined decision problem statement, or whenever possible,

well-specified decision opportunities (Keeney, 1992), proves to be a robust manner to focus health security activities on decision making and improve health preparedness.

As we described earlier in this chapter, problem situations are identified whenever the health security team judges that a given issue fulfills the four conditions stated in Table 3.1. For instance, the team may say: "we have a identified a problem with our health surveillance system". Following the rationality axioms of decision making described in the second chapter, a decision always requires at least two alternatives. Therefore, a decision problem should contain a statement that alludes to the options under consideration, or to the possibility of designing options to cope with or resolve the problem. For example, the decision problem statement regarding the health surveillance system could be defined as: "what is the best way of resolving the issue affecting the health surveillance system?"

Problem statements can also be re-phrased as opportunities; this provides a more creative approach to thinking about possible decision alternatives (Keeney, 1992). For example, the problem found to be affecting the surveillance system could be redefined as: "what is the best way of improving the health surveillance system?". This definition alludes to the opportunity of identifying new alternatives for improving the system overall or, perhaps, redesigning the entire system.

Consider another very common problem that health organizations face, that of informing the public about life-threatening risks (Keeney, 1992; Keeney & Winterfeldt, 1986). This problem of risk communication is rarely recognized as a health security decision, wherein there exist several ways of informing the public. Some forms of communication are focused on informing about a risk ("the fatality rate for this infectious disease is 1%") others seek to educate the public about an infectious disease ("vulnerable people are at greater risk than those without pre-existing health conditions"), or other forms encourage risk reduction practices ("individuals should wash their hands and avoid touching their faces"). A decision opportunity statement, such as "what is the best manner to communicate this life-threatening health risk?", could thus help decision makers to consider a broader set of options. Once the purpose of the decision has been clearly established, the health decision team should identify the scope of the decision, as described next.

3.6.2 Delineating the Scope of the Decision

There exist two main tasks to be undertaken in order to delineate the scope of a decision. At the macro level, decisions can be classified as *those that have already been made*, as *those to be decided upon later or separately*, and as *those to be focused on at present* (Spetzler et al., 2016). The decisions that have already been made shall not be considered in the health decision analysis, instead, they shall act as constraints on the decisions being made.

Let us consider a case wherein a decision was previously made that imposed a quarantine mandate for all citizens returning to their country of residence, were they

to arrive from countries wherein the infection rates of a disease were deemed to be excessively high. The decision that have already been made, to impose this mandate, prevents the consideration of any options that requires the free movement of people that have arrived from those affected countries.

Decisions to be determined at a later date, or separately, can be taken subsequently or addressed disjointedly in relation to the decisions that are being made at present. In the case above, the decision to remove the quarantine mandate, once the infection levels in the affected countries have subsided, can be taken subsequently but not at present.

The decisions to be focused on at present are those under consideration by the decision effort of the health security team. In the quarantine decision case, decisions related to how best to accommodate and contain the citizens that are in the process of quarantining could be the decisions to focus on at present.

This macro classification of the scope of decisions may help on two fronts. The first front takes into account that health security decisions operate in a complex environment, with frequent multi-organizational involvement, as discussed in the first chapter. It therefore becomes important to understand the decisions that had been made, and consequent actions established a priori constrain the possibilities of making other decisions. Existing conditions exert influence on possibility, and decisions that have been made form complex networks that either enable or constrain the present (and future) solution space.

Decisions can produce new possibilities that did not previously exist, although not all decisions are realizable all of the time. If we take this notion of complexity into account, the classification aids our second front by fostering an understanding that the identification of decisions that are deemed to be less urgent, or that are able to be postponed, can reduce the sheer complexity involved in health security decision making. By utilizing these approaches, the decision effort can be fully devoted to the decisions that require immediate attention.

Once the decisions that we must turn our immediate attention have been identified and selected, we need to establish the *specific decision context* of each decision and the *fundamental objectives* that we wish to achieve. Taken as a whole, the decision context and fundamental objectives constitute the *decision frame* of the decision situation (see Keeney (1992) for a detailed coverage of this topic, Keeney (2004) for a focus on public decisions, Barcus and Montibeller (2008) for a process coverage, and Cornelissen and Werner (2014) for an organizational perspective).

The specific decision context defines the set of decision alternatives that the health security team considers to be appropriate for a given specific decision situation. The fundamental objectives identify the consequences of fundamental concern within the specific decision situation. It is critical that the decision alternatives and the fundamental objectives be compatible, as alternatives are a means through which objectives can be achieved (Keeney, 1992). That is, the fundamental objectives should be able to help identifying the relevant consequences of each decision alternative under consideration.

A narrow set of fundamental objectives may omit important consequences in a decision, while a narrow decision context may provide a set of decision alternatives

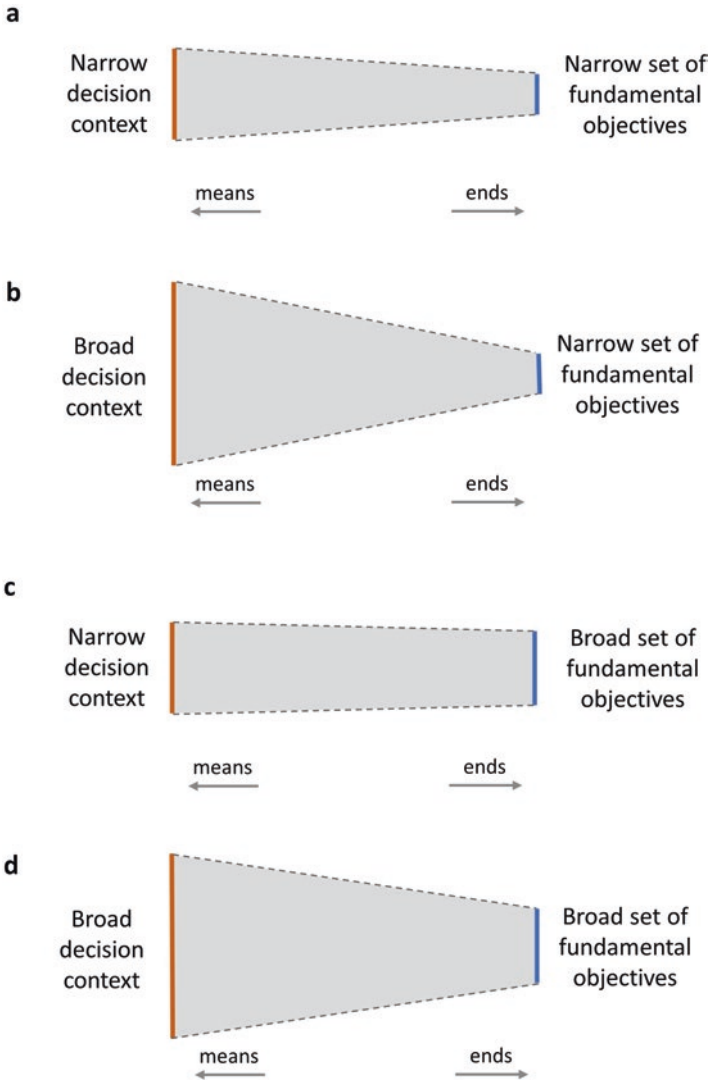

Fig. 3.5 Types of decision frame: (**a**) *Narrow* set of fundamental objectives and *narrow* decision context. (**b**) *Narrow* set of fundamental objectives and *broad* decision context. (**c**) *Broad* set of fundamental objectives and *narrow* decision context. (**d**) *Broad* set of fundamental objectives and *broad* decision context

that are too limited. Let us posit a decision situation that is often experienced in health security contexts: "how can we manage a health threat?". A rather narrow yet fundamental objective for this decision situation could be defined as: *minimize the health effects of this health threat*. Subsequently, the narrow decision context could, for instance, list *options for* the *treatment of infected patients*. This rather common decision frame is represented in Fig. 3.5a, wherein the right-hand vertical bar

represents the narrow set of fundamental objectives, and the left-hand vertical bar represents the narrow decision context. The vertical height of these bars represents the relative narrowness/broadness of the decision frame (these figures have been adapted from the 3D decision frame diagrams proposed by Keeney (1992)).

The decision context could become broader if the health security team were to consider other sets of options to achieve a fundamental objective. For example, to achieve the (narrow) fundamental objective of: *minimizing health effects of the health threat*, the team could consider not only *options for the treatment of infected patients*, but also *options for population immunization*, and *options for transmission containment*. This decision frame is represented in Fig. 3.5b, with a narrow set of fundamental objectives on the right, but a broad decision context on the left.

A less common situation is one wherein a broad set of fundamental objectives is defined, but a relatively narrow decision context is maintained. Let us consider that that fundamental objectives have been expanded to include not only the *minimization of health effects*, but also the *minimization of economic impacts* and *social effects*. The narrow decision context continues to contemplate the original *options for treatment of infected patients*. This combination is illustrated by the decision frame shown in Fig. 3.5c. Contrary to the narrow decision context in Fig. 3.5a, that is only focused on minimizing health effects, here, an expansion of the fundamental objectives follows that the appraisal of *options for the treatment of infected patients* would also consider the impacts that the decision alternatives have at the economic and social levels.

Finally, there exists the possibility of a broad set of fundamental objectives, which give rise to a broad decision context, as is depicted in the decision frame in Fig. 3.5d. As in the previous case, let us posit that the fundamental objectives encompass the *minimization of health effects*, *economic impacts*, and *social effects*. Once again, the health security team is considering a broad set of *options for* the *treatment of infected patients*, for *population immunization*, and for *transmission containment*. These options and their consequences would be assessed by considering their potential impacts from a health, economic, and social perspective, as these constitute fundamental concerns in this decision frame.

Another method to expand the decision context entails shifting from *means objectives* to *fundamental objectives* (Keeney, 1992, 2013). Let us consider the same case as above, that of managing a health threat prompted by a virus. First, let us analyze the narrow decision frame shown in Fig. 3.6. The frame is composed of the narrow objective: *minimize the viral presence*. This would lead to a narrower decision context of risk elimination, which includes *options that reduce the viral presence*, such as isolating infected individuals or suppressing disease vectors.

Second, let us now consider the intermediate decision frame in Fig. 3.6. This frame is composed of the intermediate objective: *minimize viral exposure* and by the intermediate decision context that is comprised of *options seeking to reduce viral exposure*. This broader objective is an end to the objective *minimize viral presence*. The intermediate decision frame also assumes the intermediate decision context of risk mitigation, which considers *options to reduce viral exposure*, such as the compulsory wearing of protective equipment (e.g. masks against respiratory diseases,

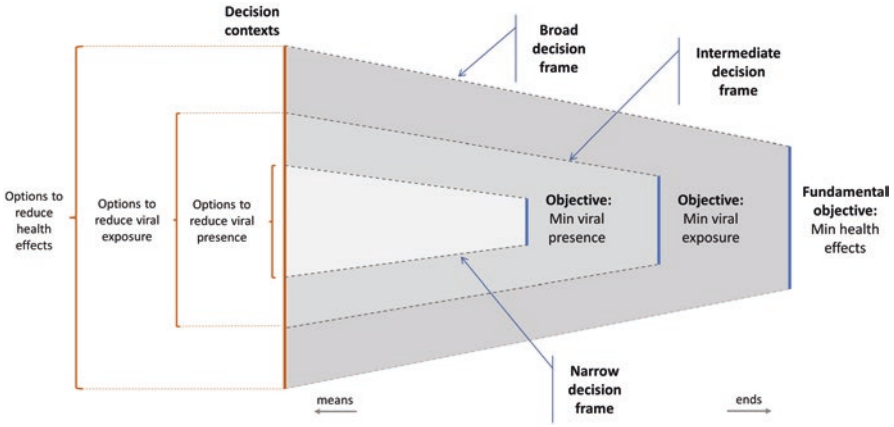

Fig. 3.6 Three decision frames for managing a health threat

mosquito nets against mosquito-transmitted diseases), personal hygiene procedures (e.g. hand disinfection), and so on. The narrow decision context of reducing viral presence also brings about options within the intermediate decision context of *minimizing viral exposure*, as *reducing the viral presence* forms a means of *reducing viral exposure*. In other words, within the intermediate decision frame, whose objective it is to *minimize viral exposure*, both the *options to reduce the viral presence* and the *options to reduce viral exposure* can be considered.

Third, let us now examine the broad decision frame in Fig. 3.6. This frame is composed of the fundamental objective: *minimize health effects* and by the broad decision context of *options to reduce health effects* from this health threat. This fundamental objective is an end to the objective *minimize viral exposure* and is thus broader. The broader decision context considers *options to reduce health effects* (e.g. post-exposure treatments). Additionally, this decision context also encompasses the *options for reducing the viral exposure* and for *reducing the viral presence*, as both decision contexts are aligned to objectives that form a means to achieve this fundamental objective (*minimize viral exposure* and *minimize viral presence*, respectively). Hence, by focusing on fundamental objectives, instead of merely means objectives, the decision context was made broader with more options available to the health security team.

A *broader* decision frame whose fundamental objectives form a comprehensive set should consider all the fundamental objectives of the key stakeholders in the specific decision situation (Keeney, 1992, 2013). A *broader* decision context should encompass an assortment of varied options (Spetzler et al., 2016) that seek to achieve the fundamental objectives under consideration. However, there exists ample behavioral evidence (Montibeller & von Winterfeldt, 2015; Nickerson & Argyres, 2018) that both the definition of fundamental objectives (Bond et al., 2008, 2010) and the identification of decision alternatives (Butler & Scherer, 1997; Pitz et al., 1980) is too narrow in practice, and as a result, the quality of the decision is reduced (Nutt, 2002). Therefore, a significant effort to extend the decision frame is needed for reasoned health security decisions. Subsequent chapters shall describe

tools that can help with both tasks that are paramount to decision framing: defining a comprehensive set of fundamental objectives and identifying a diverse set of decision alternatives.

3.7 Conclusions: Framing Health Security Decisions

This chapter has stressed the importance of problem framing for any successful decision-making process. This framing is the first, and perhaps, the most critical step in any health decision analysis, as an adequate frame establishes the purpose, perspective, and scope for the health security decision that shall be made.

Contrary to the traditional view on problem solving, we have argued that it is not possible to identify the "real problem" or the "right problem" to be solved in situations that are characterized by their high socio-technical complexity, a trait which is common to the vast majority of health security decisions. Problems are constructed from the experience, responsibilities, and the background of each member of the health security team.

Therefore, we have stressed the significance of developing a negotiated group problem definition for the decision situation. This constructivist perspective also highlights the relevance of identifying key stakeholders and carefully considering their levels of involvement in the decision process, while minimizing any dysfunctional group dynamics, negative power dynamics, or detrimental political behavior.

Public health leaders are recipients of a plethora of information and evidence, and must decide which issues require significant attention and effort at present. We have suggested establishing what are the relevant problems to be focused on proves helpful in selecting which decisions to prioritize. Subsequently, we have recommended that health security teams delineate and adequate decision frame for the specific decision situation under considaration, which is composed of fundamental objectives and the specific decision context. The fundamental objectives are required for the development, search, and selection of decision alternatives in a health decision analysis. The specific decision context defines the set of decision alternatives available to such an analysis.

A comprehensive and clear problem definition thus forms the output of the first decision stage in Health Decision Analysis. The identification of fundamental objectives, and the definition of relevant consequences associated with such objectives, is the topic of the subsequent chapter.

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Chapter 4
Specifying Relevant Objectives and Consequences in Health Security Decisions



In the last chapter we emphasized the importance of an adequate decision frame in reasoned health security decisions. Decision frames are constituted by two major components, the first of which is a comprehensive set of fundamental objectives, and the second of which is a diverse set of decision alternatives. In this chapter we focus on the first component, the definition of fundamental objectives.

Reasoned decision making necessitates that we employ fundamental objectives, as these objectives define exactly what the health security team wishes to achieve with the decision. These objectives can also guide the definition of the relevant consequences within the specific decision situation, as well as aid in identifying and developing better decision alternatives.

As we shall discuss in this chapter, fundamental objectives stem from the identification of relevant decision objectives and consequences in the specific decision context. This chapter shall provide tools that can enable public health leaders to comprehensively identify and clearly define the objectives that are relevant to decisions seeking to enhance health security. We also detail how these decision-making objectives should be specified and suggest which individuals should be responsible for establishing them in health security decision processes.

The potential impacts that emerging health threats can cause on multiple tangible and intangible dimensions pose a major challenge for public health leaders. The tangible impacts that affect both public health and individual health are major issues affecting both communities and individuals. Additionally, the economic consequences triggered by these health threats can have extensive and detrimental effects on the affected communities. The costs associated with health preparedness as well as with risk prevention and mitigation policies can also be considerable, particularly if financial resources are already scarce. Furthermore, the aspects of disruption and economic hardship all form tangible social impacts that an emerging health threat may bring about. While other impacts are of an intangible nature, they are also of relevant concern, as fear, psychological stress and civil unrest all threaten to arise as a consequence of emerging health threats.

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In this chapter, we discuss how to consistently and adequately consider these multiple consequences, given their multi-disciplinary nature and the potential involvement of multiple experts. We shall emphasize that if we wish to maximize the societal value of health security decisions, a nexus must be established between the selection of relevant consequences and the fundamental objectives that the health security team wishes to achieve.

In the second chapter we presented a diagram that illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 4.1. The second decision stage covered in this chapter, *specifying relevant objectives and consequences*, is now highlighted in this figure. When detailing this topic, we shall assume that a problem definition has been agreed upon by the health security team, and therefore, that the problem itself has been clearly defined.

4.1 Identifying Relevant Objectives in Health Security Decision

One of the most important messages propounded by this book is that the "achievement of objectives is the sole reason for being interested in any decision" (Keeney, 1992, p. 55). This statement emphasizes that decision makers are goal-driven and that decision alternatives should be seen as means to achieve their goals. However, having supported an extensive range of strategic and policy decisions, we have observed that decision objectives are rarely articulated in a clear manner and often, relevant objectives are initially neglected, until a decision analysis has been developed, leading to fully specified decision objectives.

This unclear articulation of objectives is also frequently observed in health security decisions. Indeed, the majority of the health threat assessments reported in the health policy literature focus primarily on measuring the impacts of these health threats, without a clear connection to decision objectives (Montibeller et al., 2020). However, alongside the appraisal of health threats, a health decision analysis requires that we consider the objectives that decision makers are seeking to achieve, and that we consider the objectives of key stakeholders. Hence, we see that this type of analysis necessitates that we employ a lens through which to view our decision objectives clearly, as these objectives provide an indication as to which consequences are truly significant in the given decision context, and thus, which impacts should be cogitated when assessing and comparing health threats or when evaluating health security actions.

Much like other public decisions, in health security decisions, there exist several reasons for this lack of clarity when specifying objectives and the disregard of relevant objectives. We briefly discuss subsequently the factors that result in neglecting relevant objectives.

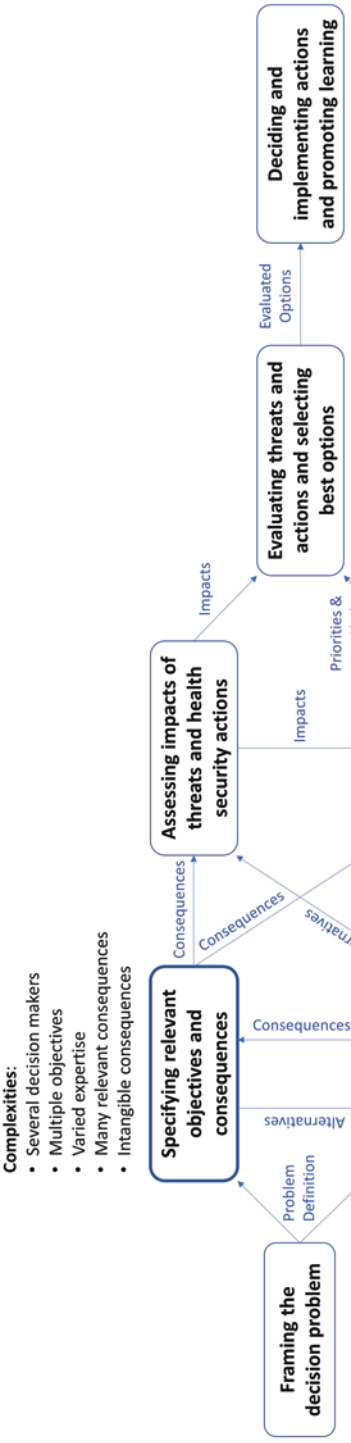

Fig. 4.1 Making reasoned health security decisions: a focus on specifying relevant objectives and consequences

4.1.1 Neglecting Relevant Decision Objectives

There exist three common causes for decision makers to neglect relevant objectives : an excessively data-driven perspective in guiding decision making, a negative influence of cognitive biases affecting the definition of objectives, and a lack of a systematic approach to compare health threats and health security actions. These three factors are detailed in the text that follows (see also Haag et al., 2019).

First, objectives may not be taken into account because health experts and public health leaders are, rightly, focused on evidence and data. However, this data-focused perspective may obfuscate the exact intentions that decision makers are seeking to achieve within the context of a specific decision. At times, this data-focus perspective leads to the use of data that is readily and extensively available, although the data itself proves to be irrelevant to a particular decision, while in actuality, data concerning a relevant consequence remains unavailable, particularly for emerging health threats.

Let us postulate that health security experts from one country (C^A) are monitoring and assessing the risk posed by foreign pathogens found in non-human animals in order to inform their health security decisions. There exists a *neighboring* country (C^N), whose surveillance system utilized to detect such diseases is underdeveloped, and a *distant* country (C^D), that has a highly developed surveillance system for tracking such diseases. The country C^N is engaged in exports of animal produce to C^A, while C^D is not engaged in any such export.

If a scenario were to occur wherein a number of cases of an emerging zoonosis in C^D are discovered, attention in country C^A would consequently be focused on the impacts of this zoonosis, even without a risk path for transmission of the diseases from C^D to C^A. However, if the same cases of an emerging zoonosis occurred in C^N, due to its underdeveloped surveillance system, country C^A would receive no such alerts as to the presence of the zoonosis, and as a result, no attention would be directed to any potential impacts. As a result of this absence of data, systems employed for controlling animal exports from C^N to C^A would not become more stringent. Here, we see that the absence of data has resulted in an absence of action by the health security team, thereby reducing the national health security in this context. Furthermore, the data-focused perspective may prevent C^A from implementing stringent risk controls on imports from C^N, despite the potential for emerging health threats from this neighboring country.

Let us again consider the original situation in this case above, although now the health security team adopts a focus on decision objectives. In this new scenario, the health security team has established the objective of *minimizing the risk of importing animal health threats*, prior to the international data gathering exercise. To achieve such an objective, specific actions would be implemented that necessitate the gathering of evidence from the different countries with whom C^A is engaged in the trade of animal produce and live exports with. This decision focus would also require that C^N improve its surveillance system as well as C^N having to introduce more stringent controls on said commodities. Actions such as these could significantly increase the national health security in this context.

Second, decision objectives may be neglected due to the pre-existing cognitive biases affecting the health security team. Indeed, there exists strong behavioral evidence demonstrating the presence of the omitted variable bias in the specification of decision objectives (Jargowsky, 2005; Montibeller & von Winterfeldt, 2015). This bias results in the frequent exclusion of relevant objectives when making important decisions (Bond et al., 2008, 2010). In addition, the identification of objectives relies heavily on the mental models constructed by decision makers concerning the decision situation (Johnson-Laird, 2001; Legrezni & Girotto, 1996). However, decision makers often suffer from the myopic problem representation bias, which leads to the construction of oversimplified mental models. This cognitive bias may have a significant, detrimental effect on the development of objectives (Legrenzi et al., 1993; Payne et al., 1999). The presence of the availability bias also has a detrimental effect when defining objectives (Bazerman & Moore, 2013; Tversky & Kahneman, 1973), whereby some more salient objectives can be recalled by memory while other relevant objectives cannot and are therefore neglected.

The availability bias can heavily influence health security settings. For instance, policymakers and the general public may direct their attention solely toward a recent outbreak of a disease and the impacts this outbreak has caused. As a consequence, resources are allocated to avoid a re-occurrence, or to minimize the impacts were a similar outbreak to occur again, and by doing so, policymakers divert attention and resources away from other potential threats with relevant consequences. The same phenomenon can also occur due to a myopic problem representation, the presence of which causes health policymakers and health experts who have been undertaking health threats belonging to the same category for an extensive period of time to disregard relevant consequences concerning other categories of health threats which are novel and emerging.

Third, a lack of clear, systematic reasoning that seeks to establish the significance of each objective may result in the neglect of relevant decision objectives and a narrow set of possible solutions (Keeney, 1992; Siebert & Keeney, 2015). As we discussed in the first chapter, unstructured decision approaches that assess and compare decision alternatives rarely consider objectives in a systematic manner (Payne et al., 1993). Although formal evaluations of health threats often consider a great number of impacts, these evaluations may also lack a decision-focused perspective. Specifically, these evaluations fail to grasp the clear connection that exists between the impact assessment and the fundamental objectives to be achieved in the decision situation (Montibeller et al., 2020).

These three factors underpin the explanation as to why decision objectives are often implicit and why relevant objectives are frequently neglected in health security decisions. The absence of a clear set of decision objectives is a major weakness in decision processes and hinders reasoned decision making.

Therefore, it is important that the planning phase of a decision-making process includes the elicitation of decision objectives, which allows for the defining and structuring of objectives in a clear manner. An internal or external facilitator can significantly support the team in the identification and structuring of decision objectives (Franco & Montibeller, 2010, 2011b; Montibeller et al., 2009). In our

experience in training senior managers and policymakers, reflective practitioners can learn how to direct and control their focus toward the objectives of their decisions with ease, and by doing so, practitioners rapidly recognize the benefits of reasoning in this manner. However, we require a clear understanding as to how decision objectives should be specified and structured, which shall constitute the topic of the remaining section (see also Keeney, 1992 for more details).

4.1.2 Specifying Decision Objectives

A *decision objective* is a statement regarding a thing that the health security team wishes to attain. An objective is comprised of three main components: a decision context, an object, and a direction of preference (Keeney, 1992, 2013). Let us consider two health security examples to illustrate this notion of a statement and the three components that form an objective.

First, let us consider the decision context: *how to better manage a health threat*, whose object is: *number of infected individuals*, and whose direction of preference is: *minimize* (as fewer infected individuals is preferable to more infected individuals). This decision objective can thus be defined as: *minimize the number of infected individuals* when considering this specific decision context (*how to better manage the health threat*).

Second, let us posit another decision context: *how to improve the health surveillance system*, whose object is: *effectiveness of the disease detection tools*, and whose direction of preference is *maximize* (as more effectiveness is preferable to less effectiveness). Hence, this decision objective can be stated as *maximize the effectiveness of the disease detection tools* when considering this second specific decision context (*how to improve the health surveillance system*).

Poorly defined objectives should be avoided as they cause ambiguity within the health decision analysis and have detrimental consequences for health security decision processes. For example, consider the objective: *quality of the health system*; the direction of preference is absent from this objective and therefore, it remains unclear as to whether one wishes to *sustain*, or else, *improve* the quality of the health system. This ambiguity proves to be important, as the decision alternatives that seek to sustain the quality can differ significantly from those that seek to improve the quality, and thus, the ambiguous definition can bring about practical consequences for the decision to be taken.

Poorly defined objectives can also result from the absence of the object itself within the statement. We see this occur with the objective: *minimize impact*. The absence of the object wholly obfuscates as to which specific impact the objective is referring to (e.g. health impacts, economic impacts, social impacts and so on). Once again, this ambiguity may lead decision makers to select alternatives that minimize impacts that were not of concern.

Objectives that are obfuscated in a less evident manner stem from the specification of a decision objective whose specific decision context remains absent from the

statement. Let us consider the objective: *minimize the number of infected individuals*. In this scenario, the absence of a clear decision context (which would otherwise have functioned to specify a particular health threat) could bring about a fragmentation of actions against multiple threats, of which may not have been the original threat that had caused concern in this decision situation.

The previous chapter introduced the notion that decision objectives can be classified into either *means* objectives or *fundamental* objectives (Keeney, 1992, 2013). A single, fundamental objective is an essential reason as to why we take an interest in the health security decision. A set of fundamental objectives represents *all* the essential reasons as to why we take an interest in the decision. A means objective is an interest that we take in a matter in order to attain a fundamental objective. This classification of objectives is always dependent upon the context of the decision frame under consideration.

Let us examine the relationships that exist between the fundamental and the means objectives in greater detail, alongside their role in decision framing. Consider the decision problem depicted in Fig. 4.2 (reproduced from the previous chapter), regarding how to manage an emerging health threat. The fundamental objective: *minimize health effects* and its associated decision context (*options to reduce health effects*) provide a broad decision frame. The objective *minimize viral exposure* and its associated decision context (*options to reduce viral exposure*) provide an intermediate decision frame. Finally, the objective *minimize viral presence* and its associated decision context (*options to reduce viral presence*) provide a narrow decision frame.

These objectives are positioned on a means-end spectrum in Fig. 4.2; the end objectives are positioned to the right and means objectives to the left. Hence, selecting the fundamental objective *minimize health effects*, establishes the means objective to be *minimize viral exposure*, and this latter objective establishes another means objective to be *minimize viral presence*. It is easier to measure as to whether these means objective have been attained than to measure the attainment of the

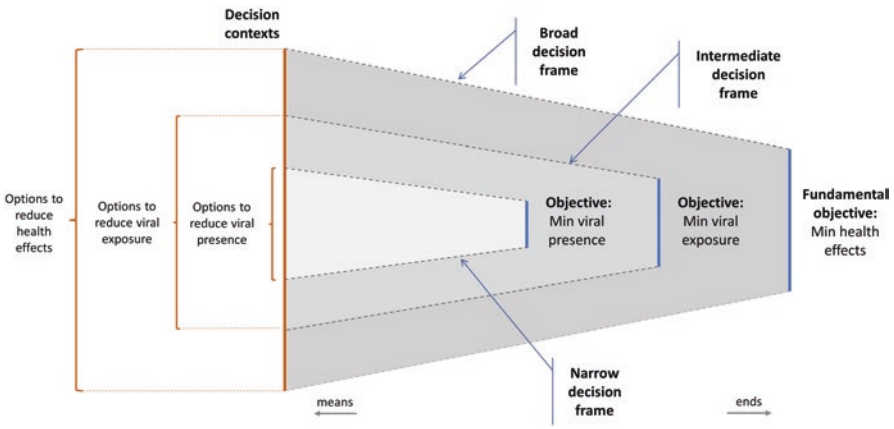

Fig. 4.2 Three decision frames for managing an emerging health threat

fundamental objective, but the means objectives produce a decision frame that is rather narrow. Specifically, in the same figure, the objective *minimize viral presence* would require the selection of a narrow decision context, which only encompasses *options to reduce viral presence*, in comparison to the wider decision context of *options to reduce health effects* that encompasses both *options to reduce viral exposure* and *options to reduce viral presence*.

The positioning of objectives on a means-end spectrum can also be contingent on the organizational structure and division hierarchy. That is, the same objective can be classed as a fundamental objective to a subordinate department but as a means objective to a superior department (see also Barcus & Montibeller, 2008 for details). If we utilize the case above, let us assume that an organization establishes a fundamental objective to be *minimize health impacts in the community* from this emerging health threat. One department from this organization is tasked with attaining an organizational means objective, *minimize the viral presence in the community*. While this latter objective is a means objective to the overall organization, the latter objective is a fundamental objective to this specific department.

There exist several benefits of adopting this focus to attain the specified fundamental objectives in health security decisions. First, defining the fundamental objectives in an explicit and precise manner enables decision makers to know the exact things that are being pursued in a decision. Second, while health security teams often turn their attention toward directly selecting a solution without an explicit concern with regards to objectives, by focusing on objectives, it becomes significantly easier for teams to agree on objectives than on decision alternatives. Third, decision objectives provide a clear rationale for selecting relevant consequences. This rationale stems from the notion that the team seeks to achieve fundamental objectives in their health security decision by measuring the impacts that health security actions have on the relevant consequences, the value of which functions to indicate the achievement of said objectives (i.e. minimizing detrimental impacts and costs alongside maximizing benefits). Fourth, there exists a possibility to reduce political behavior and motivational biases. Evidence demonstrates that a focus on decision alternatives may lead to political behavior, involving some influential stakeholders making partisan arguments in favor of a preferred option (Child et al., 2009), and motivational biases, wherein information about other alternatives is distorted to favor the preferred alternative (Montibeller & von Winterfeldt, 2015). The focus on fundamental objectives should make clear as to which interests and goals are being considered in the evaluation of different decision alternatives. Fifth, the definition of fundamental objectives defines how societal value should be measured and thus enables choices that promote the maximization of societal value, as shall be detailed in the eight chapter of this book.

The definition of objectives is an important meta-choice in decision processes, as the definition has a significant impact on how the decision alternatives shall be evaluated and selected (Ferretti & Montibeller, 2016). Hence, identifying the individual that shall be tasked with defining decision objectives proves to be a central consideration for the decision process. As mentioned in the previous chapter, these objectives should reflect the interests of key stakeholders in the health security

decision. Therefore, stakeholders whose engagement is at a level of decisional participation must influence the definition of objectives, however, the health security team or the body accountable for the decision shall ultimately be responsible for establishing the decision objectives. There exist several tools for supporting the elicitation of objectives (see also Franco & Montibeller, 2011b; Belton & Stewart, 2010; Marttunen et al., 2017 for details). Here, we present two tools that have proved to be particularly useful when we support policy makers in appraising complex policy choices and leaders in making strategic decisions. Probes and causal maps respectively constitute these tools, which function to facilitate health security decisions as well as other strategic level decision processes.

4.1.3 Eliciting Relevant Decision Objectives with Probes

The use of decision probes can support the health security team to consider the precise and exact nature of the details that form their decision objectives in a specific decision context. This chapter has already mentioned the existing behavioral evidence demonstrating that decision makers often omit relevant objectives (Bond et al., 2008). There also exists behavioral evidence demonstrating that these probes can aid decision makers both in expanding the list of objectives and in motivating decision makers to develop a comprehensive list (Bond et al., 2010).

These decision probes are described next (see also Keeney, 1992, 2007). To show how these probes can be employed in practice, we shall illustrate their use utilizing a fictious case, whose decision setting is realistic and stems from our practice in supporting health security decisions. In this case, a health security team is deciding on how best to develop a nationwide vaccination campaign against an emerging infectious disease. This is an important type of health security decision, and consequently, requires substantial financial investment that can be squandered if the campaign proves to be ineffective (WHO, 2007b).

List of Objectives The first decision probe is a list that records all the relevant decision objectives that the team wishes to achieve in the health security decision. To engender creativity, each team member can produce their own list, and only once the individual lists are finished should they be shared with the group. Creativity can also be encouraged by suggesting that the team assume that there exist no limitations or constraints in achieving these objectives.

In the vaccination campaign case, imagine that the team listed as decision objectives *maximize the immunization coverage rate* of the population and *minimize immunization errors* when administering the vaccine (such as an incorrect vaccine being administered or off-schedule vaccine administration) in their list of objectives.

It is important that these listed objectives are specific to the decision context that is under consideration, as the objectives should match the decision frame. For instance, in the vaccination campaign case, the objective: *minimize the cases of lung cancer* would be out of context, despite this objective being relevant for other public health decision contexts.

Decision Alternatives Existing or hypothetical alternatives for the health security decision are useful to underpin team reasoning regarding significant and relative objectives. This probe is more intuitive than the *list of objectives*, given that decisions are typically considered in a manner that focuses on alternatives (Keeney, 1992). Additionally, the process of directly comparing the features of existing alternatives to one another may reveal other objectives that prove to be relevant to the decision context (Buede, 1986). The features of existing alternatives may indicate consequences that the health security team or key stakeholders deem to be significant, and therefore, teams have a greater understanding as to the associated objectives that they wish to achieve.

If we apply this decision probe to the vaccination campaign case, let us posit that the team is considering two options: either that the *vaccination is to be centralized in hospitals* or *decentralized in community centers*. The differences between these two options that prove relevant for the team are: (i) the implementation cost of the campaign and its associated objective to *minimize the cost of the campaign,* (ii) the extent of the outreach campaign (that seeks to include distant or disadvantaged communities) and its associated objective to *maximize the reach of the campaign across population strata* , (iii) and the difficulties accompanying vaccine storage locally and its associated objective to *maximize the storage quality of vaccine stock*.

When comparing alternatives to recognize relevant objectives, not all features that distinguish the alternatives may be relevant, even if the alternatives themselves are relevant to the decision context. If such features do allow decision makers to distinguish between the options but prove to not be relevant, the features should not be included as decision objectives. For example, in the vaccination campaign case, let us assume that a distinguishing feature between the two alternatives (*vaccination centralized in hospitals* versus *decentralized vaccination in community centers*) involved the requirement that the doses be packaged in a different manner, as the hospital had larger cooling systems in comparison to the community centers. Unless the change in packaging incurred significant costs or logistics, such a feature would not engender any additional relevant decision objectives.

Another manner of utilizing existing alternatives to promote creativity when producing relevant objectives is to consider the particularly desirable or undesirable features of an alternative. In the vaccination campaign case, let us assume that the health security team concluded that a major advantage of deploying the vaccination campaign in hospitals is that the specialized nurses are situated there. This consideration brings about an associated objective to *maximize the quality of administering the vaccines* (which forms an end objective to the objective *minimize immunization errors* previous mentioned in their list of objectives). The team also concluded that a major disadvantage of only using decentralized community centers would be that this option requires transportation efforts. These transportation efforts would not only transgress the pre-established objectives (*minimize the cost of the campaign* and *maximize safety of vaccine stocks*) but would also require specialized vehicles and logistical management, and would bring about an associated objective *minimize logistics complexity*.

Hypothetical decision alternatives can also be employed for fostering creativity and generating relevant objectives. Features that constitute an *ideal* alternative may indicate objectives that are worth pursuing, while features that constitute an *unsuitable* alternative may indicate objectives whose direction of preference is that of minimization.

For example, in the vaccination campaign case, the health security team could speculate as to the features that form an ideal campaign and the consequences that the team values (e.g., *high coverage rates*, *very safe vaccination administration*). From these valued consequences, the team could infer as to which objectives to pursue (e.g. *maximize immunization coverage rate*, *maximize the safety of administering the vaccines*). The team could also consider the features of a campaign that would be classed as a failure, and identify consequences that they wish to avoid (e.g., a *very costly campaign*, *high level of vaccine hesitancy*). Accordingly, these consequences could indicate objectives to pursue (e.g., *minimize cost of the campaign*, *minimize vaccine hesitancy*).

Problems and Shortcomings Health security decision makers are typically undertaking a plethora of health security problems simultaneously and have had previous experience confronting a wide range of problems. Problems both in the past and at present give rise to concerns that can be used as starting points for us to cogitate relevant decision objectives.

Previous problems in similar contexts may indicate concerns that may be relevant to the current decision situation. Having managed previous problematic situations, the health security team and its members are able to work from experience, utilizing these previous problems as a foundation. Therefore, it is crucial that we not only assemble a team with the necessary expertise, but also with extensive experience in dealing with previous health threats, previous engagements in health security decisions, and knowledge concerning previous events in other areas or countries.

In the case of the vaccination campaign, let us postulate that the health security team had encountered issues with a similar campaign that had been executed a few years prior. Specifically, the campaign took an excessive period of time to be implemented, and thus, doses expired before they could be administered to some communities. In the decision context regarding how to best develop a vaccination campaign, this previous experience could bring about an associated objective such as *maximize the speed of the vaccination campaign*. In a similar manner, learning from both the failures and the successes brought about by previous decisions could help in identifying the positive features in the solutions that had been implemented and that therefore should be maximized, alongside identifying the negative features that should be minimized.

Current problems whose features are somewhat similar to the present decision situation may also provide transferrable information and aid in identifying relevant decision objectives. Recognizing these parallel features, modifying them appropriately and re-establishing them within the present decision situation draws from the knowledge and breadth of experiences of the health security team. Therefore, we see that a health security team composed of individuals that have undertaken similar

problems and related issues to the current decision problem is crucial when conducting a health security decision analysis.

Let us posit that in our vaccination campaign case, there exists an unreliable surveillance system that could significantly underestimate the number of cases and the transmission rates. Accordingly, the higher transmission rates would require that the vaccination coverage level be higher than the initially assumed level. This information could produce the objective *maximize the immunization coverage rate* as another relevant decision objective. Another manner to approach current problems is to determine what, from the present situation, requires modifications. If, in the same situation, low levels of immunization at present were to pose a concern, once again, we see that this issue could lead to the same objective *maximize the immunization coverage rate* proving to be relevant.

Consequences The consequences of implementing a specific decision alternative can help health security teams to foster more decision objectives. Health security teams possess strong health expertise, and consequently, health-related consequences are frequently listed when considering health threats (e.g., mortality rates, morbidity rates, co-morbidity implications). Other concerns may be also expressed about large-scale health security decisions, such as economic consequences (direct and indirect), as well as individual and societal consequences.

These consequences can then provide indications as to which superordinate objectives the consequences are linked to for a specific decision context. For instance, if we take into account the health consequences mentioned above, a concern about mortality rate may be associated with the objective *minimize mortality rate*; a concern about morbidity levels may be associated with the objective *control morbidity levels*; and a concern about co-morbidity implications may be associated with the objective *manage co-morbidity symptoms*.

Let us posit that the health security team managing the vaccination campaign case is concerned about impacts related to the side effects of the vaccine. This concern is illustrative of the objective *minimize the side effects of the vaccine,* of which lies outside of the specific decision context, since the choice concerning how to conduct the vaccination campaign *does not* influence this objective. Therefore, it should not be considered as a relevant decision objective for this specific decision context. However, said concern may also indicate an objective that is relevant, in that the objective does lie *within* the specific context. In our case, this objective could take the form of establishing the extent to which each type of campaign enables the monitoring of the campaign deployment and vaccination results. This latter objective could be defined as *maximize the ability of monitoring the campaign*.

On the other hand, let us consider that the decision situation is seeking to establish which vaccine is the most suitable, and the objective *minimize the side effects of the vaccine*. In this instance, this decision objective would prove to be significantly relevant, as it would direct the health security team toward the most suitable vaccine. This example illustrates the importance of considering an adequate decision frame, and the symbiosis between decision objectives and the specific decision context.

Goals, Constraints, and Guidelines Quantitative goals are common in health organizations and can indicate superordinate objectives. Constraints function to establish the level at which consequences are deemed to be either acceptable or unacceptable. Therefore, not only do constraints prove useful to determine whether alternatives are unfeasible, but also to indicate superordinate objectives. On the other hand, guidelines are less definite than goals or constraints in that guidelines indicate both objectives or alternatives that should be considered or discarded. Let us analyze each type of decision probe below.

Goals (also termed targets) indicate a level of attainment pertaining to the consequence that an organization wishes to attain, or that the health security teams has established to monitor performance. Goals can be used as a decision probe to indicate a superordinate objective.

In the vaccination campaign case, imagine that the goal "we should vaccinate at least 90% of the population" were to be emplaced. Here, the relevant consequence is the *immunization coverage rate* and the level of attainment pertaining to this consequence is 90% of the population. As previously mentioned, the superordinate objective to this goal is to *maximize the immunization coverage rate*. Translating said goal into a decision objective allows the health security team to more clearly identify a relevant objective to be achieved within the vaccination campaign.

In this same case, assume that there exists another goal that the team is concerned with in that the team wishes to eliminate the transmission of bloodborne pathogens, which may occur during the administration of vaccines with syringes: "we wish to attain zero cases of diseases caused by bloodborne pathogens during the campaign". This goal is linked to the superordinate objective *maximize the safety of administering the vaccines* (for example, by wearing adequate personal protective equipment, employing sterile, single-use syringes, and so on). Additionally, this goal is also linked to the previously mentioned superordinate objective, *maximize the quality of administering the vaccines* (e.g. by adequately training the health professional, ensuring the correct vaccine is administered, and so on).

Constraints define the levels of attainment pertaining to consequences that are considered to be acceptable or, conversely, levels that are deemed to be unacceptable. For example, if in our vaccination campaign case, there exists a limit that the maximum overall cost of the campaign, including doses and delivery, be established at $100 million. This (hard) constraint indicates a superordinate objective *minimize the cost of the campaign*, which has already been mentioned above. The budget limit would therefore exclude a priori any alternative for deploying the campaign that exceeds this threshold, regardless as to how beneficial other potential benefits were for these alternatives.

An excessive use of constraints significantly reduces the solution space and thus may hinder the possibility of creating innovative decision alternatives. Constraints may also affect group discussions and may hinder the possibility of finding compromises (Gregory et al., 2012). Hence, whenever possible, it is advisable to turn constraints into a target of an associated objective instead.

Let us consider the situation wherein we remove the constraint affecting the vaccination campaign cost and thus render this constraint into a (soft) target. The transforming of a constraint into a target would enable the health security team to cogitate other vaccination campaign options, which could cost just over $100 million, yet said option could bring about the potentiality of engendering significantly higher benefits than the options that were situated below the original limit. Furthermore, were the health security team to identify significant levels of additional benefit, an additional budget could be sought for funding these more expensive campaigns. Notice that this analysis would not have been possible if the budget were considered as a hard constraint.

Guidelines provide some general guidance that has been established either by an organization or the health security team. Guidelines indicate a *direction of travel*, which functions to direct decision makers during the process of establishing objectives.

Assume that a guidance in the vaccination campaign states that the health security team "wishes to deploy the vaccination campaign in the most effective manner", given the limited resources available within the health system. This could bring about the decision objective *maximize campaign effectiveness*.

Different Perspectives When prompted to generate objectives, each member of the health security team shall typically cogitate the decision objectives that the individual believes the group should pursue. Alternatively, each group member, (whose role it is to represent a stakeholder) may consider objectives that achieve the interests of that particular stakeholder. This rather inward-looking process may generate a narrow set of objectives, particularly if the group is composed of members with similar expertise and background and share the same perspectives with regards to the problem (Janis, 1983). Conversely, a powerful way of generating a broader set of objectives necessitates that the health security team consider different perspectives from relevant stakeholders in the decision situation.

There exist three different ways to encourage different perspectives, with each form necessitating an ascending degree of stakeholder involvement and complexity. First, the health security team could be asked to consider the objectives of other relevant stakeholders, for example, patients, drug companies, government officials, business owners, health professional, and so on. Second, we can conduct interviews or surveys with relevant stakeholders that do not are not engaged at a level of decisional participation (see Haag et al., 2019 for an example of such surveys). These consultations must be carefully designed, in such a way that the objectives are elicited for the specific decision context under consideration. Third, the health security team may consider including stakeholders that initially had not been directly involved in the decision process, thereby granting them decisional participation. Once again, as mentioned in the previous chapter, the balance between breadth of perspectives versus size of the group must be carefully considered here, as large groups are more difficult to facilitate and manage (Shaw et al., 2004).

The objectives contributed by relevant stakeholders can reveal important consequences that must be considered in the appraisal of decision alternatives. These

objectives may also indicate potential sources of resistance to the implementation of an alternative; these sources may include stakeholders themselves were they to suffer from the negative consequences as a consequence of implementation (Pfeffer, 2010). Objectives of this nature can also help to identify decision advocates among the stakeholders that benefit from some consequences that are relevant to the stakeholders.

If we turn to our vaccination campaign case, let us posit that the health security team contemplated as to what the objectives of the general population (a key stakeholder) would be. The team concluded that the population wishes to *minimize the risks of the vaccine*, as some segments of society may perceive the risks to be high.

While this objective was situated outside the specific decision context (as the type of vaccine had already been chosen), a related decision objective could be set that seeks to *minimize vaccine hesitancy*. This latter decision objective could potentially be influenced by the different decision alternatives under consideration. For instance, administering the vaccine in hospitals may create more hesitancy than in localized health clinics and community centers, as the latter could be perceived as a more amicable environment than a large hospital.

In Table 4.1 the list of relevant objectives defined for the vaccination campaign throughout this section is grouped into categories. These categories help to cluster the objectives into the relevant dimensions of assessment (Keeney, 2013), when comparing decision alternatives. Additionally, said categories also help to identify as to whether relevant consequences or objectives are missing, as the categories provide a top-down structure for the assessment. This categorization is particularly useful for decisions that involve many objectives, or wherein a large number of indices is employed to evaluate health threats or decision alternatives (such as the many models analyzed by Montibeller et al., 2020).

When supporting group decision making in complex decision problems, we typically request the list of objectives to begin generating objectives, and we subsequently request that decision makers compare potential decision alternatives and identify relevant features of said alternatives. The list of objectives is a more

Table 4.1 Relevant objectives in the vaccination campaign case

Category	Relevant objectives
Campaign coverage	Maximize the immunization coverage rate. Maximize the reach of the campaign across population strata. Minimize vaccine hesitancy. Maximize campaign effectiveness.
Campaign Quality	Minimize immunization errors. Maximize the quality of administering the vaccines. Maximize the safety of administering the vaccines. Maximize the ability to monitor the vaccination campaign.
Campaign Logistics	Maximize the storage quality of vaccine stocks. Minimize logistics complexity. Maximize the speed of the vaccination campaign.
Campaign Costs	Minimize the cost of the campaign.

creative approach although the list does allow for decision makers to develop objectives that are both too broad and are situated outside the decision context. In a similar vein, the comparison of alternatives facilitates reasoning about decision objectives relevant to the specific decision context, although this approach often provides a rather narrow perspective. We find it beneficial to alternate between the list of objectives and the comparison of alternatives, as this contraposition provides a more concrete platform for considering fundamental objectives, as participants tend to consider more clearly the specific decision frame.

We find that the use of stakeholder perspectives enables decision making groups to both visualize a broader overview of the decision situation and to produce more comprehensive list of relevant objectives. We typically request that the group consider the key stakeholders in the decision context individually, and that the group list the both the objectives of each stakeholder, as well as the consequences that the respective stakeholders are particularly concerned with.

We also find goals and constraints to be useful devices for identifying objectives in our practice, and thus, whenever possible we try to transform goals and constraints into objectives. There exist two significant reasons for this transformation. First, transforming constraints into objectives increases the solution space and removes narrow reasoning regarding possible alternatives. Second, removing constraints avoids the possibility of omitting potentially good options that are beneficial but are situated on the peripheries of the feasible ranges.

In Table 4.2 we present some useful questions to ask when employing each decision probe (see also Keeney, 1992, 2007 for additional probes). As a general principle, to assess as to whether to include an objective in the list of objectives, it is preferable to include an objective that may be relevant, and then assess the influence of this objective on the choice of the best alternative, than exclude the objective and risk neglecting an important consequence in the decision.

Table 4.2 Useful decision probes for the elicitation of objectives

Decision probe	Questions
List of objectives	What are the objectives that we wish to achieve in this health security decision?
Alternatives	What are the positive and negative features that constitute each decision alternative under consideration? Which features can be used to distinguish the decision alternatives that we are considering? What are the positive features that constitute an *ideal* decision alternative? What are the negative features of an *unsuitable* decision alternative?
Consequences	Which positive/negative consequences are we concerned with? Which are the positive/negative consequences of previous decisions in related decision contexts? Which are the possible positive/negative consequences of taking this decision?
Goals, constraints, and guidelines	Which is the superordinate objective linked to a goal? Which is the superordinate objective linked to a constraint? Which is the related objective linked to a guideline?
Different perspectives	What are the objectives of each key-stakeholder in this decision?

4.1.4 Eliciting Decision Objectives with Causal Maps

Causal maps are widely utilized when supporting groups to represent and agree on a problem definition (Eden et al., 1983; Eden, 2004; Eden & Ackermann, 2013). These models represent the perspectives of decision makers as a means-end network, with each node of the map representing a concept that is relevant to the decision context and arrow links denoting influence between a means concept (at the beginning of the arrow) and an end concept (at the end of the arrow) (Cossette & Audet, 1992; Eden et al., 1992). See Ackermann et al. (1996) for a tutorial on how to develop causal maps.

Causal maps are a robust and efficient method of gathering information from members of the group and fostering a shared understanding concerning what the group wishes to achieve (end concepts) and the actions available to them (means concepts). Digital collaboration can be used as a foundational tool, with which individuals share concepts, as this tool enables for the reduction of group pressure and group biases (Kerr & Tindale, 2004; Montibeller & von Winterfeldt, 2018). Subsequently, this task can be followed by the sharing and discussing of individual ideas and the development of a joint map.

In addition to supporting problem structuring, causal maps allow us to identify relationships between means objectives and end objectives (Belton et al., 1997; Franco & Montibeller, 2011b; Montibeller & Belton, 2006), and therefore prove to be useful when producing and structuring objectives as a team. In this mode of representation, the map represents a means-ends objectives network (Keeney, 1992), wherein each node of the map represents an objective, and the arrows represent the influence between a means objective (at the beginning of the arrow) and an end objective. We have systematically employed this tool to support health security teams, alongside other types of strategic decisions.

The causal map for the elicitation of objectives in the vaccination campaign case, described in the previous section, is depicted in Fig. 4.3 (objectives are shown in italics). The arrows represent positive or negative influence between a means objective and an end objective. For example, the objective *maximize the speed of the vaccination campaign* (located in the middle of the map) influences the objective *maximize the logistics efficiency of the campaign* in a positive manner. The former objective is a means to the latter objective.

Let us now turn our attention to the means-end structure of the map in this same figure. Shifting upward on the map leads to the ultimate objective, *maximize societal value*, which is achieved by two objectives in this specific decision context: *minimize the cost of the campaign* and *maximize campaign effectiveness* (both are means to this ultimate objective). Shifting downward on the map leads to means objectives in relation to end objectives and, if objectives are shifted even further down, to health security actions.

Two possible actions that are represented in the causal map entail the decision to either localize or centralize vaccine administration. If the health security team were to localize the vaccine administration, this action would positively influence the

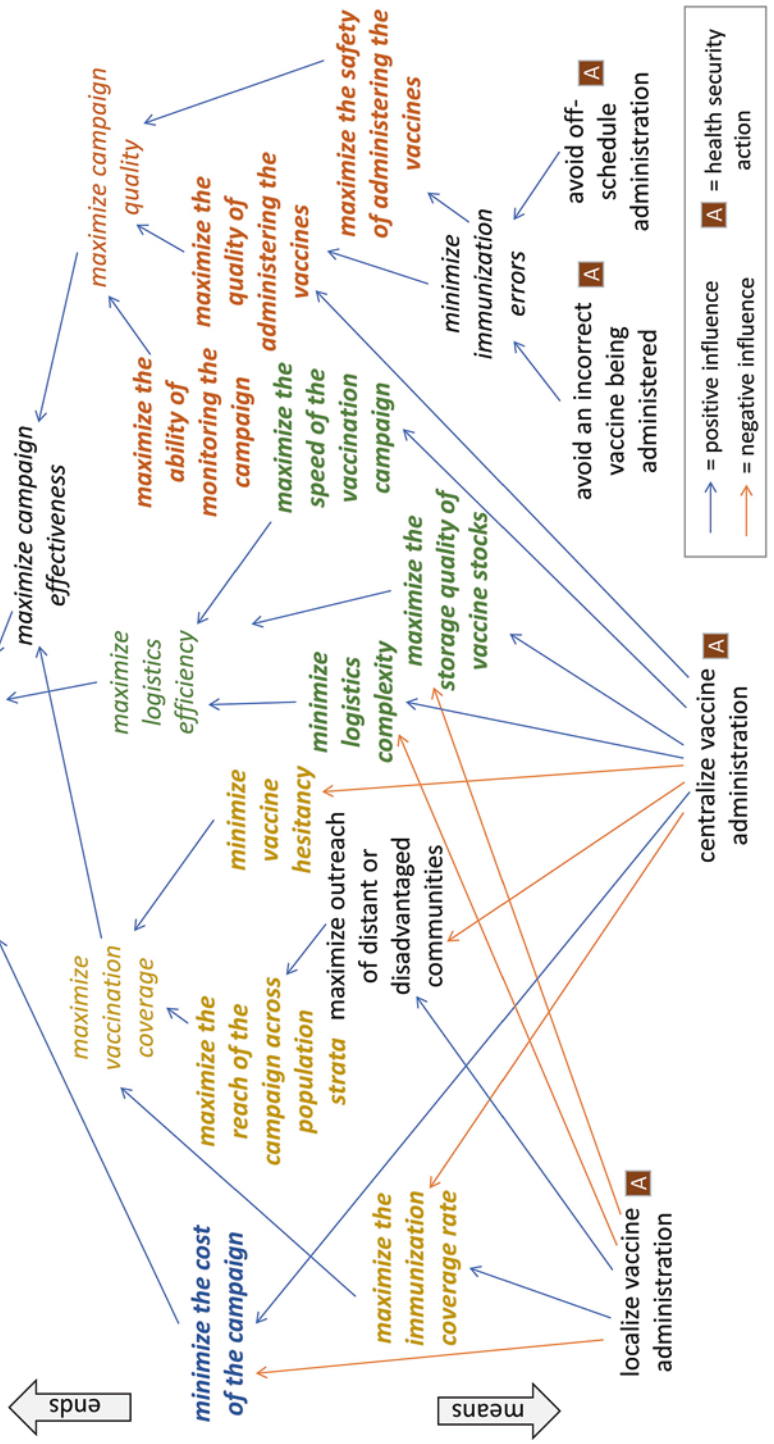

Fig. 4.3 Causal map for the identification of objectives in the vaccination campaign case

immunization coverage rate (as localizing could vaccinate "hard-to-reach" communities), while negatively influencing the *implementation cost of the campaign* (as a decentralized campaign is more costly than its centralized counterpart). This example illustrates that a causal map can provide a clear representation as to how health security actions can achieve end decision objectives, whose achievement occurs first by achieving means objectives that then function to influence these end objectives. The achievement of these end objectives is operationalized by health security actions.

Causal maps for the identification of objectives should avoid the representation of loops, whose presence is denoted by an influence link from an end concept to a means concept on the causal map. Loops dismantle the means-end hierarchy of the map (Montibeller & Belton, 2006) and instead, denote long-term dynamic behavior of the health system (Sterman, 2014). Therefore, if loops have initially appeared in a causal map that is currently being used to produce decision objectives, it is advisable that they be removed to restore the means-end structure of the map.

Typically, causal maps are developed by a group with the support of an internal or external facilitator. The facilitator must also guide the group and ensure that the influence links denote means-end relationships. We noticed that, sometimes, decision makers misunderstand said relationships and wrongly reverse a link. This mistake proves problematic, as it dismantles the hierarchal structure of the map, leading to wrong means-end inferences, and thus must be corrected when the map is being constructed.

Once relevant decision objectives have been identified, either with the use of decision probes or a causal map, it is crucial that they be structured. This structuring of decision objectives, which shall be detailed subsequently, is required for their use in assessing and comparing decision alternatives for enhanced health security. These structured decision objectives can also be employed to identify relevant consequences to assess emerging health threats.

4.2 Structuring Decision Objectives in Health Security Decisions

In the previous section, we have discussed how relevant objectives can be identified and we have provided several tools that can help decision makers to develop decision objectives. We now move to a higher conceptual level in the definition of decision objectives and discuss in greater depth the identification of fundamental objectives and how these fundamental objectives can be represented in a health decision analysis.

We have highlighted, in the previous chapter, the importance of delineating the scope of a decision and of identifying an adequate decision frame. We shall now return to this topic, as the specification of fundamental objectives is a crucial step in decision framing; these objectives indicate as to which factors are significant in the specific decision situation, aid to specify a decision context utilizing the set of

options under consideration, and enable the evaluation and selection of decision alternatives. This section details how fundamental objectives can be identified and organized.

4.2.1 *Identifying Fundamental Objectives Within the Decision Frame*

Let us start by defining the important concept in decision making of a *specific decision frame* for a *specific decision situation* (see also Keeney, 1992). This frame is composed of *a specific decision context* and of *fundamental objectives* for this decision context, as represented by the inner trapezoid in Fig. 4.4a. The specific decision context comprises the options that are available to the health security team. Said options form the means that the team may implement so as to attain the fundamental objectives for this specific decision frame. The heights of the bars in the same figure represent how broad the fundamental objectives are (right-hand side bar within the inner trapezoid) and how extensive the solution space is for the specific decision context (left-hand side bar within the inner trapezoid).

Let us again consider the vaccination campaign case. The specific decision frame is concerned with the following decision situation: what is the best way of deploying a nationwide vaccination campaign? This specific decision frame is represented by the inner trapezoid in Fig. 4.4b. Two fundamental objectives in this context are to *maximize the vaccination coverage* and *minimize the vaccination campaign cost*, among others. Decision alternatives for the *specific decision context* encompass both *options for centralized vaccination* (such as in hospitals), and *options for decentralized vaccination* (such as in community centers and home visits), as represented in the inner trapezoid of the same figure.

Every specific decision frame is embedded into a broader decision frame for a broad decision situation. The *broad decision frame* is composed of the *ultimate objectives* that the health security team wishes to achieve and a *broad decision context*, which constitutes the options available to achieve these ultimate objectives. This broader decision frame is represented in the outer trapezoid in Fig. 4.4a, wherein the height of the bars represent how broad the ultimate objectives are (right-hand side bar in the outer trapezoid) and how extensive the solution space for the broader decision context is (left-hand side bar in the outer trapezoid). Notice that the option range of the *specific decision context* is more narrow than that of the *broad decision context*, and that the ultimate objectives are positioned to the right of the fundamental objectives, as the latter are means to achieve the ultimate objectives.

Traditionally, the ultimate objectives in health security decisions are related to *maximizing the health security of a population* and *minimizing the vulnerability of the population* when managing acute public health events (McInnes, 2018; WHO, 2007a), as illustrated in Fig. 4.4b. However, these ultimate objectives are far too broad to guide a specific decision, such as the decision seeking to determine how best to develop a nationwide vaccination campaign.

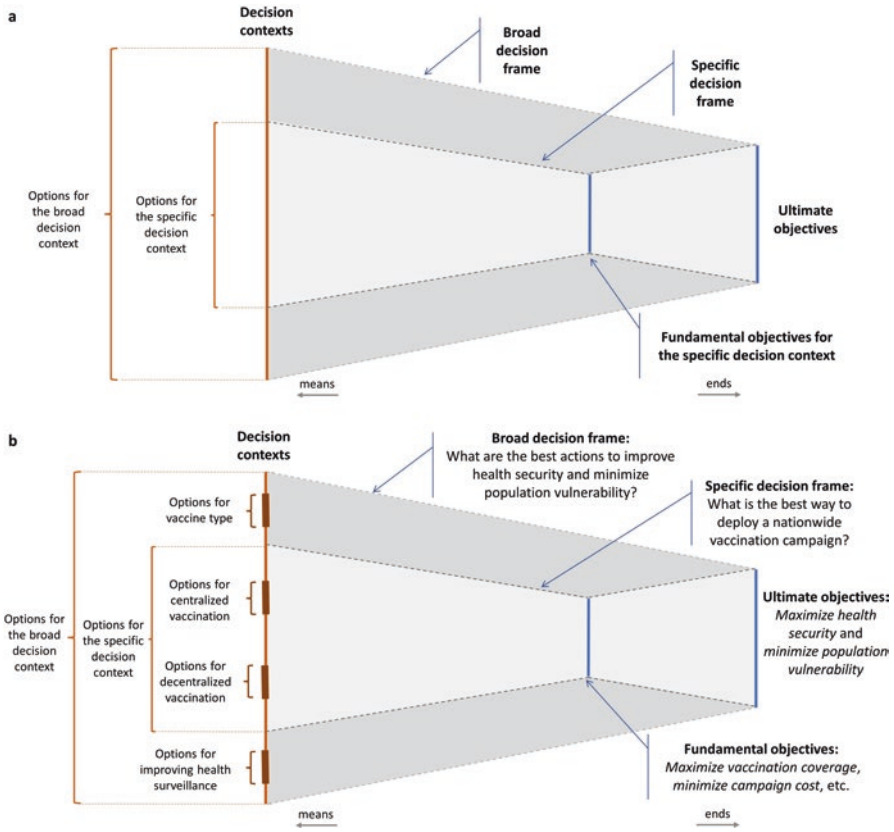

Fig. 4.4 (**a**) Broad and specific decision frames (adapted from Keeney, 1992), (**b**) Decision frames for the vaccination campaign case

Indeed, the inability of ultimate objectives to adequately guide specific decisions is a significantly common problem in practice. Ultimate or strategic objectives are typically lucid and sound, proving to be crucial in guiding the team or the organization as to the right direction, although these objectives fail to adequately guide specific decisions. Therefore, it is crucial that we delineate a *specific decision frame*, define a *specific decision context* and establish the *fundamental objectives* for this *specific* context (Keeney, 1992).

Additionally, solely choosing to define ultimate objectives gives rise to another issue, in that this choice renders the decision context too broad, as there exists a plethora of options to achieve ultimate objectives. In the vaccination campaign case, there may be different vaccines available, some of which may prove to be highly effective, and thus can enable an increase in the health security of the population and reduce their health vulnerability, as depicted in the broad decision context represented in Fig. 4.4b. Several other ways to improve health surveillance may also exist, which could help in improving health security. These options are, nonetheless,

situated outside the specific decision frame, whose concern is to establish how best to develop a nationwide vaccination campaign.

Additionally, if the specific decision frame is not clearly defined, then ultimate objectives are likely to be used to identify options, although these options may not necessarily address the issue at stake, as the options are situated outside the specific decision context. This absence of a clear definition as to the specific decision frame is another common problem that we find in practice. For example, as represented in the broad decision context depicted in Fig. 4.4b, improving a health surveillance system does not directly influence how best to develop a nationwide vaccination campaign (albeit the improvements to the system may have indirect long-term effects, for instance, in the future we may identify regions that are more vulnerable to outbreaks).

While unable to guide specific decisions, ultimate objectives do form a significant element of decision making, as ultimate objectives should be aligned with fundamental objectives (Barcus & Montibeller, 2008; Keeney, 1992). The fundamental objectives are the means to achieve ultimate objectives in the specific decision frame. For instance, in the vaccination campaign case illustrated in Fig. 4.4b, the fundamental objective *maximize vaccination coverage* is a means to achieving the two ultimate objectives: *maximize health security* and *minimize population vulnerability* within this *specific* decision context (which encompasses *options for deploying the vaccination campaign*). In a similar manner, the fundamental objective *minimize campaign cost* is also a means to those two ultimate objectives, as an efficient use of scarce resources would enable the remaining budget to be employed in other health security initiatives that seek to, essentially, achieve these two ultimate objectives.

When supporting strategic decision making and health security decisions, we have observed that usually, when we first engage with the decision making group, the fundamental objectives are seldom clearly set. In such a situation, we see that the ultimate objectives have been clearly defined, and a concern about the multitude of impacts has been demonstrated, however there is an absence of well-defined decision objectives for the specific decision situation, until an adequate decision framing is developed by the team.

Many published studies that assess and prioritize health threats have also reported a similar issue, wherein multiple impacts caused by the threats are assessed but the decision objectives are not made explicit (Montibeller et al., 2020). Therefore, the relationships between impact assessment and the achievement of health security objectives remain often ambiguous.

Given these challenges in health security decision practice, we once again stress the importance of an adequate structuring of objectives and of delineating a clear specific decision frame in health security decisions.

Once decision objectives have been produced, they must follow a set of logical properties so that they may either be employed for the evaluation and the selection of health security options, or for the prioritization of health threats. These logical properties and how they can be verified in practice are discussed next.

4.2.2 *Verifying the Properties of Fundamental Objectives*

Fundamental objectives should follow a set of logical properties. These properties make said objectives suitable for guiding decision making processes, searching for additional decision alternatives, designing new options, and evaluating decision alternatives. In this section we present these properties and explain how they can be verified in practice (see Keeney, 1992; Belton & Stewart, 2002 for details).

Essential The first logical property for a fundamental objective necessitates that it be concerned with a consequence that is considered to be *essential* in the *specific* decision situation.

To illustrate this property, let us return to the concept of an *specific decision frame*, which has been analyzed in the previous section, and is reproduced in Fig. 4.5. Notice that the fundamental objectives lie on the means-end spectrum. Fundamental objectives for the specific decision context should both reflect the ultimate objectives and delineate the specific decision context, as has been discussed previously. The more we shift objectives rightward the end objectives, i.e. shifting the fundamental objectives bar to the right, closer to the ultimate objective bar, the more essential the objectives become.

In the vaccination campaign case, whose decision frame is shown in Fig. 4.4b, one of the fundamental objectives for that specific decision context is to *maximize vaccination coverage*. We could consider shifting this objective rightward by asking the health security team: "*why* do we wish to maximize the vaccination coverage?" One answer could be that they wish to "increase population immunity". Therefore, *maximize vaccination coverage* is a means to the end objective *increase population immunity*. The latter objective is more essential than the former one.

Controllable Each fundamental objective should also be *controllable*. This requires that the objective address consequences that are influenced solely by the choice of options within the *specific decision context*.

Let us analyze this property with the specific decision frame shown in Fig. 4.5. Fundamental objectives in the means-end spectrum can also be shifted leftward. The further we shift these objectives toward means objectives, i.e. shifting the fundamental objectives bar to the left and closer to the specific decision context bar, the more controllable said objectives become.

In the vaccination campaign case, whose decision frame is shown in Fig. 4.4b, the fundamental objective *maximize vaccination coverage* could be shifted leftward by asking the health security team: "*how* could we maximize the vaccination coverage?" One answer could involve "widely promoting the vaccination campaign utilizing the media". Hence, *maximize vaccination campaign* is an end objective to the means objective *maximize the promotion of the vaccination campaign utilizing the media*.

When establishing fundamental objectives, we must always negotiate between *essentiality* and *controllability*. If the objectives selected to evaluate the decision

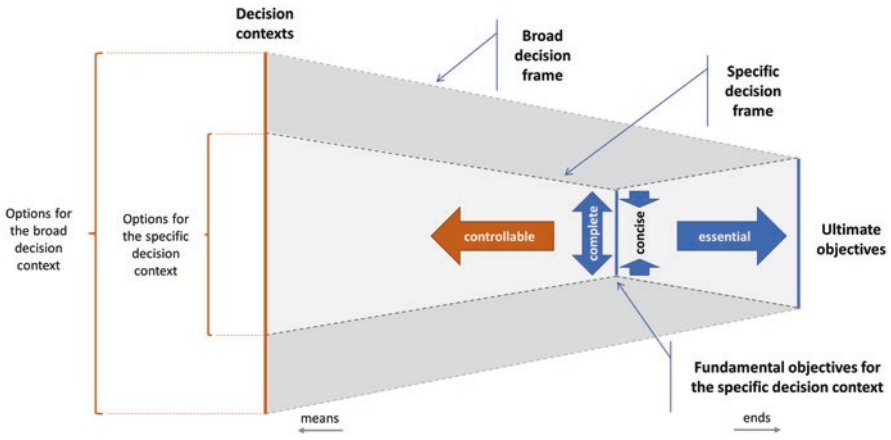

Fig. 4.5 Verifying properties for the set of fundamental objectives

alternatives are controllable but non-essential, this selection will lead to a very narrow specific decision context.

This problem, related to selecting controllable but non-essential decision objectives, is illustrated in Fig. 4.6a for the vaccination campaign case. Notice the very narrow decision context on the left, brought about by the selection of controllable but non-essential objectives. This narrow decision context would exclude a number of *options for centralized vaccination* as well as a number of *options for decentralized vaccination*, thus jeopardizing the quality of the set of decision alternatives.

This issue of selecting controllable but non-essential objectives occurs frequently in health security practice. Means objectives typically give rise to more concrete consequences than the consequences that are associated with fundamental objectives. Hence, it is significantly less challenging to measure the achievement of means objectives than fundamental objectives (Keeney & Gregory, 2005). The ease with which these means objectives are measured may lead to some unsuitable measurement choices for health security decisions, as decision makers may select consequences that are uncomplicated to measure and that are accompanied by significant amounts of available data, but may prove to be completely non-essential (Montibeller et al., 2020).

Let us return to the controllability versus essentiality trade-off involved in the selection of decision objectives. We shall consider objectives that are essential but not wholly controllable by the decision alternatives within the specific decision context. This selection shall lead to a definition of decision contexts that is too broad. Consequently, these too broad decision contexts shall include decision alternatives that fail to address the specific decision situation under consideration.

The problem pertaining to selecting essential but non-controllable decision objectives is illustrated in the decision frame depicted in Fig. 4.6b for the vaccination campaign case. Here, the incorrect selection of decision objectives gives rise to a very broad decision context, which also encompasses options that are not directly relevant to the vaccination campaign decision, such as including *options for the vaccine type* and *options for improving health surveillance*.

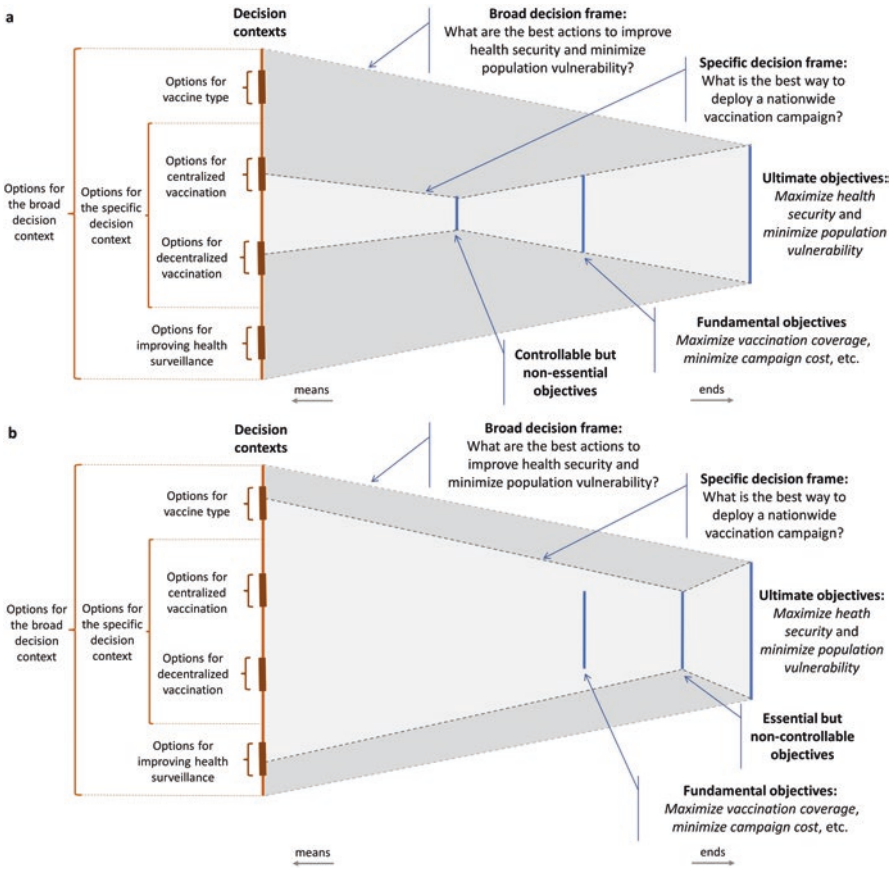

Fig. 4.6 (**a**) Controllable but non-essential objectives in the vaccination campaign case, (**b**) Essential but non-controllable objectives in the vaccination campaign case

This issue associated with selecting essential but non-controllable objectives may also occur in health security practice. This issue can occur in a situation wherein the health security team has high-achieving ideals but is unable to establish a nexus between said ideals and the decision at stake, or, alternatively, the team is unable to narrow the objectives down to actions that are feasible to implement.

Another situation wherein fundamental objectives may be specified incorrectly occurs when the specific decision situation is poorly defined, which typically brings about a definition of objectives that is too broad. These very broad objectives are then unable to function as a guide for the team when evaluating the decision alternatives contained within the specific decision context.

Complete The set of fundamental objectives should be *complete*. This necessitates that the set includes all the fundamental consequences that are relevant and all the

implications that are of interest to the health security decision. In the decision frame represented in Fig. 4.5, this property is represented by how long the bar representing the fundamental objectives is.

In practice, the fundamental objective set may be incomplete when problems are defined in a manner that is excessively narrow (Haag et al., 2019; Montibeller & von Winterfeldt, 2015), when the team converges too quickly on a choice (Russo & Schoemaker, 1989), or when the group lacks different perspectives and suffers from groupthink (Janis, 1983; Montibeller & von Winterfeldt, 2018).

One practical manner to verify the completeness of these objectives is to consider two hypothetical decision alternatives whose performance is identical with regards to all the fundamental objectives. Utilizing our vaccination campaign case, let us postulate that there exist two vaccination campaign options whose overall cost and benefits are identical We are then able to reflect as to whether it would still be possible to select one option, due to some additional benefit or reduced drawback. If, indeed, we are still able to do so, this additional benefit/reduced drawback indicates that a fundamental consequence has been neglected, which then must be included as a fundamental objective.

Concise The set of fundamental objectives should also be *concise*, i.e., the set should not include objectives that do not prove useful for the decision problem, or, that are concerned with less relevant issues.

In the decision frame depicted in Fig. 4.5, this property is represented by the extent to which the bar that represents the fundamental objectives is short. In practice, the pressure that prevents the set of fundamental objectives from being concise is derived from two trends. The first trend entails a drive toward inclusiveness, wherein there exists a desire to include all and every aspect that is considered to be relevant by every stakeholder (Gregory, 2017). The second trend entails a desire to consider all of the available evidence, involving a great number of consequences to evaluate decision options.

This inclusion of a great number of objectives or performance indices is common in public decisions (Marttunen et al., 2019) but the inclusion may result in negative consequences that affect the decision process (Montibeller et al., 2020). Specifically, a great number of objectives may either distract the health security team from the fundamental issues at stake, or may otherwise change the focus of a health decision analysis, whose new lens is one wherein the contribution of attaining each objective is negligible. Therefore, we must find an optimum balance between *conciseness* and *completeness* (see Marttunen et al., 2019 for a detailed discussion on how to develop a concise set of objectives).

Measurable Two properties of fundamental objectives concern their feasibility as evaluation tools for assessing the performance of decision alternatives. A decision objective should be *measurable*, i.e. it should be possible to develop an attribute[1] that measures clearly the performance of decision alternatives with regards to the

[1] Attributes are also denominated as performance measures, criteria, indicators, or metrics. The definition of attributes for health security decisions is detailed in the fifth chapter.

achievement of this objective (Keeney & Gregory, 2005). Conversely, the absence of a definition of a clear attribute associated with a fundamental objective, complicates the ability to identify the extent to which this objective would be achieved if a given decision alternative were to be implemented.

In the vaccination campaign case, one fundamental objective is to *maximize the immunization coverage rate*. An associate attribute could be defined as *percentage of the overall population that is vaccinated during the campaign*. This attribute would provide an assessment of the extent to which each vaccination campaign option would achieve the objective. Additionally, this attribute can evaluate the performance of the different decision alternatives in an unambiguous manner (e.g. *centralized in hospitals* vs *decentralized in local community center*s), as long as estimated performance levels for each alternative be defined reliably. As we can see, said attribute can be defined for the fundamental objective, and therefore, we can confirm that this objective is indeed measurable.

Operational An objective should also be *operational*, i.e., there exists enough available evidence to assess the possible performance of the decision alternatives with regards to the achievement of this objective. Whenever and wherever quantitative and reliable evidence is available, it should be employed. However, it is often necessary to use expert judgment for the estimations of such performances (Dias et al., 2018; Morgan, 2014). In the cases wherein experts are providing these estimates, it is important that judgments be properly debiased (Montibeller & von Winterfeldt, 2015).

One issue that we observe frequently when engaging with scientists is that there exists a tendency to exclude a given decision objective if hard evidence is not available. This neglect of hard-to-measure objectives can be significantly detrimental to the quality of a health decision analysis, if a fundamental issue were to be neglected due to lack of available data. It is therefore advisable that we include the fundamental objective and use expert judgments for estimates, instead of merely removing the decision objective from the assessment of decision alternatives due to the lack of available hard evidence.

In the vaccination campaign case, the health security team would be required to estimate the *percentage of the overall population that was vaccinated during the campaign* for each decision alternative they are contemplating (*centralized* versus *decentralized vaccination*). One extreme position would be that "this cannot be estimated as there exists no hard evidence about the different options". While this may be certainly correct, the lack of data about the future performance of decision alternatives is a common feature to any decision, thus the requirement to somehow extrapolate from current trends. If there were reliable data available about similar campaigns in equivalent countries, which had adopted centralized or decentralized vaccination campaigns, this data could be used and adjusted to the specificities of the country. Otherwise, experienced experts could be involved to construct simulation models that support any predictions as to the performance of each decision alternative with regards to this attribute. These attempts of data gathering can

certainly underpin the choice of the better vaccination campaign strategy, even if the outputs are not totally precise, and proves to be a better solution than simply neglecting this fundamental objective due to difficulties in gathering hard evidence about the performances of the decision alternatives.

Decomposable Another property for fundamental objectives(which is connected with the *operational* property) requires that the decision objective be *decomposable*. Essentially, the consequences that are related to one objective can be considered independently of the consequences that pertain to the other objectives. If fulfilled, this property will greatly assist in simplifying the assessment of decision alternatives[2], as they are able to be assessed on each objective independently of their performance relating to the other objectives (Keeney, 1981).

Let us consider that in the vaccination campaign case, the fundamental objective *maximize the immunization coverage rate* and the associated attribute *percentage of the overall population that is vaccinated during the campaign*. The estimated performance of each vaccination campaign option could be assessed on this objective, in terms of the percentage of the overall population that each possible campaign would vaccinate. If this assessment of performance on this objective could be made independently from the assessment of estimated performances of each option of other fundamental objectives, then this objective is indeed decomposable.

Non-redundant As discussed above, the set of fundamental objectives should be concise. Another property that is connected with this requirement is that the set should also be *non-redundant*. Non-redundancy avoids counting a relevant consequence twice when assessing the decision alternatives.

Let us turn to the vaccination campaign case. The objective *minimize immunization errors* is achieved by the objectives *maximize the quality of administering the vaccines* and *maximize the safety of administering the vaccines* and, hence the objective *minimize immunization errors* is made redundant. If this latter objective were to be included, it would distort the evaluation of different vaccination campaign options. Specifically, the evaluation would allocate too much weight to the aspects linked with the vaccination campaign quality.

Unfortunately, this non-redundancy property is not usually considered in the assessment of health threats. It is common to find assessments wherein multiple indicators are measuring the same consequence. This constitutes poor decision modeling practice, as the evaluation inadvertently would overweigh such consequence (Montibeller et al., 2020).

Understandable Finally, the fundamental objectives should be *understandable*. This property requires that there exists a clear understanding about what the objective is seeking to achieve and how the performances of decision alternatives shall be assessed.

[2] The assessment of decision alternatives with multiple objectives is detailed in the eighth chapter.

Table 4.3 Properties for the set of fundamental objectives

Property	Description
Essential	An objective is essential if it is considered to be a fundamental reason of interest in the health security decision.
Controllable	An objective is controllable if it addresses consequences that are influenced only by the choice of alternatives in the specific health security decision context.
Measurable	An objective is measurable if it is possible to define precisely the degree to which the objective can be achieved by the decision alternatives in the specific health security decision context.
Operational	An objective is operational if there exists enough information, either from hard evidence or unbiased expert opinion, to assess the performance of the decision alternatives in the health security decision.
Understandable	An objective is understandable if it has a clear definition and a well-defined attribute, both of which facilitate the production and communication of insights in the health security decision process.
Complete	A set of objectives is complete if it includes all the fundamental aspects of the consequences of the decision alternatives in the health security decision.
Concise	A set of objectives is concise if it has the minimal number of required objectives necessary to adequately evaluate the decision alternatives in the health security decision.
Decomposable	A set of objectives is decomposable if it allows the separate assessment of consequences of the decision alternatives on one objective, independently from the consequences of these alternatives on the other objectives.
Non-Redundant	A set of objectives is non-redundant if the possible consequences are not counted twice in the health security decision.

Adapted from Keeney (1992, 2007)

One practical recommendation to increase understandability of the objectives entails writing a precise definition for each of the objectives. This clear definition is particularly important if the health security team is varied and large, as group members may have a different understanding of concepts, evidence, and remits.

The properties of fundamental objectives are summarized in Table 4.3. The first five properties concern each individual objective, while the last four apply to the set of objectives. Notice that these properties should be verified in each specific decision situation. These are logical properties that ensure that the set of fundamental objectives can be adequately used to define the consequences that are important to the decision, develop decision alternatives, evaluate the different possible choices available, and guide the decision-making process. Once a set of fundamental objectives has been defined, they can be organized as a hierarchy of objectives, as described next.

4.2.3 *Organizing Fundamental Objectives Using a Value Tree*

Fundamental objectives, once identified and whose logical properties have been tested, can be organized as a hierarchy of objectives. This hierarchy is denominated as *a value tree* (Belton & Stewart, 2002), whose structure reflects a decomposition of objectives (Keeney, 1992). On the leftmost node of the value tree we establish the *overall objective* in the decision situation. Along the tree, an upper-level objective on the left is decomposed into lower-level objectives on the right, with each of these lower-level objectives pertaining only to the upper-level objective with whom it is linked. These lower-level objectives collectively must provide an exhaustive characterization of the upper-level objective. At least two lower-level objectives are required below an upper-level objective.

In the vaccination campaign case, a possible value tree is presented in Fig. 4.7, using the relevant objectives shown in Table 4.1. The overall objective is to *select the best vaccination campaign*. This overall objective is decomposed into four categories of objectives, each of which are represented using the categories in the table: *maximize the vaccination coverage*, *maximize the campaign quality*, *maximize the efficiency of the campaign logistics*, and *minimize the campaign costs*. These first three categories of objectives are further decomposed by the fundamental objectives identified in the table. For example, the tree demonstrates that the *maximize vaccination coverage* objective can be fully characterized by three fundamental objectives: *maximize the immunization coverage rate*, *maximize the campaign reach across population strata*, and *minimize vaccine hesitancy*. Notice that the latter

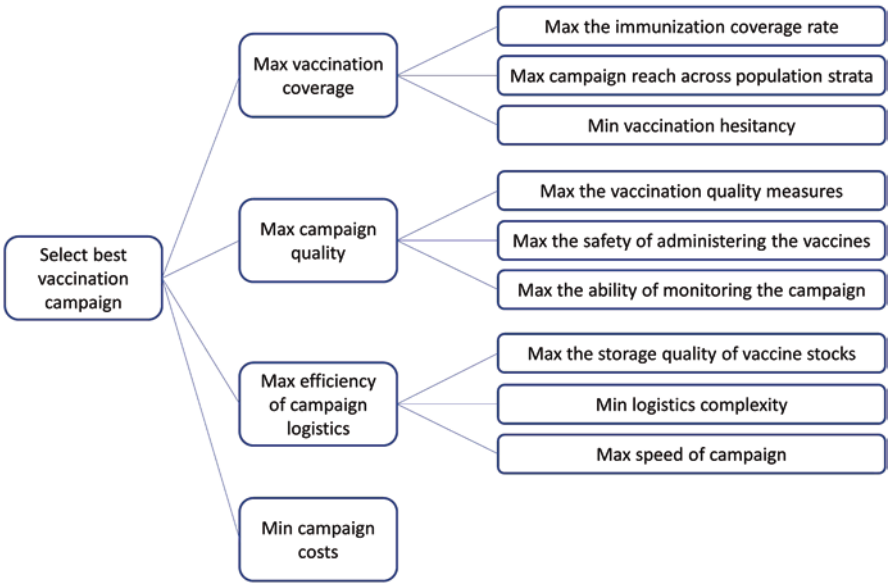

Fig. 4.7 A value tree for the vaccination campaign case

objective was included as a fundamental objective, as the issue of vaccination hesitancy was considered to be essential and not only as a means with which to increase population coverage.

Observe also that two objectives from the Table 4.1 were not included in the value tree shown in Fig. 4.7. The objective *maximize campaign effectiveness* is covered by the three categories in the value tree (*maximize the vaccination coverage*, *maximize the campaign quality*, and *maximize the efficiency of the campaign logistics*) and therefore is rendered redundant. As we have mentioned previously, the objective *minimize immunization errors* is achieved by the objectives *maximize the quality of administering the vaccines* and *maximize the safety of administering the vaccines* and, hence is also rendered redundant.

Causal maps can also be used to inform the structuring of the value tree (Belton et al., 1997; Montibeller & Belton, 2006). In the causal map used for the vaccination campaign case, shown in Fig. 4.3, we have used bold text to highlight the objectives that were included in the value tree in Fig. 4.7. Notice that the upper level objectives on the map help to indicate and group objectives of the value tree under three categories associated with maximizing the campaign effectiveness, they are highlighted with different colors in the map.

The objectives at the rightmost level of the value tree, which have not been further decomposed, are used to evaluate decision alternatives. They indicate both the objective that is being pursued in the health security decision and the related consequence of concern. In Fig. 4.7, for instance, the different options for the vaccination campaign shall be assessed on ten consequences that are significant to this case, this assessment seeks to establish information such as how each decision alternative would deliver a given level of *vaccination coverage*, a given level of *vaccination campaign quality*, a given level of *efficiency of the campaign logistics*, and the *cost of the vaccination campaign*.

There exist many benefits of starting a health security decision making process utilizing the definition of objectives, which have been organized as a value tree, instead of the typical focus on solutions or decision alternatives. First, decision objectives provide clear guidelines to the decision process and a sharp focus on what the health security team wishes to achieve (Keeney, 1992, 2013). Second, it is significantly easier for a group to agree on relevant objectives than to have a consensual agreement as to which is the "best" alternative (Gregory et al., 2012). Third, the definition of objectives can guide efforts to gather information only about consequences that are relevant to the decision (Montibeller, 2018). Fourth, a clear set of objectives provides an excellent arena for the identification and development of creative decision alternatives (Gregory & Keeney, 1994; Keeney, 1992). Fifth, the definition of objectives enables the assessment of societal value that can be provided by each decision alternative and guides the choice of high-value options.

In the next section we describe a factual project wherein we supported a health security team to define and to structure a set of fundamental objectives. We describe said project so that the application of the concepts discussed here can be appreciated in a realistic decision situation.

4.3 Structuring Objectives for the Prioritization of Low-Moisture Food Categories (FAO/WHO)

The Food and Agriculture Organization (FAO) of the United Nations is a specialized agency that spearheads international efforts to improve food security and manage food-related health risks, among other relevant aims. In a joint project sponsored by FAO and the World Health Organization (WHO), we were asked to support an international group of experts and policymakers whose task it was to assess and rank the impacts related to low moisture food (LMF) categories, so that risk management standards could be refined.

The seven categories of foodstuff (cereals and grains; confections and snacks; dried fruits and vegetables; dried protein products; nuts and nut products; seeds for consumption; and spices, dried herbs and tea) are of international importance, with high volumes of global consumption and more than US$250 billion dollars of international trade per year. However, there also exists a risk that these foodstuffs could expose populations to risks of food contamination with more than 200 reported outbreaks affecting these foods since records began (Young et al., 2015).

The overall aim of the project was to identify the LMF category with the highest overall impact, as a response to a request from the FAO/WHO Codex Alimentarius Committee on Food Hygiene (CCFH), which could then consider and manage the microbiological hazards associated with these products. It was critical that the assessment was conducted in a robust and transparent manner, utilizing the best expertise available on the subject and a sound methodology for the assessment of impacts and ranking of food categories (for details, see FAO/WHO, 2014; Montibeller, 2018).

We conducted a health decision analysis on this problem with the health policy team and successfully identified the LMF category with the highest overall impact, taking into account the relevant consequences of concern. This finding helped the Codex Alimentarius Commission to further improve their standards, guidelines and codes of practice pertaining to this food category, aiming to further protect consumer health and promote fair practices in food trade.

There existed several challenges that were addressed in this health security project: the need for a global perspective in the assessment, the existence of multiple objectives for the impact assessment, the limited amount of evidence about some of these impacts, and the need to promote the sharing of expertise and opinions among the experts involved in the assessment.

In a two-day workshop in the FAO Headquarters in Rome, Italy, the facilitators, composed of a risk analyst and me as decision analyst supported a team of top international experts and policymakers on low moisture foods from the United States, Canada, Japan, Switzerland, and the United Kingdom in the prioritization of the LMF categories. In this section, we describe the initial stage of this project using the identification and structuring of relevant objectives from these experts.

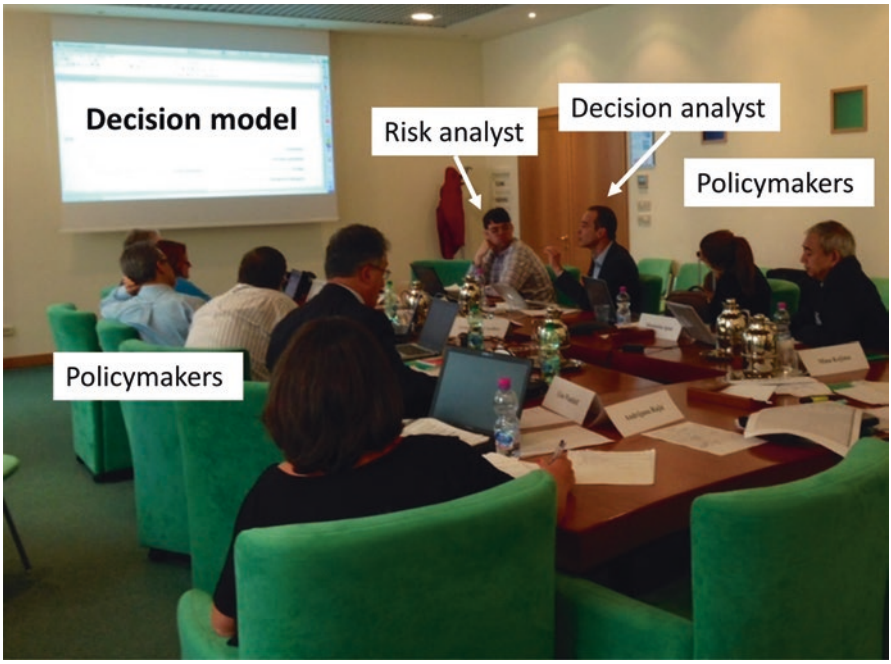

Fig. 4.8 A typical facilitated decision analysis setting for the low-moisture food prioritization at FAO. (Source: FAO) (Montibeller, 2018)

4.3.1 Identifying Relevant Objectives

We employed a causal map to help the LMF expert group identify all the relevant objectives. The decision model was interactively constructed with the group and projected onto a screen, as shown in the photo in Fig. 4.8. We were managing the model content as well as facilitating the group dynamics. Notice the layout of the meeting, with an oval table that allowed face-to-face interactions and discussions mediated by the decision model (Franco & Montibeller, 2010, 2011a; Phillips, 2007).

Utilizing their laptop computers, group members were asked to individually contribute to the concepts of the map on a shared document for online collaboration, to foster creativity and breadth. The map developed by the experts, shown in Fig. 4.9, had a means-end structure, with means at the bottom and ends at the top and representations of links that denoted influence. The map is, thus, amenable to qualitative inferences (Montibeller & Belton, 2006). For instance, from the bottom-left corner on the map shown in Fig. 4.9, the group agreed that the action *know the pathogen of concern* is a means to the objective *minimize human exposure to pathogens*. The link between the two nodes of the map represents the influence that the action may exert on objective.

As we have discussed in this chapter, means and ends are relative, and the map was shifted downward with the decision making group. Thus, from the map, the

objective *minimize human exposure to pathogen*s influences the objective *minimize the burden of disease (frequency and severity)*, which in turn then influences three end objectives at the top of the map: *(increase the) confidence on the health system*, *reduce costs in the health system*, and *maximize the perceived safety of food*.

The map was also shifted downward with the group, for instance a means to the objective *facilitate international trade* (top right corner in the map), is an end objective to *produce safe food*. There existed several means actions that influenced this latter objective, as shown in the map: *know the way that the food is consumed*, *know who is consuming the food*, *know how much is consumed*, *know the way that the food is produced*, and *know the diversity and complexity of the production chain*.

This comprehensive map, created by the LMF expert group, was developed to minimize the omitted variable bias (Jargowsky, 2005; Montibeller & von Winterfeldt, 2015). The debiasing was accomplished using the initial individual elicitation and posterior sharing of views and perspectives, until the group agreed on a shared map that represented the relationships between means and ends objectives. The colored concepts in the map were identified by the team as the most relevant categories of objectives (Eden, 2004; Montibeller & Belton, 2006): *facilitate international trade*, *minimize the burden of disease*, *minimize vulnerabilities from food consumption*, and *minimize vulnerabilities from food production*.

4.3.2 Structuring Decision Objectives

From the causal map developed with the LMF experts, we developed with this same group of experts the value tree presented in Fig. 4.10. The tree decomposes the assessment of the overall impact of each LMF category along the four main categories of objectives identified in the causal map (Fig. 4.9): *(facilitate) international trade*, *(minimize) burden of disease*, *(minimize) vulnerabilities to food consumption*, and *(minimize) vulnerabilities from food production*.

Only the first two categories of objectives in this value tree (C1 and C2 in Fig. 4.10) had been mentioned by the experts when the two-day facilitated workshop began. There was no need of further decomposing these two categories into sub-objectives, as depicted in the value tree, as levels of international trade and burden of disease could be directly assessed for each LMF category.

The other two categories of objectives (C3 and C4 in Fig. 4.10) were identified only after the causal map was developed with the expert group and a joint problem definition was clear, which illustrates the benefit and importance of a well-designed group process for the definition of objectives. These two categories were decomposed into a set of indicators that could assess the *vulnerabilities to food consumption* (C3.1, C3.2 and C3.3 in the same figure) and *vulnerabilities to food production* (C3.1, C3.2 and C3.3 in the same figure) caused by different categories of low moisture food. These indices were also defined by the experts, with our support, during the facilitated workshop.

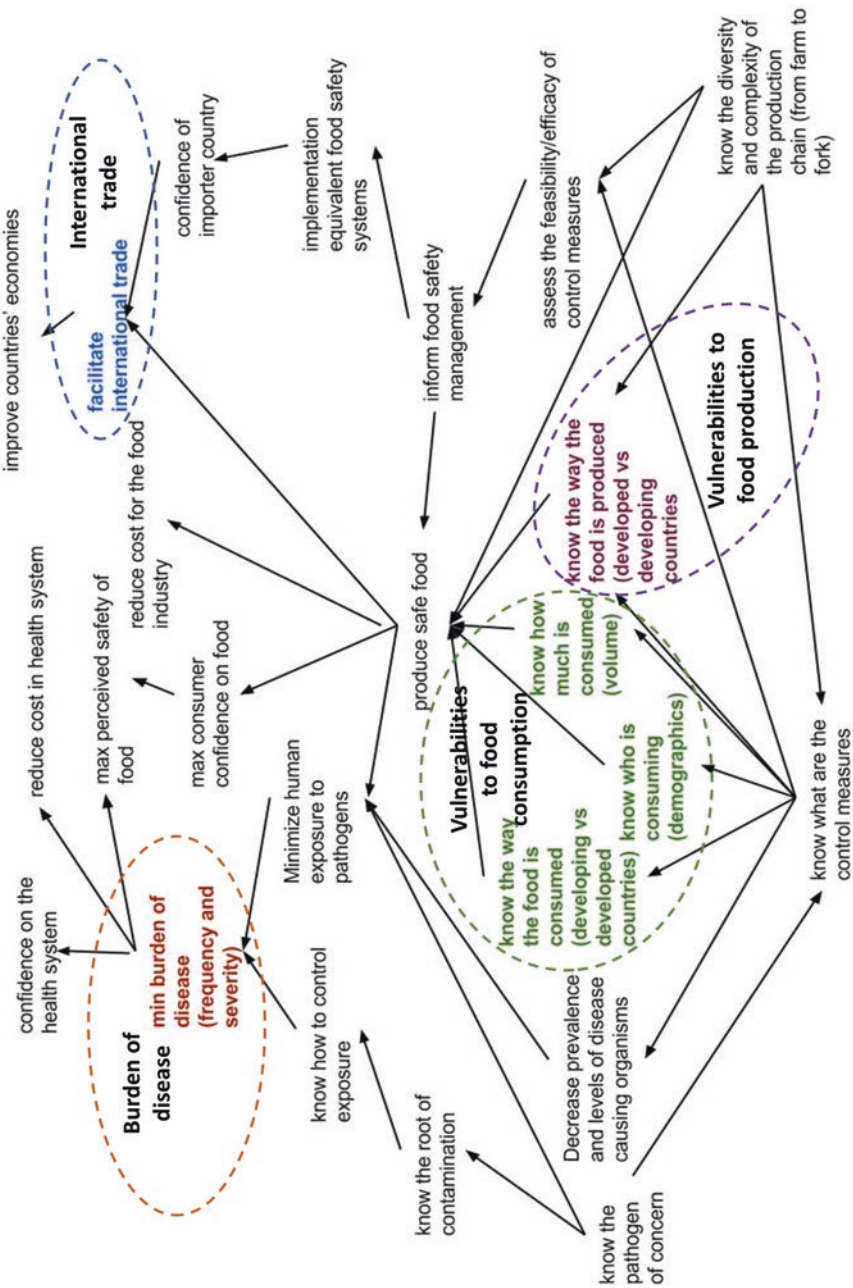

Fig. 4.9 Causal map for the low-moisture food expert group. (Montibeller, 2018)

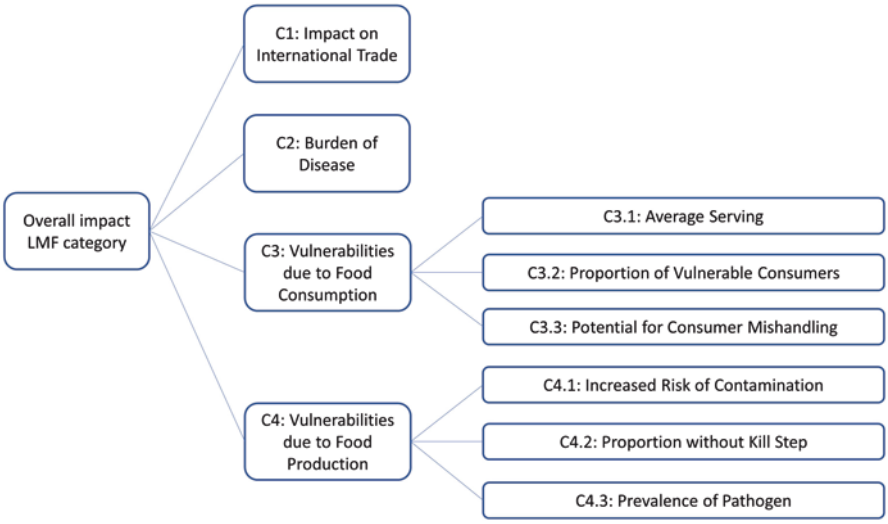

Fig. 4.10 Value tree for the prioritization of low moisture food categories. (Montibeller, 2018)

The value tree shown in Fig. 4.10 has structured the objectives of the LMF experts, making clear as to the four dimensions of consequences of interest. The rightmost level of nodes of the value tree were employed to assesses each LMF category. As mentioned above, the impact on *international trade* and the *burden of disease* were directly assessed for each LMF category. On the other hand, consequences concerning *vulnerability to food consumption* and *vulnerability to food production* were further decomposed into a set of attributes, with the impacts of each LMF category being assessed on each attribute

4.4 Conclusions: Specifying Fundamental Objectives and Relevant Consequences

In this chapter, we have stressed the crucial role that decision objectives should play in health security decisions and the importance of clearly specifying these objectives for the specific decision situation under consideration. Decision objectives should be considered as foundational elements in decision processes for several reasons, as we have argued here. First, decision objectives aid to define what the health security team wishes to achieve. Second, objectives indicate which consequences are relevant to the specific decision context under consideration. Third, objectives can support the identification and design of decision alternatives. Fourth, decision objectives may guide the gathering of information and direct efforts for evidence collection and expert engagement. Fifth, the definition of

decision objectives enables the assessment of societal value that can be provided by each decision alternative and guides the choice of high-value options.

In practice, decision objectives are often poorly defined or only implicitly assumed in many decision processes. Hence the need to develop relevant objectives and to structure them using an adequate decision frame, as has been described in this chapter. This specific decision frame should lead to the definition of a set of fundamental objectives, which must fulfill a number of logical properties.

The fundamental objectives can be organized into a hierarchy of objectives, wherein an overall objective is decomposed into objectives and sub-objectives. This hierarchy of objectives is denominated a *value tree*. This representation is a useful decision model, which can guide the evaluation of decision alternatives taking into account multiple decision objectives, or the assessment of the multiple impacts that health threats may cause.

More broadly, the definition of a hierarchy of objectives utilizing a value tree is a robust method of clearly representing what the health security team wishes to achieve. As we have mentioned in this chapter, the rightmost level of the value tree indicates both the objectives to be achieved and the consequences that are relevant to the specific decision context. These consequences shall be the input for assessing the possible impacts of health threats and of health security actions, and thus shall constitute the topic of the subsequent chapter.

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Chapter 5
Assessing Impacts of Health Threats and Health Security Actions



A comprehensive and realistic assessment of impacts of health threats and health security actions is a central component of any well-conducted health decision analysis and is essential for any reasoned health security decision. However, the uncertainty that is present in the context of every health security decision poses a core challenge that must be considered in the evaluation of health threats and health security actions.

If the decision task entails the evaluation as to how serious an emerging health threat is, the task would therefore require an assessment of the possible impacts of this health threat in the case of various possible scenarios of occurrence and severity. On the other hand, if the decision task entails the identification of the best actions to enhance health security, said task would require comparing and selecting options to improve health security. However, it is important to note that uncertainty is inevitable when considering the effectiveness of such actions and the often limited evidence about performance of different options under consideration.

To further compound the complexity of impact assessment, the dynamics intrinsic to disease transmission require that a health decision analysis considers the temporal behavior and the impact of health threats. In addition, health security actions that are focused on improving the preparedness of health systems or on reducing the vulnerability of populations, typically have long-term horizons. These long-range planning horizons encompass not only multi-year activities and budgets for health security actions but also the long-term consequences that may be caused by health threats.

In this chapter we present how we can adequately assess both the impacts of health threats, and of the decision alternatives for improving health security under uncertainty. Here, a core concept entailing decision-focused modeling is discussed, whereby we detail the adequate representation of the key decision components and their interrelationships, enabling the analysis of the consequences of each possible action in a systematic manner. Said decision focus can foster a better understanding of the decision situation and underpin a reasoned decision process.

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Decision-focused modeling is distinctive from evidence-focused modeling (e.g. the development of epidemiological transmission models or biological understanding of diseases). Evidence-based modeling is essential and critical for understanding health impacts, although it may not adequately address all the fundamental objectives and relevant consequences that must be taken into account in health security decisions.

In the second chapter we presented a diagram that illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 5.1. The decision stage covered in this chapter: *assessing impacts of health threats and health security actions* is now highlighted in this figure. When detailing this topic, we shall assume that the fundamental objectives and relevant consequences have been defined and agreed upon by the health security team and that at least two decision alternatives have already been identified.

5.1 Structuring the Health Decision Analysis

Health security decisions are almost invariably taken under uncertainty (Osterholm & Olshaker, 2017). Hence, it is important to understand how uncertainties affect these decision processes and how we can represent, understand, and better manage specific uncertainties. Additionally, an adequate characterization of uncertainty is a pre-requisite for the risk-based approach proposed by the World Health Organization framework on health systems for health security (WHO, 2021).

In this section, we shall introduce *influence diagrams* (Howard & Matheson, 2005a, b), which form a robust tool to represent decisions under uncertainty in a concise way. In the previous chapter we discussed the importance of defining an adequate specific decision frame, entailing the identification of a clear and specific decision context and the respective set of fundamental objectives for a health security decision, as reproduced in Fig. 5.2a. The decision frame provides two key components that are required for a health decision analysis, as represented in Fig. 5.2b. First, the *specific decision context* functions to delimit the relevant decision alternatives that are to be considered in a health security decision. Second, the *fundamental objectives* shall define the relevant consequences that are to be considered in the decision analysis. Once the health security decision has been adequately framed and the relevant consequences identified, we are able to consider the role of uncertainties. This decision is represented in Fig. 5.2c as an *influence diagram*. The diagram depicts the three core components of a decision analysis: *decisions* as square nodes, *uncertainties* as oval nodes, and *consequences* as octagonal nodes.

The links in the influence diagram denote an *influence* from the node at the beginning of an arrow to the node at the end of an arrow. Hence, in Fig. 5.2c, the uncertainties about the severity and occurrence of an outbreak caused by the health threat (*uncertainty* node) exert influence on the impacts caused by said outbreak on the relevant consequences (*consequences* node). For instance, if a consequence were to be the number of severe cases, the extent of the outbreak would determine

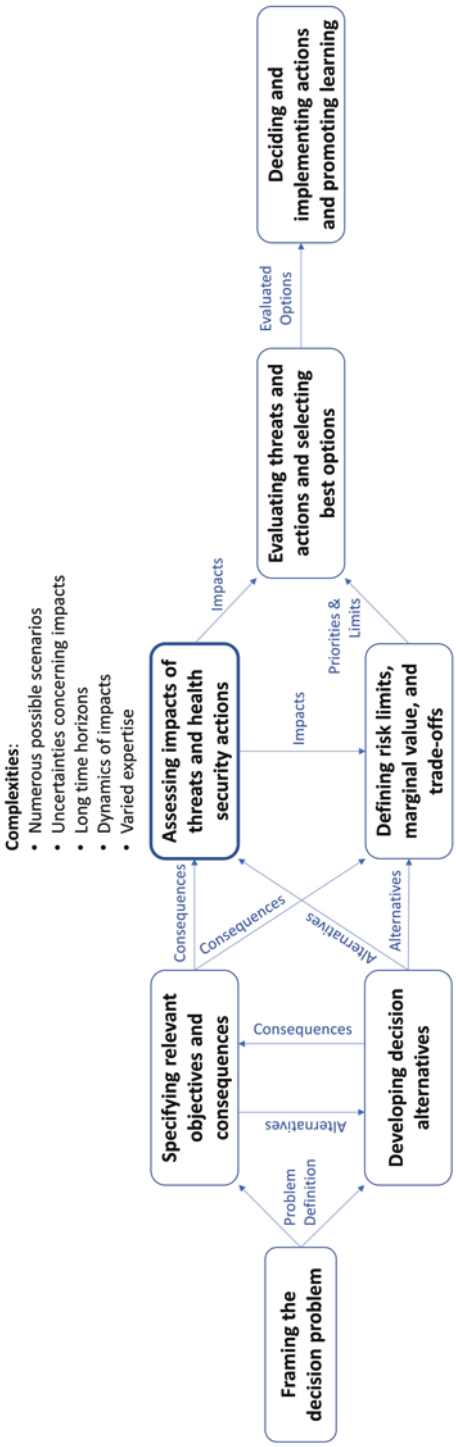

Fig. 5.1 Making reasoned health security decisions: A focus on assessing impacts of health threats and health security actions

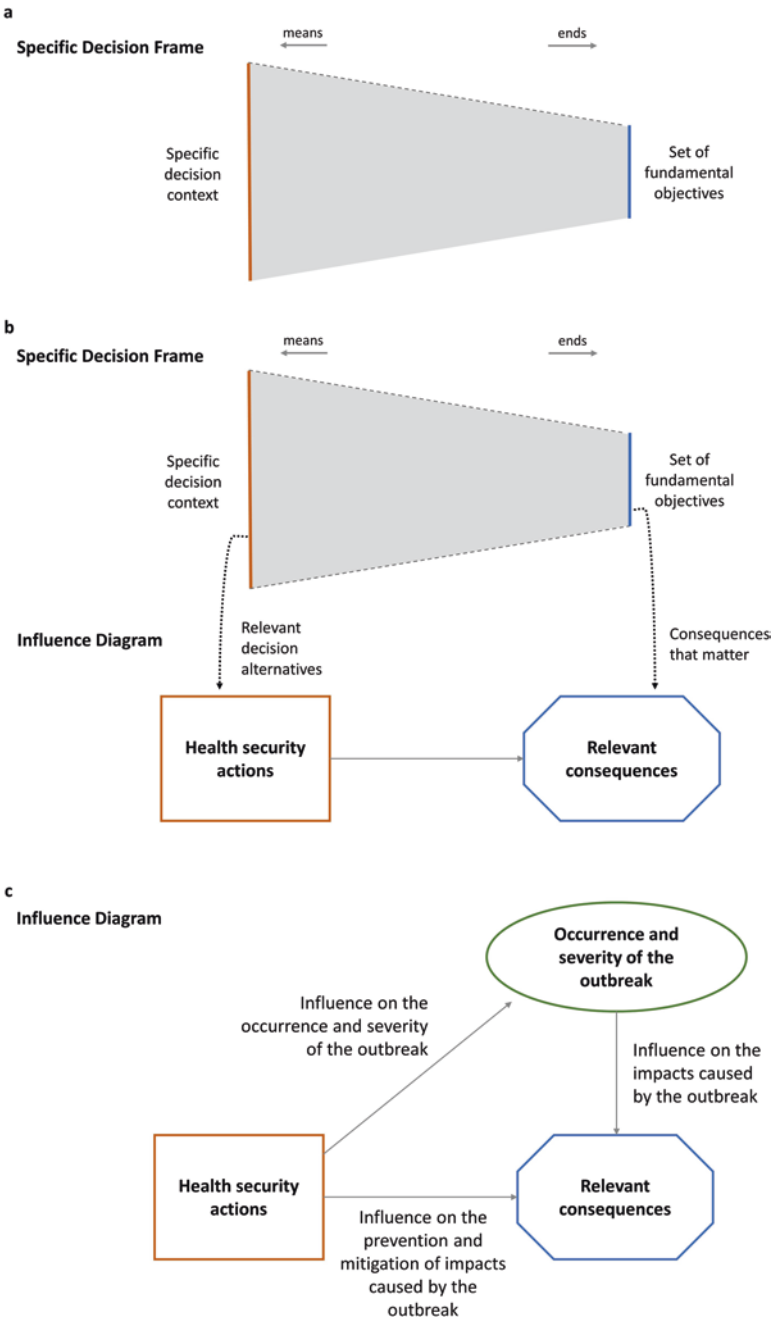

Fig. 5.2 (**a**) Health security specific decision frame, (**b**) Transition from the specific decision frame to an influence diagram, (**c**) Influence diagram of a health security decision

the number of cases (this number would range from zero if the outbreak were to not occur, or, up to a higher limit were a major outbreak to occur).

The health security actions also exert an influence on the relevant consequences, which is symbolized by the arrow that is located between the *health security actions* (*decision* node) and the *relevant consequences* (*consequences* node) in Fig. 5.2c. For health security actions, the influence is typically exerted through impact *prevention* and impact *mitigation* actions. For example, an action that is focused on impact prevention against a health threat could involve the isolation of vulnerable segments of the population, which may result in a reduction of the number of severe cases. Similarly, impact mitigation could be achieved by strengthening the health care system, for example by increasing the number of doctors and hospital beds that are available, aiming to reduce the number of cases that become severe.

The uncertainties that exist are exogenous and therefore cannot be directly controlled by health policymakers or the health security team. However, there exist ways to influence the impacts that are brought about by an uncertainty (Cox Jr. et al., 2018). This influence is demonstrated in Fig. 5.2c by the arrow linking the *health security actions* (*decision* node) to the uncertainties related to the *occurrence and severity of the outbreak* caused by the health threat (*uncertainty* node). For instance, imposing a quarantine mandate to impede individuals from leaving regions wherein known disease cases exist may reduce the *occurrence* of the outbreak in another region under consideration. The reduction in *severity* may be achieved by vaccinating a significant segment of the population against the infectious disease, which could reduce the number of severe cases.

The influence diagram in Fig. 5.2c can be decomposed in order to illustrate the contribution of three main Decision Sciences fields that support decisions under uncertainty. Risk Analysis (Aven, 2015; Vose, 2008) seeks to understand the influence that uncertainties exert on the relevant consequences and the ways in which risks can be mitigated and managed (see Fig. 5.3a). Decision Analysis (Howard, 1968; Howard & Abbas, 2016; Keeney, 1982; Raiffa, 1968; von Winterfeldt & Edwards, 1986) is concerned with decisions under uncertainty, and how choices can be improved in order to achieve the fundamental objectives reflected by relevant consequences (see Fig. 5.3b). Causal Risk Analysis (Cox, Jr. et al., 2018) is a more recent field, which is focused on how uncertainties can be influenced to alter the impacts of adverse scenarios, in a manner that reduces negative impacts and promotes positive impacts (see Fig. 5.3c). In practice, these three types of analyses can be used jointly to support reasoned decision making, with Decision Analysis providing the foundational framework for decision-focused modeling. In this book, we employ this integrated analytic framework.

As we have previously mentioned, influence diagrams are a robust and concise way of representing decisions under uncertainty (see McNamee and Celona (2005) for an accessible introduction to this type of decision modeling). These tools can be used in a facilitated manner (Franco & Montibeller, 2010, 2011) with health security teams to support health experts and health security teams to better understand the relationships between choices and consequences, as well as to represent the key uncertainties affecting the decision. The factual project that shall be described

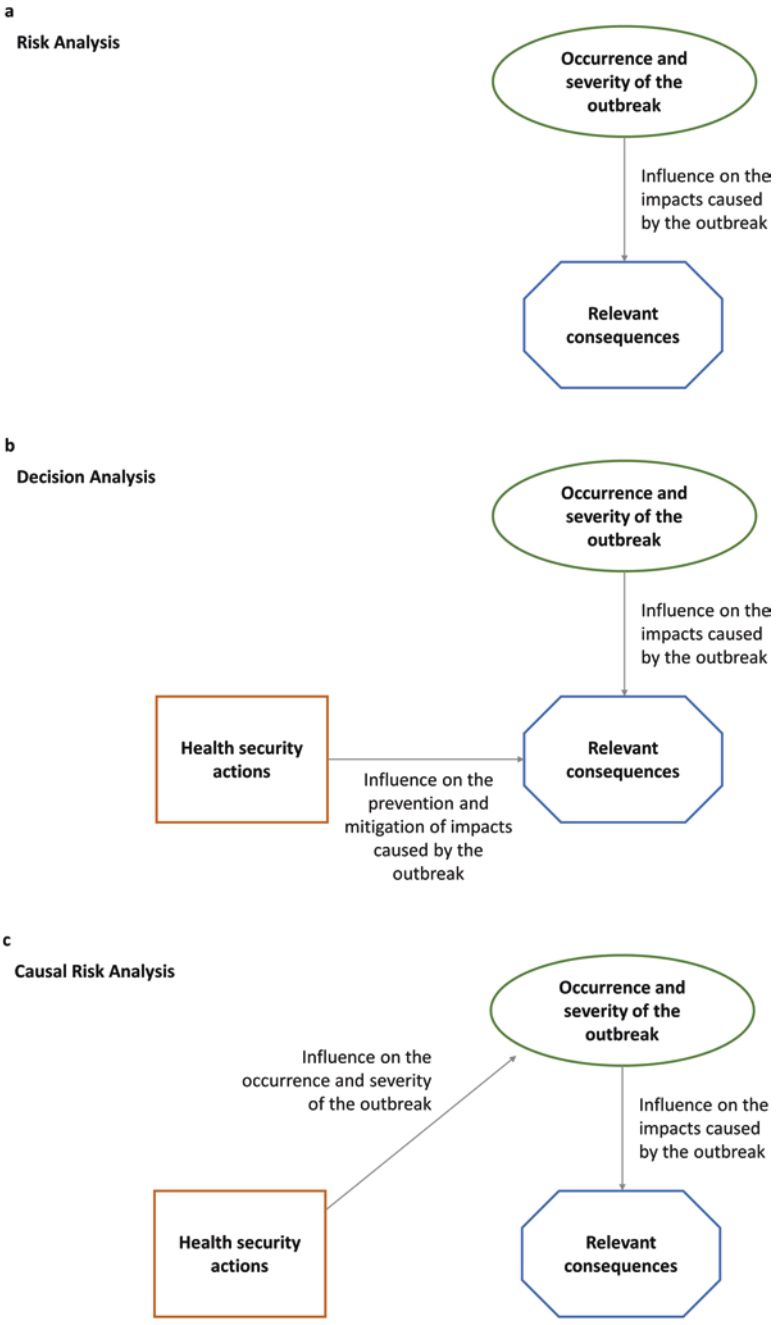

Fig. 5.3 The focus of analytical support of health security decisions: (**a**) Risk Analysis, (**b**) Decision Analysis, and (**c**) Causal Risk Analysis

below illustrates the use of an influence diagram for a health security decision in practice.

5.2 Structuring a Health Decision Analysis for the Ranking of Emerging Animal Health Threats (DEFRA)

Since the 1980s, the UK has been the locus of several emerging human and animal health threats including Bovine Spongiform Encephalopathy (BSE, commonly known as "mad cow disease") and foot-and-mouth outbreaks that caused a series of crises that affected British agriculture, trade and tourism, which led to the slaughter of millions of animals and cost the government billions of pounds.

The UK Department for Environment, Food and Rural Affairs (DEFRA) is responsible for monitoring emerging animal health threats and managing animal health threats in the country. The identification of critical emerging animal health threats is crucial to guide the decisions of the DEFRA with regards to impact mitigation and risk management.

Managing such threats poses multiple contingencies and challenges for health policymakers to undertake, including: (i) the tangible and intangible nature of impacts that a threat may cause, (ii) the great number of threats present in the environment, (iii) the emerging nature of the threats, which limits the amount of hard evidence relating to their possible impacts and probability of occurrence, (iv) the limited amount of time and resources allocated to evaluate the potential impacts of each threat, and (v) the mandate for evidence-based, value-for-money recommendations that consider hard-to-monetize impacts.

We were requested by the DEFRA Risk Veterinary Group to support the assessment and ranking of emerging animal health threats, and consequently, we developed a decision support system for DEFRA, which, since 2009, is utilized on a monthly basis and has analyzed more than 218 threats to the UK since its inception (see Montibeller et al. (2020a) for details). The system evaluates the potential impacts of each emerging health threat under concern, prioritizes the health threats in terms of their potential overall impact, and identifies the capabilities and capability gaps that DEFRA possesses for tackling each threat.

The decision situation for this health threat prioritization is demonstrated as an influence diagram in Fig. 5.4. The evaluation is focused on the assessment of consequences that could be caused by an outbreak of a given emerging animal health threat, which is represented in the diagram (see Del Rio Vilas et al., 2013b for details). There exists a set of actual impacts (indicated by an [A] in the diagram) that may be caused by each threat on four dimensions: *impact on public health*, *impact on animal welfare*, *impact on the economy, environment and society*, and *impact on international trade*. In addition, there exists a set of consequences related to perceived impacts (indicated by a [P] in the diagram) that could be caused by each

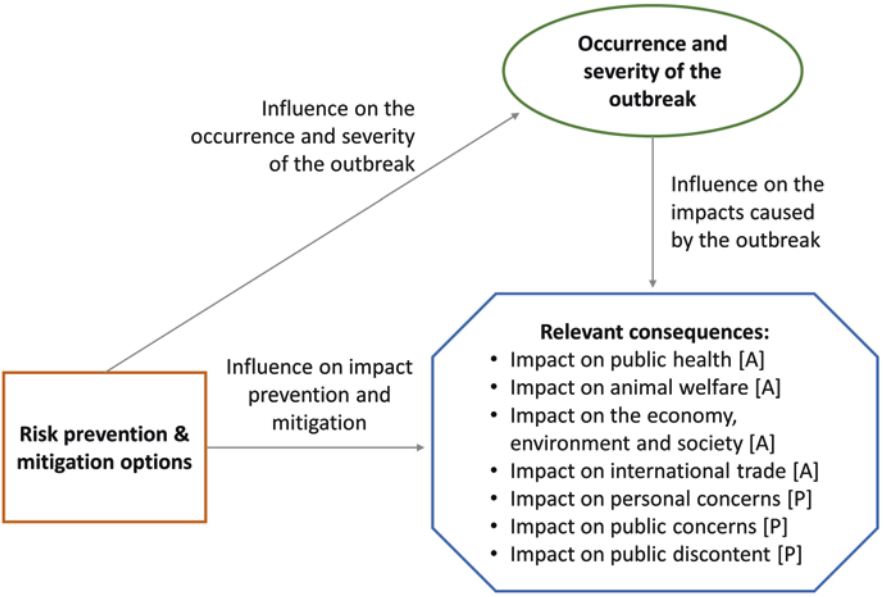

Fig. 5.4 The influence diagram for the ranking of emerging animal health threats

threat: *impact on personal concerns*, *impact on public concerns*, and *impact on public discontent*.

The main uncertainties that were involved in this prioritization problem included the probability of occurrence and the severity of an outbreak caused by each emerging animal health threat under consideration. These uncertainties were influenced by the impacts of the outbreak, as depicted by the arrow from the *uncertainty* node to the *consequences* node in the influence diagram in Fig. 5.4.

There exist many co-occurring emerging threats in the environment and expert judgment was employed to estimate these probabilities of occurrence as well as to estimate possible impacts, given the plethora of impacts and limited amount of time that was for the assessment (Jaspersen & Montibeller, 2015).

The decision alternatives that were available to the DEFRA Veterinary Risk Group involved risk prevention and risk mitigating options against each emerging health threat, as shown in the same influence diagram. These options can influence both the impact prevention and the impact mitigation of a threat. Options can also be devised to influence the uncertainty itself (i.e. actions that attempt to reduce the occurrence and severity of an outbreak). The decision support system also assesses the capabilities and capability gaps that are present in the systems which DEFRA is monitoring. Said assessment was designed to support the definition of options which could then be recommended to the Chief Veterinary Officer.

The conceptualization of a decision under uncertainty as an influence diagram highlights the three main components required by a health decision analysis (see Fig. 5.2c): (i) assessing the *relevant consequences* for a specific decision context, (ii)

determining the *key uncertainties* affecting the relevant consequences, and (iii) identifying the *decision alternatives*. The first two components are described in this chapter and the latter one is described in the seventh chapter. Let us start with the assessment of relevant consequences, which shall constitute the topic of the next section.

5.3 Assessing Relevant Consequences

In the previous section, we have discussed the role of relevant consequences in decisions under uncertainty, which are related to the achievement of fundamental objectives in health security decisions. This section describes how these relevant consequences can be assessed utilizing the development of *attributes*.

The adequate assessment of consequences shall enable the evaluation of the performance of decision alternatives, the assessment of impacts of health threats, as well as the consideration of trade-offs among competing objectives. The assessment of a consequence is operationalized in Decision Analysis via an *attribute*, otherwise known in the pre-existing literature as a performance measure, criterion, or metric (see also Keeney and Gregory (2005) for details). There exist three types of attributes and it is important that their properties be verified, so that they are able to be employed in health security assessments. In this section, we detail these types of attributes and the logical properties that are required for an attribute.

5.3.1 Defining the Type of Attribute

There exist three types of attributes that are suitable to assess relevant consequences (Keeney, 1992, 2007; Keeney & Gregory, 2005): *natural attributes*, *proxy attributes*, and *constructed attributes*. Each attribute shall be briefly explained and illustrated in the context of health security decisions subsequently.

Natural Attributes. Natural attributes are quantitative indices that are widely used in practice, and whose interpretation is characterized as being clear and unambiguous. Natural attributes directly measure the achievement of the fundamental objective of concern.

Let us consider the fundamental objectives in the vaccination campaign case that have been presented in the previous chapter and the question of how to measure the achievement of the fundamental objective *maximize the immunization coverage rate* in this decision. A natural attribute that could be employed to measure this consequence is the *percentage of the overall population that was vaccinated during the campaign*, as we have already mentioned in the previous chapter. Another fundamental objective in this decision problem is to *minimize the vaccination campaign costs*. A natural attribute to measure this consequence is the *total cost of the campaign in US dollars*.

Whenever natural attributes are available, they should be employed, as they provide an unambiguous assessment of impacts or performances. That is, a natural attribute provides a direct link between the performance that is being measured and the achievement of the fundamental objective that is under consideration.

However, not all relevant impacts are measured with such ease, such as the direct economic consequences or the vaccination levels in the vaccination campaign case. In many instances, the consequences are concerned with intangible impacts, which are nonetheless associated with achieving important objectives. In cases wherein a natural attribute is not available, we must choose whether to employ a proxy attribute or develop a constructed attribute.

Proxy Attributes. Proxy attributes are quantitative indices that are used in practice, and whose interpretation is characterized as being clear and unambiguous. Hence, to a certain extent, proxy attributes are similar to natural attributes. However, a proxy attribute measures the fundamental objective of concern indirectly, by assessing the achievement of a means objective that influences the achievement of the fundamental objective.

Let us again consider the vaccination campaign case and the question of how to measure the achievement of the fundamental objective *maximize the storage quality of vaccine stocks* in this decision analysis. There fails to exist a natural attribute that is able to evaluate this concern. However, a proxy attribute that measures the *proportion of vaccines that are undamaged at the point of application* could adequately evaluate the achievement of this fundamental objective (albeit indirectly and only partially).

Constructed Attributes. Constructed attributes are developed to directly measure the achievement of a fundamental objective when a natural attribute does not exist and when a suitable proxy attribute is also not available.

Let us again consider the vaccination campaign case and the question of how to measure the achievement of the fundamental objective *maximize the campaign reach across population strata* in this decision analysis. No natural attribute exists that is able to measure such campaign reach. One option could involve assessing the *percentage of the population that was vaccinated during the campaign for each range of the population age*. A weighted sum of these proportions, which attaches greater weight to segments deemed as vulnerable (e.g. infants and elderly individuals), could then be employed as a constructed measurement for the campaign reach across the population strata.

Public health indices that aggregate several indicators and provide an overall score, such as the INFORM Risk Index for the assessment of humanitarian crises and disasters (*INFORM* Risk, 2020), can also be classified as constructed attributes. The same can be said for health indices such as the EQ-5D index and other indices used to assess quality-of-life (Hunink & Weinstein, 2014).

Constructed attributes can also be employed to evaluate qualitative, hard-to-measure concerns. In this case, the attribute is composed of a set of qualitative labels, each one describing a given level of achievement of the objective for health security actions or, alternatively, a given level of impact from a health threat. The project for the ranking of emerging animal health threats that we conducted for DEFRA

(introduced in the previous section) employed these types of constructed attributes for assessing the impacts of said threats, as described next.

5.3.2 *Defining Constructed Attributes for the Ranking of Emerging Animal Health Threats (DEFRA)*

The DEFRA Veterinary Risk Group had a major area of concern, regarding their ranking of emerging animal health threats and the public perception that each threat could cause (Del Rio Vilas et al., 2013b). There exist three consequences under this category, as shown in Fig. 5.4: *impact on personal concern*, *impact on public concern*, and *impact on public discontent*.

There were no natural attributes that could be employed to assess these perceived impacts, and any proxy attribute employed would provide only a partial picture of each concern. Therefore, alongside the DEFRA experts, we developed a set of three constructed attributes for assessing perceived impact, whose individual definitions were clear and each attribute had been agreed upon by the Veterinary Risk Group, and which were conceived of as an ordered set of qualitative labels (ranging from Level 5 = highest impact, to Level 1 = lowest impact).

The attribute for the impact on personal concern was defined as the *degree of potential personal concerns about a threat, in terms of the health, economic or social consequences that it may cause*. The five levels of this attribute are presented in Table 5.1a. Notice that we have characterized the perceived threat as much as possible, not only as *dreadful* (Level 5) but also with the type of news ("recent alarming/frightening news in the media") and a providing a benchmark from a past outbreak ("e.g. the BSE outbreak", which describes the bovine spongiform encephalopathy outbreak that heavily affected Britain in the 1980s and early 1990s). This detailed definition functions to illustrate the elements that constitute a dreadful impact, and the example of a past outbreak significantly reduces the ambiguity of this qualitative label, when compared with the mere description as "dreadful", which is often observed in some assessments of health threats (see Montibeller et al., (2020b) for a critique of ambiguous labels in health threat assessments).

In the same decision model, the attribute for the impact on public concern was defined as the *degree of potential public concern about a threat, in terms of animal suffering and affective connection to the species*. The five levels that form this attribute are presented in Table 5.1b, and once again, each level has been described utilizing a clear definition and an example of a previous outbreak.

Finally, the attribute for the impact on public discontent was defined as the *degree of potential public discontent about the expected management of a threat and the level of constraint that risk management measures can impose*. The five levels of this attribute are presented in Table 5.1c.

Policymakers that are managing health threats typically employ the common objective of reducing the feelings of fear in the general population (Slovic, 1987; Slovic & Peters, 2006). While this is an intangible, hard-to-measure issue, it is one

Table 5.1 Constructed attributes for the prioritization conducted by DEFRA of animal health threats: (**a**) Personal concerns, (**b**) Public concerns, (**c**) Public discontent

a	Attribute: Personal concern
Level 5	Perceived threat: Dreadful. Recent alarming/frightening news in the media (e.g. the bovine spongiform encephalopathy [BSE] outbreak).
Level 4	Perceived threat: Serious. Recent alarming/frightening news in the media (e.g. the avian influenza outbreak).
Level 3	Perceived threat: Moderate. Recent adverse news in the media (e.g. the verocytotoxin-producing escherichia coli VTEC O157 outbreak).
Level 2	Perceived threat: Moderate. No news in the media (e.g. the Q-fever in the Netherlands outbreak).
Level 1	No perceived threat. No media reports (e.g. equine infectious anaemia 2010 outbreak).
b	Attribute: Public concern
Level 5	Severe suffering in a species dear to the public. High potential media interest (e.g. rabies in puppies).
Level 4	Some suffering in a species dear to the public. High potential media interest (e.g. killing of badgers to control spread of tuberculosis).
Level 3	Some suffering in a species that the public is less concerned with. High potential media interest (e.g. as bluetongue virus BTV 8 in cattle).
Level 2	Some suffering in a species the public is not concerned with. High potential media interest (e.g. Newcastle disease in poultry).
Level 1	No suffering in a species the public is not concerned with. Low media interest (e.g. an outbreak of infectious anaemia in salmon).
c	Attribute: Public discontent
Level 5	Severe constraints on a large proportion of the population. Serious mistrust in the manner that the threat shall be handled (e.g. foot-and-mouth [FMD] 2001 outbreak).
Level 4	Some constraints on a large proportion of the population. Some mistrust in the manner that the threat shall be handled (e.g. avian influenza outbreak threat 2006).
Level 3	Some constraints on some sectors of the population. Some mistrust in the manner that the threat shall be handled (e.g. Newcastle disease in pheasants).
Level 2	Some constraints on some sectors of the population. No mistrust in the manner that the threat shall be handled (e.g. VTEC O157 outbreaks on open farms).
Level 1	Not likely to impose any constraints; any constraints imposed shall affect only a minor proportion of the population. No mistrust in the manner that the threat will be handled (e.g. equine infectious anaemia 2010 outbreak).

Source: Del Rio Vilas et al. (2013b)

which proves relevant to many health security decisions. The assessment of perceived impacts in this project for DEFRA, shown in Table 5.1, forms an example that illustrates how this type of intangible impact can be adequately measured in health security practice.

We developed a more sophisticated constructed attribute for assessing the potential impact on public health that may be caused by an emerging animal health threat; the first relevant consequence is listed in the *consequences* node in influence diagram in Fig. 5.4. This attribute, reproduced in Fig. 5.5, is composed of two dimensions. One dimension is formed by the *degree of human exposure to the threat* (low, medium, or high) and the second dimension is formed by the *type of symptoms* that

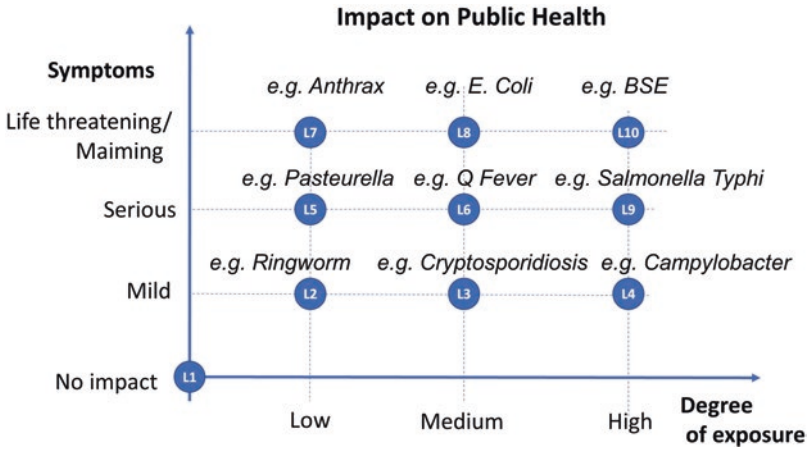

Fig. 5.5 Attribute for assessing potential impact on public health from animal health threats. (Adapted from Del Rio Vilas et al., 2013b)

the emerging animal health threat may produce in humans (ranging from no impact to life-threatening/incapacitating symptoms). The lowest level (L1) indicates no impact, and the highest level (L10) is characterized by a high degree of exposure that can produce life-threatening symptoms. The intermediate levels of impact were ranked by the DEFRA health experts. In order to reduce the ambiguity in the assessment, the experts also identified previous outbreaks that would reflect this intermediate level of impact. For instance, L10 would be representative or akin to the BSE outbreak that affected Britain in the 1980s and the early part of the 1990s.

The design of natural, proxy and constructed attributes should consider logical properties, which function to ensure that each attribute can promote rigorous and unambiguous assessments of impacts and performances. These logical properties are described next.

5.3.3 Checking the Properties of Attributes

The definition of high-quality attributes is an important component of a thorough health decision analysis, as attributes play a significant role on the quality of any health threat assessment (Montibeller et al., 2020b) or on the quality of any health security action evaluation. There exist five required properties for an attribute (Keeney & Gregory, 2005), which are described below and illustrated in the context of health security decisions.

Unambiguous An attribute is unambiguous when there exists a clear relationship between the consequences that may occur and the description of consequences that has been developed for the attribute. Therefore, unambiguous attributes should be clear and precise.

In the vaccination campaign case, the objective *minimize the campaign costs* has an associated natural attribute that is unambiguous: *total cost of the campaign in US dollars*. The cost of each campaign option under consideration can be clearly and precisely mapped onto this attribute (even if there exists uncertainty surrounding the precise cost of the campaign). In addition, the same assumptions and sources should be used to assess the costs for each campaign option in order to increase the accuracy of the estimates and comparability of the total costs among each of the decision alternatives.

Let us consider the attribute *total cost of the campaign in US dollars* and compare it with another attribute that would merely classify the costs of the campaign as either "high, medium, or low". These labels are ambiguous and therefore are open to different interpretations, in that a cost of US$50 million could be considered to be "high" by one individual assessor but "medium" by another assessor. This issue of ambiguity within a probability assessment has been observed through the lens of Behavioral Decision Research, which has demonstrated that the same qualitative estimates of probability may reflect very different quantitative estimates between subjects (Budescu & Wallsten, 1985; Wallsten et al., 1986). Similarly, ambiguity may affect the estimation of impacts of health threats or performances of decision alternatives. Hence, these ambiguous labels should be avoided.

Another common problem that we have often observed in health threat assessments is that the discretizing of a continuous attribute into ranges also increases the level of ambiguity of an attribute (Montibeller et al., 2020b). For instance, the attribute *total cost of the campaign in US dollars* could be discretized into a "high level" (between US$100 million and US$70 million), "medium level" (between US$70 million and U$40 million), and "low level" (between US$40 million and U$10 million). This poor modelling practice typically results from a lack of hard evidence.

Discretizing continuous attributes into ranges should be avoided whenever possible, for three reasons. First, these ranges have overlapping categories, rendering it impossible to determine whether US$40 million is "low" or "medium". Second, discretization unnecessarily increases the ambiguity of the assessment, particularly if the qualitative labels were to be used to assess the options, instead of the numerical ranges that define said labels. Third, the ranges reduce the granularity of the assessment, and as a result, a campaign that costs US$70 million would be considered to be equivalent to a campaign that costs U$40 million, as both campaigns are encompassed within the same ranges that constitutes the "medium" level.

Comprehensive An attribute is considered to be comprehensive if the attribute levels cover the full range of possible consequences and implicit assumptions that are deemed to be appropriate for the decision situation.

Let us consider the objective *maximize the immunization coverage rate* in the vaccination case and define a natural attribute *percentage of the overall population that was vaccinated during the campaign* (which measures the attainment of this objective). Let us assume that any campaign that would realize vaccination levels below 60% would be excluded from the evaluation, as this performance level is deemed to be unacceptable. On the other hand, no vaccination campaign would be able to vaccinate 100% of the population. Instead, for this case, the realistic estimate

is that the maximum vaccination coverage rate would be 99% of the population. Hence, the range of this attribute should be established to be anywhere from 60% to 99% of the population. This range covers the full extent of consequences that different vaccination options that are acceptable may achieve, therefore the attribute proves to be comprehensive.

The implicit assumption in the definition of this attribute (which considers the percentage of the overall population that was vaccinated during the campaign) is that any segment of the population would be allocated an equal weight when conducting the vaccination campaign. In this sense, the attribute neglects that vulnerable individuals and infants may benefit more from the vaccine. Therefore, a more refined attribute, which allocates specific weights to different population segments based on how much each segment would benefit from the vaccine, could be a more comprehensive attribute than the percentage of the overall population that was vaccinated.

Direct An attribute is considered to be direct if the attribute levels directly describe the consequences of concern.

In the vaccination case, the attribute *total cost of the campaign in US dollars* is a direct one, as it can be measured on a continuous scale. The health security team or health economists can estimate any level of cost for each campaign option under consideration. On the other hand, if we consider an alternative attribute for the objective *total cost of the campaign* "high/medium/low", we can see that this latter attribute is indirect, as the levels do not clearly describe the consequence of interest in the decision (cost in US dollars).

Checklists that record how guidelines have been met are often used in health security preparedness assessments, and are an example of an indirect measurement. These checklists neither provide a clear assessment that reveals how well-prepared the health system is, nor do the checklists indicate how much the system should be further improved. Instead, a set of well-designed direct attributes that can be employed to measure health capabilities can function to reveal the overall state of a health system and consequently, direct any further improvements that the system may require (Del Rio Vilas et al., 2013a). We detail how health preparedness can benefit from well-designed attributes in the seventh chapter.

Operational An attribute is operational if the evidence and information to describe consequences can be obtained in practice and the trade-offs among conflicting objectives can be executed.

Whenever reliable evidence about the impact of a health threat is available, said evidence should be employed to evaluate the possible impact of this health threat on the attribute that measures the relevant consequence. Similarly, whenever evidence about the performance of a decision alternative is available, said evidence should be used to evaluate the potential performance of this decision alternative on the attribute that measures the relevant consequence.

For healthcare related attributes, there exist clear protocols for evidence gathering and a hierarchy of evidence that can support health experts in acquiring the information that is required (see Hunink and Weinstein (2014) for details). The

same holds true for public health related attributes and for some socio-economic attributes. If the evidence is indeed available, it would make the attribute operational.

However, clear protocols for evidence gathering do not exist for other types of attributes, and therefore, hard evidence pertaining to many relevant consequences, in our experience, is often not available. In such cases, expert judgment is frequently employed to estimate consequences (Morgan, 2014), with the use of debiasing tools to reduce biases and improve the quality of judgments (Montibeller & von Winterfeldt, 2015, 2018), as is discussed in the tenth chapter. This use of expert judgment would also make an attribute operational.

In general, it is advisable to maintain a fundamental objective that is difficult to assess, even if the consequences must be assessed by experts, rather than to exclude the objective from the evaluation on the grounds of lack of evidence. If we were to exclude a fundamental objective, the health decision analysis would be excluding a concern that is significant, and consequently, would neglect the relevant consequence when comparing and choosing decision alternatives.

However, if evidence is not available and expert judgment cannot be used, then the attribute proves to be nonoperational. In this latter case, we are constrained to either select or design a proxy attribute or a constructed attribute that has available evidence (see Keeney and Gregory (2005) for guidelines on how to make this selection among different types of attributes).

In the sixth chapter we discuss how trade-offs among conflicting objectives can be conceptualized and defined in health security decisions. One important concept for the definition of trade-offs (which is detailed in that chapter) is that trade-offs must consider the attributes associated with the fundamental objectives. For example, in the vaccination campaign case, one trade-off involves negotiating between the objectives of *maximizing immunization coverage rate* versus *minimizing campaign costs*. Said judgment should only be made once clearly defined attributes have been specified. In this case, the trade-off involves considering how much (in US dollars) the health security team is prepared to pay for selecting a vaccination campaign option that would vaccinate 99% of the population, rather than another, less expensive campaign option that would vaccinate only 60% of the population.

Conversely, attributes are deemed to be operational if trade-offs can be made when considering said attributes. Trade-off judgements are not possible in cases wherein decision makers have some taboo trade-offs, which they refuse to consider explicitly (Fiske & Tetlock, 1997; Tetlock et al., 2000), usually due to ethical or moral concerns. In such instances, the attributes involved in the taboo trade-off would be considered to be non-operational (Keeney & Gregory, 2005).

Understandable An attribute is understandable if its meaning is intelligible and precise to all those involved in the health security decision, including decision makers, experts involved in the analysis, and key stakeholders whose level of engagement is that of a decisional participation.

Understandability is particularly important in group decision making settings, as the same concept may have different meanings attached to it by distinctive team members (Eden et al., 1981, 1983). A clear definition of the attribute allows each

member involved in the decision process to understand the consequences of concern and fosters communication among the members of the team.

In the vaccination campaign case, the attribute *total cost of the campaign in US dollars* has a high level of understandability, in that the meaning of the attribute should be clear to every member of the health security team. This typically proves to be the case for quantitative and widely employed indices. However, notice that even quantitative indices may have different levels of understandability. For instance, the use of an international monetary currency that is less well-known than the US dollar to evaluate the cost of vaccination campaigns could reduce the understandability of the attribute, for example *the total cost of the campaign in Japanese Yen* would incur a lower level of understandability for countries that are distant, or do not have a strong relationship to the Japanese economy.

Furthermore, there exists evidence that scaling biases (Poulton, 1982, 1994) (i.e. different ways of presenting and scaling an attribute) may affect the understandability of an attribute (Montibeller & von Winterfeldt, 2015). Another project that we conducted for the UK Department of Environment, Food and Rural Affairs (DEFRA) illustrates this issue.

We were asked to support DEFRA in their assessment of bio-security threats posed by invasive species, including threats to forests, crops, species of domesticated animals, and species of wild animals(Montibeller et al., 2020a). Due to the variety of threats, the possible economic impacts were very extensive, ranging from thousands to billions of pounds sterling. The choice of whether to employ a logarithmic scale was, therefore, important and said scale was indeed adopted, so that the economic impact of mild and severe threats could be better compared. In addition, we suggested that the upper level of the economic impact attribute be delineated instead of allowing the scale to remain unbounded. Had the scale remained unbounded, trade-offs required for selecting risk mitigating actions could not have been made in a sensible manner, as the delineating functioned to increase the understandability of the attribute as well as its operationality (von Winterfeldt & Edwards, 1986).

A clear and understandable definition for constructed attributes is critical, as these attributes are designed for a specific decision process and are therefore not widely known and employed. The attributes for assessing the perceived impacts of emerging animal health threats, described in Table 5.1, provide examples that demonstrate how these definitions can be developed in practice.

The fulfilment of these five properties for attributes, summarized in Table 5.2, ensures that the attribute is sufficiently adequate to evaluate the consequence of concern. Unfortunately, health security assessments are often underpinned by poorly designed attributes, which are often highly ambiguous and imprecise. There exists evidence that a poor design has a significant and detrimental influence on the prioritization of health threats (see Montibeller et al. (2020b) for a full discussion of these problems and an assessment of their impact on the ranking of health threats). Similarly, poorly designed attributes may also cause serious detrimental effects on the quality of the selection of health security actions.

Conversely, the definition of well-designed attributes (linked with the achievement of fundamental objectives) can foster a significant increase in the quality of a health decision analysis and adequately support the evaluation of decision

Table 5.2 Properties for attributes in health security evaluations

Property	Description
Unambiguous	An attribute is considered to be unambiguous when there exists a clear relationship between the consequences that might occur and the description of consequences.
Comprehensive	An attribute is considered to be comprehensive when the attribute levels account for the full range of possible consequences, and when implicit assumptions are deemed to be appropriate for the decision situation.
Direct	An attribute is considered to be direct when the attribute levels directly describe the consequences of concern.
Operational	An attribute is considered to be operational when the evidence and information to describe consequences can be obtained in practice and trade-offs can be sensibly made.
Understandable	An attribute is considered to be understandable when the meaning of the attribute is intelligible and precise to all of the key stakeholders whose level of engagement is that of a decisional participation.

Adapted from Keeney and Gregory (2005)

alternatives in health security decision processes. Said attributes function both to indicate the manner in which the health security team wishes to measure the achievement of decision objectives, and, to enable the clear and unambiguous assessment of decision alternatives.

Once the attributes have been defined, we can direct our focus to the identification and characterization of uncertainties, which constitutes one of the greatest challenges in health security decisions, and which shall be discussed in the subsequent section.

5.4 Identifying and Characterizing Uncertainties in Health Security Decisions

This section discusses how uncertainties in health security decisions can be conceptualized and represented to support reasoned decision making. First however, these uncertainties must be identified and then adequately characterized. In this book, we focus specifically on decision making *under uncertainty*, drawing from a vast literature from Decision Analysis (see also Howard (1968) and Raiffa (1968), for a modern coverage see Howard and Abbas (2016), and on health care decisions see Hunink and Weinstein (2014)) and from Risk Analysis (see also Morgan and Henrion (1992) and Morgan (2017)).

5.4.1 Identifying Key Uncertainties

The vast number of emerging and re-emerging health threats reveal the vast and complex uncertainties involved in health security decision making. Re-emerging infectious diseases are typically well-known, with extensive evidence about their

level of virulence and rate of contagion. The uncertainties that re-emerging diseases bring about are related to the extent and pattern of possible outbreaks. Therefore, while the science is typically well-established about those diseases, the uncertainties are related to how the outbreak could occur and whether the outbreak shall occur at all. Such uncertainties require addressing in health security decisions, with inputs from Epidemiology and Biomedical Sciences.

In addition to the uncertainties pertaining to endemic diseases, there exist many scientific unknowns about emerging infectious diseases, for instance, their virulence and reproduction number. Despite the absence of hard evidence, public health leaders are required to make difficult choices when managing these emerging threats, thus it is crucial to understand the role of any additional uncertainties in their health security decisions.

In our experience, scientists are rigorously trained to think probabilistically about the evidence related to pathogens and their spread, but are also less adapted to consider the repercussions that uncertainties have on the difficult policy choices, which are characteristic of health security decision making. On the other hand, health policymakers often desire certainty where there exists plenty of uncertainty and consequently, may feel frustrated that a clear, straightforward answer fails to exist.

Our overall recommendation is to identify and specify the uncertainties and assess the extent to which they play a role in the choices that must be made. One major benefit of developing a thorough health decision analysis and having a clear framework to underpin health security decisions, is that only the *key* uncertainties that may exert influence on the relevant consequences require inclusion within the analysis and need to be considered in the decision.

It is also advisable to allocate substantial effort on the characterization of uncertainties, instead of allocating this same effort on identifying risks, as there exist multiple concepts of *risk,* with each concept giving rise to a different meaning that is often poorly conceptualized. Hence, attempts to directly consider *risks* may increase the degree of ambiguity of a health decision analysis (Gregory et al., 2012), which may have detrimental effects on the quality of the decision process itself (Spetzler et al., 2016). The sixth chapter discusses this issue in more detail.

Furthermore, as large outbreaks are relatively rare events and affect populations with specific vulnerabilities and socio-economic characteristics, it proves difficult to accurately extrapolate the impacts from one particular outbreak to another. These unique circumstances necessitate that a thorough health decision analysis utilize customized inputs, formed by a combination of hard evidence and surveillance data, alongside debiased expert opinions.

Defining the key uncertainties that influence the relevant consequences and ensuring that this set of uncertainties is exhaustive constitutes a task that requires expert opinion. Experts and health policymakers typically define these uncertainties utilizing their previous experiences, available scientific evidence, and technical health-related literature.

There exists behavioral evidence (Fischhoff et al., 1978; Gettys et al., 1986) that the omitted variable bias may affect the defining of uncertainties (R. P. Thomas

et al., 2008), i.e., there may be a failure to identify some key uncertainties. This omission is brought about by several cognitive and motivational biases (Montibeller & von Winterfeldt, 2015), including a myopic problem representation (Legrenzi et al., 1993; Legrezni & Girotto, 1996), an overconfidence in the judgement concerning the exhaustiveness of the set of uncertainties (Fischhoff et al., 1978; Mehle, 1982), an excessive focus on uncertainties associated with scenarios that are considered a priori to be highly probable (Dougherty et al., 1997; Weber et al., 1993), an excessive use of readily available information from recent events (Tversky & Kahneman, 1973), and a confirmation bias that engenders a selective acquisition and recall of knowledge (Nickerson, 1998).

The issues of neglecting key uncertainties must be tackled with the use of adequate debiasing tools for expert elicitation (Montibeller & von Winterfeldt, 2015). Promoting the practice of producing precise definitions of uncertainties and events can aid in reducing ambiguity when considering future events (von Winterfeldt, 1999). The use of counterfactuals, i.e. asking experts to give alternative explanations for their predictions (Roese, 1999), can foster creativity and reduce the biases listed in the paragraph above. The use of a varied expert group can also help to increase the understanding about the decision situation. However, care should be taken to avoid group judgment biases in these group elicitation tasks (Montibeller & von Winterfeldt, 2018), such as groupthink (Janis, 1983) and group polarization (Isenberg, 1986). Processes for group debiasing typically involve a first stage that entails individual idea generation, which is then followed by group discussions that may be supported by an internal or external facilitator (Franco & Montibeller, 2010, 2011). The defining of uncertainties should lead to an exhaustive list of key uncertainties that may affect the relevant consequences in the specific decision situation.

Let us illustrate the representation of key uncertainties utilizing an influence diagram for the vaccination campaign case. The value tree for this decision problem was described in the previous chapter and is reproduced in Fig. 5.6a. As shown in the tree, four major categories of decision objectives were of concern: *maximize vaccination coverage*, *maximize campaign quality*, *maximize efficiency of the campaign logistics*, and *minimize campaign costs*.

The influence diagram that represents this decision situation is presented in Fig. 5.6b. The *decision* node presents two decision alternatives: a centralized campaign in hospitals or a decentralized campaign in community centers and home visits. The four categories of relevant consequences, associated with the respective categories of decision objectives in the value tree, are: *vaccination coverage*, *campaign quality*, *efficiency of campaign logistics*, and *campaign costs*.

The main uncertainty in this decision is the effectiveness of the campaign, represented by the *uncertainty* node in the influence diagram in the same figure. The level of effectiveness shall influence the campaign performance, as depicted by the arrow from the campaign effectiveness *uncertainty* node to the relevant *consequences* node.

Four key uncertainties were identified that could affect different aspects of the campaign effectiveness: *effectiveness of the campaign promotion among the target population*, *effectiveness of the logistics operations in transporting and storing vaccine stocks*, *effectiveness of the cost controls exerted on the campaign*, and

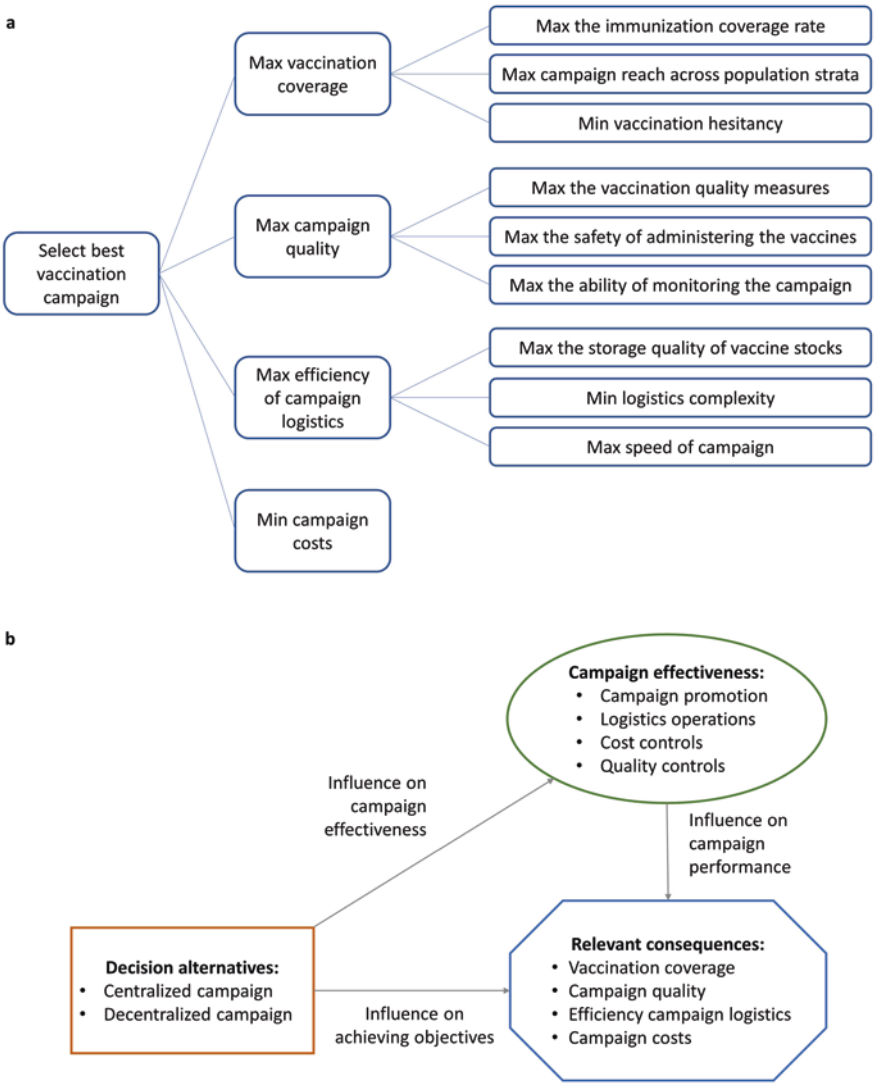

Fig. 5.6 The decision components for the vaccination campaign case, (**a**) Value tree decomposing the overall objective, (**b**) Influence diagram representing the decision alternatives, uncertainties, and relevant consequences

effectiveness on the quality controls for vaccine storage and applications. These four key uncertainties are presented in the *uncertainty* node of the influence diagram representing this decision problem shown in Fig. 5.6b. As the diagram demonstrates, the key uncertainties influence the four categories of relevant consequences in this decision.

The achievement of the decision objectives (reflected by the respective relevant consequences) is influenced by the decision alternative that is selected. This

influence is represented by an arrow from the *decision* node to the relevant *consequences* node in the influence diagram. Therefore, in this decision problem, the performance of a given vaccination campaign, on the relevant consequences, is a function of both the decision alternative that is selected and the impacts of the uncertainties that determines the performance of the alternative.

Decomposing a main uncertainty into key uncertainties is advisable, as illustrated in the vaccination campaign case, whereby the main uncertainty relating to the campaign effectiveness was decomposed into four key uncertainties. Specifically, the decomposition enables a better understanding of the influences that each uncertainty may cause on the relevant consequence(s) and can also enable more reliable estimates of the probabilities of the occurrence of events (MacGregor, 2001; Ravinder et al., 1988).

In this book, we promote a major benefit of adopting a decision making focus when considering uncertainties, in that this focus can allow us to exclude many scientific uncertainties. Although these uncertainties prove highly relevant to understanding the specificities of the health threat, they may ultimately fail to influence the specific health security decision.

For instance, the scientific uncertainty relating to the role of a specific viral characteristic would only be relevant to a health decision analysis if the evidence gathered about this virus were to indicate a potential influence on the virulence of the health threat, and consequently, a potential influence on the number of cases that an outbreak may trigger. Otherwise, said evidence would prove irrelevant to the decision that is being focused on and gathering this evidence would not increase the quality of the decision. (Of course, this notion does not deny that the resolution of this uncertainty may be extremely relevant for the scientific understanding of this specific virus.)

Indeed, from a decision-making perspective, one wishes to elucidate the scientific uncertainties that are the most relevant for the decision situation, which requires that we turn backward to identify characteristics of the health threat that could potentially influence the relevant consequences. In the same case that has been employed in the previous paragraph, observing viral characteristics may prove to be highly relevant if said characteristics influenced the virulence, and therefore, the number of cases that the virus may trigger. Again, we see that a decision-focus can also support scientists in prioritizing the pathogens that are most alarming from a societal and public health perspective, thus allocating the greatest research efforts by taking into account over 500,000 known viruses that have already been identified (GVP, 2020).

5.4.2 Characterizing Key Uncertainties

We have discussed above the importance of identifying a list of key uncertainties that may influence the relevant consequences in a specific decision situation. What, then, are the main sources of uncertainties in health security decisions?

First, uncertainties may arise due to a lack of information or evidence. For instance, deficiencies in a health surveillance system may prevent the formation of an adequate picture about the number of cases or rates of infection in a population, as Britain and Spain experienced during the early stages of the COVID-19 pandemic in 2020 (Neville & Dombey, 2020). Second, the parametrization of predictive epidemiological simulation models may rely on limited evidence and on strong assumptions (Brauer et al., 2019). Once these inputs are deemed to be sufficiently varied and these assumptions have been relaxed, the predictions are typically presented as distributions of outcomes. Third, there may exist limited scientific evidence about the biological characteristics of the health threat, as well as the impacts on humans and other species that an outbreak may cause, particularly for emerging diseases. Fourth, it is typically more challenging to assess impacts that are hard-to-measure, such as fear, or whose effects are multiple and indirect, such as economic costs, than those impacts that directly affect health. Fifth, experts may disagree on the possible impact levels. Taken as a whole, these sources of uncertainties create difficulties in establishing deterministically the levels of impacts that a health threat may cause, or the performances that health security actions may generate.

There exists an extensive literature on how to adequately characterize uncertainties in policy decisions (Morgan, 2017; Morgan & Henrion, 1992). Two important messages are presented by this literature. The first is that the key uncertainties and their dependences should be identified and their influence on the relevant consequences properly modeled. The second message is that probability is the most widely used and accepted tool to express uncertainty.

The uncertainty of an impact can be adequately represented by a probability density function over the relevant consequence. Consider the objective *minimize the number of severe cases* that may be caused by a health threat, measured by the attribute number of severe cases, represented by variable x. The uncertainty about this impact can be displayed by the probability density function f(x) shown in Fig. 5.7a. The total area under this function f(x) is 1.00, and the area under this function for a given range denotes the probability of occurrence of this range. Hence, the probability that the number of cases is at least at level $X^{'}$ is $P(x \leq X^{'})$.

The cumulative distribution function F(x) associated with the probability density function f(x) is shown in Fig. 5.7b. The function F(x) shows the area under f(x) for a given level X′. For example, in Fig. 5.7a, consider a normal distribution with a mean $\overline{x} = 9{,}000$ cases and standard deviation of 2,000 cases, and $X' = 7{,}000$ cases. The probability that the number of severe cases is at least $X' = 7{,}000$ cases is demonstrated by the area shown in the same figure $P(x \leq X') = P(x \leq 7{,}000) = 15.8\%$. This probability could be directly read from the y-axis of Fig. 5.7b.

Unfortunately, the current practices in health security decisions are often inadequate in their treatment of uncertainties in contrast with a full characterization employing a distribution function such as the one that has been described above. Four of these poor practices are discussed next and involve: ignoring uncertainties altogether when estimating impacts or other relevant consequences, the use of qualitative labels to describe uncertainty, the use of semi-quantitative risk matrices, and the definition of vague qualitative scenarios.

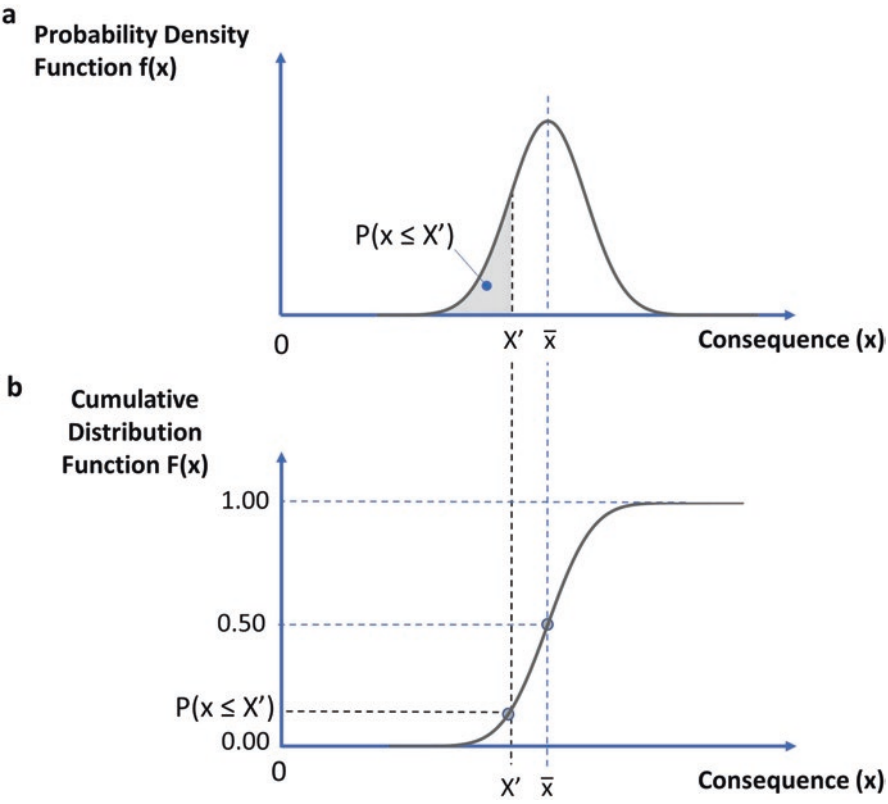

Fig. 5.7 (**a**) Probability density function for the attribute x and, (**b**) Cumulative distribution function for the attribute x

The most extreme case of poor practice involves the situation wherein uncertainties, while acknowledged, are not considered in the analysis of health threats or in the assessment of health security decision alternatives. Cases that employ multidimensional assessments of impacts (Montibeller et al., 2020b) are particularly vulnerable to this type of poor practice, as there exists an assumption of deterministic impacts that is often implicit.

To illustrate the above, let us posit an estimate concerning the health impacts for an outbreak of a given disease. This estimate determines that the disease triggers an estimated 9,000 severe cases that require hospitalization and 500 fatalities in a given city. These deterministic predictions would fail to provide any information as to the possible variability of cases or fatalities, despite the inherent uncertainties of the outbreak. This implicit assumption may foster a false sense of certainty among decision makers, and obfuscate the risks associated with reasonable worst-case scenarios (e.g. 20,000 severe cases and 1,500 fatalities in the same example).

The second type of over-simplification when considering uncertainties in health security decisions involves the use of qualitative labels to describe uncertainties. For instance, policy makers may say that this threat is "high risk" or that the impacts the threat may generate are "extensive". These high levels of ambiguity, as discussed in the first chapter, are detrimental to reasoned decision processes.

We have frequently observed this type of qualitative assessment being employed. Often, the reason stated to justify adopting these ambiguous labels is an absence or a lack of clear evidence. Unfortunately, the lack of evidence then leads to an increase in ambiguity in the assessment. A better strategy entails considering the influence of the uncertainty on the relevant consequences in a more explicit manner, and, representing the distribution of impacts when assessing impacts of health threats and health security actions.

The third type of over-simplification in representing uncertainties involves the use of risk matrices, which were discussed and critiqued in the first chapter. In this type of model, experts provide an assessment of overall impacts of a threat, employing a 1-to-5 discrete scale, and an assessment of the likelihood of the threat occurring, which also employs a 1-to-5 discrete scale. The two scores are then multiplied to produce a number, allowing for the threats to be ranked. The impact assessment is, therefore, assumed to be deterministic and the manner in which the uncertainty is dealt with is rendered overly simplistic and may lead to illogical results (Cox, Jr., 2008; Thomas et al., 2014).

The two central deficiencies pertaining to risk matrices are constituted by the highly ambiguous assessments of impacts and probabilities (Budescu & Wallsten, 1985; Wallsten et al., 1986) and the adoption of a ranking metric that fails to appropriately aggregate impacts and likelihoods. Despite their simplicity and widespread use, risk matrices should be avoided, as they may foster poor recommendations for health security decision.

The fourth type of over-simplification in the treatment of uncertainty involves the absence of a clear scenario, or, the use of a merely qualitative scenario narrative. We have in many instances observed a poor practice that entails the specification of impacts or consequences without a clear scenario for the occurrence of the outbreak or a well-defined risk path. Without a clear scenario, which functions to provide the boundary conditions for the outbreak predictions, it becomes simply impossible for experts to gather the relevant evidence or adequately simulate possible impacts.

The absence of a clear scenario increases the possibility that predictions are influenced by the availability bias (Schwarz et al., 1991; Tversky & Kahneman, 1973; Wänke et al., 1995), whereby notable events drive the estimations, even if a risk path does not exist. For instance, the Ebola outbreaks in West Africa during 2014–2016 (CDC, 2020) could have affected the estimates of impacts of the disease in other areas of the world, even if the outbreak was mostly contained within the region.

The lack of a clear scenario is even more concerning when we know that the projections of impacts typically hold several implicit assumptions, which, in these cases, typically remain unchallenged. Implicit assumptions strongly influence the estimates, and affect how decision makers approach the outbreak, patterns of spread,

behavior of the population, and so on. These assumptions typically have an important influence on the estimate of impacts for large-scale public projects, as discussed by Dillon-Merrill et al. (2002), and hence the assumptions should be made explicit and be properly scrutinized.

The use of a qualitative scenario slightly alleviates these problems but is also beset with weaknesses. Scenarios are widely employed in business strategic planning (Bishop et al., 2007; Schoemaker, 1993; Tiberius et al., 2020). Each scenario is typically composed of an internal coherent narrative of a plausible future that addresses with the key variables under consideration. There exist many benefits in designing these scenarios, such as developing robust strategies to manage these alternative futures (Montibeller et al., 2006; Montibeller & Franco, 2011; Ram & Montibeller, 2013). However, we argue that these qualitative scenarios are not particularly useful for health security decisions.

The major drawback of qualitative scenarios is that the more detailed and specific the scenario, the more likely that experts involved in their development expect the scenario to occur. Thus, an increase in the plausibility of a scenario in turn increases the perception of experts that the scenario shall indeed occur (Morgan, 2017). However, this probability estimate transgresses the laws of probability, representing a conjunction fallacy.

For example, Tversky and Kahneman (1983) found that subjects estimated that the scenario of a conjunction of an earthquake and a flood in California wherein 1,000 people drown at some point in 1983 to be roughly 40 percent more probable than the occurrence of a flood in any region of North America wherein 1,000 people drown at some point in 1983. This latter scenario is evidently more likely to occur as it is less restrictive and covers an area that is 58 times broader. Similar findings were discovered by Redelmeier et al. (1995) for judgments in medicine.

There exist three recommendations for counteracting these problems associated with the lack, or simplistic representation, of uncertainties. First, we must recognize that uncertainties do exist and should be modeled. Second, we must define explicit assumptions for any prediction of impacts. Third, we must adequately model impact, and locate a balance between comprehensiveness and simplicity. This latter task is detailed in the subsequent section.

5.5 Assessing Impact of Health Threats and Actions

Key uncertainties may generate two important effects that are related to the relevant consequences in health security decisions. First, they typically generate a dispersion of impacts of health threats and health security actions on the consequences of interest. For example, in the vaccination campaign case, uncertainty about the effectiveness of cost controls may lead to estimates for the centralized vaccination option ranging between US$45 million and US$55 million, depending on whether the controls were to be effective. Second, uncertainties may create critical risks associated with adverse consequences. In the same vaccination campaign case, uncertainties

about the effectiveness of quality controls may reveal an arena wherein there exist risks of severe adverse effects on the vaccinated population or a possibility that some individuals may not be fully immunized. We present how to model the first characteristic (dispersion of impacts) next, and suggest how to represent critical risks in the sixth chapter.

5.5.1 Assessing Dispersion of Impacts

We are able to classify distinctive levels of impact assessment that evaluate impacts on a clearly specified attribute, for instance the number of severe cases, x, caused by a health threat. We assume that these estimates are made under a specific, well-specified, and adequately bounded scenario (which provides a time dimension and geographical boundaries). Five representation levels, ranked by their increasing representational power (and complexity), are described subsequently.

Single Point Estimate The first representation level involves considering a deterministic impact on the attribute, with the most likely impact (X_{ML}), i.e. there is no dispersion in the impact assessment, shown in Fig. 5.8a. This assessment would imply a *probability mass function* f(x), which is the type of distribution employed for a discrete function, as shown in the same figure.

This representation is an acceptable simplification when the uncertainty levels are low and when multiple impacts must be considered in the decision, and therefore, this representation is indeed frequently used in health decision analysis practice (Carland et al., 2018; Montibeller et al., 2020b).

N-Point Estimate The second representation level is to define an N-point Discrete distribution, as shown in Fig. 5.8b. For each level of impact, X_L, …, X_M, …, X_H, an associated probability of the impact occurring is defined, p_L, …, p_M, …, p_H, which compose a probability mass function. These points and associated probabilities are either directly defined by health experts, or, approximated utilizing a continuous distribution function (Hammond & Bickel, 2015; Miller & Rice, 1983).

This type of evaluation is widely employed in decision analysis, due to its simplicity, strong axiomatic basis, and well-defined protocols for expert elicitation. We cover this representation in more detail in the ninth chapter and show how it can be used to evaluate decision alternatives for health security.

The next levels assume a continuous distribution and are predominantly used in Risk Analysis (Morgan & Henrion, 1992; Vose, 2008).

Range Estimate The third representation level involves defining a range of impacts, from X_{Min} to X_{Max} as shown in Fig. 5.8c. This is a simple albeit beneficial way of considering uncertainties. In this case, the Uniform probability density function f(x), shown in the same figure, assumes that any impact within this range is equally likely to occur.

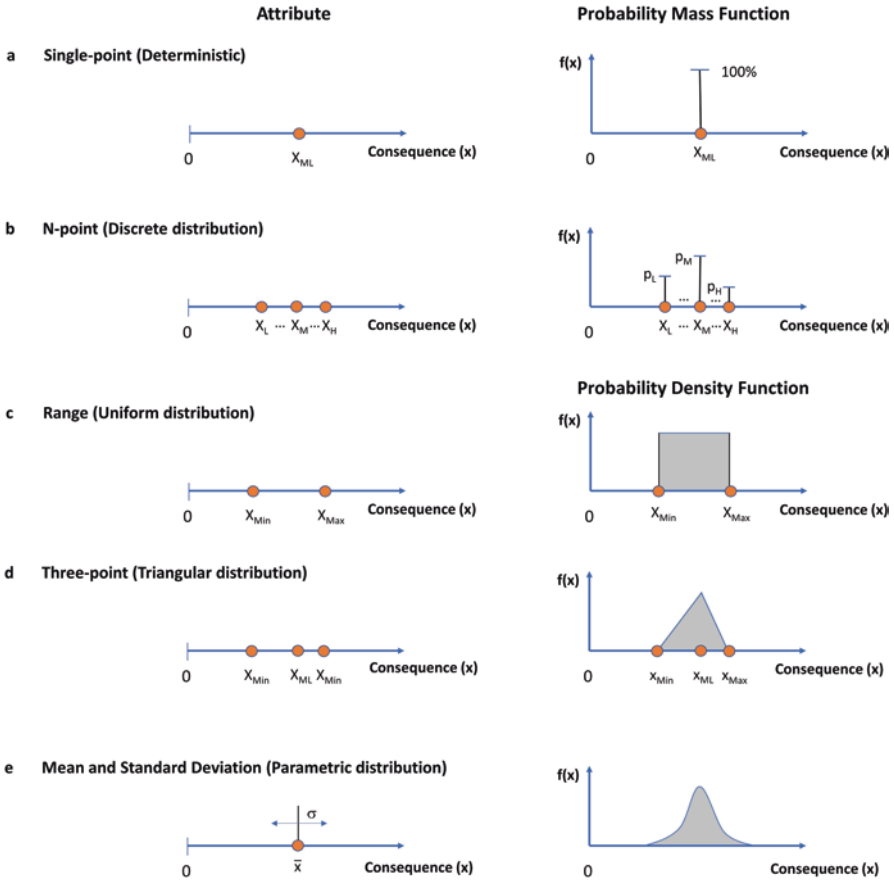

Fig. 5.8 Estimations of impact and respective probability distribution for: (**a**) Single-point estimate and mass density function, (**b**) N-point estimate and mass density function, (**c**) Range estimate and Uniform probability density function, (**d**) Three-point estimate and Triangular probability density function, and (**e**) Mean and Standard Deviation of a parametric distribution and probability density function

Triangular Distribution Estimate A fourth, and more sophisticated level of representation of uncertainty than the previous one, entails a distribution wherein not only the range, but also the most likely value (X_{ML}) is represented (see Fig. 5.8d). These three points, X_{Min}, X_{ML} and X_{Max} define the Triangular probability density function f(x) shown in the same figure.

Notice that the Triangular distribution does not require symmetry and that most of the probability density is around X_{ML}. The Discrete, Uniform and Triangular distributions are non-parametric distributions and are defined by their shape (Vose, 2008). These distributions are particularly useful for expert estimates but are bounded, and so the distributions assume that impacts located outside the pre-determined range shall not occur at all.

Parametric Distribution Estimate A fifth level of representation is shown in Fig. 5.8e, which exemplifies the use of a parametric distribution for assessing impacts. In this case, the attribute captures the mean ($\overline{x}$) and standard deviation (σ) of the probability density function f(x). This representation enables the use of non-bounded distributions whose long tails may reflect the uncertainty in the impact estimates, as well as distributions that reflect predictions that have been derived from epidemiological simulation models, or that represent phenomena whose behavior is well-understood and parametrized (Vose, 2008). Examples of these distributions are the Normal and the Lognormal distributions (the latter is particularly useful for health security impacts as it is bounded from zero and thus avoids illogical negative impacts).

The aggregation of multiple impacts for discrete distributions (Fig. 5.8a, b) is mathematically simple and can be executed using a pen-and-paper or a spreadsheet. On the other hand, if continuous distributions are employed (from Fig. 5.8c–e), a Monte-Carlo computer simulation is typically realized (Vose, 2008). These two types of analyses are detailed in the eighth and ninth chapters, respectively.

In our experience, simpler models have many benefits in practice, as they avoid being perceived as a *black box* and the results of the decision analysis can be easily interpreted and explained to policymakers and experts. The decision modeling balance here is between comprehensiveness versus the complexity of impact assessment. The level of detail in assessing impacts and modeling uncertainties must be carefully considered in relation to the decision environment and the requirements of the health security team, the health experts, and the policymakers (Montibeller, Franco, & Carreras, 2020a).

The benefits of simplified impact assessments are particularly relevant when undertaking a great number of simultaneous health threats (Jaspersen & Montibeller, 2015). We have designed several decision support systems wherein simplified assessments were implemented, albeit always employing some basic modeling of uncertainties. However, we always recommend that a scenario be clearly defined, so that the boundary conditions for the definition of impacts from a health threat are emplaced. Two factual cases, which illustrate how uncertainty was modeled in health security cases that we have led, are provided subsequently.

5.5.2 Assessing Dispersion of Impacts of Bio-Security Threats (DEFRA)

We conducted two projects for UK Department for Environment, Food and Rural Affairs (DEFRA) that illustrate how the assessments of impact can be simplified in practice, while still accounting for uncertainties (Montibeller et al., 2020a).

In the decision support system for ranking emerging animal health threats that we have mentioned previously in this chapter, only deterministic assessments were required for the different impacts (Del Rio Vilas et al., 2013a, b). This assessment

involved a single point estimate with the most likely impact (the type of assessment described in Fig. 5.8a), which was defined by the DEFRA health experts. In cases where there exists uncertainty about the impact level, the reasonable worst-case impact is selected, as this action follows a precautionary principle which is commonly used by the UK government.

In addition, the decision support system provides a record of the previous assessment of the same health threat, which is derived from the monthly evaluations. Thus, over time, DEFRA policymakers may record the spread of impacts for each threat as the knowledge and understanding about how the threat develops and as more evidence becomes available. These records can then be used to determine the uncertainty for future similar health threats.

For example, as the illustration of the attribute *impact on public health* demonstrates, which is reproduced in Fig. 5.9, a given emerging animal health threat may be evaluated initially as having the potentiality to cause a L10 impact at time t_1. After a period of few months, once more evidence about the emerging disease has been gathered and potential transmission paths have been more clearly identified, at time t_2, the degree of exposure is re-assessed from *high* to *medium*. This would denote the level of impact to be L8. This range of impacts could be employed to inform future assessments that seek to evaluate a similar emerging health threat.

In another decision support system for assessing bio-security threats that we developed for DEFRA (Montibeller et al., 2020a), attributes covered commercial impacts, environmental impacts, and social impacts (see the value tree in Fig. 5.10). For each rightmost node in the value tree, a constructed attribute with five levels, similar to the ones described in Table 5.1, was developed.

In this second DEFRA project, the health experts could provide a range of levels, thus using the type of estimate shown in Fig. 5.8c, to accommodate the high level of uncertainties involved in these assessments. These spreads of impacts were then

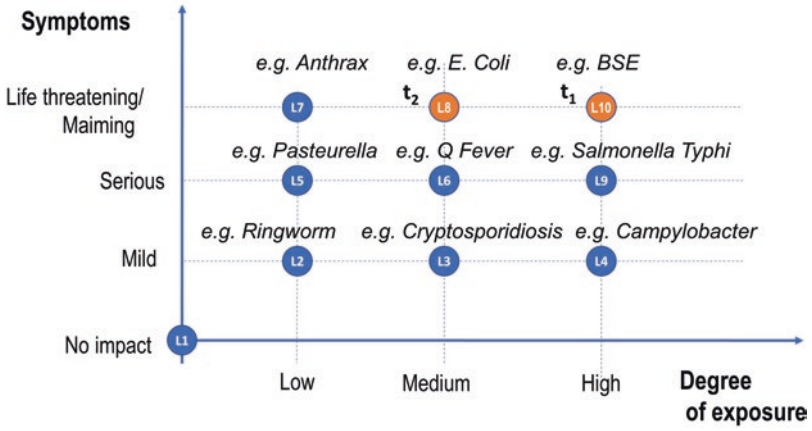

Fig. 5.9 Updating the assessment of potential impact on public health for an emerging animal health threat at times t1 and t2

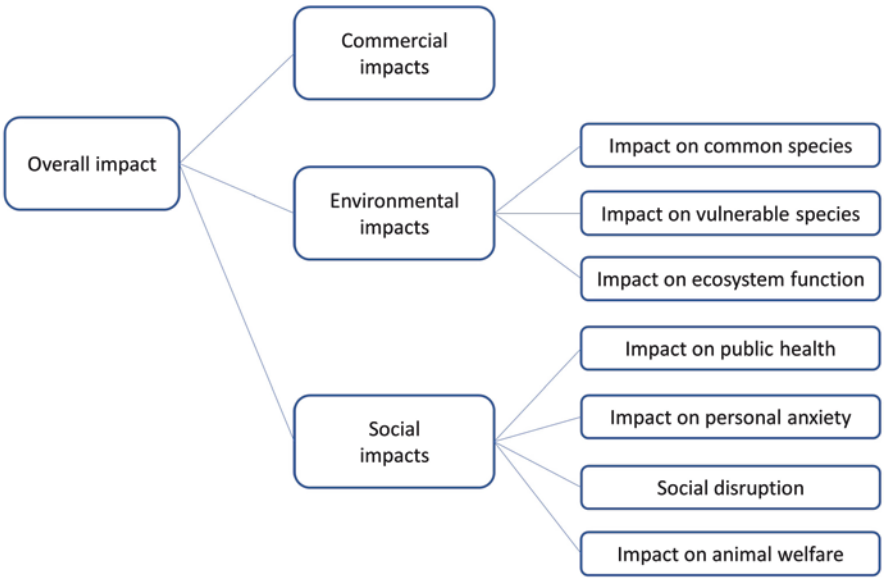

Fig. 5.10 Value tree for assessing bio-security threats for DEFRA

monetized and aggregated along the value tree to provide a range of overall impacts (in pound sterling).

Dynamic impacts and long-term impacts form two categories of impacts that deserve a more detailed discussion, as they are common in health security decisions although they are less usual in standard decision analysis applications (except for the net present value of capital investment decisions). How we can represent these impacts is discussed next.

5.5.3 Assessing Dynamic Impacts

One of the most important characteristics (and challenges) of health threats in comparison with other types of security threats is the dynamic nature of their impacts. The most advanced modeling of these impacts is the one conducted by epidemiological transmission simulations. There exists a large body of approaches available, which require adequate parametrization of sophisticated models for reliable predictions (see Brauer et al. (2019) for details). Here, we focus on how the results of these epidemiological simulations can be used to inform health security decision making, which forms a topic that has been less explored in the transmission modeling literature.

The typical shape of these dynamic impacts for a given outbreak whose wave is singular is presented in Fig. 5.11a for the number of severe cases n(t) as a function of time t [in days]. This function may provide information relating to relevant health

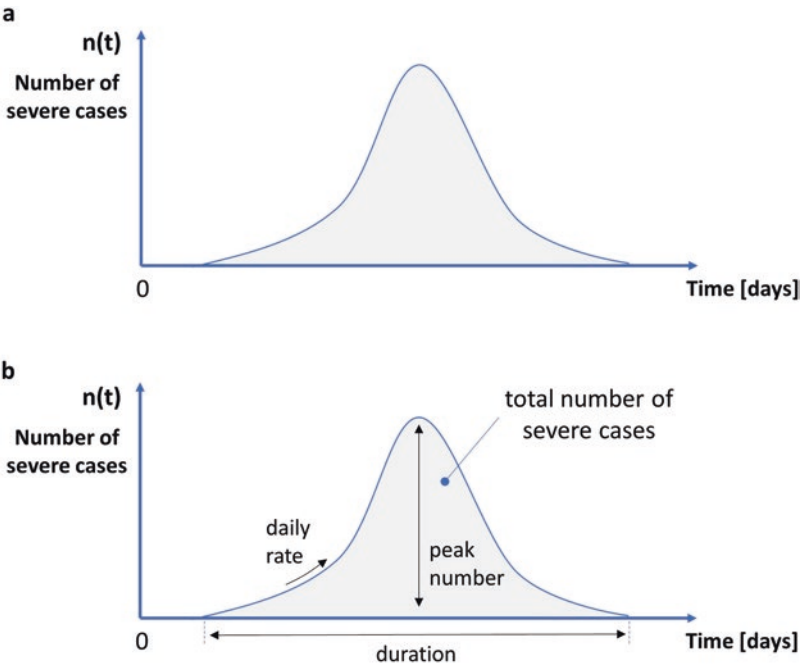

Fig. 5.11 (**a**) The predicted distribution of the number of severe cases per day for an outbreak, (**b**) Extracting relevant impacts from the epidemiological simulation

consequences in a given health decision situation, and these particular consequences are associated with the fundamental objectives that the health security team wishes to achieve. Each one of these consequences should be represented by a suitable attribute and the impacts should be adequately measured.

For instance, imagine that a health security team is concerned about the impacts that an outbreak described by function n(t), presented in Fig. 5.11a, may trigger on four consequences: the *level of disruption* the outbreak may bring, the *impact on the population health* from said outbreak, the *impact on the availability of intensive care units* for treating cases caused by this disease, and the *availability of regular hospital beds* for treating patients afflicted by this disease.

These concerns could be assessed by the respective proxy attributes (see Fig. 5.11b): the *duration of the outbreak*, the *total number of severe cases* (the area under the curve), the *peak number of cases*, and the *daily rate of infections*. The predictions from this epidemiological simulation could then be used to evaluate the impacts of this health threat on these four attributes (using an adequate representation of estimates, from the options shown in Fig. 5.8).

One important conceptual point in this example is that the epidemiological prediction models should be considered to be *inputs* to decision making. They are necessary, albeit insufficient, tools for supporting reasoned health security decisions. Ideally, the health security team must identify both the fundamental objectives that they wish to achieve and the associated attributes to measure said

objectives, and then employ the epidemiological prediction models to provide reliable estimates pertaining to the impacts of concern. This decision-focused perspective (Tsoukias et al., 2013) would provide an assessment of health impacts that is aligned with the fundamental concerns in the specific decision situation, which can more effectively aid decision makers to make difficult choices, thus minimizing detrimental impacts and maximizing societal value.

Other types of impacts, such as economic impacts, may also display a dynamic nature, although it is less common to find simulation models developed for these impacts in the health policy literature. Here, the recommendation is similar to the one provided for the health impacts above, in that the fundamental objectives and associated attributes are used to extract information about the consequences that matter in the specific decision situation. The simulation results can then be used to better support the assessment of impacts in a health decision analysis and inform the difficult trade-offs between health, economic, and social impacts.

5.5.4 Assessing Long-Term Impacts

Another important characteristic of health security decisions is their long-term horizons. Decisions related to increasing the preparedness of health systems, or vulnerability reduction of the population, can bring about long-term benefits but may also involve multi-year investments.

Investment costs and monetary investments can be included and compared using a net present valuation, wherein future expenditures are discounted by a fixed rate per annum (Brent, 2016; Hunink & Weinstein, 2014). The net present value of other economic impacts may also be calculated in this manner, however, this is a more challenging task when we take into account direct and indirect impacts, high levels of uncertainty, and situations wherein multiple potential threats are being considered.

This net present valuation may be unsuitable for other forms of impacts (Atherton & French, 1998; Keeney, 2014). For instance, consider the number of deaths from an endemic disease that afflicts a great number of people worldwide, such as malaria. Discounting would indicate that future lives would deemed to be less valuable than their present counterparts, which may not be socially acceptable (Guyse et al., 2020). In this case, it would most likely be preferable to consider the total number of severe cases caused by the disease for a given planning horizon (as illustrated in Fig. 5.11) without any time discounting. For the *burden of disease* (the sum of mortality and morbidity) impact assessments, DALYs (disability-adjusted life years) can be used at population level (Hunink & Weinstein, 2014) to assess the years of life lost (premature mortality) and the years lost due to disability caused by the disease.

Our recommendation is to refrain from monetizing these non-economic impacts, even if they have long term consequences. Instead, it is better to maintain the distinctiveness of each category of impact in the health decision analysis, and identify suitable attributes and adequate ways of considering the long-term consequences. These assessments should reflect the objectives, priorities, and trade-offs that are valued by

society. The factual case described next provides an example of how long-term monetary and non-monetary consequences can be considered following this perspective.

5.5.5 *Assessing Long-Term Impacts of Low-Moisture Food Categories (FAO/WHO)*

We return to the project that was conducted for the Food and Agriculture Organization of the United Nations and World Health Organization (FAO/WHO, 2014; Montibeller, 2018) and was discussed in the previous chapter. This project entailed assessing the impacts of low-moisture food (LMF) categories and prioritizing these categories according to their overall impact. The value tree that was defined utilizing the causal map developed with the LMF experts is shown in Fig. 5.12.

A set of attributes was defined to assess four categories of impact, on *international trade*, on *burden of disease*, from *vulnerabilities due to food consumption*, and from *vulnerabilities due to food production*, as shown in Table 5.3. The assessment considered some long-term consequences, particularly the long-term health burden impact and the annual export value of these food categories.

The impact on international trade was assessed by the attribute *export value in US$ billions/year*. The data on the value of international trade was collated from

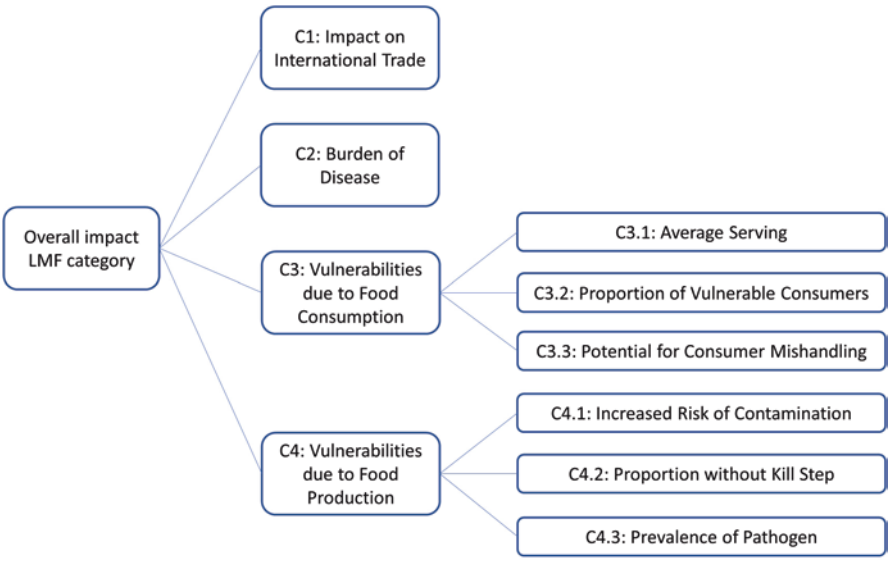

Fig. 5.12 Value tree for the assessment of low-moisture food categories (Montibeller, 2018)

Table 5.3 Attributes for assessing the impacts of low-moisture food (LMF) categories

Impact	Sub-impacts	Attribute
C1: Impact on international trade	–	Export value in US$ billions/year
C2: Burden of disease	–	Total DALYs in outbreak cases from 1990 onward
C3: Vulnerabilities due to food consumption	C3.1: Average serving	Average g/day
	C3.2: Proportion vulnerable consumers	Proportion (0–100%) consumed by vulnerable groups (toddlers and elderly)
	C3.3: Potential for consumer mishandling	Proportion (0–100%) of low moisture food products in a given category with an increased risk as a result of mishandling/poor practices at any time between final retail and consumption
C4: Vulnerabilities due to food production	C4.1: Increased Risk of contamination	Proportion (0–100%) of low moisture food products in a given category with an increased risk of contamination post kill step
	C4.2: Proportion without kill step	Proportion (0–100%) of low moisture food products in a given category without a kill step prior to retail and distribution
	C4.3: Prevalence of pathogen	Probability that a low-moisture food product is contaminated at a level with any pathogens that have the potential to cause illness in consumers

Source: FAO/WHO (2014)

FAOSTAT[1] which has been found to be the most comprehensive database for LMFs, as for many categories, the data was sufficiently disaggregated to distinguish LMFs from other products. The information collated was the most recent available data during the health decision analysis. In the case of cereal and grains, it was recognized that not all of these commodities that enter the export market are intended for human consumption. Therefore, a correction factor was applied, to account for the proportion of key commodities that are consumed as food globally. In relation to confections and snack foods, there was limited data concerning snack foods due to the difficulty in clearly defining this category. The export figures were also subjected to a correction factor that affected seeds for human consumption, in order to account for the proportion of seeds that are pressed for oil (FAO/WHO, 2014). The estimates for international trade for each low moisture food category are shown in Table 5.4.

[1] FAOSTAT is a database that provides free access to food and agriculture data for over 245 countries and territories and covers all FAO regional groupings from 1961 to the most recent year available (http://www.fao.org/faostat/en/#home)

Table 5.4 Volume of international trade for low moisture food categories

C1: International trade		
Code	Category name	Export value [US$ billions/year]
Cat 1	Cereals and grains	118.594
Cat 2	Confections and snacks	58.124
Cat 3	Dried fruits and vegetables	15.211
Cat 4	Dried protein products	22.800
Cat 5	Nuts and nut products	20.338
Cat 6	Seeds for consumption	1.150
Cat 7	Spices, dried herb and tea	14.938

Source: FAO/WHO (2014)

Table 5.5 Burden of disease for low moisture food categories

C2: Burden of disease		
Code	Category name	Total DALYs in outbreak cases from 1990 on
Cat 1	Cereals and grains	72.53
Cat 2	Confections and snacks	60.26
Cat 3	Dried fruits and vegetables	32.78
Cat 4	Dried protein products	136.44
Cat 5	Nuts and nut products	118.51
Cat 6	Seeds for consumption	18.42
Cat 7	Spices, dried herb and tea	80.71

Source: FAO/WHO (2014)

The impact of *burden of disease* considered long term trends. A detailed review of any publicly available literature on the burden of illness was identified and synthesized for each category by the FAO/WHO expert team (Young et al., 2015). This information was almost exclusively available from previous outbreaks. Total DALYs were calculated employing the data on outbreaks since 1990, as during the health decision analysis workshop the food experts agreed that earlier outbreaks were not relevant, due to improvements in food security regulation and practices. Across all LMF categories, outbreaks involving B. cereus, Cl. botulinum, Cl. perfringens, pathogenic E. coli, Salmonella spp. and S. aureus were recorded. No outbreaks associated with generic E. coli, Cronobacter spp., L. monocytogenes or Enterobacteriaceae, were identified in the scoping review (FAO/WHO, 2014). The total *burden of disease* for each LMF category is demonstrated in Table 5.5.

Notice that we evaluated each impact independently and, in the case of *burden of disease*, we considered the cumulative impact from outbreaks since 1990. Subsequently, in this project, the FAO/WHO expert team were requested to consider making a trade-off between the impact on *annual international trade* versus the *long-term burden of disease*, for the prioritization of overall impacts of the LMF categories (see Montibeller (2018) for details).

5.6 Conclusions: Assessing Impacts of Health Threats and Health Security Actions

This chapter has conveyed a pivotal message: each and every health security decision is made under uncertainty. The manner in which we approach uncertainties that are intrinsic to these decisions should be as simple as possible *but not* simplistic. Unfortunately, poor practices in assessing health threats and evaluating health security actions are recurrent in the health security field, and there exists evidence that these practices negatively affect the recommendations that are made.

We have discussed how key uncertainties can be identified and adequately incorporated into health security decisions and considered in a health decision analysis. The three main components of decisions under uncertainty are the decision alternatives, the key uncertainties, and the relevant consequences. We have suggested that influence diagrams are robust tools for representing and better understanding said decisions.

Influence diagrams model the three main decision components and are able to represent the influences that exist between them. These components and influences are: decision alternatives influencing relevant consequences, key uncertainties influencing relevant consequences, and decision alternatives influencing key uncertainties. Health security actions can be conceptualized via these influence links, for example, preparedness efforts to reduce the possibility of an outbreak (an action influencing a key uncertainty), or risk mitigating activities to reduce the number of severe cases once an outbreak ensues (an action influencing a relevant consequence).

We have also suggested several different ways to adequately represent uncertainties related to the impacts of health threats and health security actions, from simple, single point estimates to parametric distributions. We have argued for a decision-focused modeling of impacts, wherein epidemiological simulations of outbreaks and other long-term impact predictions are employed as *inputs* to a health decision analysis. This perspective provides a bridge between evidence gathering and the development of transmission models within health policymaking.

The clear understanding of relevant consequences, the correct mapping of key uncertainties that may affect said consequences, and the adequate modeling of impacts and their distributions, when taken as a whole, give rise to many benefits for enhancing health security decisions. First, this decision stage enables a systematic assessment of impacts from both health threats and health security actions. Second, this decision modeling supports the representation of the uncertainties about these impacts, from the lack of evidence, limited information, or scarce knowledge about threats and about the performance of health security actions. Third, this thorough representation of uncertainties and impacts can help us to incorporate the varied expertise available in an efficient and effective manner. Different experts may provide inputs and knowledge to specific components of the health decision analysis, based on the targeted need for their expertise. Fourth, the definition of attributes enables the definition of trade-offs and risk limits, and this shall form the subject of the sixth chapter.

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Chapter 6
Defining Risk Limits, Marginal Value, and Trade-Offs in Health Security Decisions



In this chapter we discuss three types of judgments that are required in health security decisions: defining risk limits for levels of impact, establishing marginal value over relevant consequences, and determining trade-offs among conflicting objectives. This chapter illustrates the importance of adopting clear protocols for how these judgments should be made, coupled with sound judgments by decision makers and experts, as both prove crucial for high-quality decision making.

Judgments are required to define risk limits, as it is often unfeasible to reduce a risk to zero. These limits impose constraints, determining as to which health security options are feasible and the level at which impacts are deemed to be acceptable for risk mitigating actions, while also highlighting health threats that may require immediate action due to potential impacts that are above acceptable limits.

The attainment of a decision objective is measured by the marginal value accrued over the associated consequence. For objectives whose direction of preference entails maximization, this marginal valuation requires defining the increase in value associated with achieving increased performance levels on this objective. For instance, if a very low proportion of the population has been immunized, any early increase in coverage may provide a high marginal value to a vaccination campaign. This marginal value may diminish significantly beyond the point at which vaccination coverage has already reached a threshold above the level required for herd immunity. Conversely, for an objective whose direction of preference involves minimization, this marginal valuation necessitates that we define the increased value associated with decreasing a detrimental impact. This definition of marginal value over relevant consequences also requires judgments.

Health security decisions invariably require difficult trade-offs. The multiple consequences that a health threat may require balancing, for instance, a reduction in the number of possible cases through the implementation of risk prevention actions against the cost of prevention. Additionally, health security actions to enhance health preparedness shall always involve benefits that must be traded-off against

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costs and drawbacks. These trade-offs are an important type of judgment in decisions whose objectives are conflicting.

As mentioned in the second chapter, there exists extensive evidence from Behavioral Decision Research demonstrating that judgments from experts and decision makers are frequently biased and may suffer both from cognitive biases and from motivational biases. These biases have a negative impact on the recommendations that can be derived from a health decision analysis and, consequently, on the decisions made. Hence, it is crucial that judgments used in decision models be debiased by employing adequate elicitation protocols and debiasing tools.

In this chapter, we discuss how to consider and adequately define risk limits, marginal value over consequences, and trade-offs, while simultaneously minimizing cognitive and motivational biases. Aspects of defining these judgments on the individual level, as well as the group and organizational issues involved in said judgments, are also discussed here.

In the second chapter we presented a diagram that illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 6.1. The present decision stage, *defining risk limits, marginal value, and trade-offs*, is now highlighted in this modified figure. We shall assume that relevant objectives and consequences have been defined, key uncertainties have been identified, impacts of health threats or health security actions have been reliably estimated, and at least two decision alternatives have been identified.

6.1 Identifying Critical Risks

Adequately managing critical risks represents a major challenge in health security decisions (WHO, 2021). This problem is aggravated by unclear conceptualizations of what *risk* actually means within risk management practices (Gregory et al., 2012; Morgan, 2017; Morgan & Henrion, 1992). Specifically, the absence of a clear conceptual framework may have detrimental effects on risk management, health security decision making and risk communication.

If we consider the case wherein a health security policymaker deems a given health threat to be “high risk”. What exactly does this assessment imply? Does this denote that the pathogen is highly infectious? Or that the disease can trigger serious symptoms? Or that there exists a high probability that an outbreak could happen? Or that the health system would struggle to cope with the threat? Or, that the threat may affect clinically vulnerable individuals? It is vital to recognize that rather than merely being an issue concerning the nature of meaning, each of these conceptualizations of risk would direct decision makers to adopt a different set of risk mitigating actions. Measures that are implemented to undertake a threat that is highly infectious are likely to be significantly different to those measures against a threat that may mainly affect clinically vulnerable individuals.

Fortunately, the framework that we are presenting in this book can function to elucidate the actions that are required for the identification of critical risks, and aid

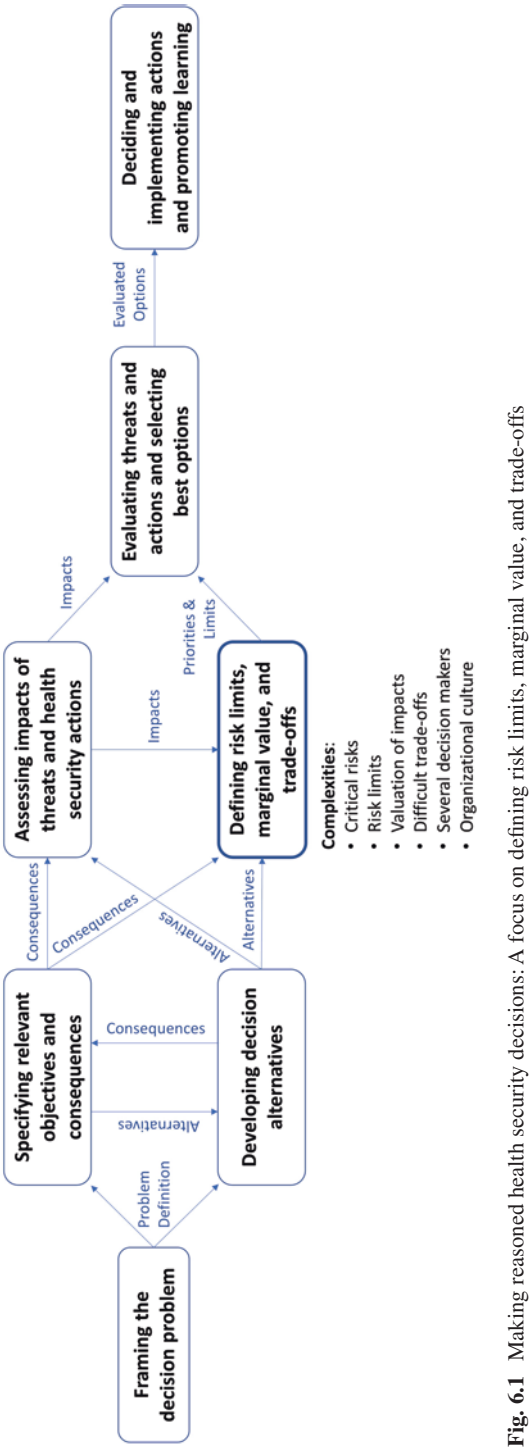

Fig. 6.1 Making reasoned health security decisions: A focus on defining risk limits, marginal value, and trade-offs

the health security team to better understand, manage, and mitigate said risks. In this section, we discuss how critical risks can be measured, and subsequently, how we should define risk limits in health security decisions.

6.1.1 *Measuring Critical Risks*

There exist three concepts of risk that are common in health security decision contexts. The overarching assumption of these concepts is that health threats pose consequences that are detrimental to health, well-being, and life (Fischhoff et al., 1993; Keeney & Winterfeldt, 2001), and as such, they must be considered, managed, and mitigated in health security decisions. These different conceptualizations are described next.

Risk as an Undesirable Consequence This characterization of risk is often used in health policy, whereby a risk is a consequence judged to be negative or undesirable by the health security team or health experts.

Let us consider the health security decision represented by the influence diagram in Fig. 6.2. The decision maker is seeking to establish which risk mitigating actions should be implemented. The fundamental objective is to *optimize the use of critical care beds*. Said objective may indicate one of the relevant consequences, which in this case is represented by the number of severe cases, which shall be analyzed here. This consequence is measured by the attribute *number of severe cases*, represented by variable x. The key uncertainty is the *occurrence and severity of a health threat outbreak*, which in turn influences the number of severe cases.

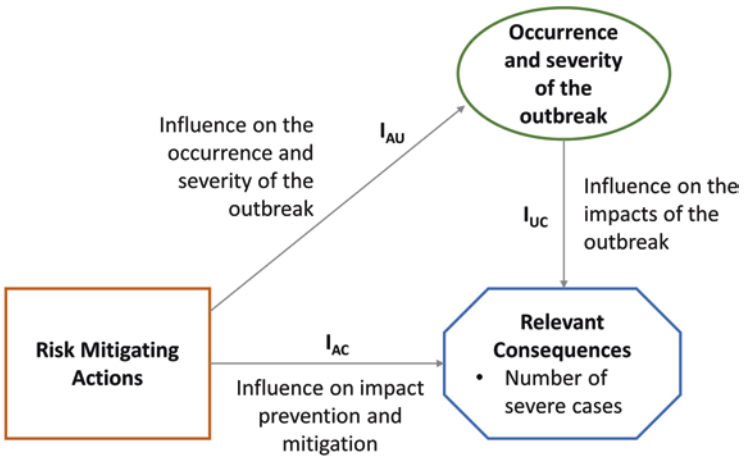

Fig. 6.2 Influence diagram for the decision on how to manage the risks posed by a health threat with a focus on managing the number of severe cases the threat may cause

Consider the function $n_1(t)$, with the daily number, measured by variable t, of severe cases that may be caused by a given health threat, as shown in Fig. 6.3a. The peak number of daily critical cases that would require treatment in intensive care units (ICUs) is $X_1^* = 15{,}000$. Assume that the number of available beds in ICUs is limited to $X_C = 11{,}000$ beds. The difference between this capacity level ($X_C = 11{,}000$ ICU beds) and the peak number of daily severe cases requiring ICUs ($X_1^* = 15{,}000$ severe cases) denotes the *risk* that the system would be operating beyond its

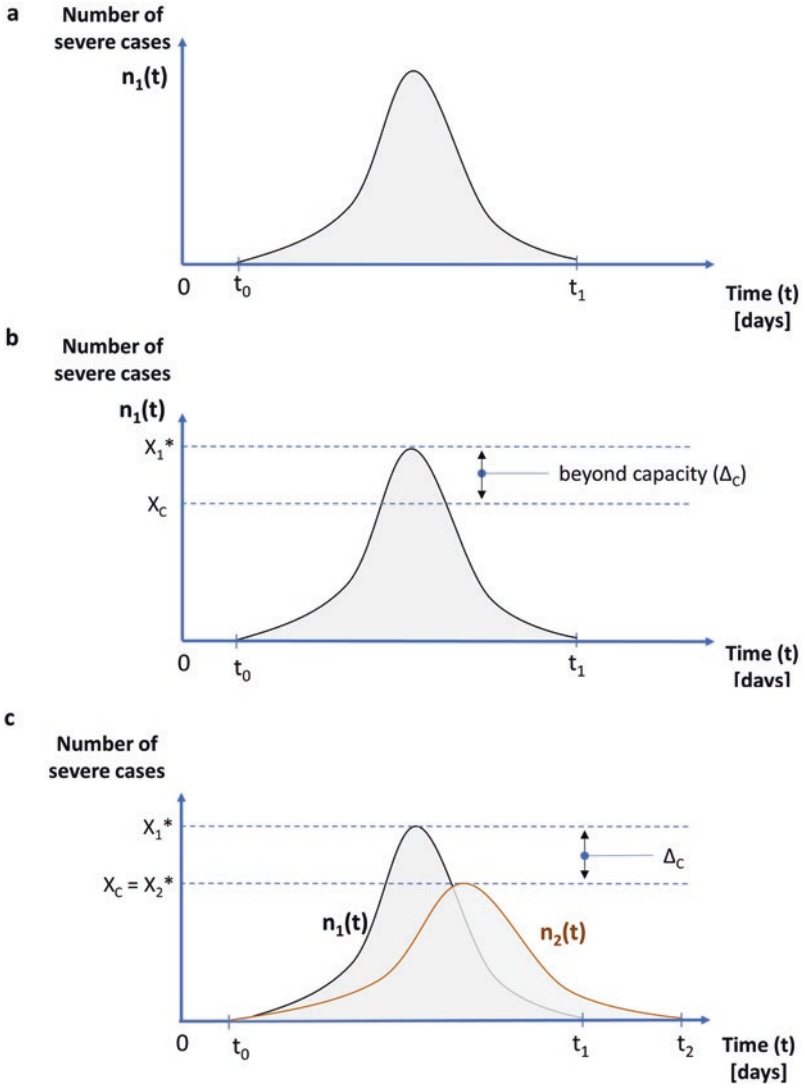

Fig. 6.3 Distribution of the number of severe cases caused by a health threat as a function of time, represented by variable t: (**a**) Original distribution, (**b**) Risk limit as an undesirable consequence, (**c**) Flatten distribution and risk reduction

maximum capacity (see Fig. 6.3b): $\Delta_C = X_1^* - X_C = 15{,}000–11{,}000 = 4{,}000$ additional ICU beds needed.

Different policies for flattening the curve, and thus compressing the peak, could then be designed, and the effectiveness of these policies in reducing this precise risk could be measured by the reduction in Δ_C. These policies may be comprised of actions such as quarantine mandates and the isolation of infected patients, leading to a flatter function $n_2(t)$, as shown in Fig. 6.3c. This function represents an outbreak whose duration is longer ($t_2 > t_1$) but whose peak number of severe cases is lower $X_2^* = 11{,}000$. Therefore, we see that this critical risk would have been neutralized by such a health security action, as $\Delta_C = X_2^* - X_C = 11{,}000–11{,}000 = 0$.

These risk mitigating actions are indicated in the influence diagram (see Fig. 6.2) as an influence (I_{AU}) of such risk mitigating actions on the *health threat outbreak* uncertainty. Subsequently, as indicated in the same figure, the health threat outbreak uncertainty shall exert an influence (I_{UC}) on the relevant consequence (number of severe cases).

Risk as a Probability of an Undesirable Consequence This second conceptualization of risk is widely employed in risk analysis, whereby a risk is concerned with the probability of an undesirable consequence occurring.

Consider again the case described above. Let us posit that the distribution shown in Fig. 6.4a represents the probability density function f(x) of the number of severe cases (measured by variable x) caused by a health threat, with mean $\bar{x} = 9{,}000$ severe cases and standard deviation $\sigma = 2{,}000$ cases. This distribution represents the uncertainty pertaining to the *actual* number of severe cases that would require treatment in ICUs.

In the same figure, the level of impact $X_C = 11{,}000$ severe cases represents a limit, as this limit is the number of ICU beds available in the health system. The probability that the number of cases rises above this level, i.e. $P(x \geq X_C)$ demonstrates the *risk* of the number of cases reaching beyond the capacity of the system. This risk can be calculated utilizing the cumulative distribution function F(x) shown in Fig. 6.4b: $P(x \geq X_C) = 1.00 - P(x \leq X_C) = 1.00–0.85 = 0.15 = 15\%$.

Risk mitigating actions could be devised to reduce this risk $P(x \geq X_C)$. For instance, the health security team could establish a reciprocal agreement with another health system, which would take patients if the number of severe cases requiring ICU beds were to exceed 11,000. This agreement would act like an insurance for the health system, in that the agreement would result in the *elimination* of the right tail area of this distribution f(x) as shown in Fig. 6.4c. This risk mitigating action is shown in the influence diagram in Fig. 6.2, wherein the risk mitigating action influences (I_{AC}) the relevant consequence (number of severe cases).

Risk as Probability of an Undesirable Consequence Multiplied by the Consequence Itself The most comprehensive definition of risk is provided by the multiplication of the probability of an undesirable consequence by the undesirable consequence itself. Formally, this conceptualization of risk is given by the expected

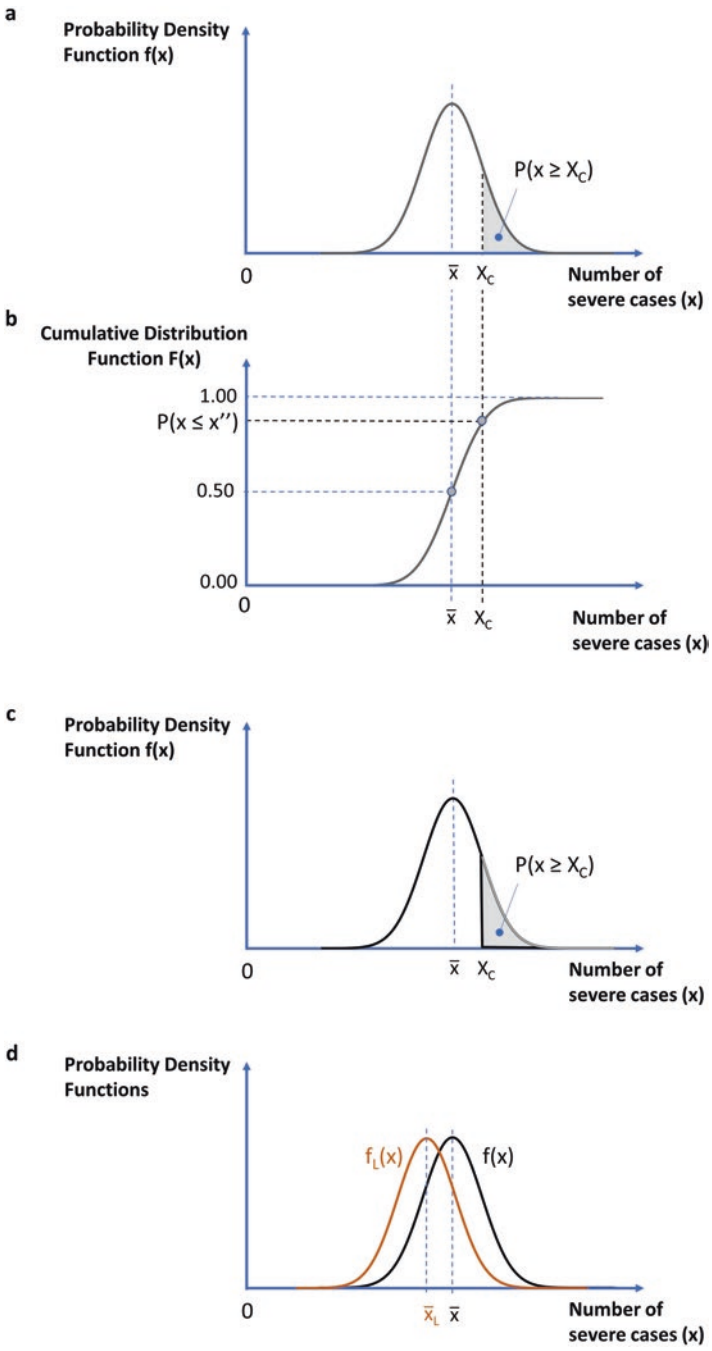

Fig. 6.4 Distribution for the number of severe cases (measured by variable x): (**a**) Probability density function (PDF), (**b**) Cumulative distribution function (CDF), (**c**) Removing the right-hand side tail of the distribution to reduce the risk, (**d**) Shifting the distribution to the left to reduce the risk

value of a distribution[1] that represents the undesirable consequence (measured by variable x), which is caused by an adverse event: EV(x).

Consider again the probability density function f(x) for the number of severe cases (measured by variable x) shown in Fig. 6.4a, with mean $\bar{x} = 9{,}000$ severe cases and standard deviation $\sigma = 2{,}000$ cases. The expected value of the undesirable consequence is identical to that of the mean of this distribution, i.e. $EV(x) = \bar{x} = 9{,}000$ expected severe cases.

Risk mitigating actions could be devised to reduce the number of expected severe cases, thus shifting the distribution to the left, as represented in Fig. 6.4d by $f_L(x)$. For instance, preventive measures such as vaccination, could reduce the number of severe cases among the entire population, bringing about this new distribution, with a mean of $\bar{x}_L = 8{,}000$ severe cases and the same standard deviation $\sigma = 2{,}000$ cases. The expected value of this new distribution is $EV_L(x) = \bar{x}_L = 8{,}000$ severe cases.

In this example, this leftward shift of the distribution would represent a risk reduction in comparison to the original situation, as $EV_L(x) = 8{,}000 < EV(x) = 9{,}000$ severe cases. This risk mitigating action is indicated in the influence diagram (see Fig. 6.2) as an influence (I_{AU}) from the risk mitigating actions on the severity of the health threat outbreak uncertainty.

To summarize the three cases that have been presented above, the fundamental objective sought to *optimize the use of critical bed units*. The key uncertainty involved the *occurrence and severity of a health outbreak*, which in turn influenced the relevant consequence (number of severe cases). Given this uncertainty, the impact that may be brought about by the outbreak is represented by the probability density function f(x) over the attribute *number of severe cases* (measured by variable x). The critical risk could be defined in three distinctive manners: (i) as the number of severe cases located above a give level of impact (measured by Δ_C in Fig. 6.3b), (ii) as the probability that the number of severe cases is located above or at a given level of impact (measured by $P(x \geq X_C)$ in Fig. 6.4a), or (iii) as the expected number of severe cases (measured by $EV(x) = \bar{x}$ in Fig. 6.4a).

These three cases highlight the extent to which the three conceptualizations of risk directly inform as to how the risk shall be measured and, consequently, shall influence the design of risk mitigating actions. The examples also function to stress the importance of establishing clear measurements for assessing critical risks, which should always be predicated on the fundamental objectives of the health security team, as well as on the key uncertainties that the team is confronted with.

There exists a second relevant issue associated with the choice of a risk metric: different metrics may indicate different levels of risk when comparing health threats or when considering actions to improve health security.

Let us again consider the number of severe cases (measured by variable x) caused by two health threats, which are provided by their probability density functions $f_1(x)$ and $f_2(x)$, as shown in Fig. 6.5a. The function $f_1(x)$ representing the first health threat

[1] The definition of expected value for both discrete and continuous distributions is detailed in the ninth chapter.

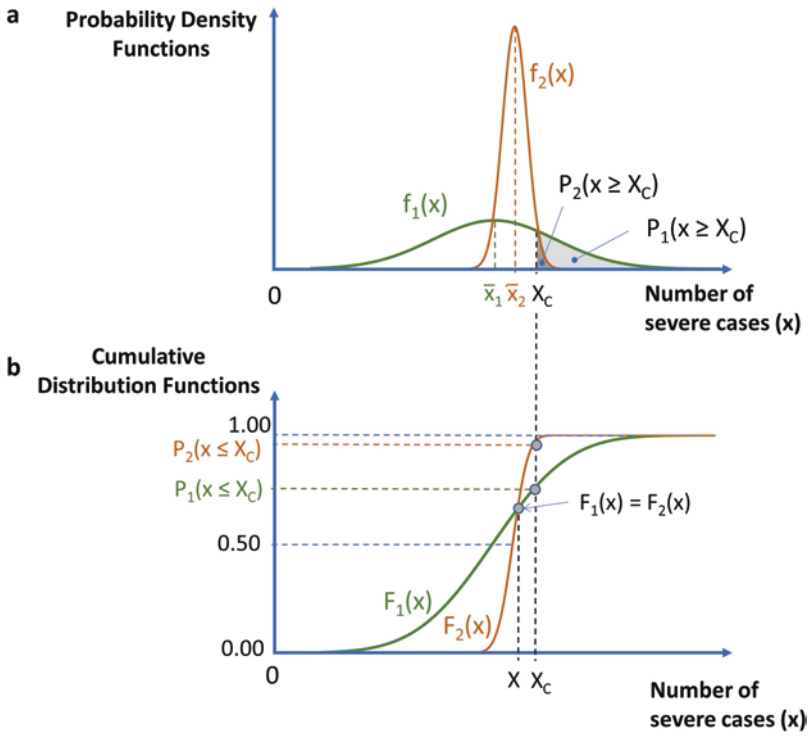

Fig. 6.5 Comparing the risk profile of two health threats causing severe cases with a risk level X_C: (**a**) Probability density functions (PDFs), (**b**) Cumulative distribution functions (CDFs)

has a mean (expected value) of $\bar{x}_1 = 9{,}000$ expected cases and a more extensive spread ($\sigma = 3{,}000$ cases), stemming from the relatively high levels of uncertainty relating to the impact of this threat. The function $f_2(x)$ for the second health threat has a higher mean (expected value) $\bar{x}_2 = 10{,}000$ expected cases, but a more narrow spread ($\sigma = 600$ cases), as there exists less uncertainty relating to the impact of this threat.

If risk is to be conceptualized as *probability multiplied by the consequence*, (i.e. expected value of the consequence caused by an adverse event) then the first threat should be considered to be a lesser risk than the second threat, as $\bar{x}_1 < \bar{x}_2$. On the other hand, if risk is to be conceptualized as a *probability of an undesirable consequence* occurring, for a risk level that is located closer to the right tail (e.g. at $X_C = 11{,}000$ cases), then the first threat would be considered to be a greater risk than the second as: $P_1(x \geq X_C) > P_2(x \geq X_C)$ as indicated by the areas in Fig. 6.5a. Indeed these values can be calculated from the cumulative distribution functions that are shown in Fig. 6.5b, for the first threat $P_1(x \geq X_C) = 1.0 - P_1(x \leq X_C) = 1–0.75 = 0.25$ and for the second threat $P_2(x \geq X_C) = 1.0 - P_2(x \leq X_C) = 1–0.95 = 0.05$.

A third relevant issue is that defining the risk level may exert an influence on the ranking of health threats. This issue necessitates that we carefully consider risk

levels and that we conduct an analysis of the influence of the risk level on the ranking of threats.

Let us again turn to the problem depicted in Fig. 6.5 and assume that risk has been defined as a *probability of an undesirable consequence*. For the risk level set as $X_C = 11{,}000$ cases, then $P_1(x \geq X_C) = 0.25 > P_2(x \geq X_C) = 0.05$, as we have seen above. Hence, for this risk level the first threat would be considered to be a *greater risk* than the second threat. This result would remain valid for any risk level (x) located above the point at which the cumulative distribution functions intersect (i.e. above X = 10,250 cases, the number at which $F_1(x) = F_2(x)$ indicated in Fig. 6.5b).

However, for risk levels located below this point of intersection (X), the reverse proves to be true, as most of the density of $f_2(x)$ is located around its mean ($\overline{x}_2$). For instance, if the risk limit were set instead as $X'_C = 9{,}000$, as depicted in Fig. 6.6a, then the first threat would be considered to *be a lesser risk* than the second threat, as $P_1(x \geq X_C) < P_2(x \geq X_C)$ as indicated by the areas in this figure and provided by the respective cumulative distributions shown in Fig. 6.6b. Specifically, the risk (probability) that the number of severe cases is located above $X'_C = 9{,}000$ for the first threat is $P_1(x \geq X_C) = P_1(x \geq 9{,}000) = 0.50$, and for the second threat is $P_2(x \geq X_C) = P_2(x \geq 9{,}000) = 1.00 - P_2(x \leq 9{,}000) = 1.00–0.05 = 0.95$. Therefore, if we consider

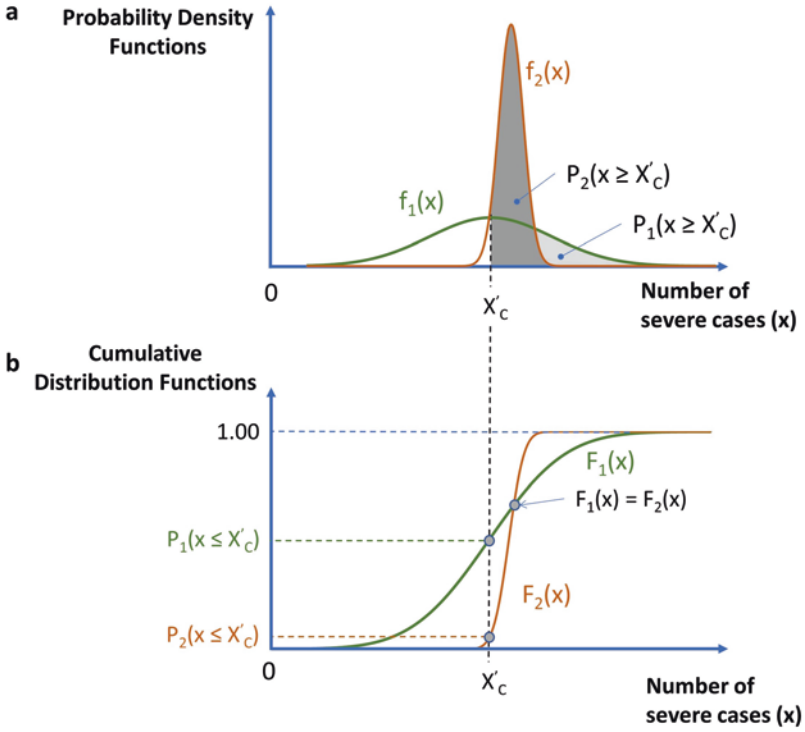

Fig. 6.6 Comparing the risk profile of two health threats causing severe cases with a risk level X'_C: (**a**) Probability density functions (PDFs), (**b**) Cumulative distribution functions (CDFs)

this latter risk limit (X'_C = 9,000), the second threat would be considered to be a *greater risk* than the first.

The discussion in this section elucidates some key aspects as to how critical risk should be conceptualized. Let us now summarize the central points relating to critical risks. First, as we discussed in the first chapter, ad hoc attempts to characterize risks, such as the use of qualitative labels or risk matrices, should be avoided. Second, distribution functions prove to be the most comprehensive method of describing the uncertainties associated with the relevant consequences. Third, adequate risk metrics must be defined to appropriately assess critical risks. These metrics can be defined as the levels of undesirable consequences, or the probabilities of the occurrence of undesirable consequences, or, as the expected value of undesirable consequences. Fourth, these risk metrics, and risk limits inform the evaluation of health threats and risk mitigating actions. Therefore, selecting which metric to employ, and which risk limits to adopt, is a process that should be conducted in a careful manner. Additionally, the risk metrics selected should be employed consistently, and the influence of risk limits on the rankings of health threats or actions should be carefully analyzed, and shall be discussed next.

6.1.2 Defining Risk Limits

Establishing risk limits is a rather delicate matter in health security decisions. Strong moral principles may make policy makers and decision security teams unwilling to contemplate the requirement that we cope with risk (Fiske & Tetlock, 1997; Tetlock et al., 2000). One consequence of this attitude is a desire to adopt "zero risks".

However, this "zero risk" position is generally unfeasible in practice and unhelpful in guiding health security actions. There exist three main reasons that render the total elimination of risk unfeasible in practice and we shall discuss in what follows.

The first reason for this unfeasibility stems from the increasingly inefficient use of resources as a risk is reduced. This is illustrated in Fig. 6.7 for a given health threat that causes X^* severe cases (for example X^* = 15,000 cases). A total mitigation of this risk would reduce the number of severe cases to $X_* = 0$. The function c(x) illustrates the marginal mitigation cost [$/case], (i.e., how much it would cost to eliminate each severe case in sequence) starting from X^*. When there exists X^* cases, the marginal cost is C_* (for example, $10,000/person). For the initial reductions of this risk, the marginal cost per case is almost flat and close to C_*. However, the marginal cost begins to increase significantly as the number of cases is reduced, and it becomes more difficult and costly to reduce the number of cases to zero. One factual example of this issue was the enormous efforts and costs associated with eliminating the last cases of smallpox toward the laudable goal of global eradication, embody a factual example of the high marginal costs required to fully eliminate the disease (CDC, 2019).

This point brings us to the second reason as to why the "zero risk" attitude is often unrealistic. Health budgets are necessarily limited and should be utilized to

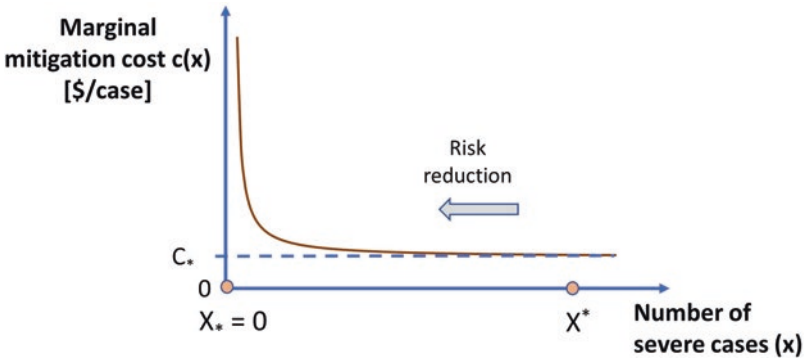

Fig. 6.7 The marginal cost of risk reduction

fund health systems, and should be distributed not only among health security areas, but also among other areas of healthcare (see also Keeney & Winterfeldt, 2001). Reducing the risk to zero may require a near infinite level of resources, as illustrated by the asymptotic function for marginal cost as the number of cases approaches $X_* = 0$, which is displayed in Fig. 6.7.

The third difficulty associated with attempting to eliminate a risk completely arises when we consider that inevitably, decision makers have a limited amount of control that they are able to exert over relevant consequences. This issue can be understood by considering the role of risk mitigating actions in an influence diagram, such as the one shown in Fig. 6.2. Two types of influence are possible within this decision setting. First, the health security team may implement risk mitigating actions that influence the outbreak itself (I_{AU} in the influence diagram), for instance early measures to contain the spread of the disease. Second, the team may deploy health security or risk mitigating actions that influence the impact on relevant consequences (I_{AC} in the influence diagram), for example, vaccinating the population to reduce the number of severe cases. However, it is not possible for the team to directly control the influence between the outbreak on the relevant consequences (I_{UC} in the influence diagram). This latter influence, from the uncertainty to the consequences, renders one unable to fully exert control over impacts caused by health threats.

The "zero risk" attitude is also unhelpful in guiding health security decision making (Fischhoff et al., 1993). While the adequate and explicit consideration of trade-offs must be made, this unrealistic goal may prevent this effort, for instance, a trade-off involving the reduction in the number of severe cases and the budget allocated to this risk reduction initiative. In practice, this avoidance of making explicit trade-offs in risk management may lead to overspending when seeking to undertake highly salient health threats while underspending when seeking to undertake other less salient threats that are equally as serious as the former category of threats.

A more progressive perspective than the "zero risk" approach involves the defining of *risk limits*. This practice is widely used in environmental decisions and although still limited, the practice can also be observed in health decision making. Defining risk limits entails establishing upper limits that characterize ranges of impacts that are deemed to be acceptable, and those ranges which are deemed to be unacceptable, on the consequences of interest.

For instance, consider an undesirable consequence such as *number of severe cases* (measured by variable x) and the *total risk mitigation cost* (measured in $), as shown in Fig. 6.8a. Both attributes have minimization as direction of preference, as fewer cases are preferred to more cases and lower costs are preferred to higher costs. A given health threat causes $X^* = 15{,}000$ severe cases, as shown in the same figure. Assume that a *risk limit* ($X_L = 11{,}000$ severe cases) has been defined by the health security team. Above this level the undesirable consequence (i.e. the risk) is considered to be unacceptable and below this level the undesirable consequence is considered to be acceptable. The current number of cases (X^*) is above the acceptable level, thus risk mitigating actions must be implemented. Let us posit that a *total cost limit* for risk mitigating actions (C_L) has also been established by the team. Total costs are deemed to be acceptable below this level, but unacceptable above this cost level. The area to the left of the level of acceptable risk (X_L) and below of the

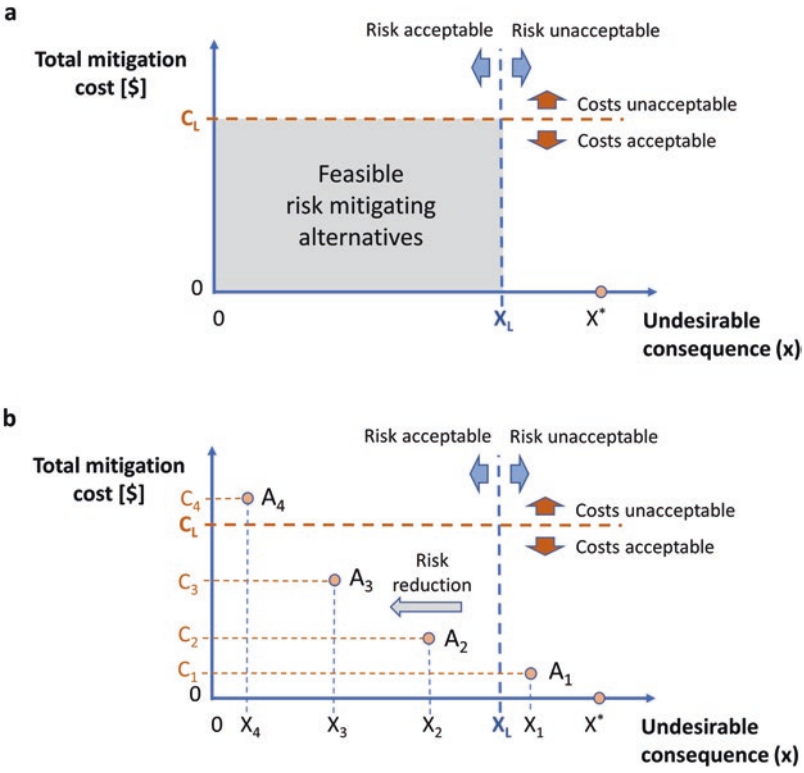

Fig. 6.8 Risk and budget limits defining: (**a**) The solution space of feasible alternatives, (**b**) Inclusion and exclusion of decision alternatives for risk mitigation

acceptable costs level (C_L = \$100 million) indicate the solution space wherein *feasible* decision alternatives for risk mitigation should be contemplated.

Let us now imagine that some risk mitigating alternatives to reduce risk are available against this health threat. Each alternative, having been implemented, would result in the remaining of a given number of severe cases (X_l) and would entail a given amount in mitigation costs (C_l), as shown in Fig. 6.8b. Alternative A_1 is relatively inexpensive (C_1) but not effective in its role as a risk mitigator, with the number of cases remaining (X_1) above the maximum risk limit ($X_1 > X_L$). On the other extreme, alternative A_4 is considerably effective as a risk mitigator, reducing significantly the number of remaining cases (X_4), but unfortunately rather expensive (C_4), above the maximum level of cost ($C_4 > C_L$). Two other alternatives (A_2 and A_3) are feasible, as they are both within budget and within the risk limit. Alternative A_3 is more effective than A_2 in reducing the risk ($X_3 < X_2$) but is also the more expensive alternative ($C_3 > C_2$).

The example illustrated by Fig. 6.8b demonstrates the role of defining risk and budget limits. First, these limits act as *constraints* by excluding alternatives that have impacts above acceptable levels, such as alternatives that are overly expensive (in the example, A_4), or overly risky (in the example, A_1). Second, these limits identify a region of feasible alternatives, which lie within risk and budget limits, such as A_2 and A_3.

However, caution should be taken when defining these acceptable levels of impact. As we mentioned in the fourth chapter, an excessive use of constraints significantly reduces the solution space and thus may hinder the possibility of creating innovative solutions. Unrealistic constraints may also negatively affect group discussions and render the finding of compromises difficult for the health security team (Gregory et al., 2012).

Let us consider some cases wherein defining risk levels may cause specific problems. The first case is shown in Fig. 6.9a, whose risk limit (X_L) is overly stringent. This very stringent risk limit delineates a narrow space for feasible decision alternatives, and as such, no options can be found or designed that could fulfill such specific requirements. Often, we see that this scenario is a consequence of a "zero risk" attitude (Fischhoff et al., 1993), or, of adopting a "precautionary principle" that avoids contemplating uncertainties (Keeney & Winterfeldt, 2001), or of excessive loss averseness (Schmidt & Zank, 2005).

The second case wherein a risk limit may ultimately prove unhelpful is shown in Fig. 6.9b. In this case, the risk limit is neither overly strictly nor has the limit been *unrealistically* set, however it has been *rigidly* set. Let us consider that only two alternatives (A_5 and A_6) are available to mitigate risks against this health threat, which causes X^* severe cases. The alternative A_5 lies slightly above the risk limit ($X_5 > X_L$), despite it being relatively inexpensive (C_5) and thus should be discarded. On the other hand, alternative A_6 lies within the budget ($C_6 < C_L$) and below the risk limit ($X_6 < X_L$) so this alternative would be chosen. However, A_6 provides only a minor improvement in relation to A_5 in the reduction of severe cases ($X_5 - X_6$), while incurring a significantly greater cost ($C_6 - C_5$). If we take into account that budgets for health security are always limited, it would most likely be preferable to select A_5 instead, and use the remaining budget for other health security initiatives.

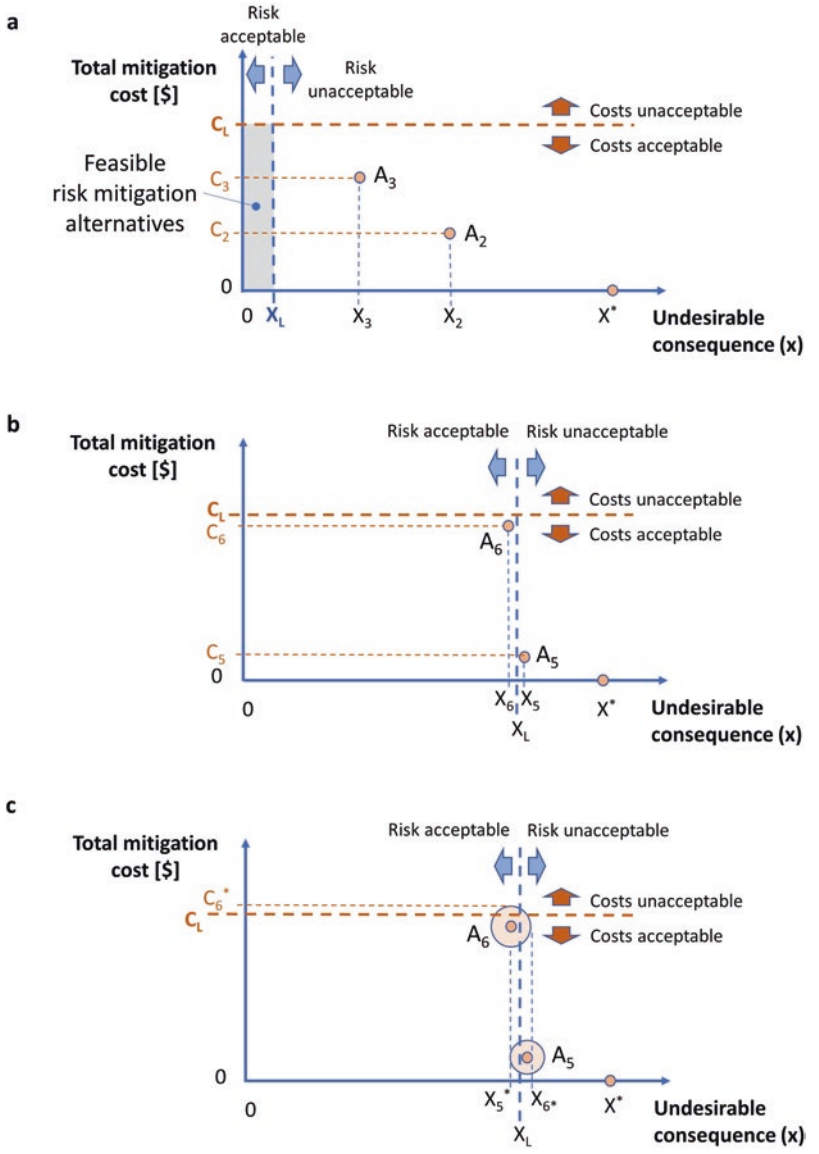

Fig. 6.9 Problematic situations in defining risk and budget limits: (**a**) Excessively stringent risk limit delimits a solution space that is too narrow, (**b**) Rigid risk limit excludes decision alternative only marginally inferior than the ones that are feasible, (**c**) Rigid risk limit ignores uncertainties in the performances of alternatives

To avoid this situation from occurring, it is advisable that a flexible risk limit be assumed, which is employed as a guide but not as a hard constraint to determine the exclusion or inclusion of decision alternatives (alongside a hard risk limit for levels of impact that are deemed to be truly unacceptable). The same holds true for budget

limits, unless it becomes truly impossible to obtain additional funds, as we suggested in the four chapter.

The third case wherein a limit may prove unhelpful is illustrated in Fig. 6.9c. This situation is similar to the previous one, whereby a rigid risk limit has been defined, but there now exists uncertainty pertaining to both the risks and costs associated with the two alternatives, A_5 and A_6. As we have discussed in fifth chapter, these uncertainties cause dispersions about the impacts of the alternatives, which are now represented by a circle indicating the range of possible impacts of each option. Notice that in some scenarios A_5 would be situated below the risk limit ($X_5^* < X_L$) and thus within an acceptable performance. Moreover, in some scenarios, A_6 would be situated above the risk limit ($X_{6*} > X_L$) or above the cost limit ($C_6^* > C_L$) and is therefore rendered unacceptable. Additionally, under some scenarios, A_6 may be inferior to A_5, as the two dispersion circles partially overlap. Once again, this situation would require that flexible risk limits be assumed, as well as malleable budget limits be considered whenever possible, were there to be any major uncertainties regarding the performance of the risk mitigating alternatives. Additionally, the comparison of these two decision alternatives must consider the uncertainty pertaining to their performances, as shall be detailed in the ninth chapter.

To summarize, risk limits and budget limits must be carefully set. These limits act as constraints that bind the solution space and, thus, exclude any option whose impacts are situated above such limits. Hard limits should only be set for truly unacceptable levels of risks, or whenever extra funding above the budget limit is unavailable. Otherwise, it is advisable to consider both risk limits and budget limits to be soft constraints and to explore the impact of shifting them slightly higher for decision alternatives that lie on the periphery of the boundaries of these limits, as illustrated in the example shown in Fig. 6.9b. In conditions of uncertainty, it also becomes important to consider the role of risk limits in including and excluding alternatives, given the dispersion of performances of the options.

Defining risk limits requires *judgments* from the health security team, health experts, or policy makers. These judgments must take into account the tangible constraints (for example, the number of hospital beds available), the scientific knowledge (for instance, how many severe cases are expected for a particular disease outbreak), and the risk tolerance of the country or health system (for example, how many severe cases are social acceptable and manageable for a given outbreak).

Having discussed the judgments necessary for defining realistic risk limits, we now move to a second type of judgment in health security decisions, required for the valuation of impacts of decision alternatives: the definition of marginal value over relevant consequences.

6.2 Identifying Marginal Value Over Consequences

The attainment of a decision objective is measured by the marginal value accrued over the associated consequence. For objectives whose direction of preference entails maximization this marginal valuation requires defining the increase in value

associated with achieving increased performance levels on this objective. Conversely, for an objective whose direction of preference involves minimization, this marginal valuation necessitates that we define the increased value associated with decreasing a detrimental impact. This definition of marginal value over relevant consequences also requires judgments from the health security team.

In health decision analyses that seek to compare health security actions in order to enhance health security, the consequences inherent to each attribute are normalized between 100 for the *most preferable level of impact* and 0 for the *least preferable level of impact*, using a *value function*. Said function is exemplified in Fig. 6.10 for the objective *minimize number of casualties* and associated attribute *number of casualties* (measured by variable x) provoked by a health threat, after a risk mitigating action has been implemented. The attribute is normalized by the value function v(x), which measures the value for risk mitigation over this consequence.

The value function shown in Fig. 6.10 assesses the marginal value that each decision alternative would provide in reducing the number of casualties from the maximum acceptable level of impact (X^*) to the minimum feasible level of impact (X_*). The function is established to be 100 for the minimum possible number of casualties $v(X_*) = 100$ and as zero for the maximum acceptable number of casualties $v(X^*) = 0$. Notice that this value function is linear, thereby denoting that each reduction by one casualty provides the same gain in value for society. The value provided by a risk mitigation action that would reduce from the maximum number of casualties (X^*) to a lesser number of casualties X' is given by the value score $v(X')$ as shown in the same figure.

The assessment of value in Health Decision Analysis entails some relevant conceptual distinctions in comparison with other tools for assessing policy options, such as Cost-Benefit Analysis (Brent, 2016; Layard & Glaister, 1994). First, the assessment considers the societal value for the *specific decision context*, instead of

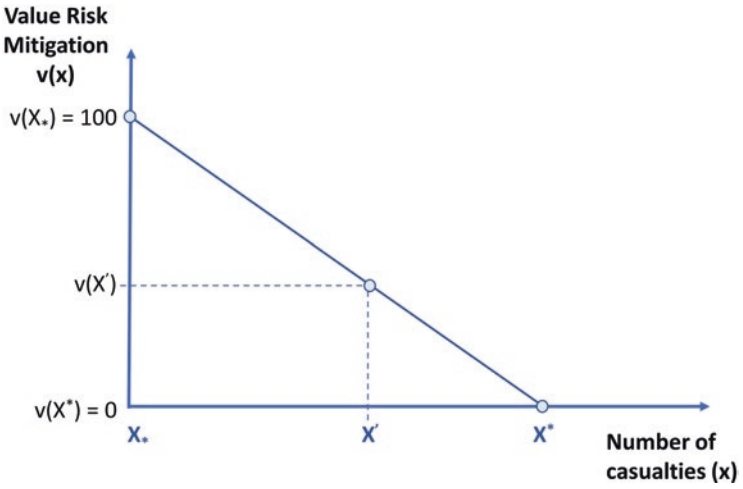

Fig. 6.10 A linear value function for risk mitigation over the number of casualties

generic societal principles. Second, the assessment of value is *relative to the ranges* of the attributes, instead of generic priorities that have been set to attain vaguely specified objectives. Third, the evaluation of value is concerned with the *relative (marginal) value* of each decision alternative, rather than attempting an absolute evaluation of their value to society. These distinctions render this assessment of societal value particularly useful for supporting health security decisions, wherein many consequences are difficult to adequately monetize and it becomes quite problematic to define absolute valuations consistently.

We must emphasize that it is important that this definition of value functions be conducted carefully, as they influence the manner in which decision alternatives are evaluated and thus may influence the choice itself (Stewart, 1996). In this section we describe how these functions should be defined by decision makers and how to avoid biases in their elicitation.

6.2.1 Eliciting Marginal Value Functions

Thus far in this chapter, we have assumed that the marginal value over consequences has been linear (i.e., each extra unit of performance or impact on the attribute would cause the same additional value). This linear value function is demonstrated by the objective *minimize the number of casualties* in the health security decision shown in Fig. 6.10. As denoted by this function, which converts the number of casualties (the unit of impact on the attribute) into a normalized value between 0 and 100 for risk mitigation, each life saved is of equal value. In other words, the marginal societal value of each life saved is considered to be constant.

This value linearity assumption is reasonable regarding attributes wherein equity is relevant, and considers human health, such as the number of casualties and the number of severe cases that may be caused by a health threat, or the number of lives saved by a risk mitigating action. The assumption is also realistic for attributes whose range is narrow, such as an evaluation of different alternatives for a vaccination campaign that may incur similar costs. In addition, linear value functions should be employed if the impacts of decision alternatives, or of health threats, are estimated to be most likely values (Keeney & von Winterfeldt, 2007).

However, some impacts have value functions whose shape is non-linear. Let us return to the vaccination campaign case to illustrate non-linear marginal valuations. One objective is to *maximize the immunization coverage rate*. The attribute for this objective is the *proportion of the population being vaccinated* (represented by variable x_R), measured in percentage points, with the value function $v(x_R)$ shown in Fig. 6.11. Within this value function, (defined by the health security team) the minimum acceptable level of coverage is $X_R^* = 60.0\%$, which would represent zero value: $v(60.0\%) = 0$. The maximum level of coverage is $X_R^* = 99.0\%$, hence the value $v(99.0\%) = 100$. Notice that this upper limit assumes that it is possible to develop a vaccination campaign that is capable of achieving this level of coverage (99% of the population immunized). Let us also assume that a coverage of 80.0% of

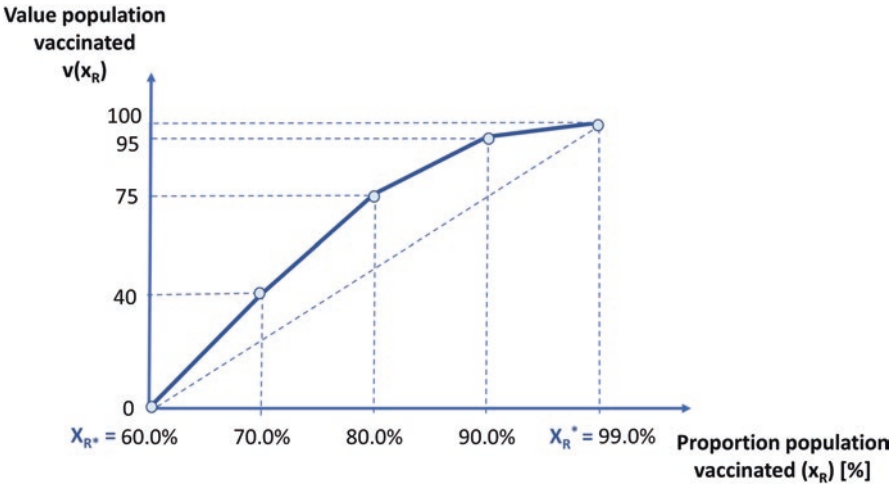

Fig. 6.11 A concave value function for enhanced health security over the proportion of population vaccinated

reach were a target that would enable the attainment of herd immunity for this disease, given its transmission patterns (Brauer et al., 2019).

To denote the non-linear valuation over this consequence, the value function is concave, which values initial increases in the vaccination levels more (from the 60.0% lower limit) than subsequent increases near the 99.0% upper limit. For example, the value gain between 60.0% and 70.0% of the population vaccinated (10 percentage points) is v(70.0%) – v(60.0%) = 40 value points, in comparison with the value gain between 80.0% and 90.0% of the population vaccinated (also 10 percentage points) of only v(90.0%) – v(80.0%) = 20 value points. Additionally, reaching the herd immunity level (80.0% of the population vaccinated) has been valued to be v(80.0%) = 75 value points. Thus, this level of vaccination coverage would fulfill three-quarters of the value in attaining this objective, which could be achieved by a vaccination campaign that can reach this 80% level of coverage.

There exist well-developed protocols for the definition of value functions (see Farquhar (1984) and von Winterfeldt and Edwards (1986) for details). Two of these methods are detailed next.[2]

The Bisection Method The bisection method is a widely used protocol for defining value functions when considering continuous attributes, such as the one shown in Fig. 6.11 (von Winterfeldt & Edwards, 1986). The protocol "bisects" the value function by locating the mid-point of value between ranges on the attribute of equiv-

[2] The understanding of these methods is optional, only for those readers who are interested in developing value functions in practice. The reader uninterested in these details may proceed to the next sub-section.

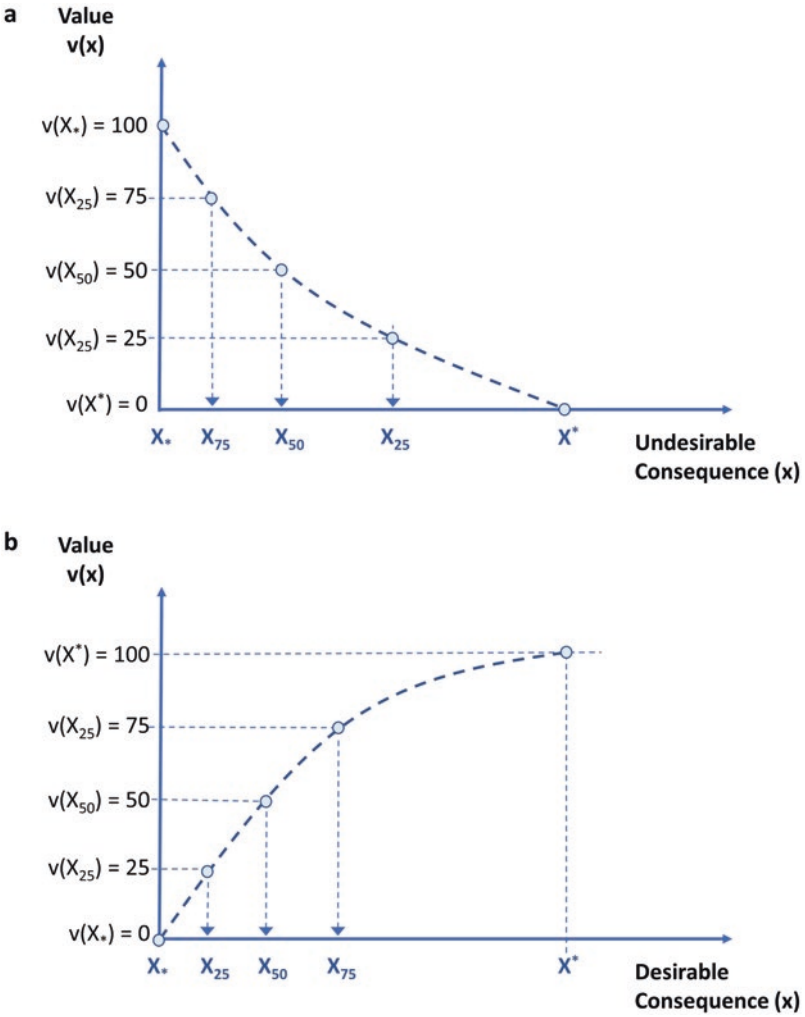

Fig. 6.12 The bisection method for defining continuous value functions: (**a**) Value function over an undesirable consequence, (**b**) Value function over a desirable consequence

alent value distance (see also Montibeller and Franco (2007) for details on how to employ this protocol in practice).

For *undesirable consequences*, as shown in Fig. 6.12a, the first stage of the method begins with establishing the values for the two extremes, with the least preferable (*highest acceptable*) level of impact (X^*) as 0 and the most preferable (*lowest feasible*) level of impact (X_*) as 100, i.e.: $v(X^*) = 0$ and $v(X_*) = 100$. The decision makers are then asked to identify a consequence level that provides a mid-point of value between the two extremes X^* and X_*. This mid-point level is denoted as: X_{50} in the same figure (with $v(X_{50}) = 50$). Subsequently, a mid-point in value

between X^* and X_{50}, i.e. X_{25}, is identified (with $v(X_{25}) = 25$); a mid-point in value between X_{50} and X_*, i.e., X_{75} is identified (with $v(X_{75}) = 75$). Once these five value points have been identified, a continuous value function can be interpolated.

The same protocol can be employed for eliciting value functions over, as shown in Fig. 6.12b. In this case, the valuation is reversed, with the least preferable (*lowest acceptable*) level (X_*) as 0 and the most preferable (*highest feasible*) level (X^*) as 100, i.e.: $v(X_*) = 0$ and $v(X^*) = 100$. The decision makers are then asked to identify a consequence level (X_{50}) that provides a mid-point of value between the two extremes X_* and X^*(with $v(X_{50}) = 50$). Subsequently, a mid-point in value (X_{25}) between X_* and X_{50} is identified (with $v(X_{25}) = 25$), as well as identifying a mid-point in value (X_{75}) between X_{50} and X^* (with $v(X_{75}) = 75$). As before, once these five value points have been identified, a continuous value function can be interpolated.

The Direct Rating Method This protocol necessitates the direct valuation of intermediate levels of impact of the attribute, anchored on the extreme levels of the attribute. This method is particularly useful for attributes whose number of discrete levels is fewer, such as the constructed attributes presented in the previous chapter for assessing emerging animal health threats (see Table 5.1).

Let us assume that there exist five discrete levels of impact that compose a constructed attribute, and they are ordered from the most preferable level (L_5) to the least preferable level (L_1), as shown in Fig. 6.13a. These two levels provide the valuation anchors, with $v(L_5) = 100$ and $v(L_1) = 0$. The intermediate level is then introduced, and decision makers are tasked with determining its value score $v(L_3)$, considering its value distance from L_1 (ΔV_{13}) in relation to its value distance to L_5 (ΔV_{35}). For instance, were these distances the same ($\Delta V_{13} = \Delta V_{35}$), then $V(L_3) = 50$.

This process is repeated for intermediate levels of impact, as shown in Fig. 6.13b. For level L_2 the decision makers should consider the value distance from L_1 (ΔV_{12})

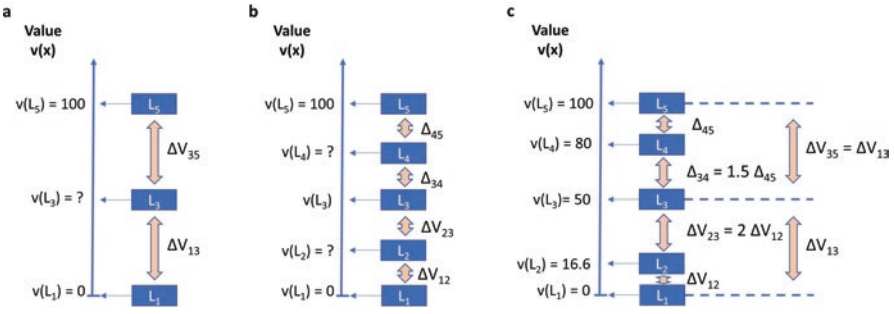

Fig. 6.13 The direct rating method for defining discrete value functions: (**a**) Eliciting the value of level L_3, (**b**) Eliciting the value of levels L_2 and L_4, (**c**) An example of elicited value scores with relative value distances between impact levels

and to L_3 (ΔV_{23}), to determine the value of this level: $v(L_2)$. For instance, if they consider $\Delta V_{23} = 2\ \Delta V_{12}$ then $v(L_2) = 16.6$ value points (as $V(L_1) = 0$ and $V(L_3) = 50$). For level L_4 the decision makers should compare the value distance from L_3 (ΔV_{34}) and to L_5 (ΔV_{45}), to determine the value $v(L_4)$. For example, if $\Delta V_{34} = 1.5\ \Delta V_{45}$, then $v(L_4) = 80$. The final value scores, after considering all these value distances, are presented in Fig. 6.13c.

6.2.2 Avoiding Mistakes in the Definition of Value Functions

When defining marginal value functions there exist some common mistakes that arise, which should be avoided and debiased. The first mistake that we have found often stems from defining unrealistic extremes. The second mistake is an assumption of linearity when there are strong non-linearities. In addition, cognitive and motivational biases may also bring about mistakes in the valuation of impacts of health threats and health security actions. We discuss each type of mistake next.

Defining Limits for Undesirable Consequences Defining unrealistic limits for attributes that measure undesirable consequences is the first mistake that we shall consider. As illustrated in Fig. 6.10 for a minimization objective, a lowermost level (X_*) and an uppermost level (X^*) must be defined for the value function. The former should indicate the *minimum feasible level of impact* and the latter the *maximum acceptable level of impact*. Establishing the lowermost level (X_*) as zero when this is not feasible in practice is a common mistake. For example, if some casualties are inevitable in a given disease outbreak, then this lowermost level should represent the minimum number of casualties that is possible, were risk mitigation actions to be put in place, and should not be representative of the idealized level of zero casualties.

Another unrealistic limit that we have observed is to maintain the upper (X^*) level of impact for an undesirable consequence unbounded. For example, if the economic impact caused by health threats forms one of the attributes (Del Rio Vilas et al., 2013; Montibeller et al., 2020a), decision makers may decide to leave the maximum level undetermined. However, this renders the defining of a value function impossible (von Winterfeldt & Edwards, 1986). It is recommended, instead, to define an uppermost level using a realistic estimate, so that a value function is able to be determined. For a similar reason, it is also important that unacceptable levels of impact be excluded from the range, and thus that X^* be carefully defined with regards to undesirable consequences. Otherwise, this inclusion of unacceptable levels would heavily distort the value function. Additionally, the health decision analysis would wrongly assume that said levels could be compensated by strong performances of decision alternatives on other consequences.

Defining Limits for Desirable Consequences Let us consider the same issue of unrealistic limits for attributes that measure desirable consequences, as shown in

Fig. 6.12b for a maximization objective. Here, the uppermost level (X^*) must be the maximum *feasible level of impact* and the lowest level (X_*) must be the *minimum acceptable level of impact*. Uppermost levels that are defined to be at points that are excessively high would indicate unrealistic expectations of performance. Conversely, lowermost levels that are defined at points that are lower than the lowermost acceptable level would distort the health decision analysis.

Consider the vaccination campaign case and the objective *maximize the immunization coverage rate*. The attribute for this objective is the *proportion of the population being vaccinated* (x_R), which measured in percentage points, with the value function $v(x_R)$ shown in Fig. 6.11. As we have previously mentioned, in this value function, the minimum acceptable level of coverage is $X_{R*} = 60.0\%$, which would represent zero value: $v(60.0\%) = 0$. Lower vaccination rates than this level, below 60.0% of coverage, would not be acceptable and thus should not be included. Were these low rates to be included, they would distort the value function, which would otherwise become too steep from the X_{R*} anchor point. Furthermore, these excessively low rates would also distort the weight allocated to this objective, which may become overweighted (the limits of the attribute must play a role in defining such weight, as shall be detailed in the next section).

A second mistake in the definition of value functions is to assume that there exists a linear function, when, in actual fact, there exist strong non-linearities on the valuation of the consequence (Stewart, 1996). This is particularly the case when the ranges are significantly broad, such as when considering a diverse portfolio of actions wherein some alternatives would cost thousands while others may cost millions of dollars. Non-linearities may also be relevant when some target levels exist, and the achievement of such target levels would provide high value for the decision alternative. This is the case for the value function on the *proportion of population vaccinated* shown in Fig. 6.11. As mentioned previously, in this function for this specific case, the 80.0% vaccination rate would provide herd immunity and thus provides three quarters of value on this objective: $v(80\%) = 75$ value points.

A third mistake occurs with the valuation of impacts of health threats and health security actions, and stems from the presence of cognitive and motivational biases which may affect the elicitation of value functions and should be minimized (Montibeller & von Winterfeldt, 2015). One of these cognitive biases that affects elicitation is the gains-loss bias, whereby framing the choice as either a gain or a loss against the status quo, may affect the shape of the value function (Frisch, 1993; Levin et al., 1998; Tversky & Kahneman, 1981). Hence, it is important that the status quo be clearly identified and that the value function express the marginal changes from this status quo. Another cognitive bias in the form of anchoring, may also affect the definition of value functions. In this case, the valuation of levels of impact on the attribute may be anchored on some irrelevant numbers. Variety in the decision making group and individual value estimates can help to remove said bias (Montibeller & von Winterfeldt, 2018).

Two motivational biases may distort value functions. One bias is that of the desirability of options bias (Montibeller & von Winterfeldt, 2015), which may skew the

function in a manner that favors a decision alternative that has been favored a priori. For this reason, we suggest and stress that it is vital that a full valuation model, including the definition of value functions and weights, be developed *before* the evaluation of decision alternatives. Another motivational bias that affects the definition of value functions is the affect influenced bias (Finucane et al., 2000; Siegrist & Sütterlin, 2014; Slovic et al., 2004), which may trigger an oversensitivity to increases in a consequence. For instance, public health leaders may find any loss of life wholly unacceptable, which may distort the shape of a value function over this consequence. Here, the recommendation is to carefully establish acceptable limits and involve a varied and balanced group of individuals as part of a health security team whose perspectives reflect this composition of the group (Montibeller & von Winterfeldt, 2018).

Thus far we have analyzed two types of judgments required to define risk limits and value functions, which are made within each attribute. We now turn our focus to the third type of judgment, required for when multiples objectives (and their respective attributes) must be considered, the definition of trade-offs, which are made across attributes.

6.3 Defining Trade-Offs Among Conflicting Objectives

Trade-offs are always required in health security decisions. These decisions invariably necessitate that we negotiate conflicting objectives, such as minimizing the number of casualties, reducing the number of severe cases, while operating under limited budgets and constrained resources that must be employed efficiently. Indeed, failing to reason clearly about trade-offs forms one of the most critical mistakes in decision making (Keeney, 1992) and in risk management (Keeney, 1996).

Judgments about trade-offs among conflicting objectives require assessments of compensation, i.e., if the gains made on one dimension can be compensated by losses on another dimension (Keeney, 2002). Classic trade-offs in health security decision are between health gains, or risk reductions, versus budget expenditures.

Notice however that this factor does *not* imply the simplistic assumption that for either large scale outbreaks of diseases with severe consequences, or for pandemics, there exists a simple choice between maintaining the economy open or, alternatively, saving lives. Economic and health impacts are interrelated in such events, as the disease affects economically active sectors of the society and individuals within a population experience fear of contagion. Recent examples of such economic disruption are the Ebola outbreaks in Western Africa in 2014–2016 (CDC, 2020; World Bank, 2014) and the COVID-19 global pandemic that started in 2020 (World Bank, 2020).

In such pandemics, actions that suppress the virus early on may result in fewer casualties and a lower degree of economic damage than protracted efforts to maintain the economy open while merely implementing mitigating actions (Oliu-Barton et al., 2021). On the other hand, limited fiscal strength that governments possess and

precarious employment arrangements may prevent the ability to impose long-duration lockdowns. Hence the real trade-off that should guide these lockdown decisions should be concerned with long-term health and socio-economic impacts versus short and medium-term health and socio-economic impacts. However, countries whose fiscal means are limited may be obliged to adopt a shorter planning horizon to assess these benefits and costs in comparison to developed countries whose fiscal positions are robust, and are therefore able to adopt longer planning horizons.

Let us introduce the concept of a trade-off by illustrating this concept in the situation introduced in the previous section. Recall that there exists a health threat that could cause $X^* = 15{,}000$ severe cases, on the *number of severe cases* attribute (measured by variable x). The second attribute is the *total cost of risk mitigation*, in $million. The risk limit has been established at $X_L = 11{,}000$ severe cases and the budget limit at $C_L = \$100$ million, thus defining a range of feasible alternatives for risk mitigation.

The trade-off concept is illustrated in Fig. 6.14, wherein two hypothetical alternatives A′ and A″, with respective consequences (X′,C′) and (X″,C″), are set by the health security team as being indifferent to one another. In other words, the reduction in the number of severe cases Δ_X from X′ to X″ is considered by the team to be beneficial enough to warrant the increase in total extra cost Δ_C from C′ to C″. Hence, if $X' = 9{,}000$ severe cases and $C' = \$30$ million for alternative A′, and $X'' = 6{,}000$ severe cases and $C'' = \$60$ million for alternative A″, then the reduction in severe cases $\Delta_X = X' - X'' = 9{,}000–6{,}000 = 3{,}000$ cases is considered to fully compensate for the additional cost $\Delta_C = C'' - C' = \$60$ million – $30 million = $30 million.

The indifference curve in Fig. 6.14 illustrates a complete set of consequences that are each indifferent to each other. Hence, any decision alternative that is situated over the curve, such as A‴ with consequences (X‴,C‴), would provide the same societal value as A′ and A″.

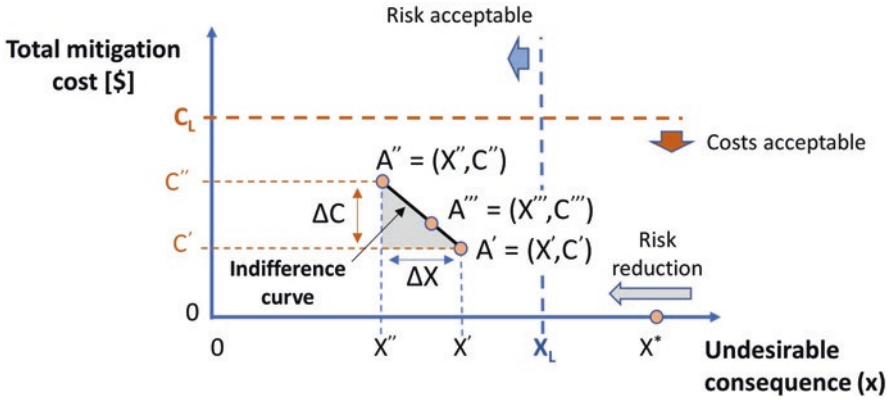

Fig. 6.14 Trade-off between an undesirable consequence and the total risk mitigation cost

This concept of trade-offs has two important central uses in decision making. First, trade-offs are able to guide the choice of decision alternatives. Second, trade-offs are required for the prioritization of decision objectives. The subsequent section begins by discussing the role of trade-offs when choosing between decision alternatives. Subsequently, we demonstrate how the concept of trade-offs can be extended in order to establish as to how conflicting objectives should be adequately prioritized. We conclude this section by stressing how biases within this type of judgment can be minimized.

6.3.1 Defining Trade-Offs in the Choice of Alternatives

When decision makers are comparing decision alternatives, trade-offs consider whether the additional benefits of a given alternative compensates for the drawbacks of this alternative, in relation to the other alternatives under consideration.

Trade-offs can help to make reasoned choices of decision alternatives in three different manners, from a more specific setting to a more generalized one: (i) the direct comparison between two decision alternatives and the assessment of compensation, (ii) the explicit consideration of the trade-off for the choice of alternatives, and (iii) the consideration of the indifference curve and the direction for value improvement in the selection of the best alternative. These form important concepts for health security decisions and shall be subsequently presented in the text that follows.

Direct Assessment of Compensation for Choice When directly comparing between two decision alternatives, decision makers should assess as to whether the advantages *compensate* for the disadvantages that each alternative provides.

We shall now revisit the decision situation that has been discussed in the previous section to illustrate how the choice of decision alternatives can be considered in a reasoned way. Assume that there exist two health threats, each having the potential to cause $X^* = 15{,}000$ severe cases if no risk mitigating actions were to be implemented.

There exist two feasible decision alternatives for risk mitigation (A_2 and A_3) against the *first health threat* which would cause $X^* = 15{,}000$ severe cases, as reproduced in Fig. 6.15a. The alternative A_2, provides a reduction in the number of severe cases that is lesser (remaining number of severe cases $X_2 = 9{,}000$) than alternative A_3 (remaining number of severe cases $X_3 = 5{,}000$). On the other hand, the former alternative proves less expensive (total cost of mitigation $C_2 = \$30$ million) than the latter alternative (total cost of mitigation $C_3 = \$60$ million).

The choice between alternatives A_2 and A_3 requires the judgment as to whether the risk reduction from A_2 to A_3 is indeed worth the additional mitigation cost, as represented in Fig. 6.15a. Specifically, the risk reduction would entail less $\Delta X_{23} = X_2 - X_3 = 9{,}000–5{,}000 = 4{,}000$ severe cases against the additional cost $\Delta C_{23} = C_3 - C_2 = \$60$ million – $\$30$ million = $\$30$ million. In this decision problem,

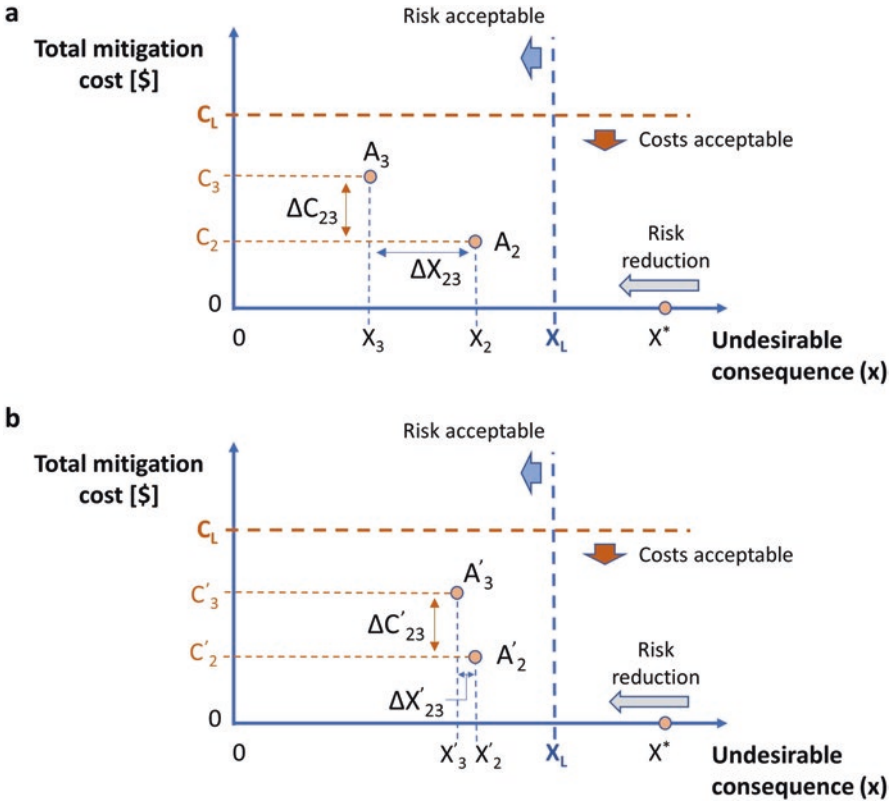

Fig. 6.15 Assessment of compensation between two risk mitigating decision alternatives: (**a**) Choice between A_2 and A_3 for managing the first health threat: (**b**) (**a**) Choice between A'_2 and A'_3 for managing the second health threat

if the risk reduction (ΔX_{23}) of less 4,000 severe cases were deemed to be worth the extra additional cost (ΔC_{23}) of $30 million then A_3 should be chosen. Otherwise, if the risk reduction (less $\Delta X_{23} = 4{,}000$ severe cases) were not deemed to be worth the additional cost (more $\Delta C_{23} = \$30$ million), A_2 should be selected.

Notice that if the choice of A_2 were to be made, this choice would not constitute a reflection of an "insensitive" attitude of the policymakers who fail to sufficiently value a human life. Rather, the choice is a consequence of limited resources, that could otherwise be employed more effectively in another part of the health system to promote a greater societal benefit in comparison to reducing the number of severe cases by 4,000 cases.

Importantly, also notice that trade-offs must be *specific*, taking into account the *levels of predicted impacts* of the decision alternatives, instead of being formed by generic statements of priorities. This point can be illustrated by the following question: If A_3 were to be selected in the decision above, would this choice imply that

any gains in risk reduction would be worth the additional mitigation cost? Or, in other words, would decision makers always prefer to trade-off a greater budget expenditure for any reduction in the number of severe cases?

Let us analyze another decision situation to consider and illustrate this issue, for the *second health threat*, which would cause the same number $X^* = 15{,}000$ of potentially severe cases, as depicted in Fig. 6.15b. To undertake this threat, a risk mitigating alternative A'_2 was designed, whose performance is identical to A_2 with regards to the first threat (i.e. remaining number of severe cases $X'_2 = 9{,}000$ and total mitigation cost of $C'_2 = \$30$ million). However, in this instance, the second possible alternative, A'_3, is less effective in reducing risks than the performance of A_3 with regards to the first threat. For this alternative A'_3 the remaining number of severe cases is $X'_3 = 8{,}500$ but with a cost of $C'_3 = \$60$ million.

Here, the trade-off shown in Fig. 6.15b, is concerned with whether the risk reduction of $\Delta X'_{23} = X'_2 - X'_3 = 9{,}000–8{,}500 = 500$ severe cases is worth $\Delta C'_{23} = C'_3 - C'_2 = \$60$ million – \$30 million = \$30 million of extra mitigation cost. It may well be that this reduction in the number of severe cases (less 500 cases) proves to not be worth the additional expense (more \$30 million), consequently, A'_2 would be selected instead of A'_3. Therefore, were A_3 to be selected over A_2 in the *previous* decision against the *first* health threat, *it is not* the case that this selection would necessarily imply a choice that would incur a lower number of severe cases (A'_3 against A'_2) being made for this decision against the second health threat.

On the other hand, were the generic statement of priorities to be employed to guide this second choice ("any gains made in the reduction of risk are worth the additional mitigation cost"), this would lead to the choice of A'_3 over A'_2 against the second health threat. However, as mentioned above, A'_3 is an alternative that results in relatively minor gains in risk reduction ($\Delta X'_{23} = 500$ severe cases) but significant increases in mitigation costs ($\Delta X'_{23} = \$30$ million). Hence, the use of this generic statement of priority to guide the choice of decision alternatives would prevent a more explicit assessment of compensations between risk reduction and increases in cost for the specific decision situation to take place. As this example highlights, these generic statements should be avoided, and instead, specific trade-offs among predicted levels of impact must be considered in health security decisions.

Consideration of Trade-Offs for Choice The second manner of using trade-offs when making choices among alternatives involves the explicit consideration of the trade-off as a guideline for choice, against the marginal gains and losses engendered by the alternatives.

Let us again consider the choice between two decision alternatives (A_2 or A_3) against the first health threat presented above, which is reproduced in Fig. 6.16a. The risk reduction from A_2 to A_3 is: $\Delta X_{23} = X_2 - X_3 = 9{,}000–5{,}000 = 4{,}000$ cases. The increase in total cost of mitigation is: $\Delta C_{23} = C_3 - C_2 = \$60$ million – \$30 million = \$30 million. As discussed previously, a trade-off identifies two hypothetical alternatives (A' and A'') that are considered to be indifferent to each other (see Fig. 6.14). Assume that these hypothetical alternatives, A' and A'', for this decision are the ones shown in Fig. 6.16a: $X' = 9{,}000$ severe cases and $C' = \$30$ million for

alternative A′; and X″ = 6,000 severe cases and C′ = $60 million for alternative A″. Thus, the reduction in severe cases ΔX = X′ – X″ = 9,000–6,000 = 3,000 cases is worth the increase in total cost: ΔC = C″ – C′ = $60 million – $30 million = $30 million.

While the additional total cost from A_2 to A_3 remains the same as the cost considered by the trade-off ($\Delta C = \Delta C_{23}$), the additional risk reduction from A_2 to A_3 is *greater* than the risk reduction defined by the trade-off ($\Delta X_{23} > \Delta X$), as represented in Fig. 6.16a. Therefore, we see that given this comparison against the trade-off and the performances of the decision alternatives, A_3 should be selected instead of A_2. The trade-off indicates that the additional risk reduction that A_3 provides more than compensates the additional cost associated with selecting this alternative.

Now let us revisit the choice between A'_2 and A'_3 against a second health threat described previously, using the same trade-off above (defined by the same

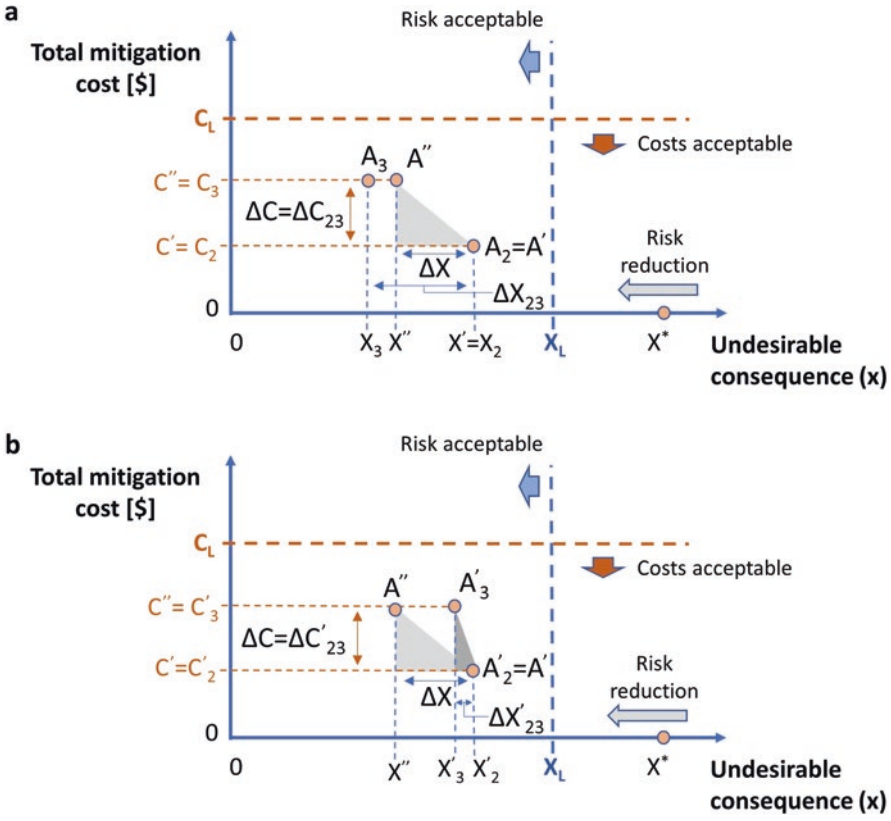

Fig. 6.16 Consideration of trade-off between two risk mitigation decision alternatives: (**a**) Choice between A_2 and A_3 for managing the first health threat: (**b**) (**a**) Choice between A'_2 and A'_3 for managing the second health threat

hypothetical alternatives A' and A'') as a guideline for the selection of the best alternative. These options are shown in Fig. 6.16b. The risk reduction from A'_2 to A'_3 is: $\Delta X'_{23} = X'_2 - X'_3 = 9{,}000–8{,}500 = 500$ cases. The increase in total cost from A'_2 to A'_3 is: $\Delta C'_{23} = C'_3 - C'_2 = \$60$ million – $\$30$ million = $\$30$ million.

In this case, while the additional total cost from A'_2 to A'_3 remains the same as the cost considered by the trade-off ($\Delta C = \Delta C'_{23}$), the additional risk reduction from A'_2 to A'_3 is *lesser* than the one defined by the trade-off ($\Delta X'_{23} < \Delta X$), as depicted in Fig. 6.16b. Therefore, given this comparison against the trade-off, A'_2 should be selected instead of A'_3. The trade-off indicates that the reduction in the number of severe cases that A'_3 provides against A'_2 is not considered enough to compensate for the additional cost associated with A'_3.

If we consider the first method of choice among conflicting objectives in relation to this second method of choice, the second is advantageous in that it enables the comparison of more than two alternatives. This concept can be further extended to facilitate said comparison among many decision alternatives, with a relative assessment of societal value, as described next.

Definition of a Direction for Value Increase Choosing among a set of decision alternatives is a choice that can be guided by the indifference curve defined in a trade-off and the identification of the direction of societal value increase for a set of indifference curves.

Recall that, as presented in Fig. 6.14, a trade-off identifies two hypothetical alternatives (A' and A'') that are considered to be indifferent to each other. These two points define a linear *indifference curve* that demonstrates a complete set of consequences that are each indifferent to one another.

Consider again the risk mitigations choices that have been employed against the first health threat in the example above. Two curves from the set of indifference curves are shown for the choice between A_2 and A_3 in Fig. 6.17a. Indeed, we can trace a family of indifference curves, with each curve being parallel to the other. As they shift from the North-East corner to the South-West corner of the diagram, the societal value of the decision alternatives increases. (The best, albeit unrealistic, option would entail a risk mitigating alternative whose number of severe cases and costs remains at zero i.e. $X = 0$ and $C = 0$.) The arrow perpendicular to the indifference curves, shown in the graph, indicates the direction of value increase. This analysis of value increase illustrates that A_3 should be selected, as the indifference curve over this alternative provides greater value than the curve over A_2.

This type of direction for value increase analysis can be used for the other decision situation, the choice between A'_2 and A'_3 against a second health threat, as shown in Fig. 6.17b. Two curves from the set of indifference curves are shown in the same figure. Here, the indifference curve over alternative A'_3 has less value than the indifference curve over A'_2. Therefore, alternative A'_2 should be selected. This result is evidently identical to the trade-off we have considered previously (Fig. 6.16b), as the indifference curve analysis is just an extension of the trade-off concept.

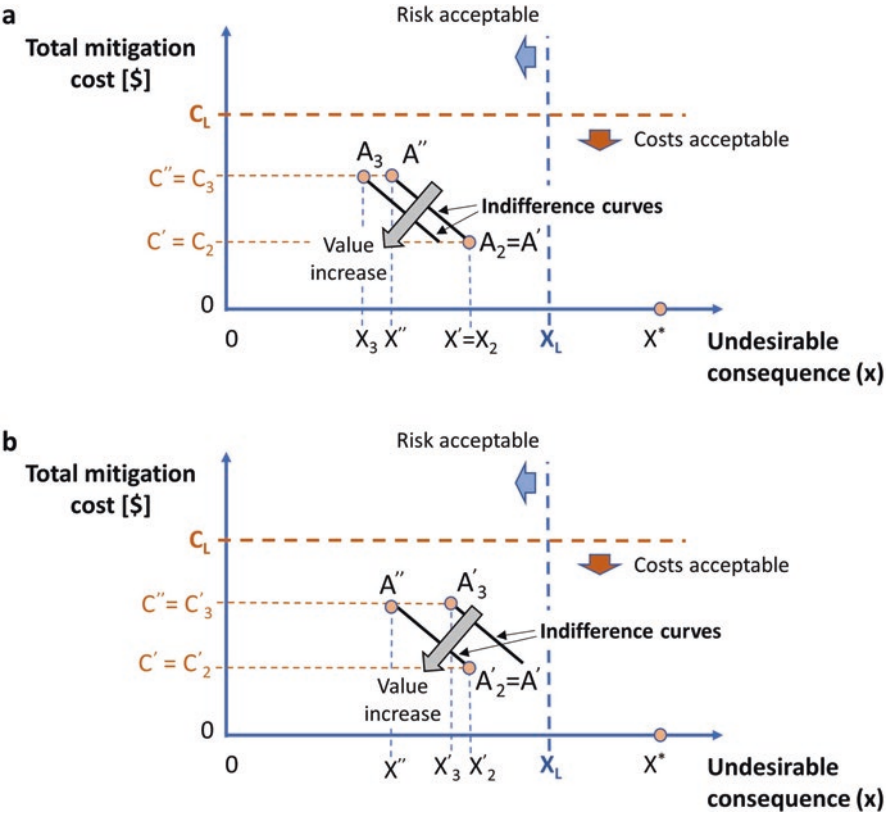

Fig. 6.17 Definition of a direction of value increase between two risk mitigation decision alternatives: (**a**) Choice between A_2 and A_3 for managing the first health threat: (**b**) Choice between A'_2 and A'_3 for managing the second health threat

Notice that this analysis of indifference curves and the direction for value increase would enable the health security team to consider a much greater number of decision alternatives. This factor forms a major advantage, as the previous two methods of choice prove more difficult to implement when many options are under consideration. This concept of indifference curve is employed again in the eighth chapter, when we extend the evaluation and choice of decision alternatives to encompass multiple objectives.

To summarize, the three manners wherein trade-offs have been employed in this section emphasize that any *specific* gain in risk reduction must be appraised against the *specific* additional mitigation cost. Therefore, we cannot generalize that actions that promote a lower number of severe cases are always preferable to those that maintain a greater number of cases, *independently* of the mitigation cost of these actions. Hence, to avoid illogical results, and misguided choices, trade-offs must be considered with regards to the specific choice between the alternatives. Once again, the limited amount of resources available for health security, which may otherwise

be more effectively used to promote greater benefits to the health system elsewhere, require significantly difficult trade-offs to be explicitly made (see also Bower and Gilbert (2005) on the strategic aspects of organizational resource allocation and Hunink and Weinstein (2014) on the need of trade-offs in healthcare decisions).

6.3.2 Prioritizing Conflicting Objectives

The concept of a trade-off has been introduced above in a specific decision situation, whereby health security decision alternatives have been considered. We now expand this idea and apply it to an important task in health security decisions: the prioritization of conflicting objectives. This prioritization enables the health security team to assign weights that denote a relative (and quantified) importance to the objectives. In turn, the weighted objectives can support the evaluation and comparison of decision alternatives, which forms the topic of the eight chapter.

The definition of trade-offs when prioritizing objectives is in some manner similar to the choice of alternatives, whereby both must consider well-specified attributes and the attribute ranges over two specific levels of impact: a lower limit and an upper limit. For objectives whose direction of preference is minimization, such as undesirable consequences and costs, these two levels are formed by the *acceptable upper limit* and the *realistic lower limit*. In the vaccination campaign case, which has been introduced in the previous chapters, the objective *minimize total cost of the campaign*, has an acceptable upper limit of $100 million (reflecting the size of the budget) and the feasible lower limit of $50 million (reflecting the minimum cost required for any such campaign).

For objectives whose direction of preference is maximization, such as health security benefits, the two levels are formed by the *acceptable lower limit* and the *realistic upper limit*. In the vaccination campaign case, for the objective *maximize the immunization coverage rate*, the acceptable lower limit is 60.0% (reflecting the lowest acceptable vaccination rate) and 99.0% (reflecting the realistic maximum vaccination rate and assuming that almost full coverage could be achieved).

These upper and lower limits of impact, should function to anchor the prioritization of objectives as illustrated next. Let us consider the same case that has been discussed in the previous section, wherein the undesirable consequence is the number of severe cases (measured by variable x) that a health threat may cause, and the total mitigation cost incurred by mitigating actions (in $ million). Once again, the estimated number of severe cases from this health threat is $X^* = 15{,}000$ severe cases if no risk mitigations were implemented. A risk limit ($X_L = 11{,}000$ severe cases) as well as a budget limit ($C_L = \$100$ million) were defined.

The health security team wishes to prioritize two objectives: *minimize the number of severe cases* and *minimize the total cost of risk mitigation*, but decision alternatives *are not* yet available. The protocol for defining the weight of objectives begins with a hypothetical situation described by alternative A_L which has the highest number of acceptable cases and uses the entire available budget $A_L = (X_L, C_L) =$ (11,000 severe cases, $100 million), as shown in Fig. 6.18a, and

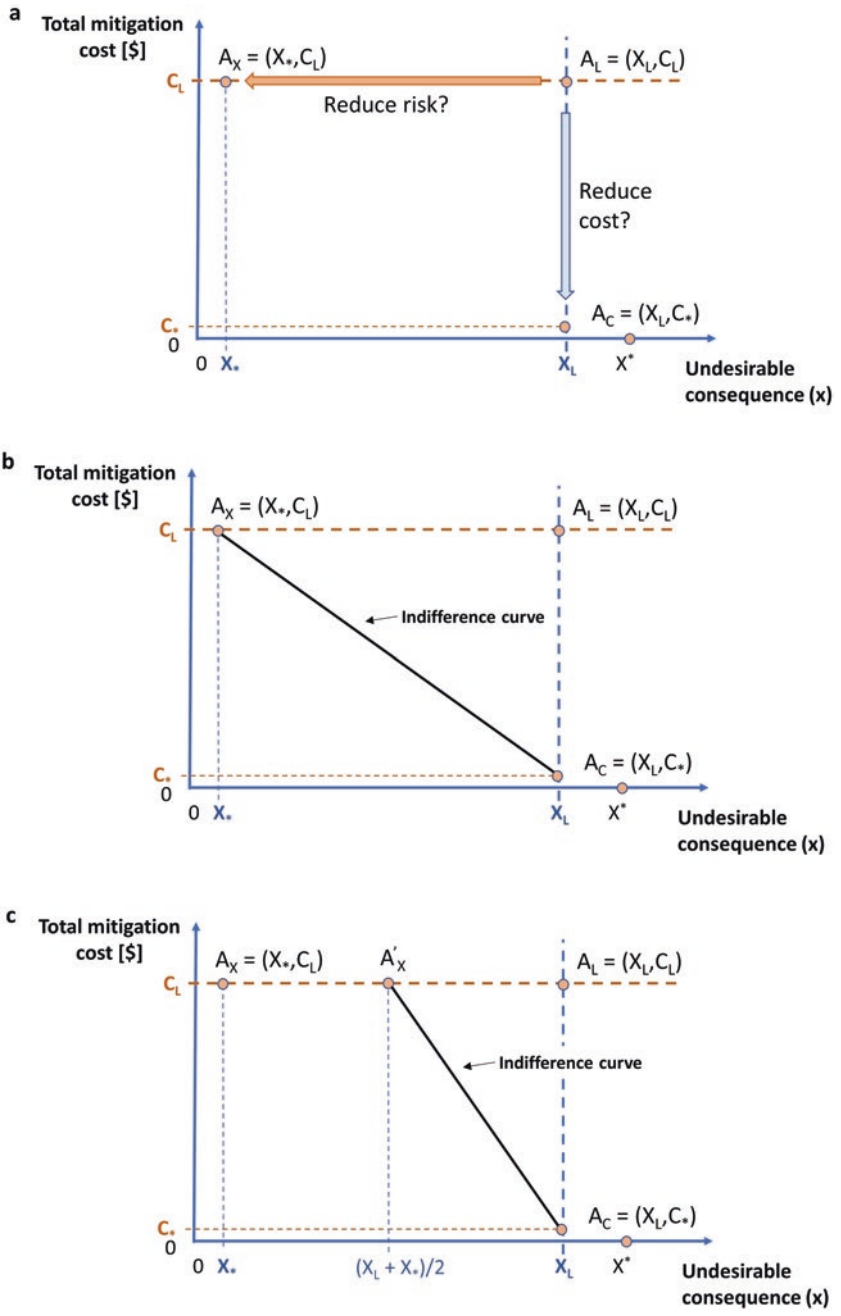

Fig. 6.18 Prioritizing decision objectives: (**a**) Hypothetical alternatives for risk reduction (A_X) and cost reduction (A_C), (**b**) Indifference curve generating objectives with the same weights, (**c**) Indifference curve prioritizing the reduction of the undesirable consequence over mitigation cost

while, most obviously, this would form an undesirable situation, it would still be considered to be feasible.

Subsequently, the protocol would assume that there exist only two possible (hypothetical) options for the health security team to improve this undesirable situation (A_L) represented by the alternatives A_X and A_C, which are also shown in Fig. 6.18a. First, it is possible to reduce the risk of the situation from X_L to X_*, while maintaining the original cost at C_L. This option is represented by alternative $A_X = (X_*, C_L)$ = (500 severe cases, $100 million). Alternatively, it is possible to reduce the cost from C_L to C_*, while maintaining the original risk level at X_L. This second situation is represented by alternative $A_C = (X_L, C_*)$ = (11,000 severe cases, $10 million).

For the prioritization of objectives, decision makers must decide: (i) as to which hypothetical alternative they would prefer (either A_x or A_C), (ii) the extent to which they would prefer one hypothetical alternative over the other. This choice can be conceptualized as a trade-off judgment over two alternatives.

For instance, if A_x and A_C are considered to be indifferent to each other, (i.e., providing the same societal value), this judgment implies an indifference curve as shown in Fig. 6.18b. In this case, the weight of the objective *minimize the total mitigation cost* would be the same as the weight of the objective *minimize the number of severe cases*. Since the weights should summate to 100%, we know that the weight for each objective would be 50%.

On the other hand, let us posit a trade-off such as the one shown in Fig. 6.18c. In this case, the alternative $A'_X = [(X_L + X_*)/2, C_L]$ was considered to be indifferent to A_C. Assuming that the reduction of each severe case holds the same value, the weight of the objective *minimize the number of severe cases* would be twice the weight of the objective *minimize the total mitigation cost* (as A'_X is located at the mid-point between A_X and A_L). Since the weights should summate to 100%, we know that the weight for the former objective would be 66.65% and the latter objective would be 33.35%.

Several protocols for the elicitation of weights are available in the literature (see Riabacke et al. (2012) for details). Well-designed protocols should always request that decision makers consider the range of the attributes and contemplate hypothetical alternatives that represent the limits of the attribute ranges, such as the ones shown in Fig. 6.18a. This consideration of ranges is critical in order to consider relative priorities among conflicting objectives (Keeney, 1992, 2002). We detail three of those methods subsequently considering two conflicting objectives.[3]

The Trade-Off Method The notion of identifying an indifference curve functions to underpin the trade-off method for defining the weights of each decision objective (Keeney & Raiffa, 1993). This method consists of four steps: (i) define two hypothetical alternatives composed by the extreme points of the attributes, (ii) identify as

[3] The understanding of these methods is optional, only for those readers who are interested in defining weights of decision objectives in practice. The reader uninterested in these details may proceed to the next sub-section.

to which hypothetical alternative is most preferable, (iii) simulate a performance reduction of the alternative that is most preferable up to the point at which this new simulated alternative becomes indifferent to the alternative that is least preferable, (iv) calculate the weight of each objective by considering the marginal value of the simulated decision alternative.

The method is illustrated in Fig. 6.19a utilizing the same case that has been explored in this section. Two hypothetical alternatives are defined, composed by the extreme points of the attribute A_X and A_C. If a hypothetical alternative A_X were preferred over another hypothetical alternative A_C, $V(A_X) > V(A_C)$, decision makers would be asked to simulate a third hypothetical alternative A''_X. This simulated alternative consists in identifying a level X'' which renders alternative A''_X indifferent to A_C, i.e. $V(A''_X) = V(A_C)$. Decision makers should then value the performance of level X'' on attribute x, i.e. $v_X(X'')$.

The normalized weight of each objective, i.e. *minimize the number of severe cases* (w_X) and *minimize total mitigation cost* (w_C), can in turn be calculated through solving two linear equations: $w_X = w_C\,[100/v_X(X'')]$ and $w_X + w_C = 1$. For example, assume that the health security team judges the marginal value of this alternative X'' on attribute x to be 60, i.e. $v_X(X'') = 60$. Consequently, the normalized weights can be calculated by solving the equations: $w_X = w_C\,[100/60] = w_C\,[5/3]$ and $w_X + w_C = 1$. The results are $w_c = 37.5\%$ and $w_X = 62.5\%$.

The trade-off method, while constituting the most rigorous method of eliciting weights of decision objectives, is also a relatively complex method to be operationalized in practice, particularly when managing a great number of objectives. The two methods that follow below prove more accessible, and we have used them extensively to support individual decision makers and groups responsible for prioritizing objectives.

The Swing Weights Method In this method for defining the weights of decision objectives, decision makers are required to consider improvements in performances with regards to different attributes, and provide the relative value of said improvements (von Winterfeldt & Edwards, 1986). The method is composed of three steps (see Montibeller and Franco (2007) for details): (i) identify which attribute demonstrates the most relevant improvement (swing) in performance, considering the extreme points of the attributes, (ii) allocate a reference value of 100 to the first swing, (iii) value the subsequent swings in relation to the reference value of the first swing.

The method is displayed in Fig. 6.19b in relation to the same example above. The decision makers have been asked whether they prefer to reduce the risk from X_L to X_* (swing S_x) while maintaining the costs at C_L level, or, alternatively, to reduce the cost from C_L to C_* (swing S_C) while the risk is maintained at level X_L. Let us imagine that the health security team opts to reduce the risk first, i.e. the swing S_x. The value of this reduction in the number of severe cases from X_L to X_* is measured by a *swing weight* of 100 ($S_X = 100$). This swing weight is a reference point that is then used to evaluate the other improvements. Subsequently, the health security team is

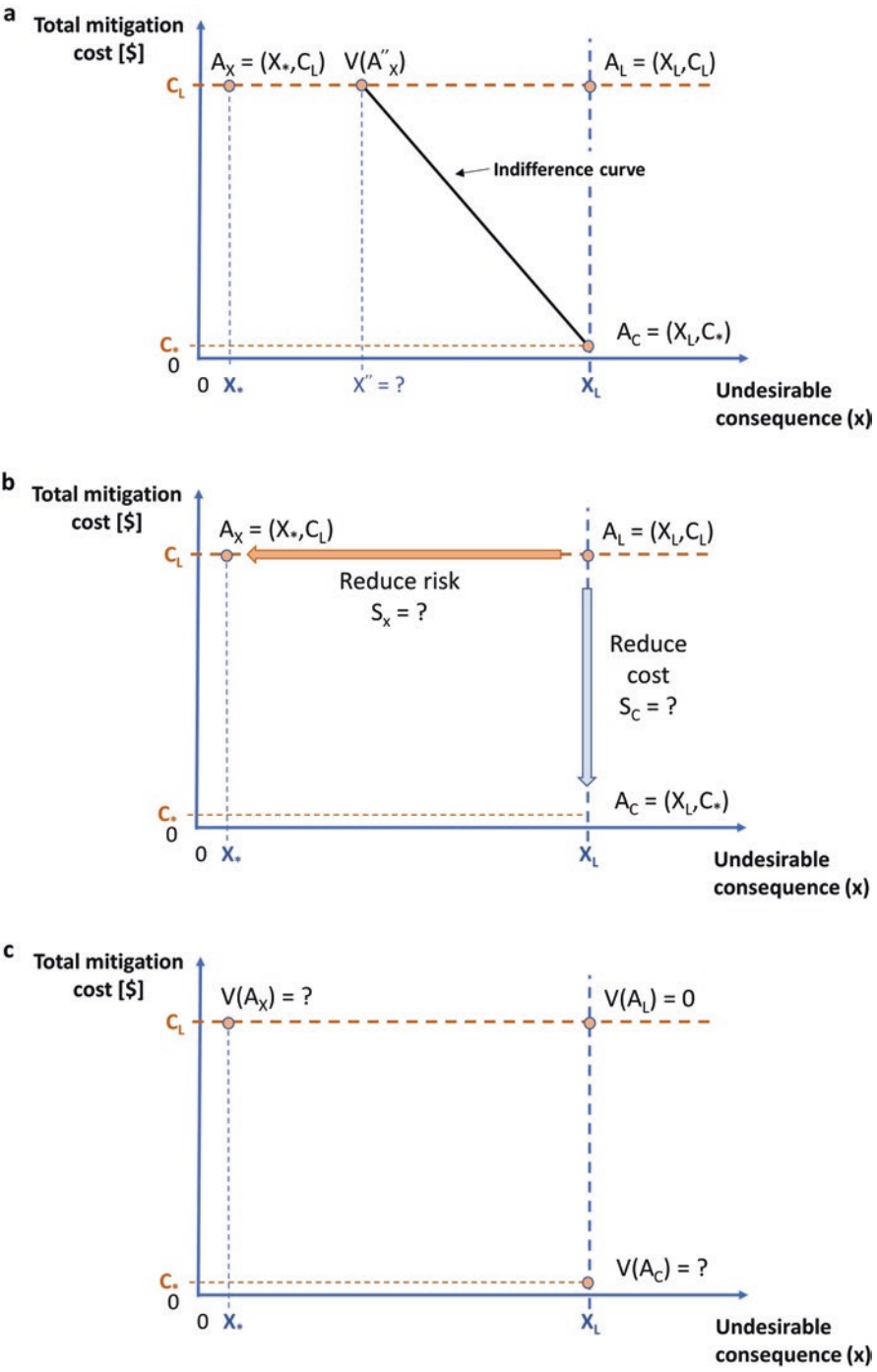

Fig. 6.19 Protocols for eliciting weights of decision objectives: (**a**) The trade-off method, (**b**) The swing-weights method, (**c**) The dummy alternatives method

tasked with evaluating the value of the second improvement, i.e. the swing S_C *in relation to* the first swing weight. Let us imagine that they assign 60 to this improvement in relation to the first improvement. This is the swing weight on the reduction of total mitigation costs ($S_C = 60$).

The normalized weights for each objective are given by the respective swing weight of each objective divided by the sum total of the swing weights. In the example, the normalized weight for the objective *minimize the number of severe cases* is: $w_X = S_x/(S_X + S_C) = 100/(100 + 60) = 62.5\%$; and the normalized weight for the objective *minimize total mitigation cost* is: $w_C = S_C/(S_X + S_C) = 60/(100 + 60) = 37.5\%$.

The swing weights method constitutes a protocol that can be easily implemented into practice and can be understood with relative ease. It is important that decision makers consider the ranges of the swing, instead of solely considering the "importance" of each objective.

However, health security teams often consider the notion of modifying the performance of a risk mitigating alternative to be unrealistic, and this constitutes a challenge that we encounter when conducting decision analysis interventions. For this reason, we have developed the dummy alternatives method (Montibeller, 2018), which shares the structure of the swing weights method while avoiding the concept of artificially swinging the performances (which is foundational to the swing weights method).

The Dummy Alternatives Method In this method, dummy alternatives (Farquhar & Pratkanis, 1993) represent the extremes points of the attributes, with each dummy alternative incurring the highest level of impact on one attribute and the lowest level on all the other attributes. In addition, a worst-case dummy alternative incurs the lowest performance on every attribute. Decision makers are tasked with ranking and valuing each dummy alternative, enabling weights to then be calculated from these relative valuations. The method consists of three steps: (i) rank the dummy alternatives in terms of their performances, (ii) identify the dummy alternative with the highest overall value and allocate a reference value of 100 to it, (iii) provide the relative value of the other dummy alternative against the first dummy alternative and the worst-case dummy alternative (value of 0).

This method is illustrated in Fig. 6.19c utilizing the same example above. The worst-case situation is represented by A_L and receives a value of zero: $V(A_L) = 0$. Decision makers are then asked to rank the two dummy alternatives in terms of their preferences: A_X or A_C. Let us assume that they select A_X over A_C, so that the reference value for alternative A_X becomes set at 100: $V(A_X) = 100$. Subsequently, decision makers would be asked to assess the value of A_C against A_X ($V(A_X) = 100$) and A_L ($V(A_L) = 0$). Let us assume that decision makers judge the value of this alternative to be 60, i.e. $V(A_C) = 60$.

The normalized weights for each objective are given by the value of the dummy alternative of the objective divided by the sum of the value of the dummy alternatives. In the example, the normalized weight for the objective *minimize the number of severe cases* is: $w_X = V(A_x)/[V(A_X) + V(A_C)] = 100/(100 + 60) = 62.5\%$; and the

normalized weight for the objective *minimize total mitigation cost* is: $w_C = V(A_C)/[V(A_X) + V(A_C)] = 60/(100 + 60) = 37.5\%$.

Notice that the choices presented by these three weight elicitation methods are similar to the choices discussed in the previous section, which considered actual decision alternatives. However, the elicitation methods for the prioritization of objectives are using hypothetical decision alternatives that cover the entire range of acceptable and feasible impacts (i.e. from X_L to X_* on number of severe cases and from C_L to C_* on total mitigation cost in the example in Fig. 6.19).

These weight elicitation protocols bring about some important advantages, which, when compared with an arbitrary definition of weights, can minimize biases in such judgments (Montibeller & von Winterfeldt, 2015). First, these protocols keep the definition of relative importance grounded on the ranges of the attributes. Second, said elicitation methods necessitate judgments that encompass the levels of impact that are both admissible and feasible. Third, the protocols support the defining of relative importance of objectives in a manner that is compatible with mathematical models for the aggregation of impacts, as discussed in the eight chapter.

6.3.3 *Avoiding Mistakes in the Prioritization of Objectives*

Defining trade-offs in choices that involve the prioritization of conflicting objectives or that encompass a multitude of impacts, is a task wherein we observe frequent conceptual mistakes. Throughout this task, there exist several conceptual and practical mistakes that should be avoided (see also Keeney (2002) for a detailed coverage) and biases that must be minimized within those judgments (see Montibeller and von Winterfeldt (2015) for details), which are briefly discussed next.

The first mistake involves a complete inability to make trade-offs. One reason for this attitude stems from an avoidance of making difficult choices that may imply moral judgments and require trading off health against economic considerations (Fiske & Tetlock, 1997; Tetlock et al., 2000). We see examples of this phenomenon when policy makers, while planning risk mitigating actions, consider any potential loss of human life objectionable on moral and ethical grounds and refuse to make any explicit trade-off between lives saved and the available budget for risk mitigation. Another reason for being unable to make trade-offs arises when decision makers regard these judgments as going against evidence-based medicine. The assumption that the choice should be entirely "objective" and evidence-led, neglects the need for difficult trade-offs (Hunink & Weinstein, 2014). However, as we continue to emphasize throughout this book, trade-offs are inherent to decisions with conflicting objectives and multiple impacts (Keeney, 1992, 2013).

The unfortunate consequences that arise due to an inability to make trade-offs are threefold. One is "paralysis by analysis" (Lenz & Lyles, 1985), whereby sophisticated models for epidemiological transmission or assessment of impacts are developed to support decision making but ultimately, decisions are delayed. Another problem involves the use of implicit or poorly conceptualize trade-offs, which guide

the choice but make the decision process highly opaque and reduce the decision quality (Spetzler et al., 2016). A third consequence entails a distorted allocation of scarce resources, with investments chosen without there being a reasoned decision process. This distorted resource allocation typically results in overspending per capita for some health-related investments, while underspending per capita for other health initiatives.

There exists a second mistake when defining trade-offs in choices that demand the prioritization of conflicting objectives or that encompass a multitude of impacts, whereby there exists an absence or an ambiguity involved in the measuring of consequences. Without the definition of an attribute to measure the achievement of an objective, members of the health security team may be considering distinctive impacts in the prioritization without realizing that a discrepancy has occurred. For example, the objective *minimize health impact* may be assumed by one member as meaning the number of casualties and by another member as meaning the number of severe cases; it is likely that these consequences do not incur the same relative importance.

The third mistake in prioritizing objectives arises from the notion of direct importance. In this case, decision makers allocate heavy weights to objectives that are considered to be "important", while disregarding the range of attributes, thus suffering from the range insensitivity bias (Fischer, 1995; von Nitzsch & Weber, 1993). This mis-conceptualization is recognized as the most critical mistake in decisions whose objectives are conflicting (Keeney, 1992), with ample evidence that this mistake does indeed occur in practice (Marttunen et al., 2018).

In the context of health security decisions, the range insensitivity bias may lead public health leaders to overweigh health-related objectives, regardless as to how narrow the ranges of the health-related attributes may be, or these leaders may under weigh other objectives, regardless as to how broad the ranges of these attributes may be. This bias is brought about by the presence of protected values, which may render health professionals insensitive to the quantities at stake (e.g. number of casualties *vs* mitigation cost) or provoke a feeling of a moral obligation to prioritize health over any other consequence (Baron & Spranca, 1997).

Moreover, a generic statement of priority, such as "we always seek to reduce health risks", or the concept of direct importance, such as "population health is the top priority", could lead to some choices that lack carefully considered elements. This was illustrated in Fig. 6.16 early in this section when considering risk mitigating actions against two health threats and the trade-off defined by the hypothetical alternatives A' and A''. While the additional total cost from alternatives A_2 to A_3 against the first health threat remains the same as the cost considered by the trade-off ($\Delta C = \Delta C_{23}$), the additional risk reduction from A_2 to A_3 is *greater* than the risk reduction defined by the trade-off ($\Delta X_{23} > \Delta X$), as represented in Fig. 6.16a. Therefore, we see that given this comparison against the trade-off and the performances of the decision alternatives, A_3 should be selected instead of A_2. The trade-off indicates that the additional risk reduction that A_3 provides more than compensates the additional cost associated with selecting this alternative.

Now let us revisit the choice between A'_2 and A'_3 against a second health threat described previously, using the same trade-off above (defined by the same hypothetical alternatives A' and A'') as a guideline for the selection of the best alternative. These options are shown in Fig. 6.16b. In this case, while the additional total cost from A'_2 to A'_3 remains the same as the cost considered by the trade-off ($\Delta C = \Delta C'_{23}$), the additional risk reduction from A'_2 to A'_3 is *lesser* than the one defined by the trade-off ($\Delta X'_{23} < \Delta X$), as depicted in Fig. 6.16b. Therefore, given this comparison against the trade-off, A'_2 should be selected instead of A'_3. The trade-off indicates that the reduction in the number of severe cases that A'_3 provides against A'_2 *is not* considered enough to compensate for the additional cost associated with A'_3.

In that second situation, if generic statement of priority were to be employed to guide choice, the decision alternative A'_3 would be selected. However, as we have argued and illustrated with regards to that example, this decision alternative provides a minor additional risk reduction ($\Delta X'_{23}$) for a substantial increase in mitigation cost ($\Delta C'_{23}$), in comparison with alternative A'_2. Were explicit trade-offs to be made, it is likely that these additional resources could otherwise be employed in other, more efficient, actions for health security enhancement.

A fourth mistake that can be present when defining trade-offs involves the assumption that there exist "correct" trade-offs which could be "objectively" defined. Trade-offs require difficult judgments that reveal a space wherein there resides longstanding collective values, and thus these judgements must be defined by *someone*; this *someone* is usually composed of multiple individuals, involving members of the health security team that is at the head of the decision, policymakers that oversee health security, or, citizens in participatory decision processes.

Traditionally, health security teams have been responsible for defining these priorities (Del Rio Vilas et al., 2013; Montibeller, 2018; Montibeller et al., 2020a; Phillips, 2007; Phillips & Bana e Costa, 2007). This responsibility is reasonable, as these teams have a robust understanding of the decision problem, are able to comprehend the different decision objectives and consequences, and are responsible for decision making and for the implementation of actions. More recently, attempts to directly involve citizens, by employing the elicitation of trade-offs through online surveys have been proposed as a means to further democratize the decision process (Aubert et al., 2020).

In health care, an important conceptual distinction exists between explicit trade-off judgments promoted by Health Decision Analysis, as detailed in this section, and implicit trade-off judgments promoted by Cost-Benefit Analysis (Brent, 2016). In the latter approach, all the impacts are monetized, with the trade-offs being implicit in the monetization (e.g. a health impact worth $10 million is twice as valuable as an economic impact worth $5 million). However, this monetization and its implicit trade-offs may prompt over-valuations of some impacts and under-valuation of other impacts, which may be incompatible with health security priorities.

The problems caused by monetization can be illustrated by the project that we conducted for the Food and Agriculture Organization of the United Nations and the World Health Organization, which entailed the ranking of low-moisture food

categories in terms of their overall impact (Montibeller, 2018), and which was initially introduced in the fourth chapter. Within this assessment, there were two major impacts for the assessment of the food categories: the *volume of international trade* for each food category (measured in US$ billion dollars per year) and the *burden of disease* caused by previous outbreaks affecting each food category (measured in total DALYs in outbreak cases from 1990 onward).

The range for international trade was established to be between US$ 118.594 billion/year (for the food category cereals and grains) and US$ 1.150 billion/year (for the food category seeds for consumption). The range of DALYs among the seven categories was established to be between 18.42 DALYs (for the food category seeds for consumption) and 136.44 DALYs (for the food category dried protein products) (FAO/WHO, 2014). Were the burden of disease to be monetized, this implicit trade-off would have considered the range of impacts for *burden of disease* (118.02 DALYs) as being negligible against the range of impacts for international trade (US$ 117.444 billion). However, an attempt to monetize health impacts in this project (an implicit trade-off) would be misaligned with the FAO/WHO remits and their organizational focus on improving human health. Indeed, the process of the elicitation of weights in conjunction with the health expert group, which was conducted by employing an explicit assessment of trade-offs, defined that the weight for the *burden of disease* impact was more than twice that of the impact on *international trade*.

When supporting public policy decisions, we have observed another issue, which arises when the elicitation of trade-offs is perceived by some experts as being "too subjective" when compared with the monetization of impacts promoted by Cost-Benefit Analysis (Brent, 2006; Layard & Glaister, 1994). No markets exist that are able to guide the monetization of all the impacts that are typical in health security decisions. Hence, cost-benefit studies in healthcare often must rely on willingness-to-pay or willingness-to-accept studies (Brent, 2016), both of which require judgments that are subjective by nature and may also suffer from cognitive biases (Gregory et al., 1993).

Therefore, any distinction between a more "objective" or less "objective" valuation is, in our view, misleading. Any decision that involves conflicting objectives, or, that must consider multiple impacts, always requires trade-offs. These trade-offs cannot be objectively defined: they must reflect societal priorities and be informed by the specific decision context. It is our opinion that making these trade-offs in an explicit manner in a health decision analysis (instead of implicitly as in a cost-benefit analysis) proves to be more helpful to decision makers, and transparent to societal decision making processes (Angelis et al., 2017).

In addition to this conceptual positioning in favor of Health Decision Analysis, the act of defining weights with health security teams that is promoted by a health decision analysis is significantly faster and more flexible than the typically time-consuming cost-benefit studies. When managing health threats, the rapidity with which decision processes that are under a time pressure are executed is an important and common consideration (Jaspersen & Montibeller, 2015).

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6.4 Making Judgments in Health Security Decisions

In this chapter we have emphasized the importance of making three types of judgments in health security decisions: defining risk limits, establishing marginal value functions over the consequences of interest, and identifying trade-offs when dealing with conflicting decision objectives.

Transparency is a crucial element in health security decisions, so that societies and communities become aware as to how policies are being considered and selected. This requirement necessitates the modeling of judgments (Dias et al., 2018; Keeney, 2002; Keeney & Raiffa, 1993; von Winterfeldt & Edwards, 1986) in a health decision analysis. Indeed, a major benefit brought about by a more explicit and structured process for evaluating health security actions is that this approach establishes a clear separation between the evidence available and the judgments that are employed, either to select risk mitigating options against health threats, or, to select the best alternatives for enhanced health security.

A major advantage of conducting a health decision analysis is that the problem is decomposed into its core components (Raiffa, 1968). Decomposing thus enables the health security team to identify as to *which* judgments are required, *the point* at which these judgements are required during the decision process, and *who* should provide each judgment. Some advice for the decomposition of judgment tasks and the involvement of experts and decision makers for each type of judgment is provided next.

Defining Risk Limits Risk limits may require judgments from either experts or policymakers. Experts are able to identify acceptable levels for technical attributes. Policymakers are able to identify acceptable budget limits and define acceptable societal levels for attributes measuring health, social, and economic impacts.

For example, in the vaccination campaign case, the risk limit associated with the objective *maximize the safety of vaccine stocks* could be established by health experts specialized in vaccines. On the other hand, policymakers could define the maximum budget available for this campaign.

Establishing Marginal Value Functions In general, experts are better positioned to define marginal value functions than policymakers, given that experts have extensive knowledge about impacts in their field of expertise. Experts are typically involved in the definition of attributes and subsequent specification of value functions over the attribute ranges. Health experts may provide such judgments for health-related attributes, economists for economic impacts and cost-related attributes, engineers for logistics and other technical attributes, and social scientists for attributes that measure social impacts.

For example, in the vaccination campaign case, experts in logistics could help to develop an attribute to evaluate the objective *minimize logistics complexity*. This could be a constructed attribute comprised of a set of discrete levels of impact that describes the logistics complexity involved in the campaign. Subsequently, these experts would provide a valuation for each level of impact by following the direct

rating method illustrated in Fig. 6.13. On the other hand, health experts could provide the value function over the attribute *proportion of population vaccinated*, using the bisection method shown in Fig. 6.12b.

Defining Trade-Offs The judgments required to define trade-offs should convey the priorities of the organization responsible for health security, given pre-defined organizational responsibilities and remits, while taking into account societal priorities. Often, these organizations are run at a national level and have a fiduciary duty of ensuring health security for their country. For this reason, high level trade-offs are thus typically defined by policymakers in charge of health security. Lower level trade-offs (when a top-level objective is decomposed into easier-to-measure attributes) are often defined by health experts, who have an understanding as to the different impacts that these attributes are measuring. Additionally, various different experts may be involved to define value trade-offs within their area of expertise.

For instance, in the vaccination campaign case, policymakers would define the trade-offs among the four categories of objectives: *maximize vaccination coverage*, *maximize campaign quality*, *maximize efficiency of the campaign logistics*, and *minimize campaign cost*. Health experts could identify trade-offs pertaining to the category of *maximize vaccination coverage*: (i) *maximize the immunization coverage rate*, (ii) *maximize the campaign reach across population strata*, and (iii) *minimize vaccine hesitancy*. On the other hand, logistics experts could provide suitable trade-offs for the category pertaining to *maximize efficiency of the campaign logistics*: (i) *maximize the storage quality of vaccine stocks*, (ii) *minimize logistics complexity*, and (iii) *maximize the speed of the campaign*.

Sound judgments made by knowledgeable experts (Morgan, 2014) and experienced decision makers, which are based on the best evidence available (Hunink & Weinstein, 2014), are critical for high quality decision processes (Spetzler et al., 2016). There exists a set of criteria for assessing the quality of these judgments (Gregory et al., 1993; Keeney, 1982, 2002) that should be met in practice. The judgments in a health decision analysis, as detailed in Table 6.1, should be informed, context-specific, consistent, stable, and transparent.

Table 6.1 Criteria for the quality of judgments in Health Decision Analysis (see also Gregory et al. (1993))

Criteria	Definition
Informed	Judgments should be informed by both the best available evidence and the input from high-quality experts and well-informed policymakers.
Context-specific	Judgments should be made about the specific decision situation, instead of generalized priorities or vague value statements.
Consistent	Judgments should be consistent and follow the axioms of Decision Theory (as discussed in the second chapter).
Stable	Judgments should evolve from when the situation has first been contemplated, but then be consolidated to guide the decision-making process. Judgments thus require careful reasoning and deliberation by experts and policymakers.
Transparent	Judgments should be transparent and their rationale explainable and openly communicated.

A major source of complexity for eliciting judgments is the presence of multiple decision makers, who may each have very different priorities, preferences, and risk tolerances. These decision makers need to be properly facilitated to reach a conclusion that can accommodate such different perspectives (Franco & Montibeller, 2010; Montibeller, 2018; Montibeller & von Winterfeldt, 2018).

Organizational culture also significantly informs the quality of judgments, particularly when considering both the manner that these priorities are interpreted and the level of transparency that is required throughout the decision process. Thus, this organizational influence necessitates a carefully designed decision process, wherein evidence, expert opinion, and judgments of policymakers are considered in a manner that maximizes the quality of the decision process (Spetzler et al., 2016), while recognizing the inherent organizational constraints (see Montibeller et al. (2020a) for details).

The two projects below illustrate how trade-offs and marginal value functions can be defined for real-world health security decision processes. In both cases we acted as facilitators, supporting the health security teams (Franco & Montibeller, 2010, 2011) and employing rigorous elicitation protocols when each team was defining judgments.

6.4.1 Defining Value Functions and Trade-Offs for the Ranking of Low-Moisture Food Categories (FAO/WHO)

The project that we conducted for the Food and Agriculture Organization of the United Nations and World Health Organization (FAO/WHO, 2014; Montibeller, 2018), for the prioritization of low-moisture food (LMF) categories, required that we define the attribute ranges, normalization of impacts and trade-offs. A set of attributes was defined to assess four categories of impact: on *International Trade*, on *Burden of Disease*, from *Vulnerabilities due to Food Consumption*, and from *Vulnerabilities due to Food Production*, as detailed in the fifth chapter. The definition of value functions and trade-offs for this project is detailed next.

Defining Value Functions Upper and lower limits for each attribute were based on the impacts of the LMF categories. The normalization of impacts over each attribute was performed utilizing linear value functions. For example, the *impact on international trade*, measured by the attribute *export value* [US$ billions/year], had a range from X^* = US$118.594 billion/year (generated by the food category *cereal and grains*) to X_* = US$1.150 billion/year (generated by the food category *seeds for consumption*). The value function over this attribute is shown in Fig. 6.20a. The linear shape of this function reflects the constant marginal value of every extra dollar of international trade.

The same type of linear normalization was created for the *impact from burden of disease*, measured by the attribute *total DALYs in outbreak cases* (since 1990).

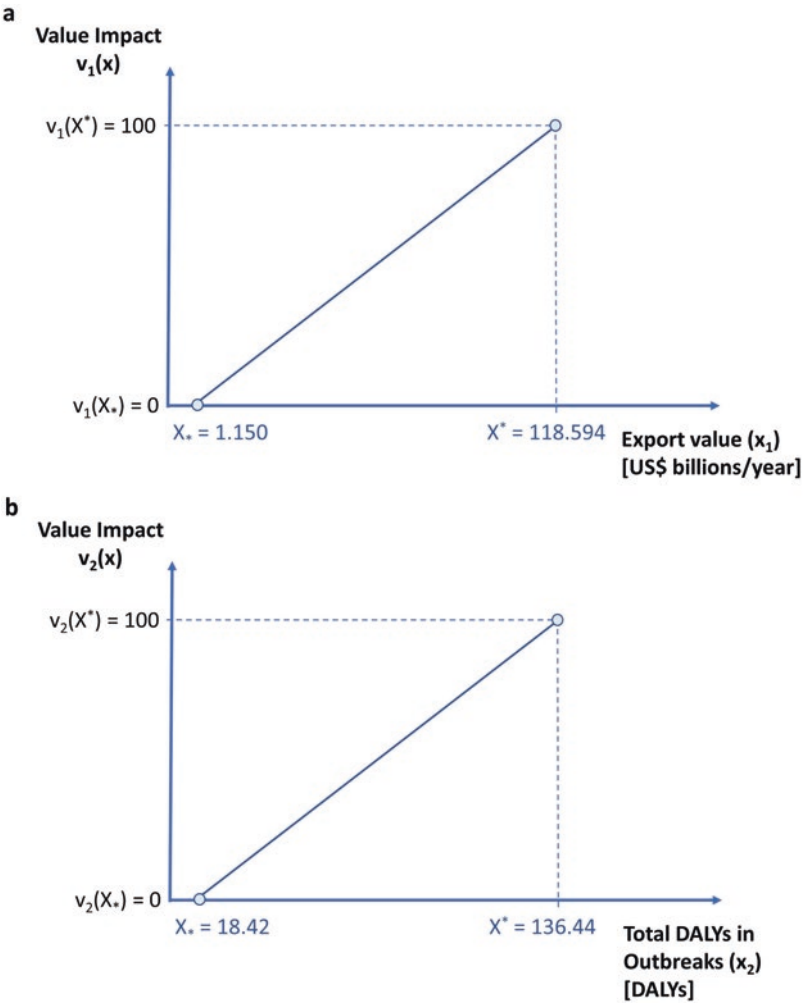

Fig. 6.20 Value functions of the impacts for the FAO/WHO low moisture food categories ranking: (**a**) Impact on international trade, (**b**) Impact from burden of disease

Here, the lowest level of impact was $X_* = 18.42$ DALYs (caused by the food category *seeds for consumption*) and the highest level of impact was $X^* = 136.44$ DALYs (caused by the food category *dried protein products*). The value function over this attribute is presented in Fig. 6.20b, whereby the higher the DALYs impact, the higher the normalized impact score. The linear shape of this function reflects that every extra DALY caused by contaminated food is of equal concern.

Eliciting Trade-Offs We employed the dummy alternatives method for the elicitation of trade-offs from the LMF expert group. For this model, the trade-off elicitation provided the weights for each branch of the value tree, which is reproduced in Fig. 6.21.

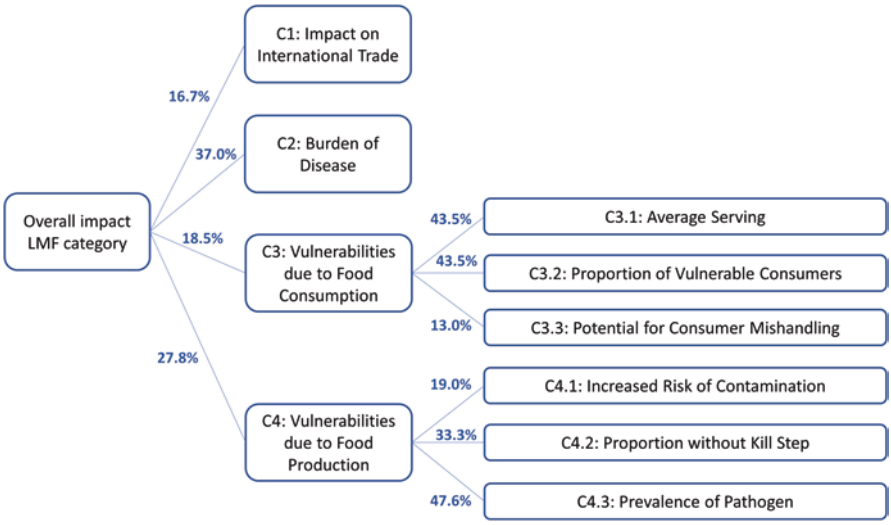

Fig. 6.21 Normalized weights for the impact categories and impacts of the value model to prioritize the overall impact of low moisture food categories

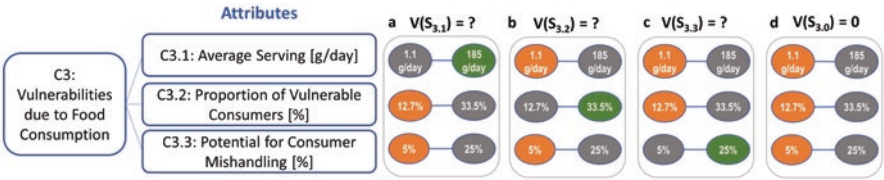

Fig. 6.22 Elicitation of trade-offs for the attributes composing the impact category *C3: Vulnerability due to food consumption* (adapted from Montibeller, 2018): (**a**) Hypothetical LMF category $S_{3.1}$ with the highest impact on attribute C3.1 and the lowest impact on attributes C3.2 and C3.3, (**b**) Hypothetical LMF category $S_{3.2}$ with the highest impact on attribute C3.2 and the lowest impact on attributes C3.1 and C3.3, (**c**) Hypothetical LMF category $S_{3.3}$ with the highest impact on attribute C3.3 and the lowest impact on attributes C3.1 and C3.2, (**d**) Hypothetical LMF category $S_{3.0}$ with the lowest impact on attributes C3.1, C3.2, and C3.3

The dummy alternatives protocol is illustrated for the attributes that decomposed the third category of impact, *vulnerability due to food consumption* in Fig. 6.22. Here, four hypothetical food categories ($S_{3.1}$, $S_{3.2}$, $S_{3.3}$, and $S_{3.0}$) were presented by the expert group. The first three categories had one impact located at the highest level on one attribute and the other impacts were located at the lowest level on the remaining attributes, while the food category $S_{3.0}$ had the lowest level of impact on all the attributes. These upper and lower levels were identified from the maximum and minimum impacts of each food category (in the same manner that was also described previously for the *impact on international trade impact* and *impact from burden of disease* attributes).

The health expert group was then asked to rank these four hypothetical food categories, scoring the highest dummy food category as 100, $S_{3.0}$ as 0, and the other

dummy food categories were scored proportionally to this first one. The group valued both $S_{3.1}$ and $S_{3.2}$ as 100 and $S_{3.3}$ as 30, thus: $V(S_{3.1}) = 100$, $V(S_{3.2}) = 100$, $V(S_{3.3}) = 30$, and $V(S_{3.0}) = 0$. From these valuations we could calculate the normalized weight of these three attributes as:

$w_{31} = V(S_{3.1})/[V(S_{3.1}) + (S_{3.2}) + V(S_{3.3})] = 100/230 = 43.5\%$;
$w_{32} = V(S_{3.2})/[V(S_{3.1}) + V(S_{3.2}) + V(S_{3.3})] = 100/230 = 43.5\%$;
$w_{33} = V(S_{3.3})/[V(S_{3.1}) + V(S_{3.2}) + V(S_{3.3})] = 30/230 = 13.0\%$.

The same protocol was employed to elicit weights for the impacts that fell under the impact category of *vulnerabilities due to food production* (i.e. weights for the attributes C4.1., C4.2, and C4.3 in the value tree shown in Fig. 6.21). Subsequently, weights were elicited in a similar manner for the four main categories of impacts (C1, C2, C3, and C4 in the same figure).

6.4.2 *Defining Value Functions Over Impacts Caused by Emerging Animal Health Threats (DEFRA)*

The project that we developed for the UK Department for Environment, Food and Rural Affairs (DEFRA), to support the ranking of emerging animal health threats is able to illustrate the use of the direct rating method for value function elicitation as well as illustrating how value function can be adapted for the assessment of health threats.

Alongside the DEFRA experts, we developed a set of three constructed attributes to assess the perceived impact that an emerging animal health threat may cause, as presented in the previous chapter. Each attribute has a clear definition agreed upon by the group and is comprised of an ordered set of qualitative labels (from Level 5, highest impact, to level 1, lowest impact) (Del Rio Vilas et al., 2013).

In evaluations that are assessing health threats, the value scores measure the *dis-value* $V^{-}(.)$ caused by a health threat (Montibeller et al., 2020b). In this case, the uppermost impact level receives a dis-value of 100 and the lowermost impact level a dis-value of 0.

The value scores for the objective *minimize personal concern*, shown in Table 6.2, were obtained with the DEFRA Veterinary Risk Group. The dis-value of the lowermost level of impact (L_1) was established to be zero ($v^{-}(L_1) = 0$) and of the uppermost level of impact (L_5) to be 100 ($v^{-}(L_5) = 100$). The dis-value scores of these intermediate levels are demonstrated in the same table.

The direct rating method, illustrated in Fig. 6.13, could be used to value the intermediate levels of impact through considering the value distance between adjacent levels. Notice that the value scores for intermediate levels in Table 6.2 are not necessarily equidistant in terms of dis-value, thus we see that it becomes important to elicit the value scores of these intermediate levels from the health security team.

The valuation of levels for the more complex attributes, such as the attribute for the *impact on public healt*h shown in Fig. 6.23, could be elicited in a similar manner using the direct rating method. Here, the level of impact L_{10} was established to be

Table 6.2 Defining the dis-value for the attribute Personal Concern in the DEFRA model for the ranking of emerging animal health threat (Del Rio Vilas et al., 2013)

Dis-Value $v^-(.)$	Level	Attribute: Personal concern
100	Level 5	Perceived threat: dreadful. Recent alarming/frightening news in the media (e.g. the BSE outbreak)
85	Level 4	Perceived threat: serious. Recent alarming/frightening news in the media (e.g. the avian influenza outbreak)
50	Level 3	Perceived threat: moderate. Recent adverse news in the media (e.g. the VTEC O157 outbreak)
25	Level 2	Perceived threat: moderate. No news in the media (e.g. the Q-fever in the Netherlands outbreak)
0	Level 1	No perceived threat. No media reports (e.g. equine infectious anaemia 2010 outbreak)

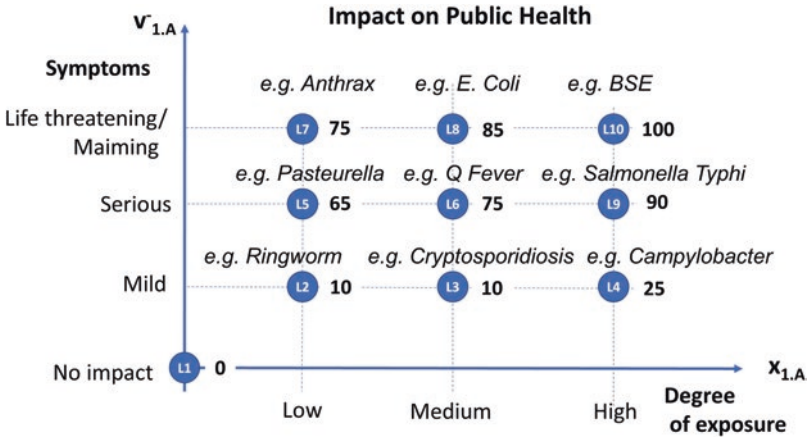

Fig. 6.23 Defining the dis-value for the attribute Impact on Public Health in the DEFRA model for the ranking of emerging animal health threat. (Adapted from Del Rio Vilas et al., 2013)

100 ($v^-(L_{10}) = 100$) and L_1 to be 0 ($v^-(L_1) = 0$). Notice that the dis-value of each level is a consequence of both the symptoms and the degree of exposure, and therefore, both dimensions required simultaneous consideration within the valuation.

6.5 Conclusions: Defining Risk Limits, Marginal Value, and Trade-Offs

Every health security decision must balance conflicting objectives, consider multiple consequences, and manage critical risks. These complexities require reasoned judgments with regards to priorities in the achievement of objectives, the marginal valuation of consequences, and the definitions of levels of acceptable risks.

In this chapter we have presented several important concepts about how these judgments should be made in decisions whose objectives are conflicting. We have stressed that there is a need for a clear definition of risk and have consequently suggested three conceptualizations that are commonly used in health security practice. We have also highlighted the importance of defining realistic risk limits, conceptualized as thresholds of undesirable consequences that demarcate acceptable and unacceptable levels of impact, and discussed the significance of defining these limits for the subsequent choice of decision alternatives.

We have argued that the marginal value over relevant consequences may not be always constant, as is typically assumed in Cost-Benefit Analysis and other types of efficiency analyses of health systems. The elicitation of value functions, which is able to measure the value added of achieving objectives, enables a more detailed assessment and precise valuation of decision alternative and health threats.

The definition of trade-offs among conflicting objectives is perhaps the most difficult judgment in health security decisions and is therefore prone to conceptual mistakes. In this chapter, we have highlighted the necessity of considering attribute ranges and the specific decision contexts when making this type of judgment, thereby avoiding the misconception of considering the intrinsic importance of an objective.

There exist many benefits to making judgments in an explicit manner, rather than implicitly and opaquely, and in adopting the conceptual tools that were covered in this chapter. First, transparent judgments enable decision makers to adequately consider how much they value the achievement of each decision objective that is being pursued. Second, transparent judgments enable a clear and transparent consideration of trade-offs among the negative impacts that the health security team is seeking to minimize, or, of the benefits and costs of health security decision alternatives. Third, transparent judgments provide clear guidelines for acceptable (and unacceptable) levels of impacts of health threats, as well as for performance levels of health security actions. Fourth, such judgments allow for transparency, accountability, and coherence to be present in decision processes and in difficult health security choices that must be made.

At this point in a decision process, we already have a fully developed understanding of the decision problem, a clear definition of decision objectives and consequences that are relevant in the specific decision context, well-designed attributes to measure said consequences, a comprehensive mapping of the key uncertainties that may affect the relevant consequences, well thought-out priorities, clear risk limits, and explicit assessments of marginal value over consequences.

This deeper understanding of the decision at stake, which is provided by a health decision analysis, is now able to support the health security team to further develop decision alternatives, beyond the set of original alternatives (that are typically few in number) under consideration. Thus, we shall take one step back and consider in greater detail how we can increase creativity and develop superior alternatives for health security decisions, which shall constitute the topic of the subsequent chapter.

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Chapter 7
Developing Decision Alternatives for Enhanced Health Security



In health security decisions, it is not possible to identify a solution for a health security problem that is better than the solution that is provided by the *best* decision option among all other options under consideration. This point highlights the importance of identifying, or, indeed, designing, strong decision alternatives for enhancing health security, or, for adequately managing health threats. Hence, the potentiality of identifying or developing decision alternatives whose societal value is high proves to be one of the major benefits of conducting a health decision analysis.

Nevertheless, there exist several cognitive biases whose presence may prevent individuals from identifying or developing strong decision alternatives. Additionally, organizational constraints and culture may exert negative pressures on health security teams, who, in turn, must make decisions regardless as to whether an adequate period of time or effort has been allocated in order to improve the quality of decision alternatives. Indeed, there exists behavioral evidence that decision makers are often focused on evaluating a single policy option and cogitate only minor adjustments to the design of this policy, instead of evaluating a varied set of decision alternatives and selecting the best alternative(s).

This chapter discusses these barriers that arise and hinder the development of robust decision alternatives, and provides several suggestions as to how we are able to generate a greater number of options that are of greater value. There exist two principal ways to either improve existing alternatives, or design new alternatives, both of which necessitate that we adopt a perspective that thoroughly takes into account the possible consequences of implementing these alternatives, and, that effectively manages the key uncertainties that affect these consequences.

In the second chapter, we presented a diagram that illustrates the decision stages required for making reasoned health security decisions, and which has been reproduced in Fig. 7.1. The present decision stage, *developing decision alternatives*, is now highlighted in this modified figure. We shall assume that the problem has been defined and agreed upon by the health security team and that relevant objectives and consequences have been defined. Additionally, decision alternatives are able to be

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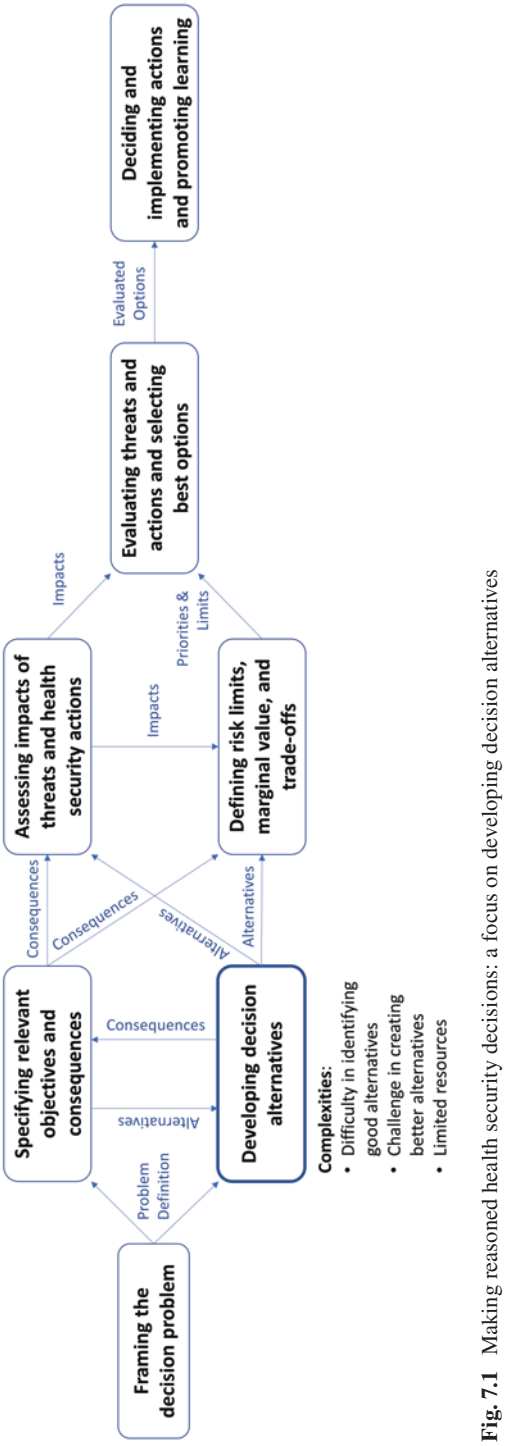

Fig. 7.1 Making reasoned health security decisions: a focus on developing decision alternatives

both improved and expanded upon once key uncertainties, trade-offs, and risk limits have been defined. Consequently, this topic of developing decision alternatives shall constitute the discussion of this seventh chapter.

7.1 Designing Decision Alternatives: Biases and Properties of Good Options

Most of the Decision Analysis and Risk Analysis literature is primarily focused on the *evaluation* of decision alternatives or risks. There exists an implicit assumption in these literatures that a set of decision alternatives has already been pre-defined and is static in character, and consequently that the main task of decision makers entails the selection of an alternative among said set. However, decision making should be viewed as a dynamic process (Roy, 1987, 1993), wherein there exists a potentiality for decision alternatives to evolve and improve until a choice is made (Franco & Montibeller, 2011b; Roy, 1996).

This dynamic perspective on decision making processes brings to the forefront the crucial task of developing, instead of merely choosing, decision alternatives (Keeney, 1992, 2004). Unfortunately, the Decision Sciences literature that addresses the topic of designing better decision alternatives remains rather limited, especially when compared with the extensive developments that have been made on evaluating decision options. This chapter draws from this limited yet relevant literature, which seeks to address how to develop better decision alternatives (see Keeney (1992, 2004), Keller and Ho (1988), and Franco and Montibeller (2011b) for details).

As we have mentioned above, it is impossible to select a better alternative than the alternatives available in the option set. If all the options have been poorly designed, (and could therefore incur potentially major drawbacks, high costs, and limited benefits) then regardless as to how much effort is expended making reasoned choices, we shall inevitably select a an option that is inadequate (Brown, 2005; Keeney, 1992).

Selecting risk mitigating actions that prove extremely costly while incurring few additional benefits form a common example of this issue. For instance, consider a country that is well-prepared against a bio-weapon attack. An over-zealous attitude may act as a motor, propelling the country toward maintaining an investment in more sophisticated defense policies, even if the additional (and minor) reduction in bio-security risk proves extremely expensive, and expends resources that could otherwise be allocated to other parts of a health system (on this diminishing marginal risk reduction see the analysis by Zawadzki et al. (2022) for security defense investments).

We know that identifying or developing potentially good alternatives underpins a reasoned decision making process. On the other hand, the history has been riddled with decisions wherein poor health security solutions have been selected and subsequently implemented (Harrison, 2004). Thus, we find ourselves confronted by this

paradox and, ergo, the question must be asked as to why these poor solutions have historically been chosen. The reason for these poor solutions stems from a set of cognitive and organizational barriers which hinder the development of strong alternatives, and shall be discussed in the subsequent section.

7.1.1 Identifying Barriers against the Development of High-Value Alternatives

Several individual cognitive and motivational biases, as well as group and organizational biases, may affect the identification or development of good alternatives. Let us start with the cognitive biases (Montibeller & von Winterfeldt, 2015). First, there exists ample behavioral evidence that the omitted variable bias (Jargowsky, 2005) significantly influences the generation of decision alternatives. Additionally, due to the presence of this bias, important options are excluded from a given set of options, or, these options are not generated at all (Butler & Scherer, 1997; Jungermann et al., 1983; Pitz et al., 1980). Second, like the anchoring bias for quantitative estimates (Furnham & Boo, 2011), the anchoring of all generated alternatives to the initial option set may occur (Keeney, 1992). Third, a myopic problem representation (Legrenzi et al., 1993; Legrezni & Girotto, 1996) may lead to decision makers adopting a focus that is excessively narrow, preventing them from cogitating potentially attractive options (Payne et al., 1999; Russo & Schoemaker, 1989). Fourth, the availability bias may influence the development of alternatives, whereby the initial consideration of some alternatives prevents the generation of new alternatives whose character is particularly distinctive in comparison with the character of the set of alternatives under appraisal (Del Missier et al., 2007).

Additionally, motivational biases may also affect the generation of decision alternatives (Montibeller & von Winterfeldt, 2015). One such motivational bias is the desirability of options bias (von Winterfeldt, 1999), which may lead to the exclusion of alternatives that could compete with the alternative that has been initially and intuitively identified as being preferable. The affect influenced bias is another relevant motivational bias (Finucane et al., 2000; Slovic et al., 2004) whose presence may lead to the exclusion of alternatives that provoke some negative feelings even if they may have strong benefits.

Health security teams may also suffer from biases affecting group judgments, which may hinder the identification or generation of decision alternatives (Montibeller & von Winterfeldt, 2018). Cohesive groups are particularly prone to reaching a false consensus (Ross et al., 1977), whereby individual participants overestimate the similarities between their own individual opinions and those of other group members, while simultaneously viewing alternative perspectives as being uncommon or unorthodox. False consensus may divert the attention of the group toward a narrow set of options, which is then falsely believed to be shared by the group. Decision making groups may also suffer from groupthink (Janis, 1983) whose presence results in group members aiming to attain a general consensus,

regardless as to how this consensus is actually formed or whether the consensus proves detrimental when appraising other courses of action that could lead to new decision alternatives. In such cases, there exists a strong pressure to conform to the group opinion; groupthink may also lead the team to form dysfunctional shared representations of the decision situation (Kerr & Tindale, 2011). False consensus and groupthink form two group biases that may lead to an incomplete search for alternatives (Jones & Roelofsma, 2000) and an excessively fast convergence toward a simplistic solution.

There also exist organizational biases that affect the development of decision alternatives, and thus prove to be a major cause of failures in strategic decision processes (Nutt, 1993). Four of these biases are particularly significant, and the presence of which has been demonstrated by ample empirical evidence (Nutt, 2004). First, we often observe that decision makers act precipitately, and that this behavior is rooted in an understandable desire to rapidly manage a health threat. This precipitancy is particularly the case for many health security decisions, which are time sensitive. Furthermore, decision makers are often under pressure to "be in control", "be decisive" and "do something about the problem".

Indeed, while some decision are urgent and thus demand immediate action, such as firefighters that must extinguish a high-rise building fire (Klein, 2017) or doctors that treat patients afflicted by a contagious disease in a hospital, most health security decisions would otherwise benefit from a greater amount of time being allocated to the generation of creative solutions. Often, we observe that managers characterize a decision as urgent merely as a way to reduce the amount of time spent deliberating and to expedite a preferred alternative.

The second organizational bias entails the rapid adoption of a simplistic solution which is lobbied by an influential stakeholder. Typically, this stakeholder has their own interests and motivations regarding an issue, which leads to the proposal of a simplistic solution which is in accordance with their narrow perspective. Decision makers then act precipitately on such claims, while lacking a clear understanding as to the complexities of the decision setting, not cogitating the consequences of interest, or, not understanding the key uncertainties involved in the decision. This attitude constricts the decision effort by shifting the effort onto a single solution and preventing the exploration of other alternatives.

The response of the UK government during the first year of the COVID-19 pandemic in 2020 may be explained by this organizational bias, which was characterized by wide action swings driven by stakeholders which were focused on health (and were consequently promoting a full lockdown during the spring), followed by business sectors that were lobbying for the re-opening of businesses by utilizing incentives for the population to socialize and consume over the summer period (Calvert et al., 2020a, b).

The third organizational bias involves a limited effort allocated to the generation of decision alternatives (Gregory et al., 2012; Nutt, 2004). In this case, most effort is placed on the consideration of a single solution that has been preferred a priori. Subsequently, arguments are developed to "defend" said solution against criticism (Garvin & Roberto, 2001) and to perform minor adjustments to this single

alternative. Any data analysis in these situations is partial and distorted, and is focused on promoting the solution while neglecting any major drawback or costs that the solution may incur. Organizational efforts and resources are fully devoted to supporting this single solution, and therefore shift away from expanding the set of decision alternatives. This situation is a common problem in policymaking, where, rightly, there exists a pressure to foster transparency and evidence-based recommendations, while simultaneously the need to justify a pre-made choice gives rise to the process of biased data gathering.

Another relevant organizational bias, which may prevent the design of high value decision alternatives, is a lack of clear decision objectives that are fundamental to the specific decision situation (Keeney, 1992, 2013). If there occurs a failure to clearly define objectives, it becomes simply impossible to find, or develop, a high-value alternative. This may sound rather obvious, yet nonetheless, an absence of a clear definition of fundamental decision objectives is an issue that we have frequently identified when supporting strategic decision making.

Consider the example of a country that is preparing against a bio-weapon attack. If the country does not have a clear understanding as to the impacts that it wishes to minimize, (such as number of casualties, levels of fear, impacts on the economy, etc.) then decision makers shall be rendered unable to design a preparedness policy that can effectively minimize these impacts and, in trying to mitigate security risks that have been poorly understood, may allocate scarce resources inefficiently.

However, there exist three solutions to prevent or minimize these biases. Cognitive and motivational biases must be dealt with using debiasing tools (Montibeller & von Winterfeldt, 2015), which we shall describe throughout this chapter for improving the generation of decision alternatives. Group biases must be addressed through improving group decision making processes (Franco & Montibeller, 2010, 2011a) and reducing group judgment biases (Kerr & Tindale, 2004, 2011; Montibeller & von Winterfeldt, 2018). Organizational biases must be addressed by better organizational processes which focus on improving decision quality (Spetzler et al., 2016) in health security decisions (Montibeller et al., 2020). If we are to break down these barriers and thus, generate a greater number of alternatives, how can we know whether these are potentially high-value alternatives? The properties that must be present in a set of alternatives in order for these alternatives to be deemed as good can aid in this assessment, and shall be detailed in the subsequent section.

7.1.2 Verifying Properties of Potentially High-Value Decision Alternatives

A decision alternative is a complete solution to a specific decision situation which can be assessed on all the relevant consequences under consideration. The decision alternatives in the option set should be mutually exclusive, (i.e. only a single

alternative can then be selected for implementation[1]). In addition, in order for an alternative to be of potentially high-value, several properties are desirable as detailed next (Gregory et al., 2012; Parnell et al., 2013; Spetzler et al., 2016).

Focused on Fundamental Objectives Decision alternatives should be developed with a focus on achieving the fundamental objectives for the specific decision situation (Keeney, 1992), as defined by the relevant consequences and assessed by the respective attributes.

For instance, consider the vaccination campaign case that has been introduced in the fourth chapter. A design of decision alternatives which is focused on achieving the fundamental objectives in this specific decision situation would seek to identify different types of vaccination campaigns that could achieve said objectives: *maximize vaccination coverage*, *maximize campaign quality*, *maximize logistics efficiency*, and *minimize campaign costs*.

This decision-focused design directly contrasts with the defining of decision alternatives whose objectives are not explicitly listed and relevant consequences that are not clearly specified. In this common situation, it is unlikely that the implemented alternative shall provide solutions with high societal value for the specific decision situation.

Complete and Comparable Decision alternatives must address all the relevant consequences pertaining to the specific decision situation over the same time horizon and under the same underlying assumptions about events and conditions (Gregory et al., 2012). Isolated health security actions to alleviate some of the issues of concern thus do not constitute a complete decision alternative.

In the vaccination campaign case, a decision alternative would necessitate that the actions pertaining to each category of interest be specified. This specification would entail question such as: How shall the coverage be assured? How shall the quality of the vaccine stocks be maintained? How shall the vaccines be transported, delivered, and stored? What shall be the total cost that these actions incur? Additionally, the decision alternatives for the vaccination campaign (each one constituted by a set of well-specified actions) would need to be assessed with regards to the same time horizon, covering the same geographical area, and covering the same population. For instance, the alternatives could either consider a campaign duration of 6 months, whose aim it would be to vaccinate the population of a specific region, or, conversely, a campaign duration of 12 months, which also aims to vaccinate an entire country. This consideration is in contrast with alternatives whose assumptions have been poorly defined, and consequently would prevent a like-for-like comparison of benefits and costs of said decision alternatives.

The alternatives for the vaccination campaign would also necessitate that we consider the immunization against the same well-specified health threat (i.e., a

[1] In the tenth chapter we discuss the case wherein a portfolio of alternatives must be selected, which occurs when this requirement of mutually exclusive alternatives is relaxed.

specific infectious disease with clearly defined characteristics). While this consistency may prove easier to achieve for well-known infectious diseases such as rubella or measles, consistency proves much harder for emerging diseases, given the scientific uncertainties about their evolution and the potentiality of rapid mutations. Once again, this requirement highlights the importance of making explicit assumptions about the health threat, so that the decision alternatives address the same levels of impacts caused by the threat.

Fully Specified and Internally Coherent The decision alternatives should be specified with a sufficient level of detail, thereby avoiding ambiguities that would cause errors and inconsistencies in the estimation of potential consequences. The combination of actions that compose an alternative should be internally coherent, i.e., the individual elements are both feasible and make logical sense (Gregory et al., 2012; Parnell et al., 2013).

Let us again consider the vaccination campaign case again. The two options that had originally been developed, *centralized in hospitals* or *decentralized in community centers* are not yet fully specified. The health security team must define precisely how each alternative would be configured, (i.e. a detailed set of actions that would be required by a vaccination campaign centralized in hospitals, as well as a similarly detailed set of actions for a campaign decentralized in community centers). The absence of this level of detailing would render a realistic appraisal of the benefits and costs of each alternative impossible.

The actions that compose each decision alternative for the vaccination campaign must be internally coherent. For example, the campaign must plan suitable logistics solutions for the transportation of vaccines, and these solutions are contingent on whether the campaign is centralized (large batches of vaccine stocks would require transporting from producers to hospitals), or, whether the campaign is decentralized (small batches would require transporting to community centers). Furthermore, these logistics solutions must be compatible with the storage facilities that are available in hospitals, and, must take into account which storage facilities are able to be emplaced in community centers.

Creative and Diverse The alternatives should provide creative solutions to a complex decision problem while being potentially feasible given the available resources. The option set should also be diverse enough. Specifically, the set of options should provide distinct ways of, and emphases on, achieving the competing objectives that the decision makers are seeking to address (Gregory et al., 2012; Spetzler et al., 2016). Alternatives should therefore not be conceived as solutions that incur minor variations to a single base-line option, a practice which is often observed in public policy design.

The two decision alternatives in the vaccination campaign case (centralized or decentralized campaigns) are clearly diverse, as each option would lead to different impacts on the four category of objectives (*vaccination coverage*, *campaign quality*, *logistics efficiency*, and *campaign costs*). For instance, a vaccination campaign that would take place in community centers would likely incur higher costs than if the

Table 7.1 Properties of potentially high-value decision alternatives

Property	Description
Focused on fundamental objectives	The decision alternatives should be developed with a focus on achieving the fundamental objectives for the specific decision situation
Complete	The decision alternatives must address all the relevant consequences of the specific decision situation
Comparable	The decision alternatives must be planned over the same time horizon, and must adopt the same underlying assumptions about events and conditions
Fully specified	The decision alternatives should be specified with a sufficient level of detail so that a realistic appraisal of their consequences (if implemented) be rendered feasible
Internally coherent actions	The combination of actions that compose each alternative should be internally coherent, logical, and potentially feasible
Creative and diverse	The decision alternatives should provide creative and diverse solutions to address the specific decision situation under consideration

campaign took place in hospitals, while vaccination coverage may prove higher were the former to be selected over the latter. Undeniably, these two solutions are polarized, and creative solutions could be developed by amalgamating some features from both alternatives in order to form hybrid options.

It is important that we treat the feasibility requirement with care. Often creative options are discarded immediately under claims that they are not feasible, but this attitude may be due to the status quo bias (Kahneman et al., 1991; Samuelson & Zeckhauser, 1988), which favors conservative solutions. Specifically, decision makers suffering from this bias prefer the current status quo option and are unwilling to adequately value alternative options. Hence, only truly unfeasible alternatives, whose performances fall outside acceptable levels of a hard constraint should be eliminated (Parnell et al., 2013). The six properties for decision alternatives are summarized in Table 7.1.

We now turn toward and focus on concepts and ideas that can aid in the development of decision alternatives by considering the properties listed in this table. We begin with a focus on decision alternatives that can better manage the relevant consequences, which is discussed in the next section.

7.2 Developing Decision Alternatives: Managing Relevant Consequences

Ultimately, we choose a health security alternative in order to achieve the fundamental decision objectives in the specific decision situation. As we have seen in the fourth chapter, the achievement of each fundamental objective is reflected by the relevant consequence associated with said objective. When making reasoned health security decisions, we wish to both reduce the negative consequences caused by health threats and to gain positive consequences from health security actions which

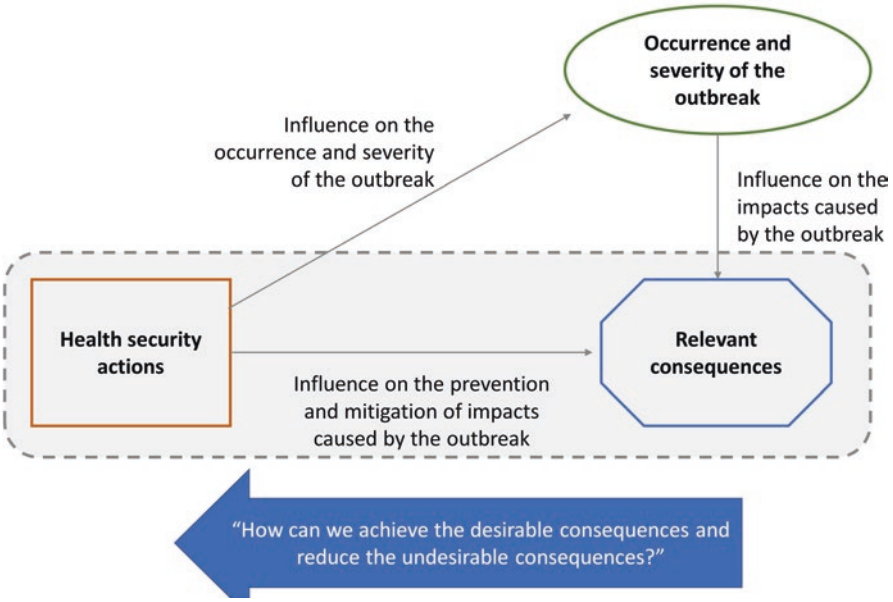

Fig. 7.2 Developing decision alternatives – a focus on managing consequences

are able to enhance the population health and generate other benefits. Indeed, the choice of alternatives is a mere *means* to achieve these fundamental objectives, and the greater the extent to which they are achieved, the higher the societal value of the selected option shall be (Keeney, 1992, 2013).

Therefore, a robust way to search for potentially high-value alternatives, or to develop better alternatives, necessitates this exact focus, which seeks to achieve (to the greatest possible extent) the fundamental objectives which are associated with the relevant consequences. This aim can be achieved by identifying health security actions that influence both the achievement of desirable consequences and the reduction of undesirable consequences. This process can be conceptualized and presented utilizing an influence diagram which represents health security decisions, described in the fifth chapter and modified in Fig. 7.2. Here, we make suggestions as to the tools that can be employed to expand the option set, which are based on this focus on fundamental objectives and the associated relevant consequences (see Keeney (1992) and Gregory et al. (2012) for a more detailed coverage).

7.2.1 Generating Decision Options

The fundamental objectives listed in a value tree represent all the relevant objectives and associated consequences pertaining to a specific decision situation, as detailed in the fourth chapter. The greater the extent to which an alternative is able to achieve

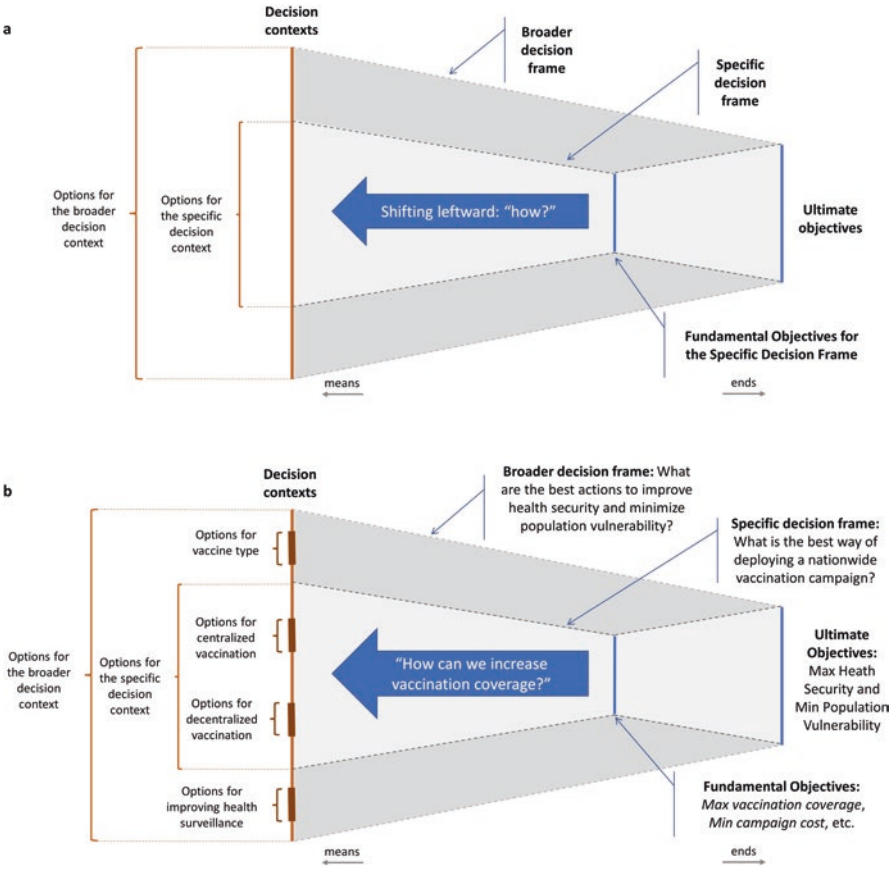

Fig. 7.3 Shifting leftward from fundamental objectives to decision alternatives: (**a**) The question probe "how?" in the specific decision frame, (**b**) The question probe "how" in the vaccination campaign case

the desirable consequences and reduce the undesirable consequences, the greater the degree of societal value that this alternative can generate. An effective way to expand the number of alternatives entails focusing on a single objective at a time and in turn, identify options that can perform particularly well with regards to that objective (Butler & Scherer, 1997; Keeney, 1992). These options would involve actions or solutions that could reduce a consequence that is undesirable or, instead, increase a consequence that is desirable. It is likely that this alternative would perform poorly when evaluating with regards to other objectives, ergo, this evaluation and screening process should be delayed during the process of generating options to avoid constraining creativity.

In order to relocate from the *ends* that decision makers wish to achieve, to the *means* that shall enable the achievement of these ends, we must ask the question probe: "how?" (Keeney, 1992). Using this probe recursively shall direct the health security team from the fundamental objectives (ends) to the decision alternatives

(means). This probe acts as a motor, shifting the perspective leftward, and is depicted in the decision frame shown in Fig. 7.3a. Here, the fundamental objectives for the specific decision frame should guide the search of options for the specific decision context. Notice that this value-focused brainstorming (Keeney, 2012; Montibeller & Franco, 2011b) is quite distinct from the traditional, open-ended brainstorming of ideas, as solutions should be considered for the specific decision context that is under consideration. This clear and deliberate focus on achieving objectives facilitates the generation of possible options which provide societal value for the specific decision situation, which are aligned with the ultimate objectives of the organization, and which are situated within the scope of the *specific* decision frame.

Let us return to the vaccination campaign case. One fundamental objective is to *maximize vaccination coverage*. Two options have originally been devised; the campaign is either centralized (and conducted in hospitals) or decentralized (and conducted in community centers). The health security team could be encouraged to engage in shifting the perspective leftward from the original locus of the fundamental objectives, by asking the question "how can we increase vaccination coverage?", as shown in Fig. 7.3b. A focus on this fundamental objective could generate further improvements to action plans, such as establishing decentralized vaccination in schools and arranging home visits for those members of the population that are affected by mobility issues. An educational campaign could also address vaccine hesitancy among the population and, therefore, increase the attendance levels of vaccination appointments.

In the same vaccination campaign case, notice that vaccination strategies that contemplate actions which increase the level of vaccination coverage would generate more societal value, as represented by the value function over the attribute *proportion of the population vaccinated* (measured by variable x) in Fig. 7.4. This point reinforces the notion that decision alternatives should be considered as *means* to achieve high societal value in health security decisions.

Additionally, the shape of the value function indicates the marginal gain of additional efforts for a relevant consequence. In the same case above, consider that one type of vaccination campaign (a decision alternative) could vaccinate 90.0% of the population. The value function v(x) in Fig. 7.4. demonstrates that this level of vaccination would provide 95 points of value, v(90.0%) = 95. Therefore, additional planned actions to further increase the performance of this decision alternative, such as vaccinating a larger proportion of the population above the 90.0%, would deliver a maximum of 5 additional value points v(99.0%) – v(90.0%) = 100 – 95 = 5. This narrow value gap indicates that such efforts may not be required for this specific example.

On the other hand, if a second type of vaccination campaign (decision alternative) were to exist, which could vaccinate only 70.0% of the population. In this case, the value gap is significant, v(99.0%) – v(70.0%) = 100 – 40 = 60 value points. This latter (lower) vaccination rate indicates that efforts to identify actions that are able to increase the proportion of the vaccinated population would provide significative societal value increases to this second type of vaccination campaign.

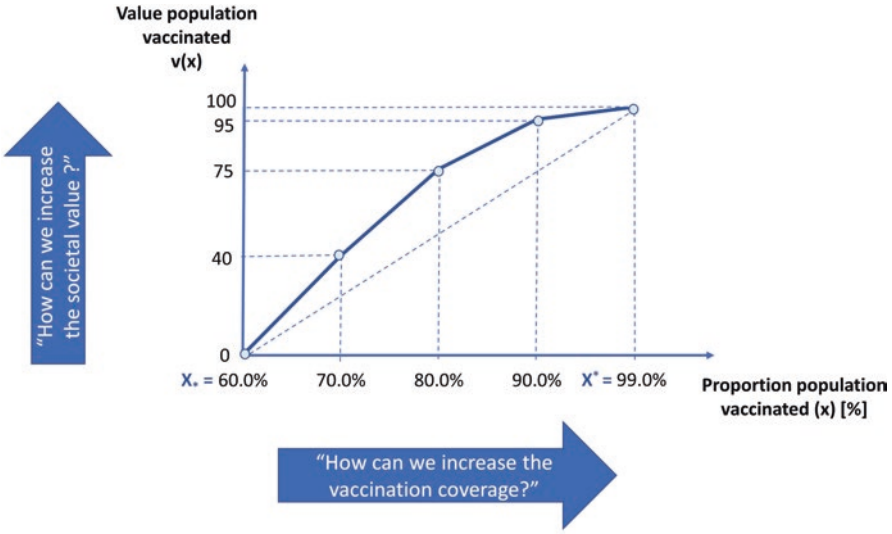

Fig. 7.4 Increasing the societal value of decision alternatives

This value-focused brainstorming relating to fundamental objectives (Keeney, 2012; Montibeller et al., 2009), which seeks to identify or design options that would achieve a single objective at a time, plays two major roles (Gregory et al., 2012). First, this value-focused brainstorming fosters creative thinking and encourages decision makers to explore a broad range of ideas, unconstrained by concerns as to whether other objectives shall also be attained, or, whether other stakeholders shall also consider the alternative to be acceptable. While an initial alternative may truly prove to be unfeasible, this alternative often forms the starting point for designing an alternative which is superior to the ones that had originally been available.

By focusing on a single fundamental objective at a time when exploring decision options, a safe environment is created, wherein decision makers feel at ease explore different alternatives. This constructive process promotes learning (Roy, 1993) about the benefits and drawbacks of different possible alternatives, and encourages an exploration of a broader decision space, thereby avoiding defensive or adversarial attitudes (Garvin & Roberto, 2001). This environment should also prevent either a hasty agreement involving a simplistic solution (Selart & Johansen, 2011), or, early criticisms from members that disagree with the proposals being explored.

Behavioral evidence has demonstrated that brainstorming sessions focused on fundamental objectives are likely to generate a greater number of alternatives than a standard brainstorming of ideas (Butler & Scherer, 1997; Jungermann et al., 1983; Pitz et al., 1980). There also exists some evidence demonstrating that this focus increases the quality of the generated decision alternatives (León, 1999; Selart & Johansen, 2011; Siebert & Keeney, 2015).

This same concept of a value-focused brainstorming can be employed when generating health security actions against a health threat. In this case, the health security

team should focus on options that can help to mitigate negative consequences and reduce undesirable impacts triggered by the threat. The predicted impacts that may be triggered by a health threat on the relevant consequences can be represented as an *impact profile*. The further the impact exceeds the acceptable level, the worse this impact is. Targeted actions can then be individually designed to lower the impact profile of health threats on consequences of interest. These actions, which should prove internally coherent, can then be grouped into a risk mitigating alternative. The project for ranking emerging animal health threats (which has been introduced in previous chapters) illustrates this process in practice.

7.2.2 *Identifying Health Security Actions for Managing Emerging Animal Health Threats (DEFRA)*

The project for supporting the ranking of emerging animal health threats that we conducted for the UK Department for Environment, Food and Rural Affairs (DEFRA), and which has been introduced in previous chapters, assessed four main consequences that may be triggered by a health threat (Del Rio Vilas et al., 2013b; Montibeller et al., 2020): *impact on public health*, *impact on animal welfare*, *impact on wider society*, and *impact on international trade*.

With the DEFRA expert group, an attribute was developed for each type of impact, and was composed of a discrete set of levels, with the lowest (L1) describing no impact and the highest describing maximum impact. An example of a past animal disease outbreak that characterized a given level of impact was included for some levels in order to reduce the ambiguity in the assessment (see the fifth chapter for details). A dis-value scale was also defined with the team, whereby no impact scored 0 dis-value points and the highest level of impact scored 100 dis-value points (see the sixth chapter for details).

These four attributes are shown in Fig. 7.5. Now, let us assume that a hypothetical emerging animal health threat[2] has been analyzed by the DEFRA Veterinary Risk Group. The most likely impacts of said threat have been assessed on the four attributes (levels highlighted in blue on each attribute): level L9 is the estimated impact on public health (Fig. 7.5a), level L6 is the estimated impact on animal welfare (Fig. 7.5b), level L5 is the estimated impact on wider society (Fig. 7.5c), level L9 is the estimated impact on international trade (Figure 7.5d). These highlighted levels that are depicted in the same figure constitute the *impact profile* of this hypothetical health threat.

This impact profile of the health threat can then be used as a platform on which to generate health security actions which can reduce impacts. Consider the attribute

[2] Information about actual threats is confidential to DEFRA. Since the implementation of a system in 2009 until 2020, more than 218 emerging animal health threats to the UK have been analyzed by this decision support system (Montibeller et al., 2020).

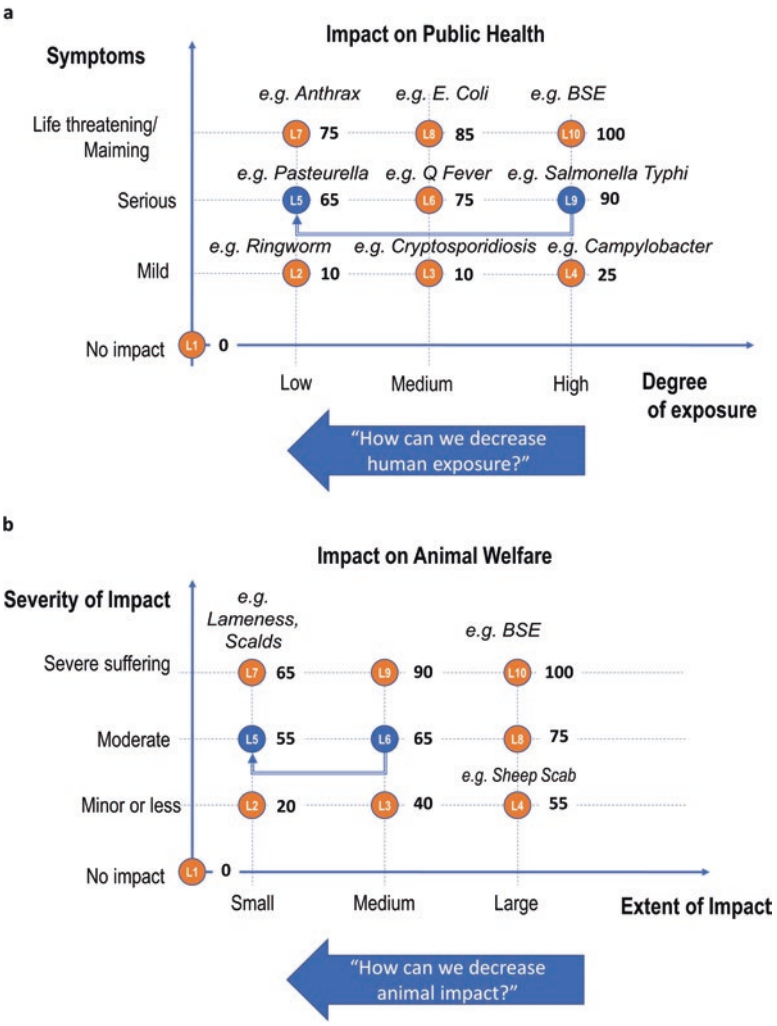

Fig. 7.5 Impact profile for a hypothetical emerging animal health threat: (**a**) Impact on public health (level L9), (**b**) Impact on animal welfare (level L6), (**c**) Impact on wider society Level L5), (**d**) Impact on international trade (Level L9) [*BSE* Bovine spongiform encephalopathy, *FMD* Foot and mouth disease, *BTV* Blue tongue virus, *EIA* Equine infectious anemia. The year after the disease acronym represents the year of the outbreak in Britain]

for *impact on public health*, shown in Fig. 7.5a. Obviously, it is not possible to reduce (at least in the short term) the symptoms of an emerging animal health disease that is transmitted to humans. Hence, the efforts to generate risk mitigating actions should address how DEFRA could decrease human exposure, and in doing so, reduce impacts from level L9 to level L5. Possible actions could entail isolating animals from humans, isolating affected farms, and euthanizing the infected animals.

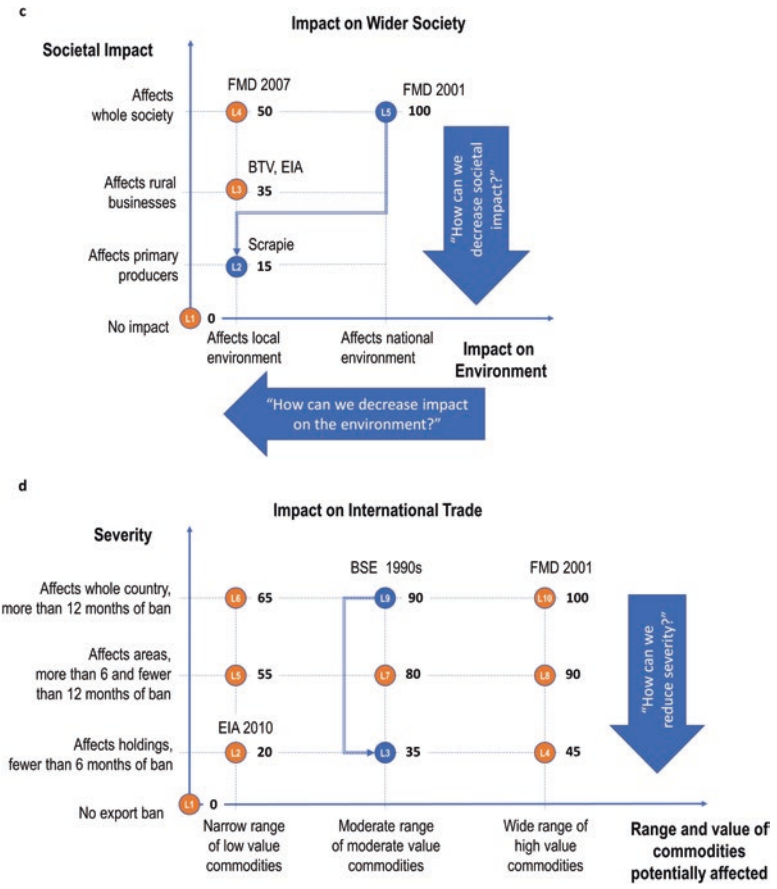

Fig. 7.5 (continued)

A similar thought process could be employed for the second attribute, the *impact on animal welfare*, as shown in Fig. 7.5b. Once again, it may not be possible to exert control over the severity of impact caused by the disease. Risk mitigating actions could consider how to decrease the impact the disease has on animal welfare, thereby moving said impact from Level L6 to level L5. Possible actions could involve isolating infected animals from non-infected animals, euthanizing infected animals, and reducing the movement of non-infected herds.

For the third attribute, which assesses the *impact on wider society*, both levers could be considered for shifting the high impact of this health threat from level L5 downward (see Fig. 7.5c). Actions for decreasing the social impacts could be designed, aiming instead to confine the impacts to narrower groups than the whole of society. Actions for decreasing the impact on the environment could be considered, aiming to reduce these impacts from a national to a regional level.

Finally, the DEFRA Veterinary Risk Group could consider the fourth attribute, which measures the *impact on international trade*. Actions to mitigate risks could

be devised to reduce the severity of trade impact of this health threat from L9 downward (see Fig. 7.5d). Possible actions for reducing the scale and duration of an export ban could entail compartmentalizing the country into isolated areas by maintaining unaffected regions open for exportation of animal produce and live animals, as well as further increasing the number and frequency of animal inspections to allow for the early detection and isolation of cases.

Generating health security options that pertain to the specific decision situation, or, generating health security actions against a health threat, is likely to bring about a lengthy list of decision actions and potential solutions. Some screening may be necessary, particularly for those options whose consequences are deemed to be truly unacceptable, or due to legal constraints, rules, or regulations. However, with the exception of these instances, it is advisable to avoid excessive screening at this stage, as screening may prevent the design of creative decision alternatives as a set of options, as is detailed next.

7.2.3 Structuring Health Security Actions into Decision Alternatives

A decision alternative is developed by combining a list of potential actions into a coherent, logical and complete set. Each decision alternative must follow the properties listed in Table 7.1. When considered as a whole, the decision alternatives should be diverse and comparable.

A useful way of designing these decision alternatives entails employing a strategy table (Howard, 1988), whereby each alternative is conceptualized as a strategy to improve health security or to minimize the impacts of a health threat. The table is composed of categories that are able to address the fundamental objectives in the specific decision situation. Within each category, sets of mutually exclusive actions are listed, and/or levers are defined. An alternative is defined by selecting an action from a discrete set of mutually exclusive actions, or, by setting a lever at a specific level.

The vaccination campaign case can be used to illustrate a strategy table. Recall that the objectives have been organized into four main categories: *maximize vaccination coverage*, *maximize campaign quality*, *maximize logistics efficiency*, and *minimize campaign costs*. Two broadly defined decision alternatives have been identified (centralized in hospitals and decentralized in community centers), but, no detailed specifications have been defined thus far.

An example of strategy table for this decision problem is shown in Table 7.2. The first category, *vaccination deployment*, is related to the first category of objectives in the value tree (*maximize vaccination coverage*). This category is composed of three levers: *proportion of the population vaccinated in hospitals*, *proportion of the population vaccinated in community centers*, and p*roportion of the population vaccinated at home*. Evidently, the strategy table demonstrates that there exists a great

Table 7.2 Strategy table for the decision alternatives in the vaccination campaign case

	Alternative A_1	Alternative A_2	Alternative A_3	Alternative A_4	Alternative A_5
	Fully centralized in hospitals	Fully decentralized in community centers	Hybrid centralized	Centralized with home visits	Decentralized with home visits
Vaccination deployment					
Proportion population vaccinated in hospitals [%]	100%	0%	60%	80%	0%
Proportion population vaccinated in community centers [%]	0%	100%	40%	0%	80%
Proportion population vaccinated at home [%]	0%	0%	0%	20%	20%
Vaccination quality measures					
Level of staff training [higher or standard]	H	S	S	H	S
Level of safety controls [higher or standard]	H	S	S	S	S
Level of results monitoring [higher or standard]	S	H	H	S	H
Campaign logistics					
Size of batches [larger or regular]	L	R	R	L	R
Transportation of batches [large or small lots]	L	S	L & S	L	S
Frequency of stock replenishment [higher or standard]	S	H	H	S	H
Overall cost campaign [$million]	50	80	70	80	100

Legend: *H* Higher level, *S* Standard level, *L* Larger size, *R* Regular size

number of combinations available. (Often an infinite number, particularly whenever the table contains continuous levers such as the ones in the first category of Table 7.2 assessing the *vaccination deployment* of each vaccination strategy under consideration.) Instead of trying to accommodate all the variations, it is advisable to focus on the properties for a potentially high-value set of alternatives (listed in Table 7.1) and create a set of options that is diverse and not excessively extensive. A carefully designed option set, ranging between five and nine decision alternatives, usually proves sufficient for most decision situations.

The health security team can design a decision alternative by establishing each lever at a given level. For instance, the decision alternative A_1 (f*ully centralized in hospitals*) establishes the proportion vaccinated in hospitals to be 100%, in community centers to be 0%, and at home to be 0%. On the other hand, the alternative A_2 (*fully decentralized in community centers*) establishes the proportion vaccinated in hospitals to be 0%, at home to be 0%, and in community centers to be 100%.

The second category in the strategy table, *vaccination quality measures*, is aligned with the category of objectives *maximize campaign quality* in the value tree. This category in the strategy table is composed of three sets of discrete actions: *level of staff training*, *level of safety control*, and *level of results monitoring*. For each set, two mutually exclusive levels are available: Higher (H) or Standard (S). Notice that more levels could be defined for each set were more granularity in the definition of the action to be required.

The third category in the strategy table, *campaign logistics*, is related to the category of objectives in the value tree *maximize the efficiency of campaign logistics*. This category of the strategy table is also composed of three sets of discrete actions, each with a binary choice between two mutually exclusive levels: *size of batches* [Larger or Regular batches], *transportation of batches* [Large or Small lots], and *frequency of stock replenishment* [Higher or Standard frequency].

For these second and third categories, an alternative can be designed by selecting a given level for each available set. For instance, in the strategy table, alternative A_1 (*fully centralized in hospitals*) has been defined as having: higher levels of staff training (H), higher levels of safety controls (H), standard levels of results monitoring (S), large size of batches (L), large lots for transportation (L), and standard frequency of stock replacement (S). On the other hand, alternative A_2 (*fully decentralized in community centers*) was defined as having: standard levels of staff training (S), standard levels of safety controls (S), higher levels of results monitoring (H), regular size of batches (R), small lots for transportation (S), and high frequency of stock replacement (H).

Each decision alternative would incur an overall cost, which is shown in the last row of the strategy table. These costs arise as a consequence of the design choices that have been made, and therefore, must be based on realistic and unbiased assessments (Montibeller & von Winterfeldt, 2015). For instance, the cost of alternative A_1 (*fully centralized in hospitals*) was estimated to be $50 million, while alternative A_2 (*fully decentralized in community centers*) is more expensive and estimated to be $80 million. These estimates were based on the most likely overall cost for implementing each decision alternative.

Three new decision alternatives have been designed for this case: a *hybrid centralized* (A_3) option wherein 60% of the vaccines are administered in hospitals and 40% in community centers; a c*entralized with home reach* (A_4) option, wherein 80% of the vaccines are administered in hospitals and 20% are administered in home visits for those individuals who would otherwise struggle to reach hospitals; a *decentralized with home reach* (A_5) option, wherein 80% of the vaccines are administered in community centers and 20% are administered during home visits for those individuals who would otherwise struggle to reach hospitals. Levels of vaccination quality measures and campaign logistics actions were defined for each of these new decision alternatives. The overall cost of each campaign was then estimated based on the actions that compose the vaccination strategy.

In the vaccination campaign case, the most expensive option is A_5 ($100 million), given its decentralized nature and focus on "hard-to-reach" communities. This strategy is likely to result in a high performance on the objectives focused on maximizing vaccination coverage. On the other hand, the least expensive option is A_1 ($50 million), as full centralization in hospitals brings about economies of scale, allowing for gains and increased efficiency. However, this latter decision alternative is likely to result in a relatively low performance on objectives linked to maximizing vaccination coverage.

It is advisable that each decision alternative receive a label that describes the theme of this alternative(Gregory et al., 2012), as this practice increases the clarity of discussion and fosters learning among members of the health security team. Examples of these labels for the vaccination campaign case are shown in the second row of Table 7.2. Care should be taken to avoid labels that either denote implicit preferences for one alternative over the others, that evoke emotional reactions, or that employ technical jargon which may reduce clarity.

Designing decision alternatives with a strategy table incurs many benefits (Gregory et al., 2012; Spetzler et al., 2016). First, a strategy table supports the development of creative alternatives which meet multiple objectives, utilizing initial actions as a foundational concept, which, individually, may not be feasible. Second, when we consider a given decision alternative, strategy tables highlight the set of actions that must be selected if said alternative were to be chosen. Third, these tables emplace the decision alternatives both within the specific decision frame, and as components of the specific decision context, as each alternative forms a set of actions, which in turn, forms a means to achieve the fundamental objectives. Fourth, a strategy table helps to organize complex policy decisions, which involve actions and co-ordination among different organizational divisions and/or organizations. We have often employed strategy tables in practice to structure complex decisions. The factual case described next illustrates the use of this tool when managing a health security of decision situation.

7.2.4 *Formulating a Strategy Table for the Design of Malaria Rapid Test Kits (Malaria Consortium/USAID)*

Malaria rapid diagnostic test kits (mRDT) offer a fast and accurate means of diagnosing malaria in settings wherein microscopy is either unavailable or unreliable. In much of the developing world, many febrile patients are diagnosed with malaria without confirmation by either a rapid diagnostic test or microscopy. Diagnosing malaria solely on the basis of clinical symptoms proves significantly challenging, as many malaria symptoms are nonspecific and overlap with symptoms of other conditions. Accurate diagnosis is important, since non-discriminant treatment could lead to a widespread resistance to artemisinin, which forms the base compound for the primary treatment against the disease.

In a project that we conducted jointly with the MIT Humanitarian Supply Chain Lab for the Malaria Consortium and which was supported by the United States Agency for International Development (USAID), we employed a strategy table to identify alternative designs for malaria rapid diagnostic (mRDT) kits. The aim of the project was to identify high value designs for the kit, considering the different objectives and priorities of a multi-echelon supply chain composed of three agents: first-line buyers, distributors, and retailers (see Carland et al. (2018) for details).

The strategy table devised to elucidate the different designs for the mRDT kits are shown in Table 7.3. We considered thirteen different decision alternatives. There existed four original options, which were actually available to the decision makers (A, B, C and E) and nine hypothetical options (D, F–M) that we subsequently designed to evaluate potential interventions that the health organizations could consider. These newly designed options were focused on increasing the value of the kits for the different agents in the supply chain.

The first three original options (A–C) were available to all agents without humanitarian organization (HO) involvement: do not sell mRDTs, sell non-WHO approved devices, and sell WHO-approved devices without humanitarian organization services. The fourth original option was the enhanced malaria RDT bundle introduced in the pilot by the humanitarian organization (Option E). Option D considered the most common health intervention of subsidies alone. The piloted option (E) combined a subsidy with a bundle of services, which we allocated into three sub-packages: training for retailers, biohazard disposal with the barcoding of devices, and advertising.

To identify a greater number of sustainable private sector solutions that were not compelled to rely on long-term financial incentives, we were particularly interested in evaluating various service sub-packages without subsidies. Options F–L in Table 7.3 (along with Option C, which serves as a "control" without services) considered the complete combinatorial enumeration of the three service sub-packages with prevailing market prices. Finally, Option M was defined based on the observation that retailers fundamentally view the mRDT as a service, which entailed a notion of time allocation, rather than merely as a product. The "malaria service" model necessitates that the retailer allocate more time than Option C but offers a

Table 7.3 Strategy table for different designs of malaria rapid test kits

	Decision alternatives												
Categories	A	B	C	D	E	F	G	H	I	J	K	L	M
WHO approved devices	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subsidy	No	No	No	Yes	Yes	No	No	No	No	No	No	No	No
Training	No	No	No	No	Yes	Yes	No	No	Yes	Yes	No	Yes	No
Advertising	No	No	No	No	Yes	No	Yes	No	Yes	No	Yes	Yes	No
Biohazard + Barcoding	No	No	No	No	Yes	No	No	Yes	No	Yes	Yes	Yes	No
Retailer Business Model	Do not sell RDTs	Same	Same	Same	Same plus services	Same plus services	Same plus services	Same plus services	Same plus services	Same plus services	Same plus services	Same plus services	Sell RDTs as a service

Source: Carland et al. (2018, p. 539)

Table 7.4 The description of each decision alternative and its bundle of services and products

Decision alternative	Description
Alternative A	Do not sell malaria rapid diagnostic tests
Alternative B	Sell non-WHO approved devices
Alternative C	Sell WHO-approved devices with no HO services
Alternative D	Subsidy with no HO services
Alternative E	Subsidy with HO services of advertising, biohazard/barcoding, training (the "enhanced bundle" in the case study pilot)
Alternative F	HO services of training only; no subsidy
Alternative G	HO services of advertising only; no subsidy
Alternative H	HO services of biohazard/barcoding only; no subsidy
Alternative I	HO services of advertising and training; no subsidy
Alternative J	HO services of biohazard/barcoding and training; no subsidy
Alternative K	HO services of advertising and biohazard/barcoding; no subsidy
Alternative L	HO services of advertising, biohazard/barcoding, and training; no subsidy
Alternative M	Sell malaria rapid diagnostic tests as part of a "malaria service" model, no HO services

Source: Carland et al. (2018, p. 539)

higher degree of customer satisfaction along with a slightly higher price and sales volume. Table 7.4 shows the structure of each bundle with the components of a decision alternative.

In this section, we have discussed how a focus on managing the relevant consequences of health security actions can be employed to foster creativity when developing decision alternatives. Next, we turn our attention to managing the uncertainties that affect such consequences, of which forms a second source of insights as to how we are able to improve decision alternatives.

7.3 Developing Decision Alternatives: Managing Uncertainties

As we have discussed in the fifth chapter, uncertainties are a key component of every health security decision. In many sources that compose part of the Decision Analysis literature, uncertainties are conceptualized as being completely exogenous, and as such, managers are envisaged as lacking any capacity to exert influence on uncertainties. However, we know that decision makers are often able to exert *some* influence on many uncertainties or, if decision makers find themselves unable to do so, they are at least able to limit the negative impacts that accompany uncertainties (Chelst & Bodily, 2000). As mentioned in the second chapter, the field of Causal Risk Analysis is dedicated to modeling this latter type of uncertainty management (Cox et al., 2018).

In this section, we first discuss how the analysis of uncertainties pertaining to impacts can be employed to generate decision alternatives to manage exogenous uncertainties. Subsequently, we consider the case wherein public health leaders can exert some influence over uncertainties, thereby reducing the risks of undesirable consequences or increasing the positive impacts of health security initiatives. In both cases (*managing impacts* and *influencing uncertainties*) we consider the use of continuous distributions to represent the dispersion of impacts (which is brought about by the uncertainties). Subsequently, this discussion is extended to include discrete representations of uncertainty, as they are also useful in supporting the development of decision alternatives.

7.3.1 Managing Uncertain Impacts: Continuous Distributions

The previous section has discussed how decision alternatives can be designed with a focus on achieving fundamental objectives and their associated relevant consequences. Actions can be conceptualized to improve positive performances of health security actions, such as the *proportion of the population being vaccinated* in the vaccination campaign case. Solutions can be planned to reduce negative impacts of health security actions, such as the *overall cost of the vaccination campaign* in the same case, or to mitigate the detrimental impacts of health threats.

As discussed in the fifth chapter, many of the impacts that may be caused by health security threats are uncertain, for instance the number of severe cases that a health threat may cause. Similarly, many of the performances of health security actions are uncertain, such as the reduction in severe cases that a risk mitigating action against an outbreak may promote.

Given the presence of these uncertainties pertaining to the impacts of health threats and health security actions, an effective way of identifying decision alternatives entails considering how to undertake these impacts over the relevant consequences (Chelst & Bodily, 2000; Keller & Ho, 1988). Specifically, options can be designed to mitigate (uncertain) negative impacts and improve (uncertain) positive impacts, as represented by the influence diagram in Fig. 7.6.

Consider an emerging health threat and the fundamental objective *minimize the number of severe cases* caused by this threat, with the relevant consequence being the *number of severe cases*. The fifth chapter described how uncertainties about impacts can be represented as distributions over the relevant consequences. The possible impact of this health threat is represented in Fig. 7.7a by a probability density function f(x) of the *number of severe cases* (measured by variable x), characterized by a continuous distribution with an expected value (mean) $\bar{x}$ and standard deviation σ. Risk mitigation actions can be devised by identifying how could the right tail be removed and generate a new probability density function $f_C(x)$ as shown in Fig. 7.7b.

Let us assume that this probability density function f(x) represents the number of cases for a given region, with an expected value of $\bar{x}$ = 9,000 severe cases and

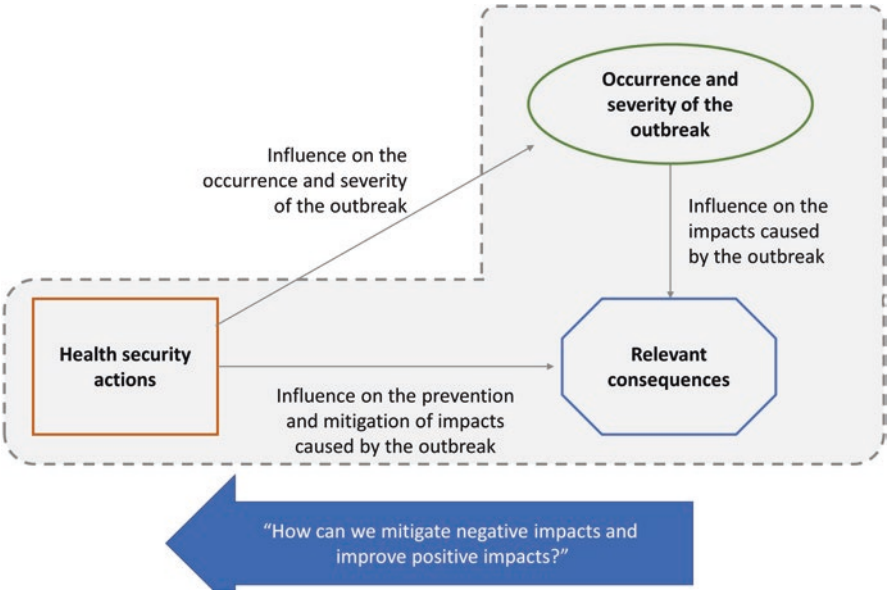

Fig. 7.6 Developing decision alternatives – managing uncertain impacts

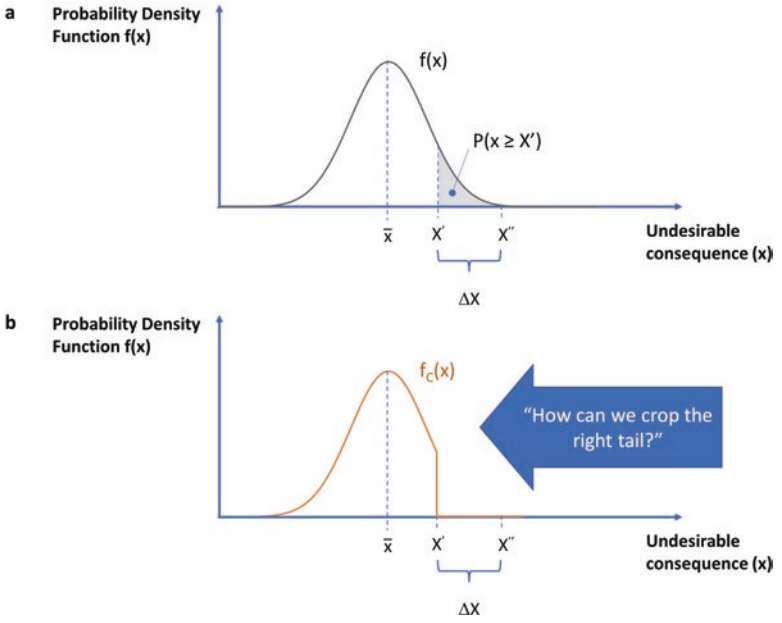

Fig. 7.7 Developing decision alternatives by cropping undesirable tails: (**a**) Probability density function for the severe number of cases, (**b**) Cropping the probability density function for the severe number of cases

standard deviation of $\sigma = 2{,}000$ severe cases. Let us posit that the number of hospital beds available in the region that are suitable for treating patients suffering from symptoms that could be triggered by the emerging health threat is $X' = 12{,}000$. Therefore, when considering the health system in this affected region, the health security team is required to identify ways in which to "crop" the right hand side of this function i.e. $f_C(x)$, as shown in Fig. 7.7b. Notice the subtle distinction between $f(x)$, the probability density function for the number of severe cases *affecting* the region, and $f_C(x)$ the number of severe cases that *must be treated* in the region.

Several actions could be devised to promote this risk reduction (Chelst & Bodily, 2000) and, therefore, bring about the probability density function $f_C(x)$ instead of the full function $f(x)$. For instance, a risk sharing agreement could be devised with hospitals from another region, which could treat patients if the number of patients were to exceed levels above the $X' = 12{,}000$ severe cases. From the area under the curve to the right of X', there exists a $P(x \geq X') = P(x \geq 12{,}000) = 6.7\%$ chance that this scenario could occur, which demonstrates that this risk is not negligible.

Actions to mitigate other types of consequences are also able to be analyzed in a similar manner. For instance, imagine that the probability density function $f(x)$ in Fig. 7.7 were illustrating the overall costs of a health security alternative, with $\overline{x}$ = \$80 million, σ = \$20 million, and a maximum budget of X' = \$100 million. There exists a risk of overspending of $P(x \geq X') = P(x \geq \$80 \text{ million}) = 15.9\%$. In order to mitigate this risk, solutions to avoid exceeding the budget could include: (i) buying an insurance policy that would cover the excessive costs, (ii) providing incentives for the project managers so that costs associated with the overall budget remain under control, and (iii) establishing strict cost controls on project activities which play a significant role in the overall budget. The assessment of these cost control initiatives could be monetized, as a way to determine the extent to which initiatives would reduce the likelihood that the project would exceed the \$80 million budget limit.

7.3.2 Influencing Uncertainties: Continuous Distributions

Public health leaders are not passive observers, on the contrary, these leaders are actively seeking to influence the future with their actions and initiatives to enhance health security. When managing decisions under uncertainty, such as the ones that we encounter in health security situations, some of these actions are targeted at influencing and managing the uncertainties that affect the relevant consequences of these decisions.

This type of process is represented in the influence diagram shown in Fig. 7.8. Notice that the health security team can only exert direct influence on the uncertainty node (*occurrence and severity of the outbreak*). The influence that exists between the *uncertainty* node and the *consequences* node thus lies outside of the control of the health security team, as this influence is solely determined by external

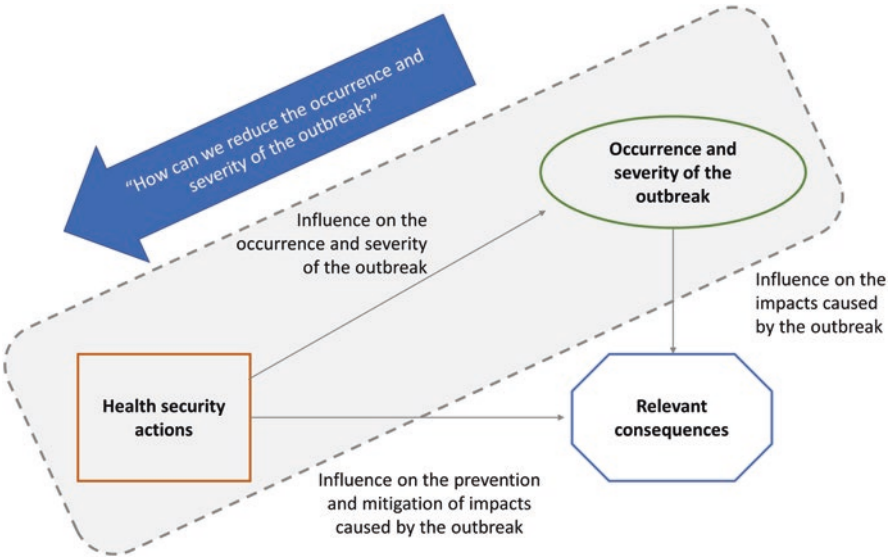

Fig. 7.8 Developing decision alternatives – influencing uncertainties

circumstances. In practice, this characteristic inherent to the decision situation means that the uncertainty *cannot* be fully controlled, but instead, only *adequately managed* and *indirectly influenced*.

There exist two main ways of influencing uncertainties. The first requires that we consider actions that are able to make the distributions of impacts tighter. This narrowing of the distributions can be accomplished by fostering knowledge concerning the health threat and improving the accuracy of predictive models for the assessment of impacts that the threat may cause. In the case of health security actions, this aim can be obtained by improving the quality of predictions about possible performances and gathering more information about the decision situation that may reduce uncertainties.

For instance, let us again consider the probability density function f(x) for the *number of severe cases* that a health threat may cause for a given region, with an expected value of $\bar{x} = 9{,}000$ severe cases and standard deviation of $\sigma = 2{,}000$ severe cases, shown in Fig. 7.9a. The health security team may consider how they could tighten the probability density function, i.e. $f_T(x)$, as shown Fig. 7.9b.

In our experience in supporting health security decisions, the type of uncertainty that health scientists are most focused on are related to the lack of scientific knowledge. Actions to foster said knowledge necessitate that we acquire a better understanding about the physiology and behavior of the health threat, transmission patterns, severity of the symptoms, among many other important scientific questions. One practical benefit that is brought about by fostering such knowledge and, consequently, reducing the possible dispersion of impacts, is that any additional knowledge enables for a better planning of resources (e.g. hospital beds, doctors, hospital equipment).

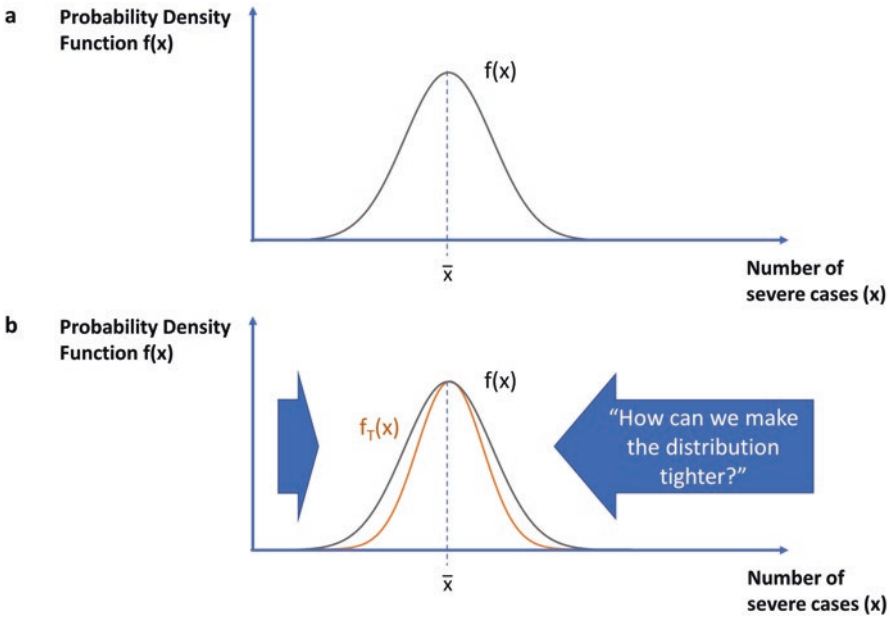

Fig. 7.9 Developing decision alternatives by tightening the distribution: (**a**) Probability density function for the severe number of cases, (**b**) Tighter probability density function for the severe number of cases

However, while a better understanding of the phenomenon proves significantly important, such understanding may not suffice for managing a health threat. Notice, for instance, that in the example shown in Fig. 7.9b the tighter probability density function $f_T(x)$ still incurs the same expected number of severe cases ($\bar{x}$ = 9,000 cases). If we consider the expected value of these distributions to be the measure of risk, as detailed in the previous chapter, the risk itself *has not* been reduced by the additional scientific knowledge. Hence, more proactive measures to influence key uncertainties in health security decision making are still required, as discussed next.

The second way in which we are able to influence uncertainties requires that we consider actions that are able to shift the distribution, in a manner that reduces the undesirable impacts or increases the level of desirable consequences. The distribution of undesirable consequences should be shifted to the left, and the distribution of desirable consequences to the right.

Let us consider the same example above, with an original probability density function f(x) for the *number of severe cases* (measured by variable x) that may be caused by a health threat for a given region, shown in Fig. 7.10a, with an expected value of $\bar{x}$ = 9,000 severe cases and standard deviation of σ = 2,000 severe cases. The health security team could consider how to shift this probability density function f(x) to the left, i.e. $f_L(x)$, as shown in the same figure. This shift may be accomplished by a variety of ways, from employing preventive measures (such as

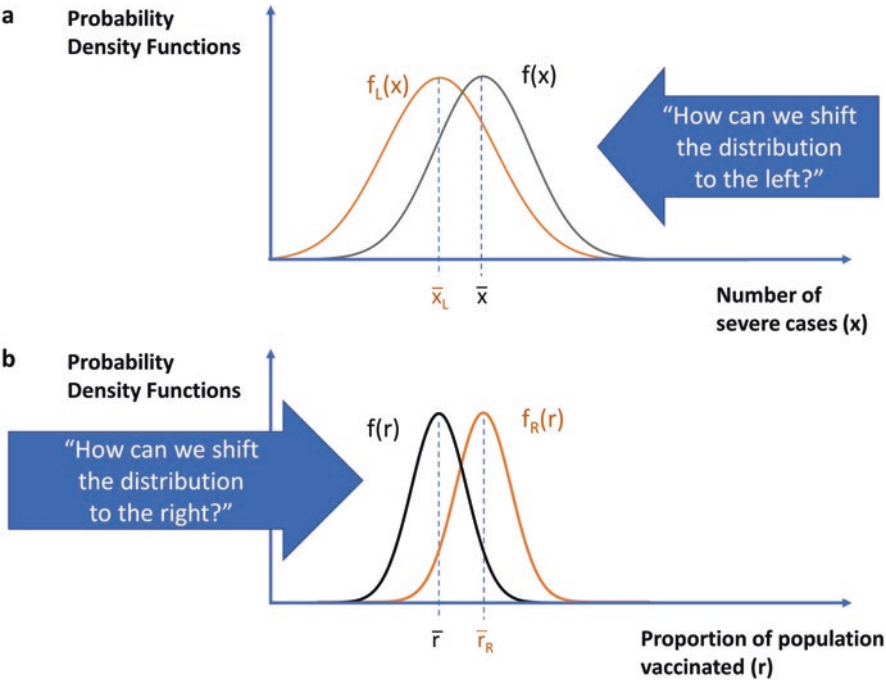

Fig. 7.10 Developing decision alternatives by shifting the distribution: (**a**) Shifting the distribution of an undesirable consequence to the left, (**b**) Shifting the distribution of a desirable consequence to the right

vaccination campaigns) to implementing risk mitigating actions (such as the isolation of infected patients and social distancing).

This same logic can be applied to situations wherein we seek to shift distributions of consequences that are desirable. For instance, assume that the probability density function f(r) of the *proportion of population vaccinated* (measured by variable r) in a vaccination campaign shown in Fig. 7.10b, with $\bar{r}$ = 50.0% and σ = 5.0%. The health security team could consider how to shift this distribution to the right, i.e. $f_R(r)$, as shown in the same figure. This improvement may be accomplished by a better strategy to reach the population, which could include home visits and local health clinics in order to target "hard-to-reach" individuals.

We often see that actions which are intended to influence uncertainties are often considered in a more informal manner in health security decisions. In more sophisticated decision settings, such as the those that have informed the early response during 2020 of the COVID-19 pandemic in Britain, transmission models are used to predict the temporal pattern of transmission and the number of cases were a given action to be implemented (Brauer et al., 2019). In less sophisticated decision settings, the assessment of impacts that accompany alternative health security actions is typically more ad hoc and sometimes purely deterministic.

So far, we have discussed the role that analyzing continuous distributions can play in the development of health security actions. This is the most generic case and the most comprehensive way of representing uncertainties about impacts, and is therefore widely employed in Risk Analysis. Frequently, in Decision Analysis, discrete distributions are employed instead to support decision makers when generating decision alternatives, as we discuss next.

7.3.3 *Managing Uncertain Impacts and Influencing Uncertainties: Discrete Distributions*

In Decision Analysis, we frequently use discrete distributions to characterize the uncertainty about impacts of health threats and health security actions. In this case, as we have discussed in detail in the fifth chapter, a small set of points of the distribution of impacts (usually three or five) is selected. For each point, an impact level, X_j, and an associated probability of this level of impact, p_j, is defined.

This discrete representation of impacts is illustrated in Fig. 7.11a for impact levels X_L, …., X_M, …, X_H and respective (discrete) probabilities of these impact levels p_L, …., p_M, …, p_H that represent a probability mass function f(x). Discrete distributions are typically represented as a tree in Decision Analysis. The equivalent tree representation, shown in Fig. 7.11b, is a chance node (a circle) with the arcs representing the possible outcomes, each arc with an impact level on the relevant consequence (X_L, …., X_M, …, X_H) and associated probability p_L, …., p_M, …, p_H. The sum of these probabilities should be equal to 1 and the set of j-th levels of the consequence should be both mutually exclusive (i.e. only one must occur) *and* collectively exhaustive (i.e. the set of levels for this relevant consequence should represent

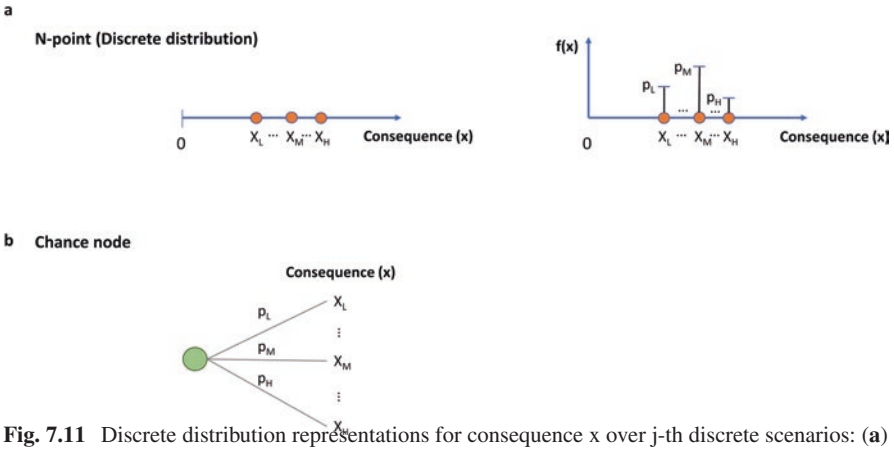

Fig. 7.11 Discrete distribution representations for consequence x over j-th discrete scenarios: (**a**) Probability mass function representation, (**b**) Chance node in a tree representation

all the possible scenarios). (See McNamee and Celona (2005) for details and a didactic coverage of probability theory for Decision Analysis.)

Discrete representations of distributions are particularly useful when employing expert judgment, in situations where there exists an absence of reliable predictive models or enough hard evidence (Morgan, 2014, 2017) and are frequently used in health decision making (Hunink & Weinstein, 2014). The chance node representation of this type of distribution is useful to identify possible actions for risk mitigation and health security enhancement, both for managing impacts and influencing uncertainties, as detailed next.

Managing Uncertain Impacts Let us first illustrate how discrete representations of distributions of impacts can be used for developing alternatives which are focused on managing said impacts. For instance, consider the distribution that has been discussed throughout this section: the *number of severe cases* (measured by variable x) caused by a health threat. The representation of this uncertainty as a discrete distribution using a chance node is shown in Fig. 7.12a with three impact levels: X_{05} = 5,710 severe cases with an associated probability p_{05} = 0.185, X_{50} = 9,000 severe cases with an associated probability p_{50} = 0.630, and X_{95} = 12,290 severe cases with an associated probability p_{95} = 0.185. (See Hammond and Bickel (2015) for details on how continuous distributions can be adequately discretized.)

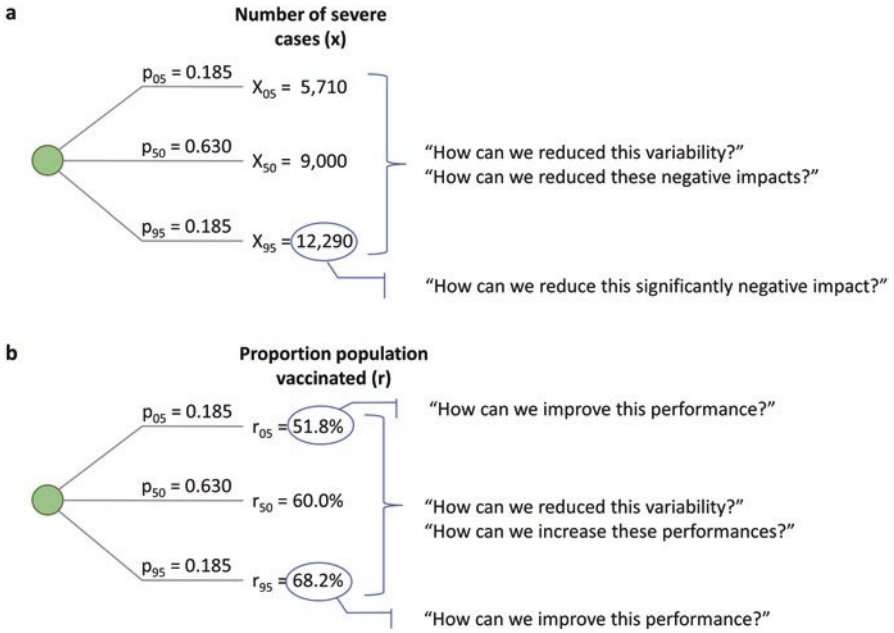

Fig. 7.12 Developing alternatives with discrete distributions by managing impacts: (**a**) Chance node for the number of severe cases (measured by variable x), (**b**) Chance node for the proportion of population vaccinated (measured by variable r)

Risk mitigation actions could be devised by focusing on how these negative impacts could be reduced, as indicated in the same figure. Additionally, actions that target the branch with the highest level of impact (X_{95} = 12,290 severe cases) could be conceptualized and implemented so that this case number could be reduced. Efforts to reduce the variability of impacts could also be cogitated, as this reduction would facilitate the planning of resources, rather than allocating time and effort to manage a broader set of possible impacts.

Let us posit another example which has been discussed in this section, involving the *proportion of the population vaccinated* (measured by variable r) by a vaccination campaign. The discretized distribution is presented as a chance node in Fig. 7.12b, with three performance levels: r_{05} = 51.8% with an associated probability p_{05} = 0.185, r_{50} = 60.0% with an associated probability p_{50} = 0.630, and r_{95} = 68.2% with an associated probability p_{95} = 0.185.

This tree representation of the discrete distribution, presented in the same figure, could be employed to foster creativity and improve the performance of this health security option (vaccination strategy). For example, actions could be devised to reduce the variability in the estimates of the proportion of the population that has been vaccinated. This reduction in variability would facilitate the comparison between different decision alternatives and make clear the advantages of this option.

Additionally, let us postulate that a rather cost-effective vaccination campaign is desired. In this case, efforts could be devised to increase the performances of this option under each outcome branch, to increase the possible proportion that is being vaccinated. Furthermore, actions could be devised that would further increase the weak performance of the top branch (moving r_{05} beyond 51.8%), or further improve the best performance of the bottom branch (moving r_{95} above 68.2%).

Influencing Uncertainties Discrete representations prove to be also useful tools when generating alternatives focused on influencing uncertainties. For instance, consider the same discrete distribution described above for the *number of severe cases* (measured by variable x). The health security team could consider actions for influencing the probabilities of the chance node in a such a manner as to reduce the probabilities of the most negative outcomes (X_{95} = 12,290 severe cases), as shown in Fig. 7.13a. For example, the team could contemplate actions that enable a reduction in the probability of the bottom branch (p_{95}), either by executing actions that would crop this outcome (as discussed before for continuous distributions), or, by shifting this probability to the other branches whose impacts are lesser.

Similarly, actions that influence the probabilities of outcomes could be posited when determining the *proportion of the population that shall be vaccinated* (measured by variable r) using a given vaccination strategy. For instance, the health security team could devise ways to increase the probability (p_{95}) of the best outcome (r_{95} = 68.2%), as well as ways to reduce the probability (p_{05}) of the worst outcome (r_{05} = 51.8%), as shown in Fig. 7.13b.

In this chapter, thus far, we have presented a number of tools which can be used to help foster creativity during the development of health security actions. We have suggested a more decision-focused approach to support the development of

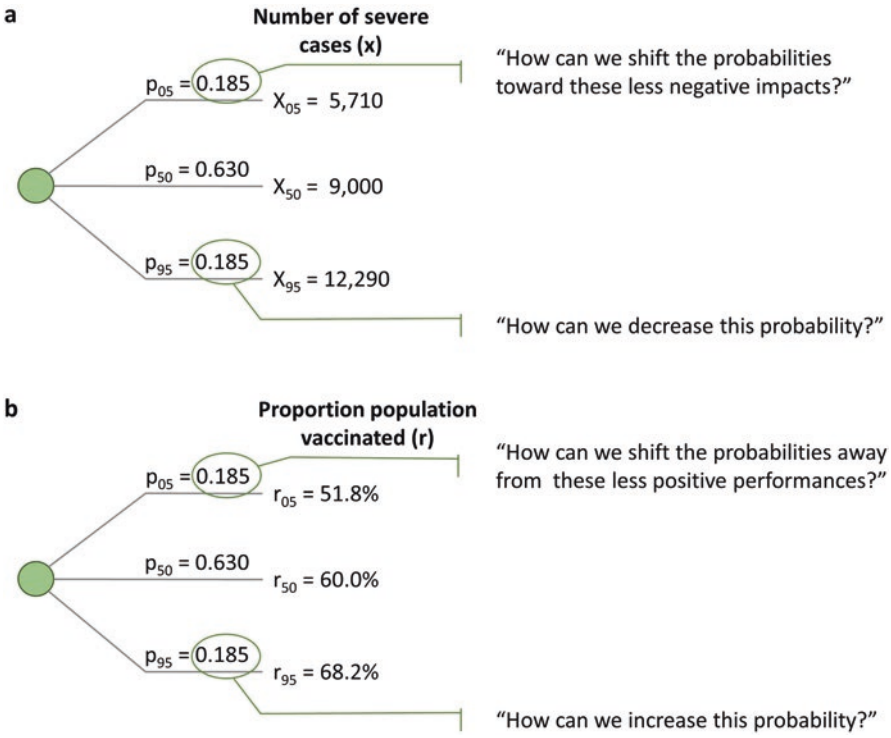

Fig. 7.13 Developing alternatives with discrete distributions by influencing uncertainties: (**a**) Number of severe cases (x), (**b**) Proportion of population vaccinated (r)

decision alternatives and the design of health security actions. This particular approach is focused on the relevant consequences in the specific decision situation and is concerned with mitigating undesirable impacts and improving desirable consequences. Once these different possible options have been identified, predictive models can be used to estimate the possible impacts of implementing each possible alternative. This decision focus renders the likelihood of generating alternatives with high societal value greater than if the decision makers were to adopt an ad hoc search for solutions which lacked clear decision objectives.

We shall now extend these ideas to discuss the ways in which health security options can developed to support three core activities in health security decisions, in order to improve the preparedness, robustness, resilience, and responsiveness of health systems. These ideas shall form the topic of the next section.

7.4 Developing Decision Alternatives: Improving Preparedness, Robustness, Resilience, and Responsiveness

As we have discussed in the first chapter, we conceptualize health preparedness as the capability of a health system to prevent and protect against emerging health threats, as well as rapidly respond to and recover from outbreaks (Nelson et al., 2007). In this section we suggest as to how decision alternatives can be developed to achieve four systemic goals for health systems, drawing from the Risk Analysis, Decision Analysis, and Operations Management literatures, these goals are to: *improve preparedness*, *enhance robustness*, *increase resilience* and *improve responsiveness*.

Here, our discussion is targeted at improving the quality of decision alternatives in health security decision making. We argue that this can be achieved by adopting a lens that is uniquely tailored to attain each one of these four systemic goals, thereby allowing decision makers to develop specific options (pertaining to specific decision situations) that are of a high societal value. However, we recognize that there exist many systemic and organizational issues that require addressing if we wish to attain these goals in national health systems that extend beyond health security decision making (see Khor & Heymann, 2021; Oppenheim et al., 2019; WHO, 2017, 2021).

7.4.1 Improving the Preparedness of Health Systems

The preparedness of a health system against emerging, or re-emerging health threats, is based on two major components: *capacities* and *capabilities*. These two terms are sometimes used interchangeably in the health security literature, but a clear distinction such as the one that has been proposed by Stoto and Nelson (2012), proves valuable and thus shall be adopted here.

Assessing Health Capacities Capacities represent the resources, infrastructure, response mechanisms, and health personnel that is available to a health system (Stoto & Nelson, 2012). Organizational activities such as planning against health threats, training for emergency situations, acquiring equipment that would be required during an outbreak, and expanding buffer stocks of medicines are all actions which seek to build capacity against health threats.

There exists a valuable body of research in Operations Management concerning health capacities management (see Keskinocak and Savva (2020) and Gupta et al. (2021) for references) as well as a significant number of predictive models which function to estimate surge hospital capacity in the context of pandemics (see Klein et al. (2020) for a review focused on the COVID-19 pandemic).

The process of health capacity analysis requires that we assess: (i) the current capacity, (ii) the future capacity under adverse scenario(s) of outbreak(s), (iii) the capacity gap that exists between the current capacity and the required future capacity, and (iv) health security actions that must be executed to close this gap. Thus, as we have proposed in this book, health capacity analysis necessarily demands that uncertainty be adequately managed, which is in direct contrast to a mere efficiency analysis under certainty that may otherwise disregard different scenarios posed by health threat(s), as is often observed in healthcare planning.

Decision alternatives can be developed by considering surge demands which may be brought about by a health threat, exceeding the current capacity. For instance, let us assume that the distribution in Fig. 7.7a represents the number of severe cases that a health threat may trigger, which would determine that patients be admitted to intensive care units (ICUs). The current number of available ICUs is X' in the same figure, which may be below the number required (X'') when facing a risk of demand surge, an event with a probability $P(x \geq X')$. As discussed in this chapter, alternatives for cropping this distribution would reduce this risk, as is represented in Fig. 7.7b. This health security action could involve risk sharing among different health systems or other collaborative agreements.

Another possible health security action in this example would entail expanding ICU capacity, given the capacity gap (ΔX) (which is shown in the same figure) that exists between the future required capacity (X'') and the current capacity (X'), with: $\Delta X = X'' - X'$. The additional societal value of this expanded capacity, against the additional cost of this investment, can then be compared with other capacity building actions in terms of the value-for-money of this investment. Consequently, we are then able to identify the best portfolio of capacity building actions, which seeks to maximize the additional overall value by efficiently employing the available budget (Kleinmuntz, 2007; Montibeller & Franco, 2011b; Salo et al., 2011), as shall be discussed in the tenth chapter.

Health capacity assessments against emerging health threats should also contemplate the possibility of multiple health threats, and the simultaneous outbreaks from different infectious diseases (Del Rio Vilas et al., 2011; Del Rio Vilas et al., 2013b; Jaspersen & Montibeller, 2015). In this situation, the distribution of impacts should consider the total impact stemming from the different outbreaks on each relevant consequence (for instance the total number of severe cases that each outbreak may cause). This joint assessment would require the estimation of a probability density function for each outbreak and the summation of these probability density functions.[3]

Assessing Health Capabilities The term capabilities is used to describe the actions that a health system is capable of undertaking effectively in order to identify, characterize and respond to health threats (Stoto & Nelson, 2012). Organizational processes such as surveillance, epidemiological investigations, disease prevention, risk

[3] The summation of probability density functions is calculated by the convolution operator. Monte-Carlo simulation can be used to estimate these total distributions, as shall be described in the nineth chapter (see also Vose (2008) for details).

communication, coordination of responses, among others, are all classified as capabilities.

Capabilities are latent characteristics pertaining to a health system, whose dynamic performances can be better assessed and measured during outbreaks.[4] Nonetheless this dynamic nature of health capabilities, the evaluation of the health capabilities of a health system and the identification of capability gaps, can all aid the health security teams in identifying opportunities for improvement and in developing decision alternatives for specific decision situations. The process of health capability analysis requires that we assess: (i) the current capability, (ii) the future capability under adverse scenario(s) of outbreak(s), (iii) the capability gap that exists between the current capacity and the required future capacity, and (iv) health security actions that must be executed to close this gap. The factual case described next shall illustrate this process in practice.

On behalf of the Pan-American Health Organization (PAHO), we developed a capability assessment of national health systems against human rabies whose transmission has resulted from a dog vector. (See Del Rio Vilas et al. (2013a) for details; while we have used the term "capacities" in the 2013 paper, this term would be better characterized as "capabilities" following the taxonomy we employ here.) The decision model successfully supported the allocation of resources for capability building, here however, our focus is on describing how this capability assessment model could be used to identify capability gaps to subsequently underpin the development of health security actions.

A value tree was developed to organize two categories of capabilities: those in the *public health area* and those in the *animal health area*, as shown in Fig. 7.14. Under the *capabilities in the public health area*, six capabilities were considered: *risk analysis*, *pre-exposure prophylaxis*, *post-exposure prophylaxis*, *case control*, *education*, and *surveillance*. Similarly, under the *capabilities in the animal health area* five capabilities were considered: *risk analysis*, *vaccination*, *import control*, *surveillance*, and *case control*.

Attributes could be developed for assessing each capability level, ranging from zero capability to full capability. As we have detailed in the fifth chapter, natural attributes should be employed whenever possible, or alternatively, proxy or constructed attributes could be employed were the employment of natural attributes to prove unfeasible. Given the intangible nature of many organizational capabilities, it recommended that constructed attributes with fewer levels that describe capability achievement be developed. This assessment is illustrated in the same figure, wherein each capability was assessed by an attribute with five discrete levels, from L1 (zero capability) to L5 (full capability).

[4] This dynamic characteristic of health capabilities may explain as to why the well-developed Global Health Security Index (https://www.ghsindex.org/) ranked the USA and the United Kingdom as top performers in their 2019 assessment, while the health systems of both countries demonstrated a sub-optimal response against the early stages of the COVID-19 pandemic in 2020. The latent nature of health capabilities also poses a challenge to the use of checklists for capability assessment, as are commonly used in health security practice.

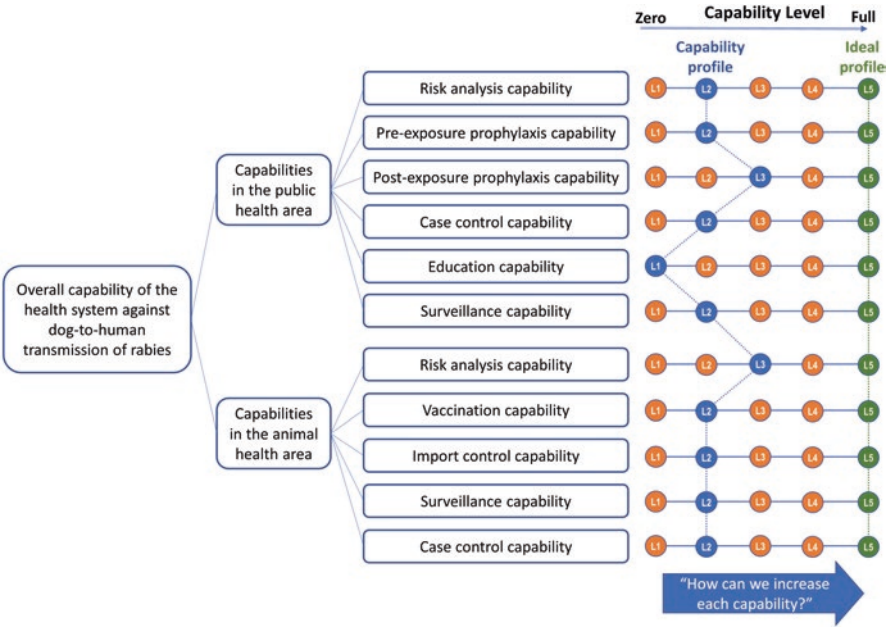

Fig. 7.14 Capability assessment of health systems against dog-to-human transmission of rabies for the Pan-American Health Organization

The capabilities of a national health system against dog-to-human transmission of rabies could then be assessed by this evaluation model. For instance, let us posit that a hypothetical country had the *capability profile* indicated in Fig. 7.14 (e.g. L2 on *risk analysis capability* under the *capabilities in the public health area*, and so on). The *capability gap* represents the distance between the capability profile and the *ideal capability profile* of full capabilities (i.e. achieving level L5 on each capability).

Health security actions can be identified to close or reduce the distance of each capability gap by employing the probe question: "how can we increase each capability?". In a similar manner to the capacity analysis, each capability increase would bring about some additional societal value and incur an additional investment cost, which in turn can be computed as a value-for-money measure. We are then able to identify the optimal portfolio, which increases the additional overall value, depending on the available budget for capability development. We detail in the tenth chapter how this value-for-money analysis can be conducted for health security actions.

These suggestions to conduct a targeted analysis of health capacity building and health capability development can significantly aid in executing concrete actions instead of merely cogitating laudable plans to improve the preparedness of national health systems. Specifically, this targeted capacity and capability analyses provide four benefits. First, they enable both a clear assessment of each capacity or

capability, and the identification of capacity or capability gaps. Second, targeted health security actions can subsequently be devised to close these gaps. Third, it is possible to quantify the societal value that is added by each health security action. Fourth, by assessing the value-for-money of each health security action, it is possible to optimize the use of scarce resources for capacity building and capability development.

7.4.2 Enhancing the Robustness of Health Systems

The robustness of a health system is determined by the extent to which the system is able to cope with varied health threats under different scenarios and ranges of impacts. The tools for managing impacts and influencing uncertainties which have been discussed in this chapter can help us to develop decision alternatives which improve the robustness of a health system against adverse events such as outbreaks of infections diseases and pandemics.

Mitigating Negative Impacts A focus on health security actions aimed at mitigating possible impacts can increase the robustness of the health system. Let us consider the fundamental objective of *minimizing the number of severe cases* (measured by variable x) and the estimates relating to the number of such cases in the context of different scenarios shown in Fig. 7.12a. The probe questions in this figure could aid in the development of decision alternatives. The variability associated with these impact predictions could be reduced through the gathering of evidence, which would in turn facilitate capacity planning. Similarly, risk sharing with other health systems could be considered for scenarios wherein the number of severe cases exceeds the available healthcare capacity. The number of severe cases could be reduced by implementing preventive actions, such as vaccination and improving public health provision to reduce health vulnerabilities.

Influencing Uncertainties A focus on health security actions that are geared toward influencing uncertainties can also increase the robustness of the health system. Let us again consider the fundamental objective *of minimizing the number of severe cases* (measured by variable x) and the estimates relating to the number of such cases in the context of different scenarios shown in Fig. 7.13a. The probe questions in this figure could aid in the development of decision alternatives. Cropping the most adverse scenarios could be achieved by establishing risk sharing agreements with other health systems. Thus, we may be able to reduce the probabilities of these scenarios occurring by establishing preventive measures.

At macro level, we wish to design strategies that increase the robustness of health systems against possible large-scale adverse scenarios (Montibeller & Franco, 2011a). General strategies to increase robustness involve: (i) developing redundancies which form part of the core capacities (e.g. supply chains of medical equipment that are sourced by multiple suppliers which are based in different geographical

locations), (ii) expanding surge capacity (e.g. additional ICU units beyond the levels required by regular demand), and (iii) developing flexible facilities and health personnel teams that can be adapted to unexpected requirements brought about by an outbreak (e.g. treatment rooms that can be quickly adjusted for the different patient care needs and teams that can rapidly adapt to treating a new disease).

7.4.3 Increasing the Resilience of Health Systems

The framework for measuring resilience against natural disasters (Bruneau et al., 2003; Zobel, 2011) can be adapted to health systems to provide a useful conceptualization of resilience against health threats. The *resilience triangle* is represented in Fig. 7.15a. The quality of the health system as a function of time (t) is measured by a function Q(t). The steady-state quality level is Q^*. An outbreak caused by a health threat erupts at time t_0, degrading the quality of the health system to level $Q_L < Q^*$. Health security actions to recover from the initial reduction in quality ($\Delta Q = Q^* - Q_L$) may then be deployed, thereby supporting the recovery of the health system, until the system reaches the original level Q^* at time $t_0 + T$.

In this analysis, the same figure indicates three relevant parameters. The first parameter is the *robustness* of the health system; a greater robustness results in a lesser reduction in the quality of the health systems (ΔQ). The second parameter is the *rapidity* with which the health system returns to functioning at the original level Q^*, with rapidity being measured by the time T. The area under the triangle (which has been highlighted in the figure) indicates the *loss of resilience* (see also Baghersad and Zobel (2022) for a discussion on organizational resilience within this perspective).

From this diagram, we can identify two ways of improving resilience, as shown in Fig. 7.15b. First, we can seek to improve the *robustness* of the health system through using the ideas described previously in this section to generate health security actions that can aid in attaining this goal. Second, we can increase the *rapidity of recovery* of the health system, which, once again, is achieved by developing health security actions for this intent. A rapid recovery typically requires strong and realistic contingency plans, task forces responsible for rebuilding the systems, the fast and efficient allocation of resources, and clear, tangible targets for the health security team. Simulations of large-scale outbreaks which are conducted with the health security team and other key stakeholders may help to identify the bottlenecks and weak points that may hinder recovery efforts, as well as the capabilities and capacities that these adverse events would necessitate.[5]

[5] However, these "war games" may also create a narrow view of the decision problem (Bracken, 1977; Morgan, 2017). Therefore, these pandemic simulations must be designed in such a way that they genuinely aid health security teams in increasing the resilience and preparedness of the health system.

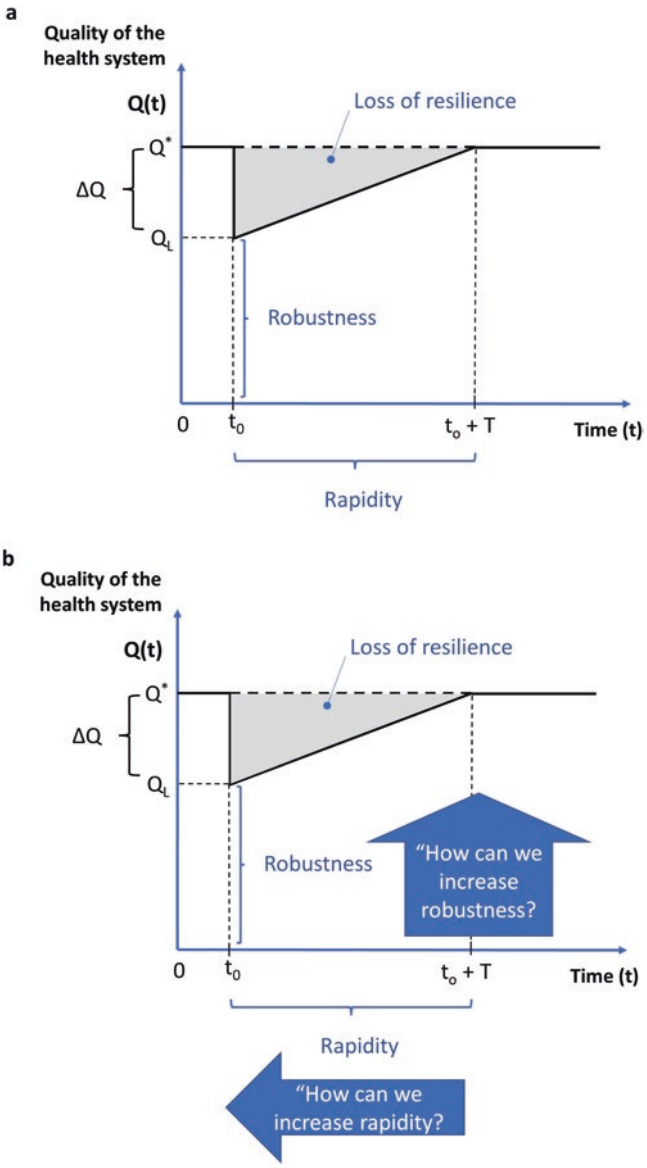

Fig. 7.15 Assessing the resilience of health systems: (**a**) The resilience triangle (adapted from Zobel (2011)), (**b**) Probes to identify health security actions to improve resilience

7.4.4 Improving the Responsiveness of Health Systems

The responsiveness of a health system against health threats measures the extent to which this system is able to fulfill the demands that have been placed on it by an outbreak. The dynamic nature of system responses can be estimated with System Dynamics simulation (see Sterman, 2014) and with Discrete Event simulation (this

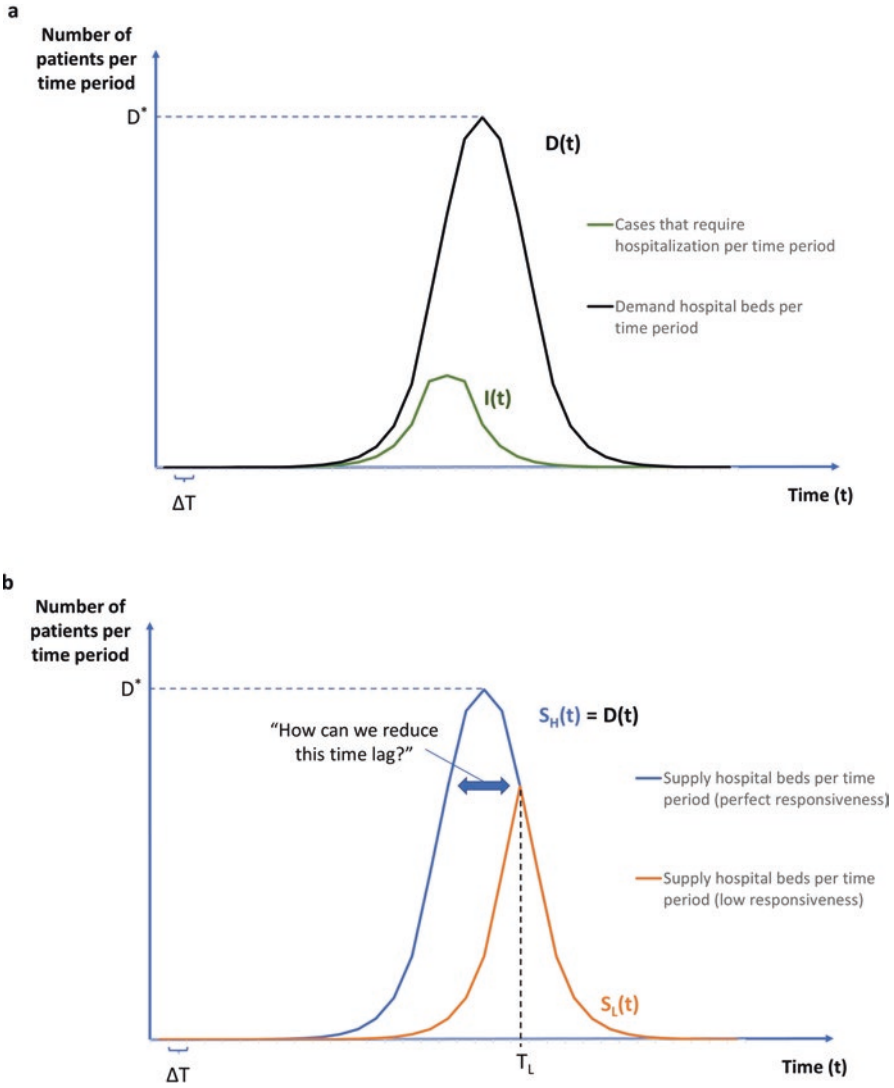

Fig. 7.16 Considering the responsiveness of health systems: (**a**) Cases that require hospitalization and demand of hospital beds per period of time for a hypothetical outbreak, (**b**) The supply of hospital beds per period of time for a system with perfect responsiveness and for a system with low responsiveness

latter simulation is particularly suited for estimating discrete capacities such as hospital beds and intensive care units, for details seeRobinson, 2014).

Let us posit a hypothetical outbreak which incurs a number of patients that require hospitalization for a specific period of time (ΔT) represented by the function I(t), as shown in Fig. 7.16a. For the sake of simplicity, let us assume that there occur no casualties and patients can be safely discharged from the hospital after 4 time

periods, generating the demand function D(t) for hospital beds shown in the same figure.

A health system whose responsiveness is perfect would be able to meet the demand for critical care beds by responding with an immediate supply of beds without there occurring a time lag. This supply function $S_H(t)$ of beds per period of time in the context of a system with perfect responsiveness is shown in Fig. 7.16b. Hence, for this perfect system, the two curves of supply and demand would overlap, with $S_H(t) = D(t)$.

Let us now imagine another health system, whose responsiveness is low and which is already operating at full capacity before the beginning of an outbreak. This system must expand its original capacity and thus, there occurs a time lag to match this new demand. For this reason, the bed capacity for each current time period is equal to that of the demand from the previous four time periods, providing a supply function $S_L(t)$ of hospital beds per time period, as shown in Fig. 7.16b. This low responsiveness system shall only match the new demand at time T_L. The unfulfilled demand per period requires expensive patient transfers to a third-party health system, so that all patients are able to be hospitalized.

Decision alternatives can be devised to improve the responsiveness of health systems. Consider the low responsiveness health system that has been discussed in the case above. Health security actions could be devised to reduce the time-lag in order to meet the demand that has been placed on the health capacities, as illustrated in Fig. 7.16b. Computer simulations can be employed to estimate the performance of different decision rules and alternative policies that are required in order to improve the responsiveness of the system, such as in the analysis conducted by Bam et al. (2017) which focused on the stocks of essential tuberculosis medicines.

7.5 Conclusions: Developing Decision Alternatives for Enhanced Health Security

In this chapter, we have emphasized that a real effort into an extensive search for creative solutions, and into the design of high-value decision alternatives, proves crucial for enhancing health security. Unfortunately, decision makers often allocate little time or effort in generating alternative options, hastily select a course of action, and these actions result in a poor solution with low societal value. Indeed, we have described many barriers that hinder the development of high-value decision alternatives, from individual cognitive and motivational biases, to group judgment biases and organizational dysfunctional behaviors.

In addition to individual and group biases, organizations often retain decision processes and organizational cultures that prevent the development of high-value alternatives. Specifically, organizations may place emphasis on decision rapidity over decision quality for non-urgent decisions, promote an adversarial group decision making style that inhibits creativity, and exhibit a culture of conformity and

orthodoxy. In practice, these biases and dysfunctionalities may lead to a decision process wherein a single option is considered, or, only very few variations of this single option are appraised.

One significant way to reduce these biases entails the introduction of a specific decision stage for the development of decision alternatives in health security decision processes. To support this development process, in this chapter, we have presented several tools which can be utilized to foster creativity during the process of option generation, thereby potentially increasing the societal value of decision alternatives.

There exist two core ideas from Decision Analysis and from Risk Analysis that should guide this search. First, decisions are created to achieve fundamental objectives in the specific decision situation, with decision alternatives forming the means to achieving these objectives. Second, decision alternatives should be able to manage the uncertainties caused by the decision environment. Hence, an important way to improve these alternatives involves devising actions that improve the performance of these alternatives under uncertainty.

This chapter has focused on how health security teams are able to improve the content of a health decision analysis in such a way that said analysis stimulates the search for creative solutions and the design of superior decision alternatives. The management of decision processes is of equal importance, in that this management should function to foster creativity, curb constrained thinking, plan a decision stage whose sole focus is to generate options and to develop decision alternatives, and finally, to continuously seek to identify better solutions until a choice is eventually made.

Once a strong set of potentially high-value alternatives has been identified, and the remaining stages and components of the health decision analysis have been emplaced, as has been presented in previous chapters, we have now reached a stage wherein it is possible to evaluate these decision alternatives. This evaluation shall consider the relevant consequences, the key uncertainties, the benefits and costs that each alternative is likely to generate, the trade-offs required among conflicting objectives, and the risk limits imposed by the decision situation. The evaluation of the decision alternatives in health security decisions with multiple objectives shall form the topic of the subsequent chapter.

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Chapter 8
Evaluating Health Threats and Health Security Actions with Multiple Consequences



The previous chapters described the initial decision stages that are required for reasoned health security decision processes. As we have discussed so far, we must adopt an adequate decision frame which is underpinned by a clear problem definition. Within this decision frame, the fundamental objectives for the specific decision situation must be specified, as these objectives serve to determine the relevant consequences. The decision frame also encompasses a diverse set of potentially high-value decision alternatives, which in turn must be identified or developed. Additionally, the possible impacts of health threats and health security actions must be assessed on the relevant consequences, clear risk limits must be defined, and explicit trade-offs must be specified. Thus, these previous decisions stages produce content which proves fundamental to executing the assessment of health threats and the evaluation of health security actions for enhanced health security..

In this chapter, we shall detail the ways in which decision alternatives can be evaluated in a situation wherein multiple objectives must be achieved and negotiated, alongside discussing the ways in which we must assess and rank health threats with multiple impacts. We shall commence with a discussion concerning the defining of screening criteria that shall underpin the pre-selection of decision alternatives, the step of which proves essential prior to the stage wherein we evaluate alternatives, as this screening should omit any alternatives whose performances prove unacceptable from the selection processes.

Subsequently, we shall introduce the evaluation of alternatives which incurs two consequences, as this decision problem provides us with an opportunity to discuss several important concepts which are embedded in this type of decision. More specifically, this type of decision situation enables us to discuss the need for establishing difficult trade-offs among conflicting objectives and for considering both evidence and societal values in such choices.

The evaluation of decision alternatives is subsequently extended to multiple consequences. This extension enables the evaluation of alternatives on the extent to

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which they achieve the multiple fundamental objectives of the health security decision. We shall also demonstrate how, when we consider the impact of health threats on the multiple relevant consequences, we are subsequently able to employ this evaluation to rank health threats.

In the second chapter, we presented a diagram which illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 8.1. The present decision stage: *evaluating health threats and health security actions and identifying best options*, is now highlighted in this modified figure. This stage shall be discussed in this chapter and in the two chapters that follow. In this chapter, we shall focus on the evaluation of health security actions and health security threats with *multiple consequences*. We shall assume that: i) the problem has been defined and agreed upon by the health security team, ii) relevant objectives and consequences have been defined, iii) a creative and diverse set of decision alternatives has been developed, iv) key uncertainties, trade-offs, and risk limits have been defined, and v) the impacts of health threats and health security actions have been reliably estimated.

8.1 Screening Decision Alternatives for the Evaluation

The evaluation of decision alternatives on multiple decision objectives requires an assessment as to whether weak performances in achieving some objectives can, in some manner, be compensated by strong performances in achieving other fundamental objectives. Indeed, this notion of *compensation* is key to decision making with conflicting objectives, and thus, is required in any reasoned decision processes (Keeney, 1992, 2002, 2013). Moreover, the performances of decision alternatives often demonstrate correlation, such that a health security action with ample benefits typically incurs high implementation costs. Conversely, health security actions that incur low implementation costs usually bring about limited benefits.

With every choice, decision makers must judge as to whether the potential benefits that the choice could bring about do in fact compensate for the amount of resources invested, as we have argued in the sixth chapter. This specific trade-off forms a difficult judgment call which health security teams frequently must make in health security decisions. It would be rather naïve to think that such judgments could be avoided and to assume that choices with conflicting objectives could be selected solely based on the available evidence while omitting any human input.

However, in health security decisions, this requirement for compensation does not imply that a poor performance of a decision alternative, or, that any negative impact that arises as a result of a health threat should be deemed to be acceptable (Fischhoff et al., 1993). On the contrary, unacceptable performances of decision alternatives and negative impacts of both health security actions and health threats should be directly addressed and managed in the earlier steps of the evaluation stage.

In decision making, the need to consider trade-offs and to manage unacceptable levels of performance or impacts gives rise to a conundrum. More specifically, if

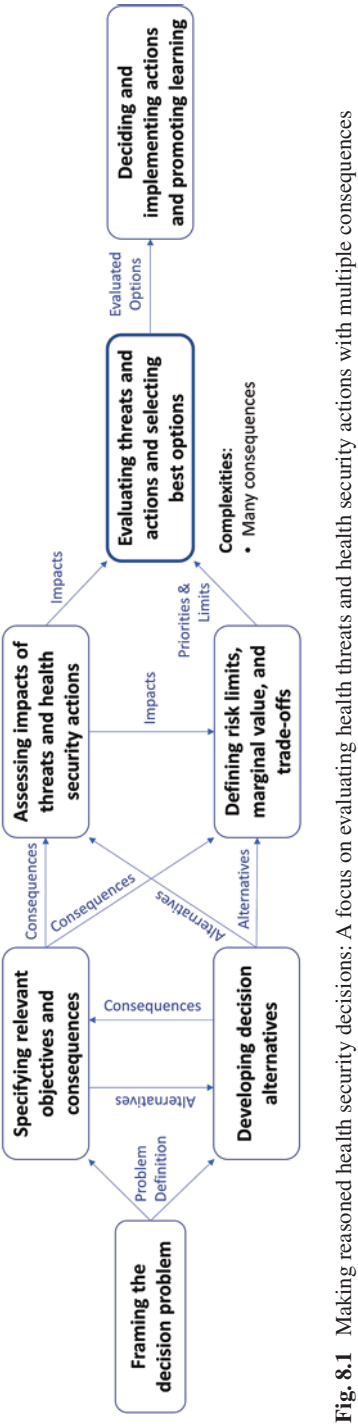

Fig. 8.1 Making reasoned health security decisions: A focus on evaluating health threats and health security actions with multiple consequences

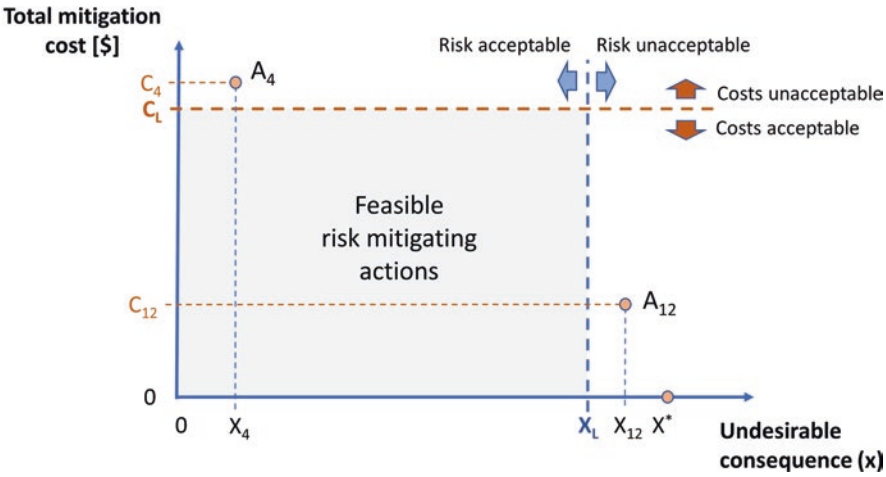

Fig. 8.2 Two screening criteria in this decision problem which is defining feasible and unfeasible alternatives

decision alternatives with unacceptable performance levels were to be included in the evaluation, this inclusion would result in a heavy distortion of the trade-offs in order to avoid selecting these alternatives at all costs. To resolve this issue, *screening criteria* should be implemented before decision alternatives are to be evaluated. Said criteria remove from the evaluation process any decision alternative whose performance levels, risk levels, or impacts levels are deemed to be unacceptable. (See Keeney (2014) for a detailed coverage of this topic in the context of siting energy facilities.)

This concept of screening criteria is analogous to the permission that must be requested for human trials in drug approval decisions by national and supra-national regulators, such as the Food Administration Agency (FDA) in the USA, the National Institute for Health and Care Excellence (NICE) in Britain, and the European Medicines Agency (EMA) in the European Union. In decision such as those, drugs with unacceptable levels of risk are not approved for human trials. Similarly, in health security decisions, decision alternatives that demonstrate unacceptable levels of performance should be excluded from the option set.

Let us turn to the case introduced in the sixth chapter, whereby a hypothetical health threat may cause X^* severe cases. Two undesirable consequences that could be brought about by this health threat entail: the *number of severe cases* (measured by variable x) and the *total mitigation cost* (in $), as shown in Fig. 8.2. The two levels X_L and C_L indicate the maximum acceptable number of severe cases and the maximum tolerable (total) mitigation cost, respectively, and form screening criteria in this decision.

Assume that a set of risk mitigating actions (**A**) has been identified to manage the health threat, each action functioning to reduce the number of severe cases (measured by variable x) from the original level (X^*) to a lower level. Imagine that if two

actions in this option set (A_4 and A_{12}) were to be implemented, the two actions would demonstrate the performance shown in the same figure (i.e., X_4 remaining severe cases and C_4 implementation cost for alternative A_4, and X_{12} remaining severe cases and C_{12} implementation cost for alternative A_{12}). In this case, the option A_4 would be screened out from the evaluation, as $C_4 > C_L$ (the cost exceeds the budget limit C_L) as well as A_{12}, given that $X_{12} > X_L$ (number of severe cases exceeds the risk limit X_L).

The area that is located to the left of the threshold representing acceptable risk (X_L) *and* that is below the threshold delimiting the acceptable costs (C_L) in the Fig. 8.2 indicates the solution space, wherein *feasible* decision alternatives for risk mitigation should be contemplated. Within this area, the performances of risk mitigating actions can be *compensated*, i.e., stronger reductions in the number of severe cases may be worth the additional investment into risk mitigation.

There exist many useful sources of screening criteria which are available to decision makers, one source of which involves requesting that members of the health security team postulate possible *poor* decision alternatives whose performances would be deemed to be unacceptable, taking into account this alternative in the context of the current decision situation, but also in the context of previous decision situations. This particular process can aid the team to develop a list of consequences, which could include items such as risk limits, excessive costs, unacceptable health and social impacts, among others. Once the list of consequences has been refined and agreed upon, an attribute can be identified or developed, as detailed in the fifth chapter, to measure each consequence and thus establish levels of acceptability and unacceptability.

Another source of screening criteria takes the form of the attributes which have been defined for the evaluation of decision alternatives and have been emplaced at the rightmost nodes of a value tree. Each attribute indicates a relevant consequence for the evaluation. It is often the case that performances of decision alternatives above a given level (for minimization decision objectives) or below a given level (for maximization decision objectives) are judged to be unacceptable.

For instance, let us consider the vaccination campaign case, which has been detailed in the previous chapters. One fundamental objective is to *minimize the campaign costs*, which is then measured by the attribute *total cost of the vaccination campaign [$ million]*. If the available budget were to be $100 million, while maintaining a degree of flexibility so that up to $110 million could be spent, then the latter limit would be rendered as a screening criterion for this decision. In this instance, no vaccination campaign that would cost over $110 million would be considered, regardless as to how beneficial and effective this campaign could prove. This example illustrates the necessity of imposing a screening criterion as a response to a *material constraint* (such as the size of the budget).

Another fundamental objective of this decision problem is to *maximize the immunization coverage rate*, which is measured by the attribute *proportion of the population vaccinated [%]*. Let us assume that, given the transmissibility of an infectious disease, (Brauer et al., 2019), levels below 60% were considered to be unacceptable. This screening criterion would thus exclude any vaccination

campaign that would vaccinate fewer than 60% of the population, regardless as to how many other benefits this campaign could bring about or how inexpensive the campaign could prove. In a similar manner to the imposition of a screening criterion as a response to a material constraint, this example illustrates that a screening criterion is also required as a response to *health-related issues*. Furthermore, screening criteria could be derived from concerns about the quality of the vaccination campaign.

It is important that only truly unacceptable levels be used to screen out decision alternatives. As emphasized in the sixth chapter, at times, decision makers assume an excessively orthodox position and consequently become intolerant to even a minor undesirable impact. This attitude may excessively constrain the solution space and lead to the elimination of potentially high-value alternatives, whose inclusion may otherwise provide strong benefits and only entail exceptionally minor risks or negligible detrimental effects.

Furthermore, in this sixth chapter we had also discussed the frequent issue involving the concept of a fixed budget, whose implementation brings about a hard constraint and may exclude high-benefit alternatives which require further investments (since these alternatives lie on the periphery of the budget limit). However, at times it becomes possible to acquire additional funding, (e.g. from external organizations and international donors). This inclusion of additional resources may in turn enable the inclusion of high-benefit options, which, would otherwise be disregarded (Phillips & Bana e Costa, 2007). Hence, here, we recommend that decision makers consider the budget to be a soft constraint, and eliminate only the options that prove truly unaffordable by employing a cost-limit screening criterion.

8.2 Evaluating the Value of Decision Alternatives with Two Consequences

Once an exclusion of decision alternatives whose performances or impact levels have been deemed to be unacceptable has been effectuated, we are able to compare the remaining alternatives and select the best alternative(s). First, we shall analyze a relatively simple case, wherein only two relevant consequences are under consideration when evaluating decision alternatives. We conduct this analysis in order to reveal a space wherein fundamental concepts in decisions with conflicting objectives may be introduced and discussed in detail. This type of evaluation shall be subsequently extended to multiple relevant consequences in the next section.

We shall employ the concept of trade-offs,which has been discussed in the sixth chapter, in order to guide the choice as to which is the best alternative(s). Given the inherent trade-offs that are required when considering multiple objectives, the best alternative is that which maximizes the *societal value* for the *specific* decision situation under consideration (Keeney, 1992, 2002).

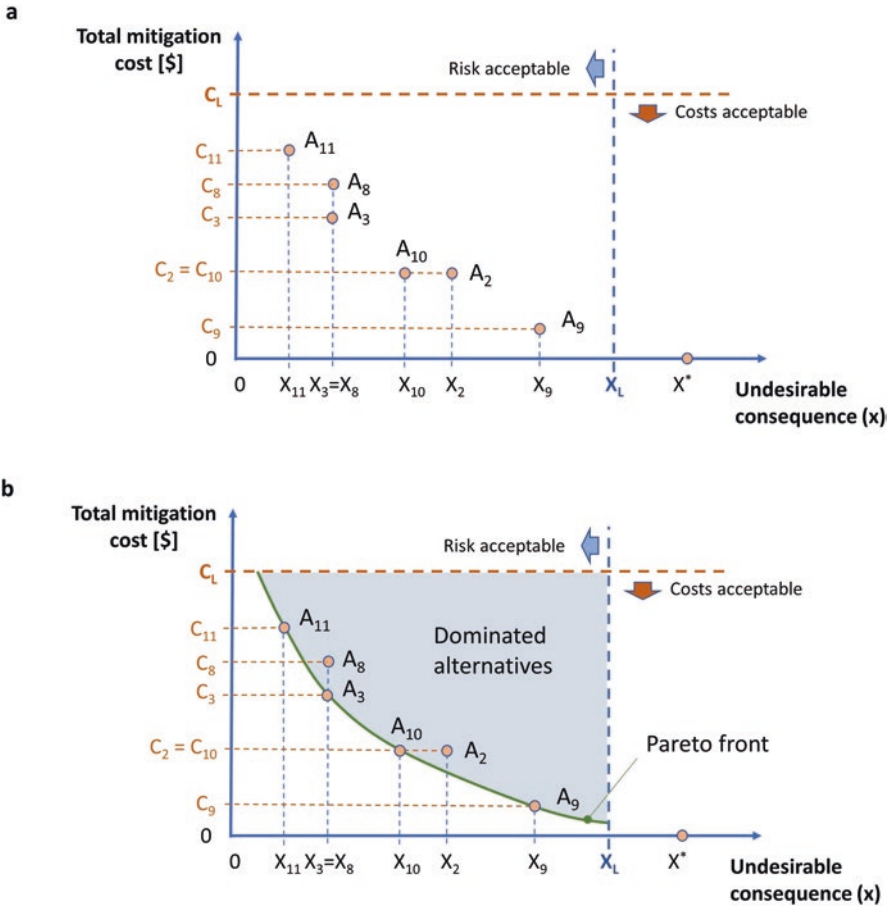

Fig. 8.3 Decision alternatives for a decision with two consequences: (**a**) All feasible decision alternatives, (**b**) Dominated alternatives and non-dominated alternatives along the Pareto front

When cogitating objectives that decision makers wish to minimize, such as costs and health impacts, a *lesser* impact gives rise to an alternative of greater value. Conversely, for objectives that decision makers wish to maximize, such as vaccination coverage and other health and socio-economic benefits, a *higher* impact and performance gives rise to an alternative of greater value.

Let us consider the first case (wherein we wish to minimize impacts) and revisit the example from the previous section wherein two attributes were being considered. The decision alternatives under evaluation are those that lie within the feasible region, as illustrated in Fig. 8.2. Assume that more alternatives have been identified and compose the set of risk mitigating actions (**A**) to manage the health threat, each action functioning to reduce the number of severe cases (measured by variable x) from the original level (X^*) to a given (lower) level of severe cases (X) and each action incurs a given implementation cost (C), as shown in Fig. 8.3a. For instance,

if we focus on alternative A_9 in the same figure, we can see that this alternative, if implemented, would reduce cases from X^* to X_9 and would cost C_9 to be implemented. Consequently, A_9 proves to be the least effective alternative in reducing the number of severe cases among the options under consideration, but, also proves to be the least expensive to implement. Among the set of decision alternatives, A_{11} proves the most effective option for risk reduction with X_{11} severe cases remaining although this option incurs a relatively higher cost of C_{11}.

This case permits us to introduce two important concepts in decision making with multiple consequences: dominance among decision alternatives and the Pareto front. An alternative A_x *dominates* another alternative A_y if the performance of the former is at least as strong as that of the latter on any attribute, and if the performance of A_x is stronger than the performance of A_y for at least one attribute. Conversely, if this condition were to hold, A_y is said to be *dominated* by A_x (see von Winterfeldt and Edwards (1986) for details). For instance, in Fig. 8.3a the decision alternative A_8 is *dominated* by alternative A_3, as both demonstrate the same risk mitigation performance ($X_3 = X_8$), while A_3 is less expensive ($C_8 > C_3$). Similarly, alternative A_2 is *dominated* by alternative A_{10}, as both incur the same cost ($C_2 = C_{10}$) while A_{10} is more effective in mitigating the risk ($X_{10} < X_2$). Following this logic, alternatives A_{11}, A_3, A_{10}, and A_9 are *non-dominated alternatives*, and consequently, the best alternative should be chosen from this set (Keeney, 2014).

In addition, a curve could be traced linking the non-dominated alternatives, as shown in Fig. 8.3b. This curve is called the *Pareto front*, and, any alternative positioned along this curve would be denoted as a non-dominated alternative. On the other hand, alternatives that lie above the Pareto front (in relation to the South-West corner of the diagram) are dominated and could thus be excluded from the possible options under consideration. This proves to be the case for alternatives A_2 and A_8, as illustrated in the same figure.

Selecting the best option (among the non-dominated options) should be guided by a trade-off judgment. As discussed in the sixth chapter, the trade-off can be graphically represented by an indifference curve. For example, assume that the health security team decides that the option should reflect a balance between the minimization of the number of severe cases and the total mitigation cost, the concept of which is represented by an indifference curve I_B as shown in Fig. 8.4a. In this case, the societal value of the alternatives increases in accordance with the direction of the arrow. Consequently, A_{10} would be rendered the alternative whose value is the highest out of all the other options, as A_{10} is the last point touched by I_B on the Pareto front.

Following this same rationale to guide the selection process, other options could be selected, depending on the trade-off that is made between the two relevant consequences. For instance, let us posit that the reduction in costs takes significant precedent over the reduction in the number of critical cases, a situation which is reflected by an indifference curve I_C as shown in Fig. 8.4b. In this case, the alternative with the maximum societal value, for this indifference curve (I_C) is A_9. On the other hand, if the health security team significantly prioritized the reduction in the number of severe cases, a situation which is reflected by an indifference function I_X,

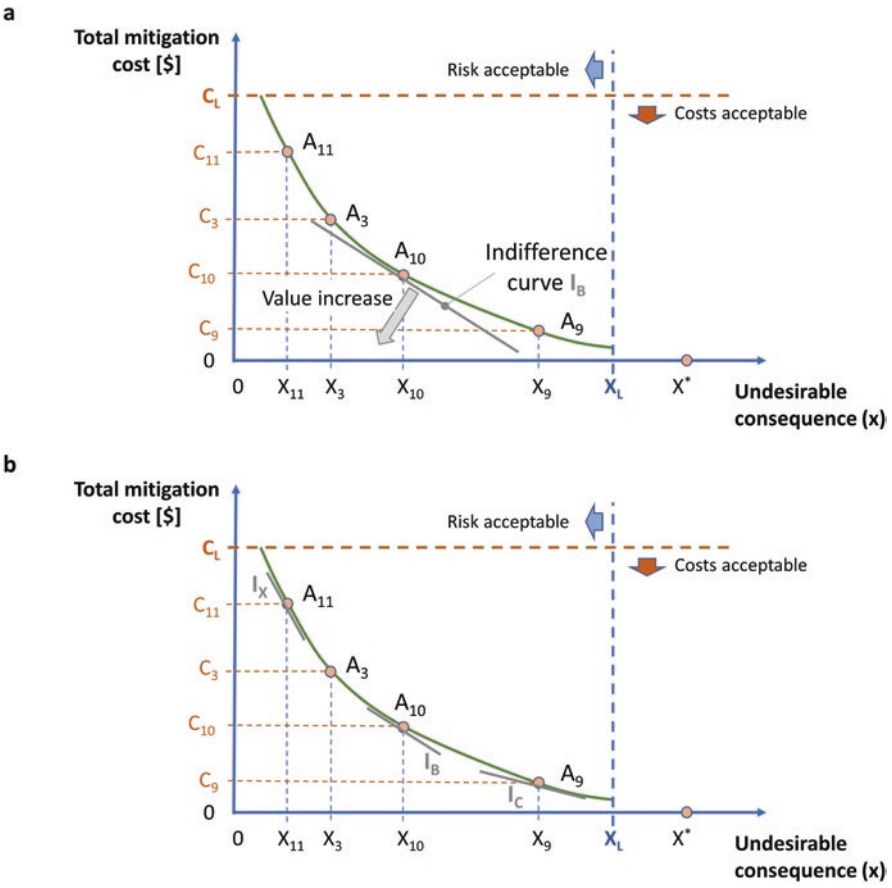

Fig. 8.4 Indifference curves guiding the assessment of societal value and choice of a decision alternative (**a**) Indifference curve IB guiding the choice of alternative A10, (**b**) Indifference curves IX and IC guiding the choice of alternatives A11 and A9, respectively

then alternative A_{11} would be the alternative with the highest societal value, as represented in the same figure.

This simple example illustrates several important concepts which are involved when making choices with conflicting objectives. The first concept entails the notion of dominated and non-dominated decision alternatives, and the subsequent selection of the best alternative which is made among the non-dominated options. The second concept entails the Pareto front, which is a curve that identifies all possible non-dominated alternatives. The third concept entails the notion that the selection of the best alternative is dependent upon the trade-off made between the two conflicting objectives (reduction in number of severe cases versus the implementation cost). This trade-off shall define an indifference curve, and, similarly, the direction of value increase of this indifference curve shall define which option maximizes the societal value.

The example also illustrates the relevance (and the limits) of employing evidence in health security decisions. The importance of evidence-based decision making in health policy is widely accepted, and justifiably promoted (Cairney & Oliver, 2017). Specifically, in a health decision analysis, the best available evidence should be gathered to inform decision makers as to the possible consequences of implementing alternative courses of action. However, evidence proves insufficient, in that it constitutes only part of the conceptual foundation which is used to underpin the selection of a choice, and therefore, public health leaders must also consider trade-offs.

For instance, in Fig. 8.4a, the best evidence available should be employed to make reliable estimates concerning the remaining levels of severe cases for each risk mitigating alternative (X_3, X_9, X_{10}, and X_{11}), as well as for the implementation cost of each option (C_3, C_9, C_{10}, and C_{11}). However, regardless as to the quality of the evidence about performances and implementation costs, this evidence is insufficient to guide a choice. There exists a need for a trade-off judgment in health policy decisions (Schoemaker et al., 2020) in order to identify the option with the highest societal value, as illustrated by the indifference curve in the same figure. Different trade-offs, represented by distinctive indifference curves (I_x, I_B, or I_C), would render a different option preferable (A_{11}, A_{10}, or A_9, respectively), as presented in Fig. 8.4b.

The graphical value analysis which is presented in this section proves unpractical when there exist more than two relevant consequences in the evaluation of decision alternatives. When there exist three consequences, the analysis would become three dimensional, and the Pareto front would transform into a surface that indicates the spatial positioning of non-dominated alternatives. Yet, when there exist more than three consequences, a simple visualization of the decision problem is rendered unfeasible, and consequently, the development of a multi-attribute model (which is able to assess the value of each alternative on multiple dimensions) is advisable, as we shall discuss in the subsequent section.

8.3 Evaluating the Value of Decision Alternatives with Multiple Consequences

In Decision Analysis, multi-attribute value analysis is a very well-established methodology for assessing the value of decision alternatives with multiple objectives (Keeney & Raiffa, 1993; von Winterfeldt & Edwards, 1986). Ergo, multi-attribute value analysis has been extensively used in a variety of applications, such as environmental analysis (Ferretti & Montibeller, 2016; Gregory et al., 2012), facilities location (Keeney, 2014), health technology (Angelis et al., 2017), and health security (Montibeller, Franco, & Carreras, 2020a; Montibeller, Patel, & Del Rio Vilas, 2020b), among other fields. This section presents both an overview of this type of evaluation model, which is employed to evaluate the value of decision alternatives

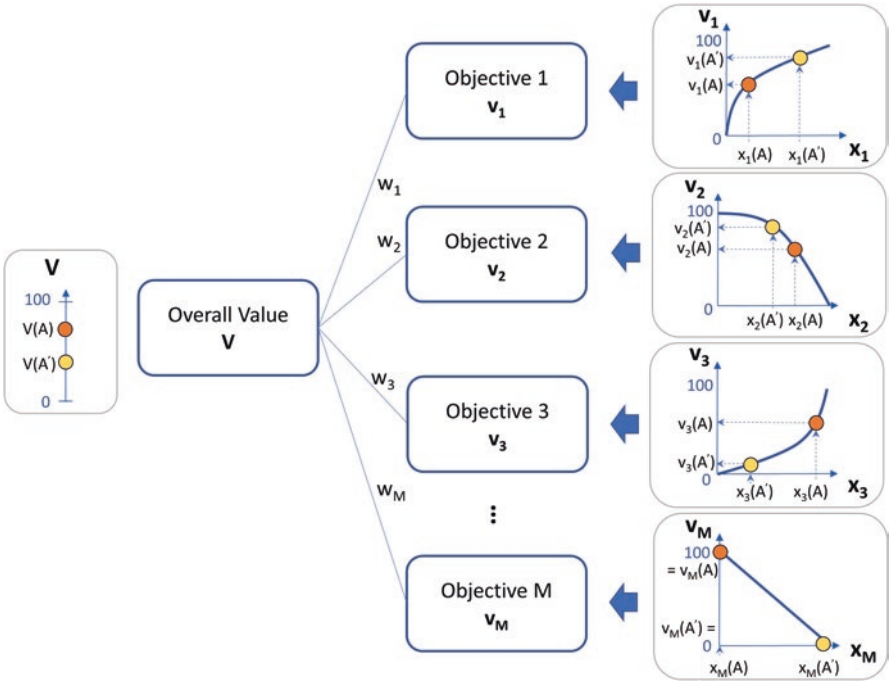

Fig. 8.5 A multi-attribute value analysis of two health security decision alternatives A' and A

with multiple relevant consequences, and a discussion on the logical requirements that must be present when utilizing a weighted sum to aggregate the multiple consequences.

8.3.1 Defining a Multi-Attribute Value Model

The principal steps of a multi-attribute value analysis when evaluating decision alternatives are illustrated in Fig. 8.5 (see also Montibeller and Franco (2007) for a step-by-step coverage of this type of decision modeling). Two decision alternatives for enhancing health security have been identified, A and A′, and there exist M fundamental objectives in this decision, the presence of which should lead to the definition of relevant consequences.

For each i-th fundamental objective, an attribute x_i has been defined in the value model to measure the relevant consequence and a value function $v_i(x_i)$ has been elicited to assess the marginal value over each i-th attribute and normalized between 0 (least preferred level of impact) and 100 (most preferred level of impact), as illustrated in Fig. 8.5. Evidence concerning the performance or impact of each decision alternative (A and A′) must be obtained in order to estimate their performance on

every x_i attribute, i.e. $x_i(A)$ and $x_i(A')$. This information enables the assessment of the value score for each alternative on every i-th attribute: $v_i[x_i(A)]$ and $v_i[x_i(A')]$.

For maximization objectives, such as that of Objective 1 in Fig. 8.5, the higher the performance of a given decision alternative on attribute x_1, the higher the value $v_1(x)$ this alternative provides. For example, this attribute could measure *the number of rapid test kits distributed during a pandemic*, with A' providing a higher proportion than A, therefore: $x_1(A') > x_1(A)$ and $v_1(A') > v_1(A)$. For minimization objectives, such as that of Objective 2 in the same figure, the higher the performance on attribute x_2 of a given alternative, the lower the value $v_2(x)$ this alternative provides. For instance, this attribute could assess t*he overall cost of producing and delivering rapid test kits*, with A' being less expensive than A, hence $x_2(A') < x_2(A)$ and $v_2(A') > v_2(A)$.

Notice also that in this model, there occur different shapes of the value functions, such as a function that is concave for v_1, convex for v_3, and linear for v_M. These shapes are dependent upon either the marginal value that is gained when increases in performance occur (for maximization objectives, such as v_1 in Fig. 8.5), or, the marginal value that is reduced when increases in impact occur (for minimization objectives, such as v_2 in the same figure), as we have discussed in the sixth chapter.

For each objective, the attribute weights are denoted by w_i in this model, and represent trade-offs among conflicting objectives and their associated relevant consequences. The elicitation of these attribute weights should follow an adequate protocol, which takes into account the ranges of the attributes (the topic of which has also been detailed in the sixth chapter).

The overall value V for each alternative, i.e. V(A) and V(A') in Fig 8.5, can then be calculated for each decision alternative as a multi-attribute value function of the value scores on every attribute for each alternative and the attribute weights (Keeney, 1992, 2014; von Winterfeldt & Edwards, 1986).

If specific independence conditions were to hold among the attributes, then a simple weighted sum can be used to aggregate the value scores. In this case, the overall value V(A) of alternative A is calculated as a simple weighted sum of the value $v_i[x_i(A)]$, which values the performance of alternative A on this attribute, $x_i(A)$, and the attribute weight w_i for the M objectives:

$$V(A) = \sum_i w_i v_i\left[x_i(A)\right] = w_1 v_1\left[x_1(A)\right] + w_2 v_2\left[x_2(A)\right] + w_3 v_3\left[x_3(A)\right] + \ldots + w_M v_M\left[x_M(A)\right]$$

The overall value of each alternative (A and A′) can be calculated and compared with this function. For instance, as illustrated on the left-hand side of Fig. 8.5, the value of the former alternative is greater than the value of the latter alternative: $V(A) > V(A')$.

This multi-attribute value function presupposes two conditions. First, the function assumes that decision alternatives can be valued on every attribute, independently as to the performance of these alternatives with regards to other attributes. Second, the function assumes that stable indifference curves can be established

among the attributes and, therefore, constant attribute weights are able to be defined. In order for these two assumptions to hold, specific independence conditions must be fulfilled by the attributes.

This independence requirement is made more comprehensible when an example is employed, wherein an independent attribute valuation is rendered not meaningful in a health security assessment. Let us posit that health threats are being assessed on two attributes: the *number of disease cases* and *disease severity* that a threat may cause. Furthermore, an assessment shall be conducted that wishes to evaluate the overall impact of each threat. Let us assume that there exist four health threats whose impacts are the following: (i) threat T_{SM} would cause a *small* number of cases with *mild* symptoms, (ii) threat T_{SS} would cause a *small* number of cases with *severe* symptoms, (iii) threat T_{LM} would cause a *large* number of cases with *mild* symptoms, and (iv) threat T_{LS} would cause a *large* number of cases with *severe* symptoms.

It is not possible to evaluate as to which threat would cause the most overall impact *without* considering jointly the two types of impact. Specifically, for the two threats that may cause a *severe* health impact (T_{SS} and T_{LS}), the value distance that arises from the interstice between a small and a large number of cases is likely to be much wider than, for two threats that may only cause mild health consequences (T_{SM} and T_{LM}). There occurs a preferential *dependence* among these two attributes: *number of disease cases* and *health severity*.

Therefore, we see that in this example, a simple weighted sum *could not* be employed to assess the overall impact of each threat from an independent assessment of the threats on the *number of disease cas*es attribute and another independent assessment of threats on the *disease severity* attribute. Unfortunately, several published studies have adopted this score-and-sum assessments for health threats, which do not observe logical requirements for a multi-criteria evaluation (see also Montibeller, Patel, and Del Rio Vilas (2020b) for a more detailed discussion of this modeling mistake in health threat assessments).

Another common issue (particularly among scientists) entails confounding preferential dependence with a statistical dependence pertaining to the performances of decision alternatives. Performances of decision alternatives are often correlated, for instance, vaccination campaigns that are more expensive are more likely to be prove more effective and vaccinate a greater proportion of the population. This positive correlation does *not* prevent the use of a simple weighted sum to aggregate value performances in a multi-attribute value function that evaluates *independently* the cost and the effectiveness of the vaccine, as long as the two attributes observe preferential conditions. Next, we shall describe how these independence requirements can be verified.

8.3.2 Testing Independence Conditions for the Attributes

There exist two main independence conditions which must be met in order to use a simple weighted sum to aggregate the value scores in a multi-attribute value function, the conditions of which are *preferential independence* and the *weak-difference*

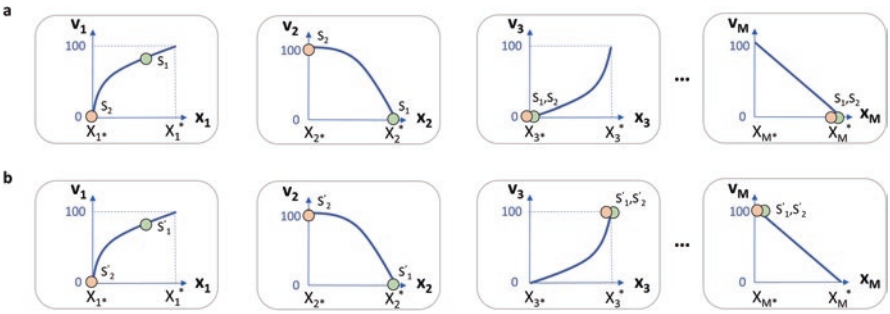

Fig. 8.6 Testing preferential independence for two attributes x_1 and x_2: (**a**) Two strategies: S_1 and S_2, which are considered indifferent to each other, (**b**) Two strategies: S'_1 and S'_2, which must be considered to be indifferent to each other for the independence condition to hold

independence (Dyer & Sarin, 1979; Keeney, 1992; von Winterfeldt & Edwards, 1986). There often exists a lack of clarity as to how the independence conditions should be tested (see also the discussion by Smith and Dyer (2021)). The use of logical tests shall be described and exemplified next.[1]

Preferential Independence This condition requires that preferences for alternatives over two attributes be independent of the performances of these alternatives on the other remaining attributes.

Consider a decision which seeks to determine how many rapid test kits should be produced and delivered during a pandemic. Assume that only two fundamental objectives are being considered in this decision: *maximize the number of rapid test kits delivered* and *minimize the production and delivery cost of the kits*. The respective attributes for measuring the performance of different strategies of production and delivering the kits are: the *number of rapid test kits delivered* (measured by variable x_1) in million kits, and the *production and delivery cost of the rapid test kits* (measured by variable x_2) in $ million.

Value functions have been developed for these attributes, represented by v_1 and v_2 in Fig. 8.5, respectively. The number of rapid test kits delivered (which is dependent upon on the selected option) ranges from $X_{1*} = 200$ million to $X_1^* = 400$ million. The overall cost of the strategies under consideration ranges from $X_{2*} = \$50$ million for the cheapest to $X_2^* = \$100$ million for the most expensive one. These boundaries define, correspondingly, the ranges of these two attributes (x_1 and x_2).

Now, let us imagine two hypothetical strategies for producing and delivering the kits, with their performances shown in Fig. 8.6a. Strategy S_1 delivers 350 million kits ($v_1(S_1) = 70$ value points) while costing $100 million ($v_2(S_1) = 0$ value points). Strategy S_2 delivers 200 million kits ($v_1(S_2) = 0$ value points) while costing $50 million ($v_2(S_2) = 100$ value points). In addition, both strategies incur the lowest

[1] The remainder of this sub-section details how independent conditions can be verified. The reader that is uninterested in such technical procedures may proceed to the next section.

performance on the other attributes, and thus, both strategies score 0 value points on these other attributes: $v_i(S_1) = 0$ and $v_i(S_2) = 0$ for i = 3, 4, …, M. Let us assume the decision makers to be indifferent toward either S_1 or S_2, i.e. the lower cost of S_2 compensates for the smaller number of delivered kits provided by this strategy.

Consider now two additional hypothetical strategies: S'_1 and S'_2, represented in Fig. 8.6b, which sustain the same performances as S_1 and S_2 on attributes x_1 and x_2, respectively. However, these two additional strategies have the highest performance on the other attributes and therefore, both additional strategies score 100 value points on these other attributes: $v_i(S_1) = 100$ and $v_i(S_2) = 100$ for i = 3, 4, …, M.

If the decision makers were to continue expressing their indifference toward S'_1 and S'_2, (such as the indifference that had been originally expressed between S_1 and S_2) then there exists *preferential independence* between this pair of attributes (x_1 and x_2) and the remaining attributes (x_3, x_4, ..., x_M). Importantly, this test should hold for any level of impact on attributes i = 3, 4, …, M, instead of only holding for levels that are situated at the lower and upper extremities as illustrated here. (However, in practice, preferential dependencies are typically able to be detected solely by utilizing the extremities as inputs.)

Weak-Difference Independence This condition requires that the difference in value between any two levels of performance of the alternatives on one attribute remains the same, irrespective of the levels of performances of these alternatives on the other attributes.

Let us test this property utilizing the same case as above, that of the difference in performance between the attributes: *number of rapid test kits delivered* (measured by variable x_1) and the *cost of producing and delivering the rapid test kits* (measured by variable x_2). The weak-difference condition would require that the *value difference* between $X_{*1} = 200$ million and $X^*_1 = 400$ million rapid test kits be independent of the cost that the strategies would incur. Conversely, this condition would require that the *value difference* between $X_{2*} = \$50$ million and $X_2{}^* = \$100$ concerning the cost of the vaccinationstrategy be independent of the number of kits the strategies would produce. This condition can be tested in practice with four hypothetical situations.

In the first situation, let us posit that there exist two new strategies for producing and delivering the rapid test kits (S_3 and S_4), with the former delivering 200 million kits ($v_1(S_3) = 0$ value points), the latter producing 400 million kits ($v_1(S_4) = 100$ value points), and both costing \$100 million ($v_2(S_3) = v_2(S_4) = 0$ value points). The performances of these alternatives are shown in Fig. 8.7a. There exists a value difference ΔV_{34} between these two decision alternatives on attribute x_1, as represented in the same figure.

Now let us posit a second situation, shown in Fig. 8.7b. Here, two additional hypothetical vaccination strategies are being considered (S'_3 and S'_4), whose performances are the same as that of S_3 and S_4 on attribute x_1: $v_1(S'_3) = 0$ value points and $v_1(S'_4) = 100$ value points. However, both S'_3 and S'_4 strategies cost \$50 million on attribute x_2: $v_2(S'_3) = v_2(S'_4) = 100$ value points. The value difference between these two latter alternatives on attribute x_1 is $\Delta V'_{34}$, as represented in the same figure.

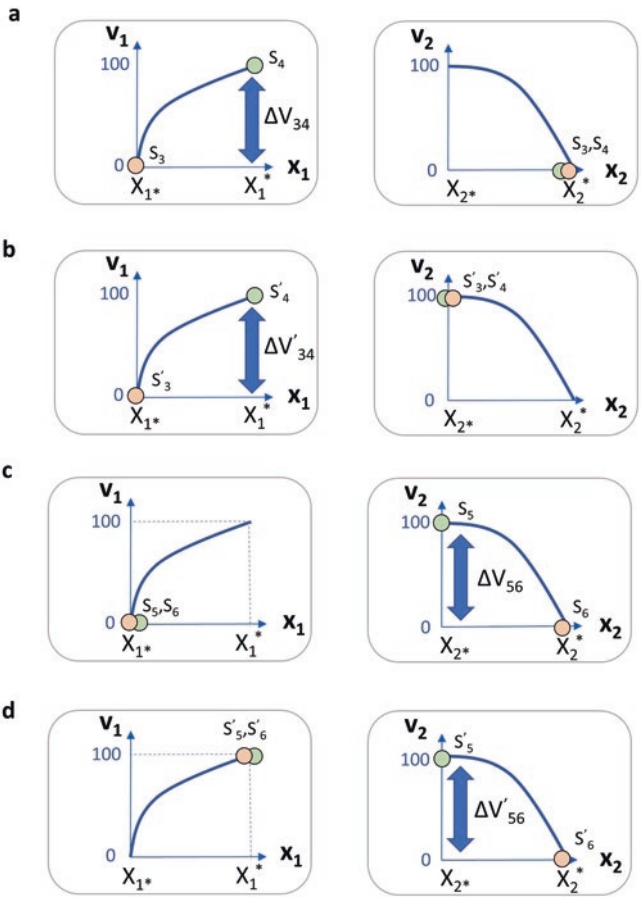

Fig. 8.7 Testing weak-difference independence between attributes x_1 and x_2: (**a**) Value difference between strategies S_3 and S_4, (**b**) Value difference between strategies S'_3 and S'_4, (**c**) Value difference between strategies S_5 and S_6, (**d**) Value difference between strategies S'_5 and S'_6

If the weak-difference independence were to hold between attributes x_1 and x_2, this would require that the value difference remain the same across these two situations, i.e. that $\Delta V_{34} = \Delta V'_{34}$. This property is not symmetrical, so the same test would also need to be executed on the x_2 attribute, as described next.

Consider a third situation wherein there exist two hypothetical strategies: S_5 costing \$50 million ($v_2(S_5) = 100$) and S_6 costing \$100 million ($v_2(S_6) = 0$), as shown in Fig. 8.7c. Both decision alternatives have the same performance on attribute x_1, and result in 200 million kits being delivered: $v_1(S_5) = v_1(S_6) = 0$ value points. There exists a value difference ΔV_{56} between these two alternatives on attribute x_2, as represented in the same figure.

Finally, consider a fourth situation, where two other hypothetical strategies (S'_5 and S'_6) incur the same costs as S_5 and S_6: $v_2(S'_5) = 100$ value points and $v_2(S'_6) = 0$ value points. However, as shown in Fig. 8.7d, both S'_5 and S'_6 deliver 400 million kits, thus: $v_1(S'_5) = v_1(S'_6) = 100$ value points. The value difference of these two alternatives on x_2 is represented by $\Delta V'_{56}$ in the same figure.

If the weak-difference property were to hold between attributes x_2 and x_1, this would require that the value difference remain the same across these two latter situations, i.e. $\Delta V_{56} = \Delta V'_{56}$. If the two conditions were to be verified (i.e., $\Delta V_{34} = \Delta V'_{34}$ and $\Delta V_{56} = \Delta V'_{56}$) then these two attributes would be weak-difference independent.

If the two independence conditions (preferential independence and weak-difference independence) that have been discussed above were to hold, then a simple weighted sum could be used to calculate an overall value score between the two attributes. Specifically, the *preferential independence condition* allows for the defining of constant attribute weights (w_i in Fig. 8.5), as the indifference curves remain fixed between pairs of attributes, regardless as to the levels of performance on the other attributes. This property has been illustrated in Fig. 8.6 for attributes x_1 and x_2 and the remaining attributes i = 3, 4, …M. Additionally, the *weak-difference independence* condition enables both the establishment of value functions over each attribute (v_i in Fig. 8.5) and the possibility for decision makers to define attribute weights from decision makers. This second property has been illustrated in Fig. 8.7, in which the value difference between the extremes attribute levels over attribute x_1 remain undisturbed by the level of performance on attribute x_2. Conversely, the value difference between the extremes attribute levels over attribute x_2 remain undisturbed by the level of performance on attribute x_1. Hence, this second condition allows for the independent elicitation of these value functions (v_1 and v_2), as the value distance between the extreme levels of each attribute remains constant. Moreover, the defining of weights must consider the extreme points of the attributes whose value distances should be fixed, and so, this weak-difference independence condition is also required for weight elicitation (in this example, w_1 and w_2).

On the other hand, if these independence conditions do not hold, then a more sophisticated aggregation function would be required to model such value dependencies (Abbas, 2018; Keeney, 1992). The use of other aggregation functions, such as multiplicative multi-attribute value functions occurs rather rarely in practice. Instead, practitioners prefer to redesign attributes by removing the dependencies (Keeney & Gregory, 2005), or, by selecting objectives that are truly fundamental for the specific decision situation, as fundamental objectives are less likely to display preferential dependencies than non-fundamental objectives (Keeney & von Winterfeldt, 2007).

8.4 Evaluating the Value of Health Security Actions with Multiple Consequences

We shall now illustrate how a value assessment of health security actions can be performed through discussing the vaccination campaign case which has been introduced in previous chapters. The process of selecting the best vaccination campaign considers four fundamental objectives and five decision alternatives. This decision problem is represented by the influence diagram in Fig. 8.8, with the *decision* node influencing the achievement of objectives, which, in turn, influence the *relevant* consequences node. In this section, we shall present the steps that form the evaluation. However, for now, we shall disregard the uncertainty about the campaign effectiveness, and instead, focus on the highlighted nodes in the influence diagram (this issue of campaign effectiveness shall be revisited in the next chapter in order to illustrate how the uncertainty could be modeled in the evaluation).

8.4.1 Defining the Evaluation Model

The value tree for this problem is reproduced in Fig. 8.9. The tree shows the objectives and associated variables that shall assess the value of the different decision alternatives (campaign strategies) under consideration. The evaluation as to the overall value V(.) of each decision alternative has been decomposed into four categories of objectives, each with an associated variable v(.): *maximize vaccination coverage* (v_1), *maximize campaign quality* (v_2), *maximize efficiency of campaign logistics* (v_3), and *minimize campaign costs* (v_4).

The first three categories of objectives in the value tree have been further decomposed into objectives, while the last objective has not. For instance, the category of

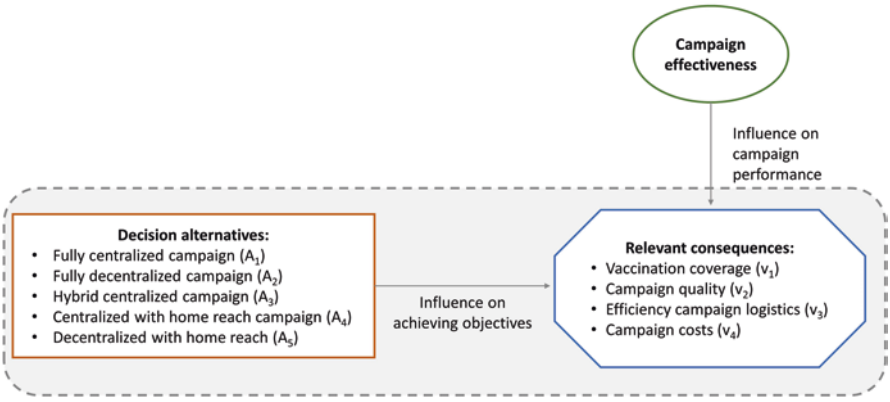

Fig. 8.8 Influence diagram representing the value assessment of the decision alternatives in the vaccination campaign case

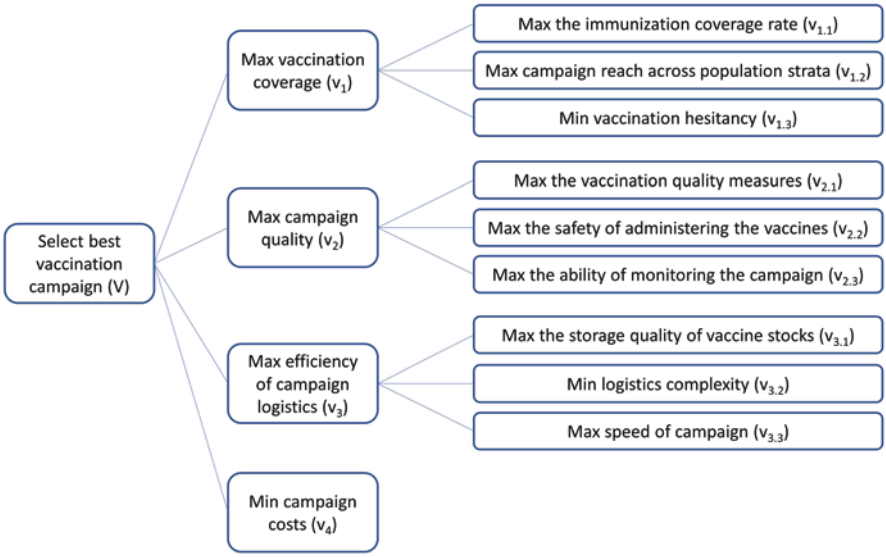

Fig. 8.9 Value tree and associated variables for the vaccination campaign case

objectives *maximize vaccination coverage* (v_1) has been decomposed into three objectives: *maximize the immunization coverage rate* ($v_{1.1}$), *maximize campaign reach across population strata* ($v_{1.2}$), and *minimize vaccination hesitancy* ($v_{1.3}$).

8.4.2 *Defining Attributes and Value Functions*

An attribute has been defined for each rightmost variable in the value tree (see the fifth chapter for details on how to define attributes). For example, the sub-objective *maximize the immunization coverage rate*, with the associated attribute $x_{1.1}$, measuring the *proportion of population vaccinated* [%], is shown in Fig. 8.10a. The range of the attribute is defined from $X_{1.1*} = 60.0\%$ to $X_{1.1}^{*} = 99.0\%$, the definition of which reflects the range of performance for the vaccination strategies that are under consideration. Consequently, it is assumed that any campaign which would provide vaccination levels below 60.0% would be excluded from the evaluation, with a performance level deemed unacceptable. Hence, in the context of this evaluation, this 60.0% rate constitutes a screening criterion. Similarly, it is assumed that a coverage rate of 99.0% is feasible in this context.

The same figure displays the value function $v_{1.1}(.)$ over attribute $x_{1.1}$ (see the sixth chapter for a discussion on how to define value functions). This function measures the marginal value pertaining to increases in performance of the different vaccination campaigns which are under consideration. The best performance on this

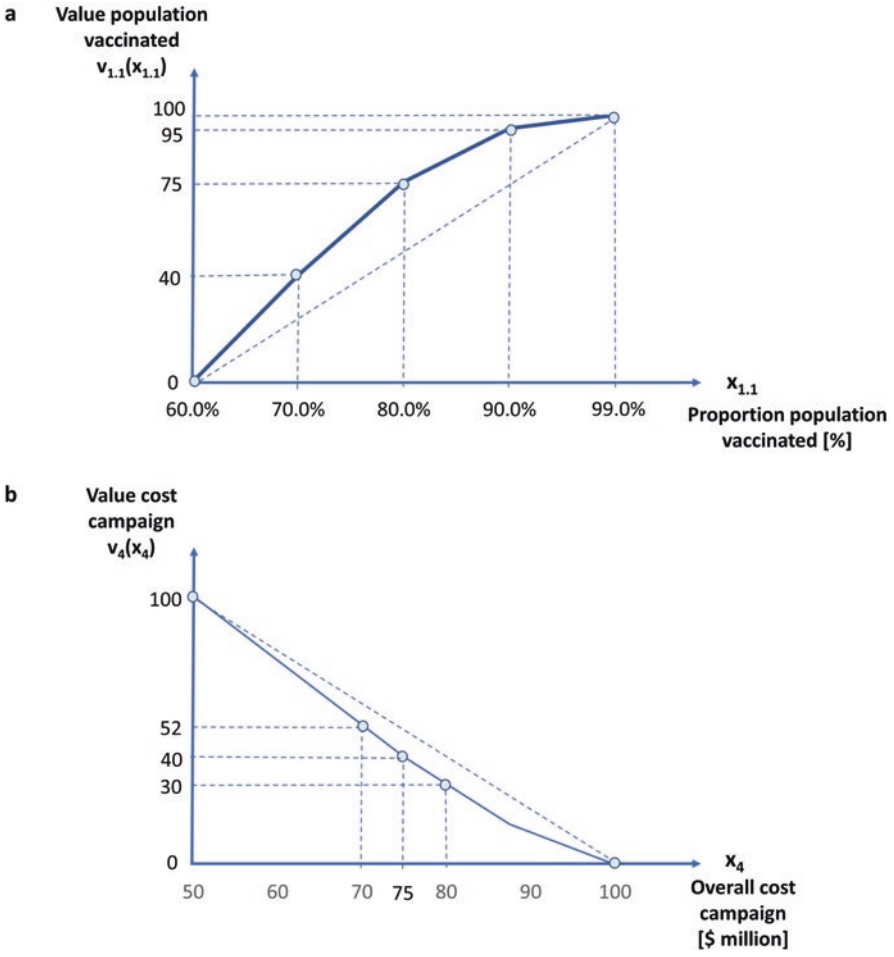

Fig. 8.10 Examples of two value functions for the vaccination campaign case

attribute ($X_{1.1}^{*}$ = 99.0%) scores 100 value points and the worst performance scores $X_{1.1*}$ = 60.0% scores 0 value points. Notice that the value function is non-linear to reflect the strong gains in additional value from 60% to 80% of the population (75 value points), particularly when compared with the increase from 80% to 99% (25 value points).

For minimization objectives, value functions demonstrate a marginal decreasing value as the impact increases. This is illustrated in Fig. 8.10b, for the objective *minimize the cost of the campaign*, with the attribute x_4, *overall cost of the vaccination campaign* [$ million] and the associated value function $v_4(.)$. Here, the range is also defined, extending from the least expensive to the most expensive decision alternative under consideration (within the available budget limit). The lowest possible

cost ($50 million) scores 100 value points and the highest possible cost ($100 million) scores 0 value points. Once again, the value function is non-linear, with a decrease in value of 60 value points (= 100–40) if the campaign costs were to increase from $50 million to $75 million, in comparison with a further decrease of 40 value points if a further increase from $75 million to $100 million were to occur. This shape represents the undesirability of increasing campaign costs, from the lowest feasible level of $50 million (which in this case represents the minimum possible cost for delivering a vaccination campaign).

8.4.3 *Defining Weights for Objectives and Attributes*

We illustrate the process of defining weights for the sub-objectives under the category of objectives *maximize vaccination coverage* (v_1). Figure 8.11 shows the three attributes and respective value functions for this branch of the value tree. As mentioned above, the achievement on the objective *maximize the immunization coverage* rate ($v_{1.1}$) is measured by the attribute $x_{1.1}$, *proportion of population vaccinated* [%], ranging from $X_{1.1*}$ = 60.0% (least preferable level) to $X_{1.1}^{*}$ = 99.0% (most preferable level). The objective *maximize campaign reach across population strata* ($v_{1.2}$) is operationalized by the attribute *dispersion of income of population vaccinated* ($x_{1.2}$). This index measures the relationship between the income distribution and the proportion of the population being vaccinated[2] and ranges from $X_{1.2*}$ = 10% (most preferable level) to $X_{1.2}^{*}$ = 50% (least preferable level). Finally, the third

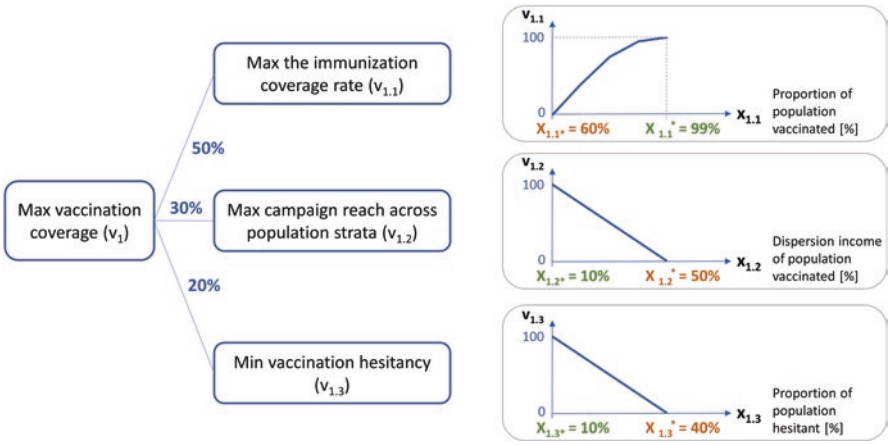

Fig. 8.11 Branch of the value tree that assess the objective maximize vaccination coverage, with attribute and value functions for the sub-objectives

[2] Functioning in a similar manner to the Gini coefficient, which measures income inequality (Dorfman, 1979).

objective *minimize vaccination hesitancy* ($v_{1.3}$) is operationalized by the attribute that measures the *proportion of population that may be hesitant to being vaccinated* ($x_{1.3}$). This attribute range is from $X_{1.3*} = 10\%$ (most preferable level) to $X_{1.3}^{*} = 40\%$ (least preferable level).

The weights for these sub-objectives can be defined with the *dummy alternatives* method that has been detailed in the sixth chapter. This elicitation protocol is depicted in Fig. 8.12, whereby three dummy alternatives were created, with each alternative representing an extreme situation wherein one objective is optimized (attaining the most preferable level) while the other two objectives remain unfulfilled (attaining the least preferable level) by the decision alternative. Furthermore, there exists a fourth dummy alternative, wherein the three objectives remain unfulfilled (attaining the least preferable level).

Specifically, the first dummy alternative ($S_{1.1}$ in Fig. 8.12a) optimizes objective $v_{1.1}$ (with the most preferable level $X_{1.1}^{*} = 99\%$ on attribute $x_{1.1}$), while the alternative attains the least preferable levels on objectives $v_{1.2}$ and $v_{1.3}$ ($X_{1.2}^{*} = 50\%$ and $X_{1.3}^{*} = 40\%$, respectively). The second dummy alternative ($S_{1.2}$ in Fig. 8.12.b) optimizes objective $v_{1.2}$ ($X_{1.2*} = 10\%$ the most preferable level of attribute $x_{1.2}$), but attains the least preferable levels on objectives $v_{1.1}$ and $v_{1.3}$ ($X_{1.1*} = 60\%$ and $X_{1.3}^{*} = 40\%$, respectively). The third dummy alternative ($S_{1.3}$ in Fig. 8.12c) optimizes objective $v_{1.3}$ ($X_{1.3*} = 10\%$ the most preferable level of attribute $x_{1.3}$), but attains the least preferable levels on objectives $v_{1.1}$ and $v_{1.2}$ ($X_{1.1*} = 60\%$ and $X_{1.2}^{*} = 50\%$, respectively). Finally, the hypothetical alternative $S_{1.0}$ (Fig. 8.12d) has the least preferable performance on all sub-objectives: $X_{1.1*} = 60\%$, $X_{1.2}^{*} = 50\%$, and $X_{1.3}^{*} = 40\%$, respectively.

In order to define the weights, the dummy alternative $S_{1.0}$ (Fig. 8.12d) receives a reference value score for the objective *maximize vaccination coverage* of zero, i.e. $v_1(S_{1.0}) = 0$ value points. The health security team is then asked to evaluate the relative value of the other three dummy alternatives, $v_1(S_{1.1})$, $v_1(S_{1.2})$, and $v_1(S_{1.3})$, with the preferable alternative receiving a value score of 100 and the other two alternatives receiving a score in relation to both the preferable alternative and the least preferable alternative ($S_{1.0}$). These value assessments can then be employed to calculate normalized weights.

For instance, if $S_{1.1}$ were to be selected by the health security team as the preferable dummy alternative to achieve the objective *maximize vaccination coverage*, then $v_1(S_{1.1}) = 100$. The team would subsequently evaluate the value of $S_{1.2}$ and $S_{1.3}$ against $v_1(S_{1.1}) = 100$ value points and $v_1(S_{1.0}) = 0$ value points. Let us assume that the team would assign $v_1(S_{1.2}) = 60$ value points and $v_1(S_{1.3}) = 40$ value points.

Normalized weights for the objectives in the first category of objectives could then be calculated by dividing each value score by the sum total of the value scores:

$$w_{1.1} = v_1\left(S_{1.1}\right) / \left[v_1\left(S_{1.1}\right) + v_1\left(S_{1.2}\right) + v_1\left(S_{1.3}\right) \right] = 100 / 200 = 50\%;$$

$$w_{1.2} = v_1\left(S_{1.2}\right) / \left[v_1\left(S_{1.1}\right) + v_1\left(S_{1.2}\right) + v_1\left(S_{1.3}\right) \right] = 60 / 200 = 30\%;$$

$$w_{1.3} = v_1\left(S_{1.3}\right) / \left[v_1\left(S_{1.1}\right) + v_1\left(S_{1.2}\right) + v_1\left(S_{1.3}\right) \right] = 40 / 200 = 20\%.$$

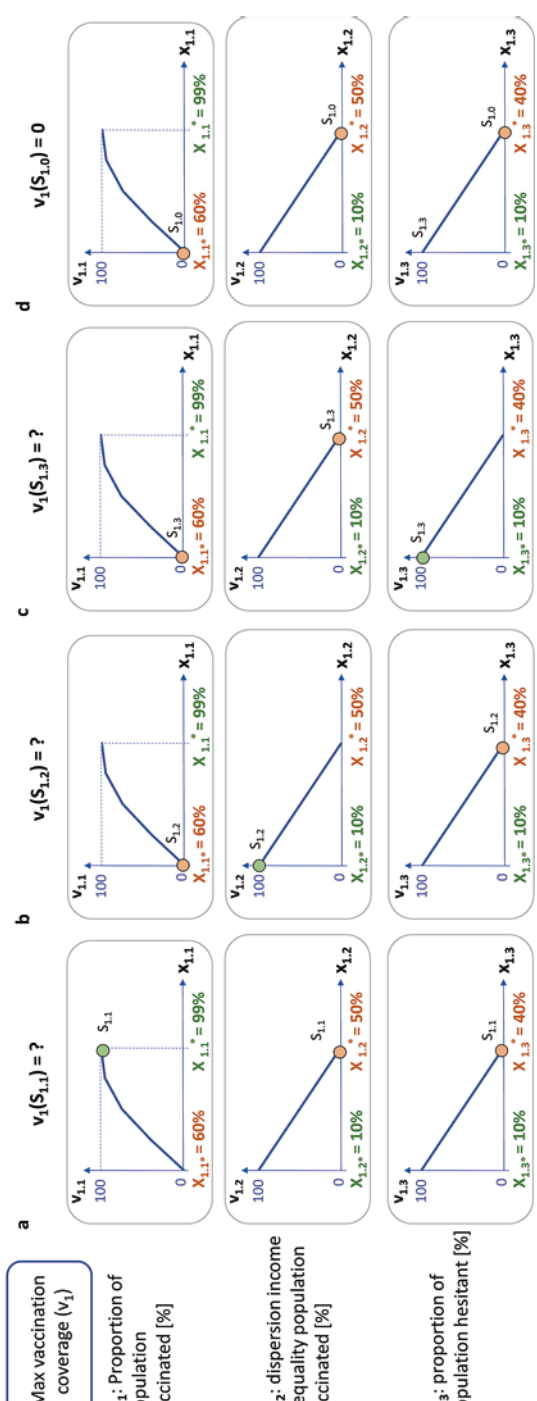

Fig. 8.12 Dummy alternatives for defining of weights in the first category of objectives in the vaccination campaign value model: (**a**) Dummy alternative $S_{1.1}$ with the most preferable performance on attribute $x_{1.1}$ and the least preferable performance on attributes $x_{1.2}$ and $x_{1.3}$, (**b**) Dummy alternative $S_{1.2}$ with the most preferable performance on attribute $x_{1.2}$ and the least preferable performance on attributes $x_{1.1}$ and $x_{1.3}$, (**c**) Dummy alternative $S_{1.3}$ with the most preferable performance on attribute $x_{1.3}$ and the least preferable performance on attributes $x_{1.1}$ and $x_{1.2}$, (**d**) Dummy alternative $S_{1.0}$ with the least preferable performance on attributes $x_{1.1}$ and $x_{1.2}$, and $x_{1.3}$

These normalized weights are shown for each branch of the value tree under this category of objectives in Fig. 8.11. This same protocol for eliciting attributes weights can be employed for defining the weights of the objectives under the other two category of objective in the value tree (i.e for eliciting $w_{2.1}$, $w_{2.2}$, and $w_{2.3}$ and for eliciting $w_{3.1}$, $w_{3.2}$, and $w_{3.3}$).

Moreover, a similar protocol can be used to elicit the weights (w_1, w_2, w_3, and w_4) for the four categories of objectives in the value tree: *maximize vaccination coverage* (v_1), *maximize campaign quality* (v_2), *maximize efficiency of campaign logistics* (v_3), and *minimize campaign costs* (v_4). In this case, five dummy alternatives must be proposed, as shown in Fig. 8.13. The first dummy alternative (S_1) attains the most preferable level on *maximize vaccination coverage* attributes and attains the least preferable level on the remaining attributes (see Fig. 8.13a). The second dummy alternative (S_2) attains the most preferable level on *maximize campaign quality* attributes and attains the least preferable level on the remaining attributes (see Fig. 8.13b). The third (S_3) attains the most preferable level on *maximize efficiency of campaign logistics* attributes and attains the least preferable level on the remaining attributes (see Fig. 8.13c). The fourth (S_4) attains the most preferable level on the *minimize campaign costs* attribute and attains the least preferable level on the remaining attributes (see Fig. 8.13d). Finally, a fifth dummy alternative (S_0) attains the least preferable level on all four attributes (see Fig. 8.13e) and thus the overall value of these alternative is zero ($V(S_0) = 0$ value points).

Decision makers are asked to rank these four dummy alternatives, associate a value score of 100 to the most preferable alternative, and score the intermediate alternatives between 0 and 100, as indicated in Fig. 8.13. For instance, if the health security team were to consider the overall value of the dummy alternatives to be $V(S_1) = 100$ value points, $V(S_2) = 85$ value points, $V(S_3) = 55$ value points, and $V(S_4) = 40$ value points, then the normalized weight for the four categories of objectives would be:

$$w_1 = V(S_1)/\left[V(S_1)+V(S_2)+V(S_3)+V(S_4)\right] = 100/280 \approx 35\%;$$

$$w_2 = V(S_2)/\left[V(S_1)+V(S_2)+V(S_3)+V(S_4)\right] = 85/280 \approx 30\%;$$

$$w_3 = V(S_3)/\left[V(S_1)+V(S_2)+V(S_3)+V(S_4)\right] = 55/280 \approx 20\%;$$

$$w_4 = V(S_4)/\left[V(S_1)+V(S_2)+V(S_3)+V(S_4)\right] = 100/280 \approx 15\%.$$

These normalized weights are shown for each category of objectives in the value tree presented in Fig. 8.14. The weight of each attribute in the evaluation model (w'_i) (which are located on the rightmost level of the tree and are also presented in the figure) can be obtained by multiplying the weights located across each path, from the overall objective to the rightmost objective on the tree. For example, the weight of attribute $x_{1.1}$ is calculated as: $w'_{1.1} = w_1 * w_{1.1} = 0.35 * 0.50 = 17.5\%$. Notice that the weight of the fourth objective is identical to the respective attribute

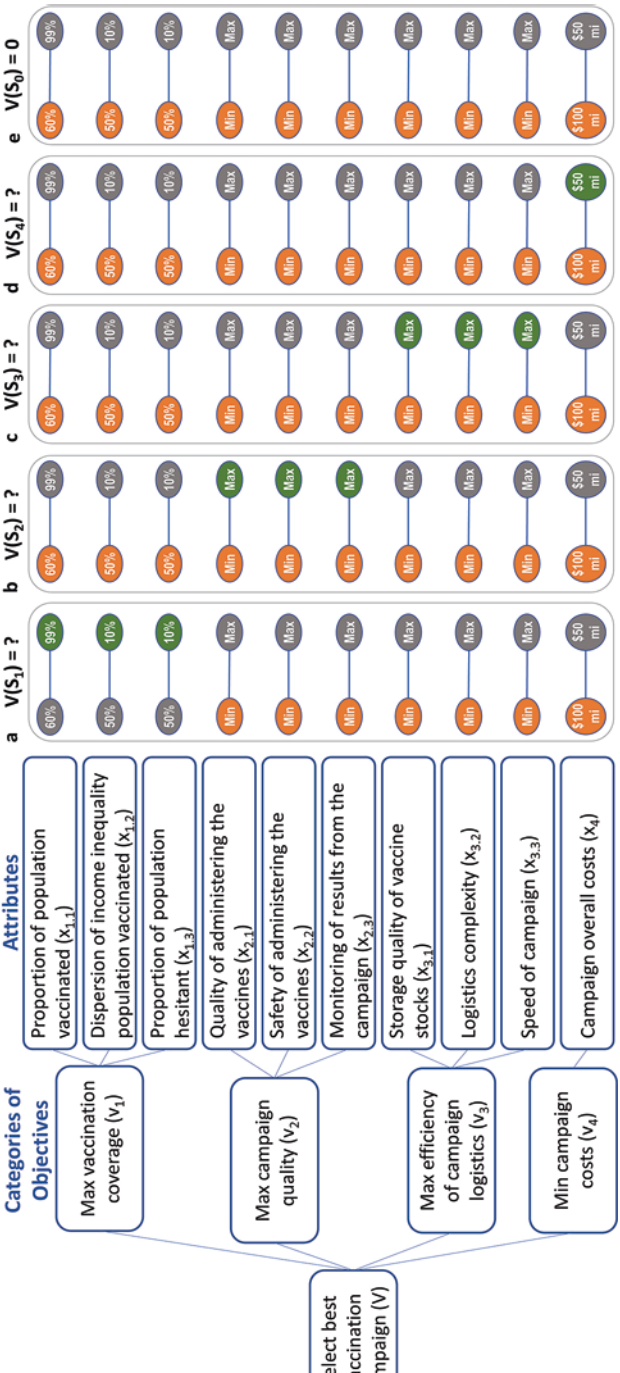

Fig. 8.13 Dummy alternatives for the defining of weights for the four categories of objectives in the vaccination campaign value model: (**a**) Dummy alternative S_1 with the most preferable performance on attributes $x_{1,1}$, $x_{1,2}$, and $x_{1,3}$ and the least preferable performance on the other attributes, (**b**) Dummy alternative S_2 with the most preferable performance on attributes $x_{2,1}$, $x_{2,2}$, and $x_{2,3}$ and the least preferable performance on the other attributes, (**c**) Dummy alternative S_3 with the most preferable performance on attributes $x_{3,1}$, $x_{3,2}$, and $x_{3,3}$ and the least preferable performance on the other attributes, (**d**) Dummy alternative S_4 with the most preferable performance on attribute x_4 and the least preferable performance on the other attributes, (**e**) Dummy alternative S_0 with the least preferable performance on all attributes

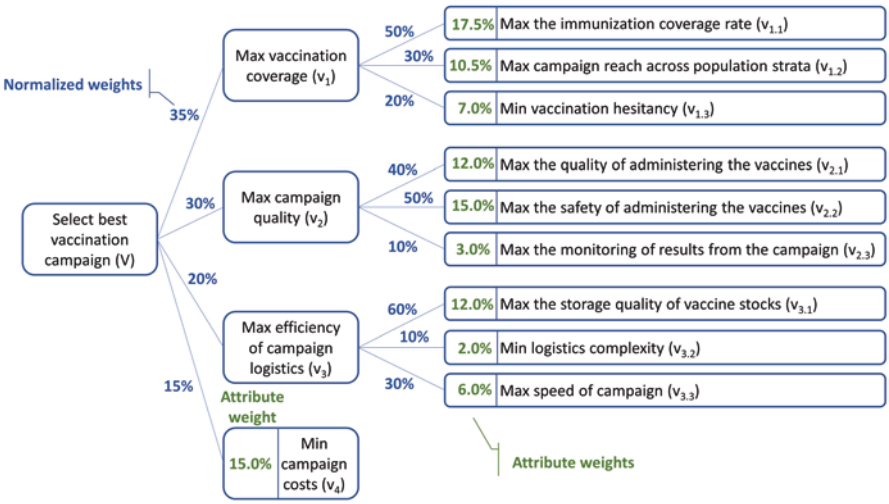

Fig. 8.14 Normalized and attribute weights for the vaccination campaign value model

weight, i.e. $w_4 = w'_4 = 15\%$, since, on this branch of the tree, there occurs no further decomposition.

As we have previously discussed in the sixth chapter, for two main reasons, it is important that a suitable protocol such as the *dummy alternatives* method be employed by the health security team in order to define the weights of the evaluation model. First, the protocol necessitates that priorities explicitly consider the ranges of the attributes, thereby avoiding both the range insensitivity bias (Fischer, 1995; Weber & Borcherding, 1993) and any misleading notions concerning direct importance (Keeney, 2002). Second, the protocol defines these parameters in such a way that attribute weights become compatible with a multi-attribute value function wherein weighted value scores can be summated.

At this point in the discussion, it becomes pertinent to highlight that, thus far, we yet to consider the *actual* decision alternatives that compose this decision problem of selecting the best vaccination campaign (the exception being that realistic ranges for the attributes have been established). Instead, the value model has been defined using value functions and weights, before commencing the appraisal of vaccination campaign strategies. This process of defining the value model forms a robust way to avoid motivational biases that could otherwise distort the preference parameters to favor an alternative which is deemed to be preferable a priori and perhaps favored by decision makers due to some salient positive features (Montibeller & von Winterfeldt, 2015). Furthermore, the process encourages the decision makers to consider and agree upon their priorities and trade-offs in a more deliberate manner than would otherwise occur had the actual alternatives been considered prior to this process. For these two reasons, whenever possible, we adopt this modeling principle in our practice, thereby developing a value model *before* including any decision alternative for value assessment.

8.4.4 *Assessing the Performance and Value of Decision Alternatives*

Once the value model has been completed, it can then be employed to evaluate the overall value of each alternative. As described in the previous chapter, five decision alternatives (A_1, A_2, A_3, A_4, and A_5) are available in this decision problem, each one representing a vaccination strategy.

The performance of each alternative should be carefully estimated, and subsequently valued, on each attribute. The performance of the alternatives shown in Fig. 8.15 on the attribute $x_{1.1}$: *proportion of population vaccinated* [%], forms an

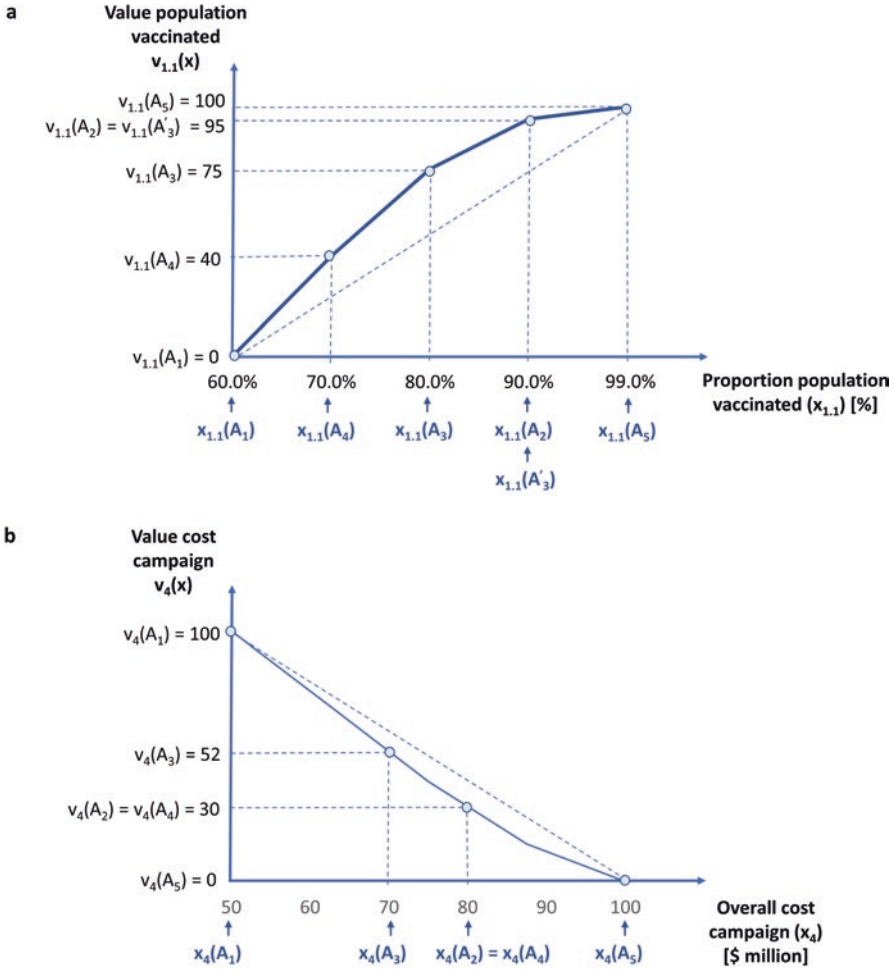

Fig. 8.15 Examples of the evaluation of five decision alternatives on two attributes for the vaccination campaign case: (**a**) Proportion of population vaccinated ($x_{1.1}$), (**b**) Overall cost of the campaign (x_4)

Table 8.1 Value scores for the five decision alternatives in the vaccination campaign case

Objective	Sub-objective	Value A_1	Value A_2	Value A_3	Value A_4	Value A_5
Max vaccination coverage (v_1)	Max immunization coverage rate ($v_{1.1}$)	0	95	75	40	100
	Max campaign reach across population strata ($v_{1.2}$)	0	90	80	50	100
	Min vaccine hesitancy ($v_{1.3}$)	0	80	60	30	100
Max campaign quality (v_2)	Max the quality of administering the vaccines ($v_{2.1}$)	100	10	60	80	0
	Max the safety of administering the vaccines ($v_{2.2}$)	100	20	40	70	0
	Max the monitoring of results from the campaign ($v_{2.3}$)	0	80	100	20	70
Max efficiency campaign logistics (v_3)	Max the storage quality of vaccine stocks ($v_{3.1}$)	100	10	60	80	0
	Min logistics complexity ($v_{3.2}$)	100	10	30	50	0
	Max speed of campaign ($v_{3.3}$)	60	20	80	100	0
Min campaign costs (v_4)		100	30	52	30	0

example of this decomposed evaluation. If implemented, decision alternative A_1 would vaccinate 60.0% of the population (thus $x_{1.1}(A_1) = 60.0\%$), alternative A_2 would vaccinate 90.0% of the population (thus $x_{1.1}(A_2) = 90.0\%$), and so on. The value function $v_{1.1}$ values and normalizes these performances on a 0 to 100 value score. Hence, as shown in the same figure, the decision alternative A_1 scores zero on this sub-objective (thus $v_{1.1.}(A_1) = 0$ value points), alternative A_2 scores 95 (thus $v_{1.1.}(A_2) = 95$ value points), and so forth. These value scores have been transferred to the first row of Table 8.1.

Another example of this decomposed evaluation is shown in Fig. 8.15b, wherein the overall cost of each vaccination campaign is estimated and valued. Alternative A_1, which would cost \$50 million ($x_4(A_1) = \$50$ million) and receives 100 value points ($v_4(A_1) = 100$), while alternative A_2, would cost \$80 million ($x_4(A_2) = \$80$ million) and receive 30 value points ($v_4(A_2) = 30$), and so on. These value scores have been transferred to the last row of Table 8.1. The other value scores in this table have been obtained in a similar manner as to the other attributes of the value model.

Notice that the zero value scores that an alternative receives on an attribute only signify that the alternative does not provide any additional value in relation to the least preferable level of the attribute. For instance, in Fig. 8.15a, the campaign A_1 has received a zero value score on this attribute, as this alternative would lead to only 60% of the population being vaccinated, which constitutes the minimal performance required. This zero value indicates that there exists no additional value in relation to the lower limit of 60% of the population being vaccinated. On the other

hand, alternative A_5 received a value score of 100, as this alternative brings about the highest additional value against the lower limit (vaccinating 99% of the population).

In our experience, decision makers often feel uncomfortable in attributing a zero value to a positive performance of a decision alternative, a situation of which is illustrated in this example. However, these value functions are assessing marginal values against pre-established minimal limits, instead of evaluating absolute intrinsic value. This relative valuation is much easier to conduct than an absolute evaluation of value and provides a strong rationale, which is able to underpin the selection of the best decision alternative among a set of possible options.

If the preference conditions for the model shown in Fig. 8.14 were to hold (as has been discussed in the previous section), then a simple weighted sum can be employed to calculate the overall value V(.) of each decision alternative A as both a function of the value score of the alternative on each attribute $v_i[x_i(A)]$ and as the weight of each attribute w'_I (located on the rightmost branches of the value tree in the same figure):

$$V(A) = \sum w_i' v_i(A). \tag{8.1}$$

The overall value of each alternative is shown in Fig. 8.16, with alternative A_3 providing the highest overall value $V(A_3) = 62.3$ value points, followed by A_1 with

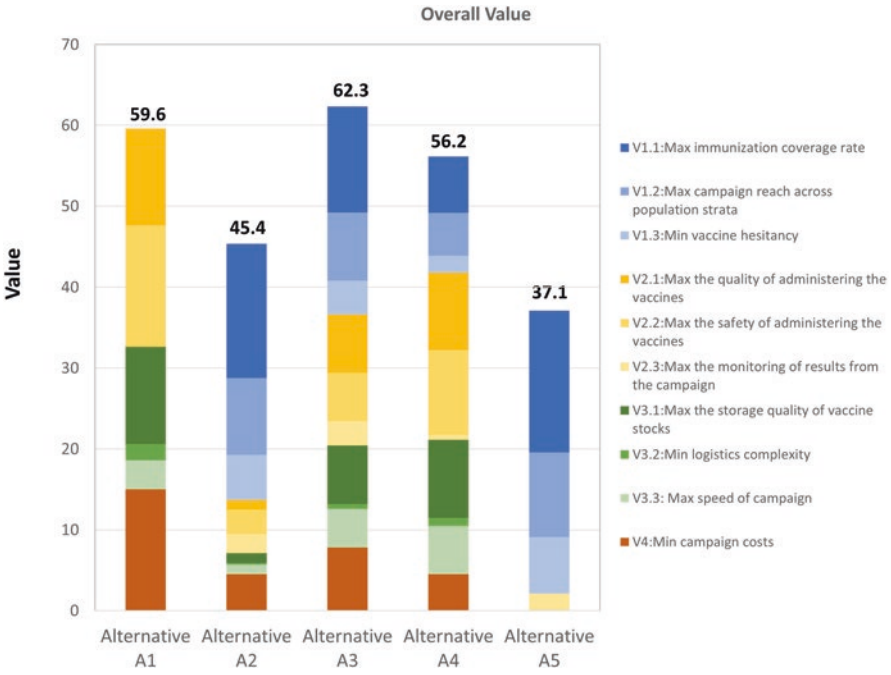

Fig. 8.16 Overall value of the five decision alternatives in the vaccination campaign case

$V(A_1) = 59.6$ value points, and so on, thus providing a full value ranking. The colored bars in the same figure display the value contribution of each attribute (weighted value scores). For instance, alternative A_3 demonstrates a strong value performance on the objectives that assess vaccination coverage (v_1), despite the performance being weaker than alternative A_1 on the objectives that assess campaign quality (v_2), logistics efficiency (v_3), as well as cost (v_4).

In our experience in supporting groups which are in the process of making strategic decisions, employing this type of value analysis has proven extremely beneficial for several reasons. First, the value analysis enables decision makers to better understand the value drivers underpinning the achievement of their fundamental objectives (Keeney, 1992). This understanding is in direct contrast to unstructured decision-making processes, wherein there typically exists a disconnection between the evaluation of performances for which there exists available data and the objectives that are being pursued. Second, the analysis provides a like-for-like comparison of decision alternatives ,which are all measured on the same attributes, and is therefore characterized by low levels of ambiguity (Keeney & Gregory, 2005). Often, in unstructured decision making, a list detailing the benefits and drawbacks involved in each decision alternative is inconsistent, which prevents the possibility to conduct a systematic and fair comparison of the options (Gregory et al., 2012). Third, the evaluation makes a clear distinction between valuation parameters (weights and value functions) and evidence (performance of alternatives on attributes), thus increasing significantly the transparency of the evaluation. This marks a significant improvement in the evaluation process, particularly when compared with simplistic assessments (which are often observed in unstructured decision making), which often maintain the valuation stage opaque, trade-offs implicit, and assumptions hidden (Montibeller, Patel, & Del Rio Vilas, 2020b).

8.4.5 Analyzing the Sensitivity of the Solutions to Priorities

Evidently, the overall values that have been calculated by a multi-attribute value analysis are a function of the attribute weights of the model (shown in Fig. 8.14). These weights represent the priorities of the decision makers who are confronted with conflicting objectives which must be negotiated. Therefore, an interesting way of further exploring the solution space entails executing an analysis into the sensitivity of the (overall) values to possible changes in these priorities .

This sensitivity analysis has been conducted for the weight allocated to the cost of the campaign (w'_4) and is presented in the graph shown in Fig. 8.17 (see Montibeller and Franco (2007) for details and the next chapter for a more detailed example on how to draw this graph). In this graph, the overall value of each decision alternative is calculated as a function of the attribute weights and the value scores of the alternative on the attributes. When inputting the baseline weight of this attribute ($w'_4 = 15.0\%$) into the value model, alternative A_3 has the highest overall value

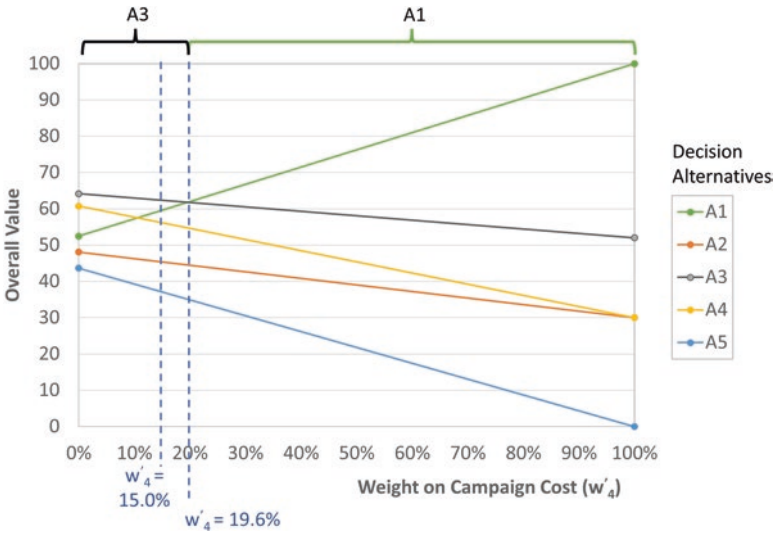

Fig. 8.17 Sensitivity analysis on the role of the weight allocated to campaign cost as to the overall value of different vaccination campaign strategies

($V(A_3) = 62.3$ value points), whose performance is then followed by A_1 ($V(A_1) = 59.6$ value points) as has been presented and displayed previously in Fig. 8.16.

However, if the weight of this attribute were to be increased, as shown in Fig. 8.17, the overall values would change. Since a higher priority would be placed on minimizing costs with this higher attribute weight, the overall value of alternative A_1 would increase (as A_1 is the least expensive strategy), while the overall value of alternative A_3 would decrease (as A_3 is a more expensive strategy). The point at which both alternatives intersect (meaning they would have the same overall value) occurs when the weight is $w'_4 = 19.6\%$, as represented in the same graph. Above this weight level, alternative A_1 should be selected as A_1would have the highest overall value, while below this level, alternative A_3 remains the most valuable option.

As the sensitivity analysis has demonstrated, the results of the evaluation model for the vaccination campaign strategies are rather sensitive to the weight allocated to the cost of the vaccination campaign. Hence, it is advisable that the health security team discuss and agree as to how much weight should be allocated to the objective *minimize overall cost of the campaign*. A similar analysis should be performed for the other attributes of the value model.

On the other hand, there exist evaluation models wherein the intersection points are located a considerable distance away from the baseline weights in the sensitivity analysis (i.e. displaying results that are less sensitive to the levels at which the weights had been established). This feature of a value model facilitates the selection of the decision alternative, as the ranking of alternatives is rendered less dependent upon the different priorities among achieving the conflicting objectives.

8.4.6 Improving the Value of Decision Alternatives

A value analysis is able to support not only the selection, but also the development of superior decision alternatives, a step of which is crucial in any health decision analysis (as was highlighted in the previous chapter). This process can be guided by the analysis of value contributions and by identifying opportunities to improve the best alternatives.

For example, let us again consider alternative A_3, which has the highest overall value in the vaccination campaign evaluation, as detailed in Fig. 8.16. The alternative fails to have a strong performance with regards to the objectives measuring the efficiency of the campaign (v_3). The health security team could consider if there exist ways in which this alternative could be redesigned and its efficiency increased, without incurring additional costs or other detrimental impacts on the other performances. If such improvements were to be realizable, this modification would increase the value contribution of this alternative and, therefore, the overall value of this alternative.

Indeed, these value increases which are brought about by the modifications of decision alternatives can be quantified. This quantification enables the subsequent comparison with other possible modified alternatives among the best performing options. For instance, consider that alternative A_3 could be modified (as A'_3) in such a way as to increase the proportion of the population being vaccinated from the baseline of 80% to 90%, without incurring any detrimental impact to the other performances or increases in the overall cost. In this case, as shown in Fig. 8.15.a, the value of this modified alternative would demonstrate an increase on $v_{1.1}$ from the original $v_{1.1}(A_3) = 85$ value points to $v_{1.1}(A'_3) = 95$ value points, thus 10 additional value points. The value added from this improvement is $\Delta v_{1.1}(A'_3) = w'_{1.1} * [v_{1.1}(A'_3) - v_{1.1}(A_3)] = 0.175 * 10 = 1.75$ value points. Therefore, the overall value of this redesigned alternative is $v(A'_3) = v(A_3) + \Delta v_{1.1}(A'_3) = 62.3 + 1.75 = 64.05$ value points.

This type of analysis could be executed for the other attributes of the modified alternative A'_3 and every improvement could be quantified (although of course, this only occurs when such improvements are indeed feasible in practice). The same process could then be used to improve and redesign options A_1 and A_4, which also have demonstrated high overall performances in the original value analysis (Fig. 8.16). Subsequently, the overall value of these three redesigned alternatives is able to be compared, and the alternative with the highest overall value can be selected.

The same evaluation method described in this section (for the evaluation of decision alternatives to improve health security) can be adapted for prioritizing health threats, as discussed in the next section.

8.5 Evaluating the Impacts of Emerging Animal Health Threats (DEFRA)

A multi-attribute value analysis is also a powerful tool for assessing the multiple impacts of health threats, ranking health threats, and prioritizing the leading threats in order to direct and execute risk mitigating actions and other health security initiatives.

Indeed, multi-criteria assessments have been conducted to evaluate a variety of human and animal health threats, (as reviewed by Montibeller et al. (2020b)). However, many of these assessments have employed ad hoc methods when evaluating impacts, often using a simplistic score-and-weight approach, which is entirely devoid of a Decision Sciences foundation. The use of multi-attribute value analysis brings with it an element of rigor to this type of assessment, while maintaining the evaluation model relatively simple and highly transparent.

When health threats are being assessed, we typically normalize impacts on the dis-value (V^-) that each threat may trigger, whereby 100 is attributed to the highest impact and 0 is attributed an absence of impact (Montibeller et al., 2020b). Since the analysis itself is focused on ranking health threats, instead of a choice of a single decision alternative as in the vaccination case above, it proves important that each attribute be accompanied by a zero-impact level[3] (Clemen & Smith, 2009).

The project that we conducted for the UK Department for Environment, Food and Rural Affairs (DEFRA), for supporting the ranking of emerging animal health threats (Del Rio Vilas et al., 2013; Montibeller et al.,, 2020a), provides an illustration on how the assessment of dis-value caused by health threats is conducted in practice.

In the fifth chapter, we have introduced this health threat prioritization problem (which was confronted by the Veterinary Risk Group of DEFRA), whose influence diagram is reproduced in Fig. 8.18. In this particular chapter, we focus on the assessment of impacts that may be caused by a health threat, a focus of which pertains to the *uncertainty* and *consequences* nodes which has been highlighted in the same figure. There exist two categories of impacts, one of which is formed by *actual impacts* [A] (those which may be caused by the threats), while the other is formed by *perceived impacts* [P] (those which may be a cause for public concern). Consequently, in order to assess each category of impact, two multi-attribute value models have been developed, which shall be presented in sequence in the subsequent sub-section.

[3] This evaluation constitutes a portfolio decision, and as a result, there arises the requirement that a zero-impact level be defined. This type of decision is detailed in the tenth chapter.

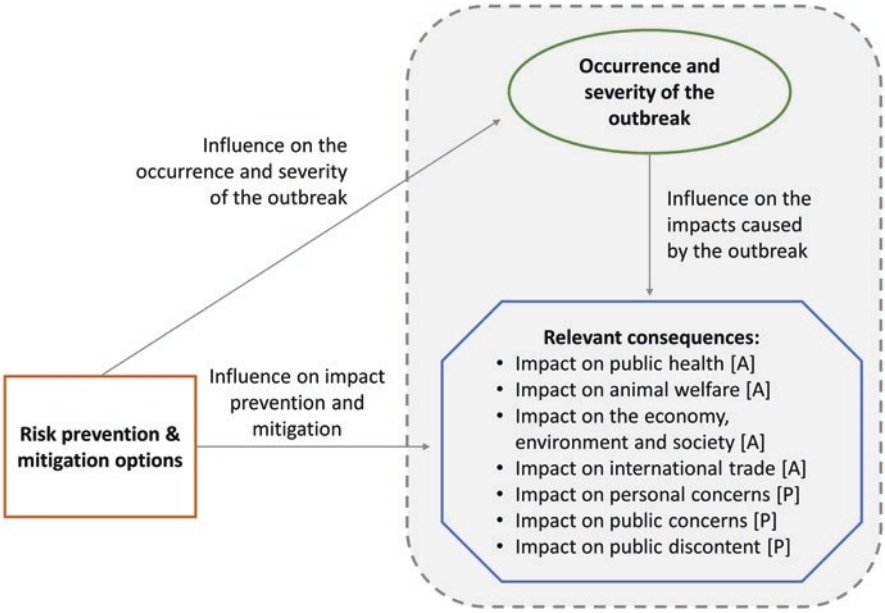

Fig. 8.18 Influence diagram for the prioritization and risk management of emerging animal health threats

8.5.1 Evaluating Actual Impacts Caused by Emerging Animal Health Threats

The value tree for the evaluation of actual impacts, which decomposes the overall impact into four key impacts, is shown in Fig. 8.19. The tree represents the variables that assess the dis-value of animal health threats caused by actual impacts. The evaluation of the overall actual impact $V^{-}_{A}(.)$ of each health threat is decomposed into four impacts, each accompanied by an associated variable $v^{-}_{A}(.)$: *impact on public health* ($v^{-}_{1.A}$), *impact on animal welfare* ($v^{-}_{2.A}$), *impact on wider society* ($v^{-}_{3.A}$), and *impact on international trade* ($v^{-}_{4.A}$).

An attribute was defined for measuring each impact in an unambiguous manner; the four attributes for this value model are presented in Fig. 8.20. A dis-value function over each attribute was defined by the DEFRA Veterinary Risk Group, with the highest level of impact scoring 100 (maximum dis-value) and no impact scoring 0. The dis-value scores are shown in the same figure near each impact level.

The full value model to assess actual impacts, with a weight (w_A) allocated to each attribute, is shown in Fig. 8.21. The elicitation of weights employed the *dummy alternatives* method, thereby providing realistic situations that created a space wherein the group was able to cogitate and express their priorities. Four dummy threats ($T_{1.A}$, $T_{2.A}$, $T_{3.A}$, and $T_{4.A}$) were presented, each threat with the maximum

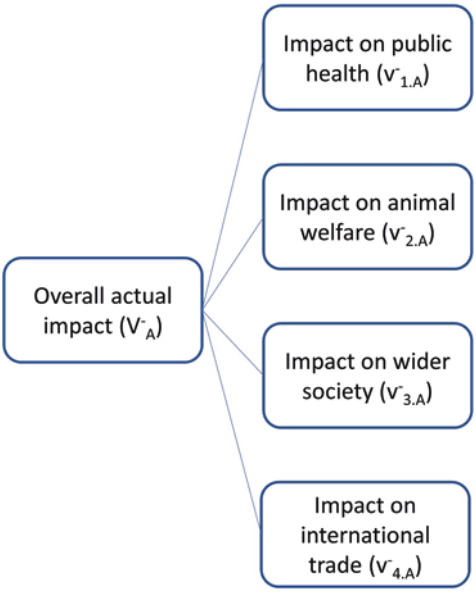

Fig. 8.19 Value tree for the assessment of actual impacts from animal health threats

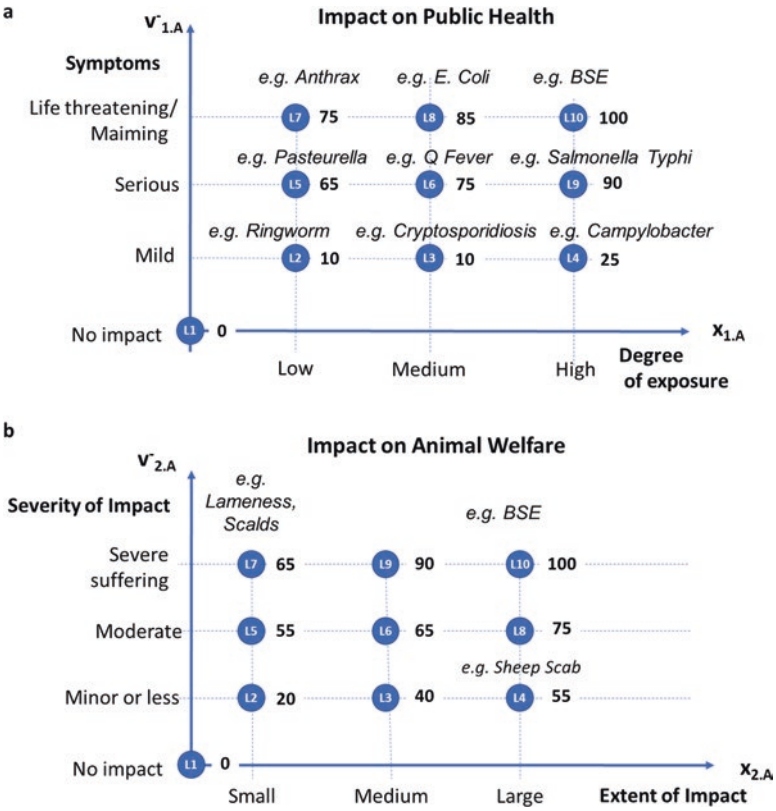

Fig. 8.20 Attributes for assessing actual impacts of animal health threats: (**a**) Impact on public health, (**b**) Impact on animal welfare, (**c**) Impact on wider society, (**d**) Impact on international trade

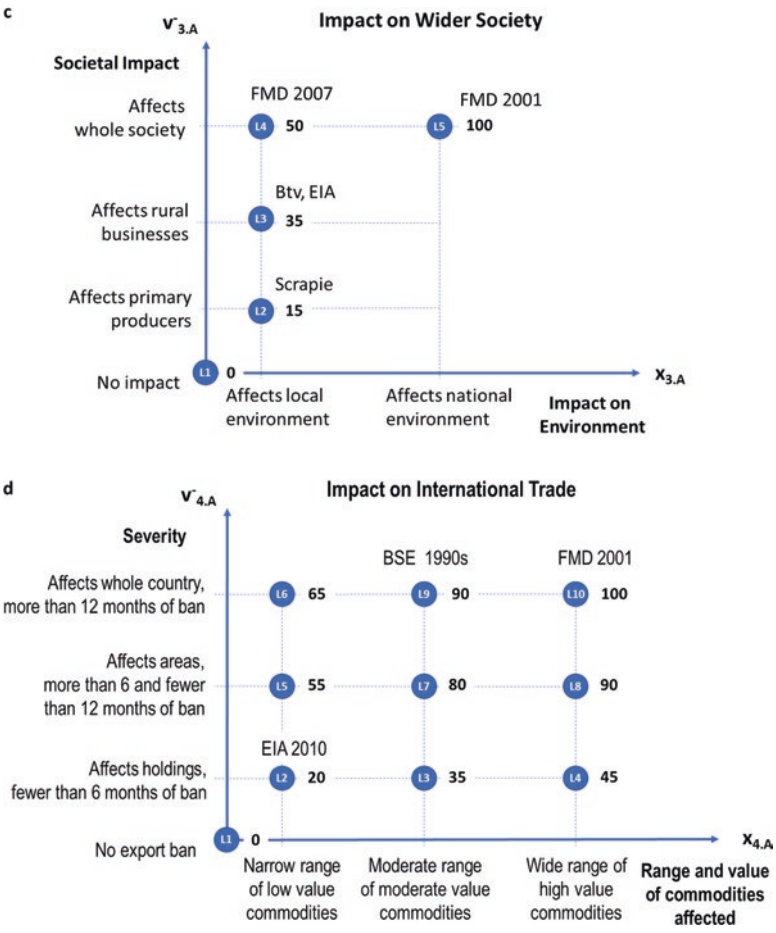

Fig. 8.20 (continued)

impact on one attribute and no impact on the other three attributes (Fig. 8.22a-d). A fifth dummy threat ($T_{0.A}$) was presented which had no impact on the four attributes (Fig. 8.22e).

Decision makers were asked to rank the overall impact of each dummy threat, with the threat with the highest impact receiving a 100 dis-value score, and the threat with no impact receiving a 0 dis-value score: $V^{-}_{A}(T_{0.A}) = 0$. Decision makers selected the first threat ($T_{1.A}$) as the highest dis-value score, thus: $V^{-}_{A}(T_{1.A}) = 100$. The other threats (with intermediate positions in the ranking) were scored in relation to both this uppermost ranked threat and the threat with no impacts on all attributes ($T_{0.A}$). Their dis-value scores were: $V^{-}_{A}(T_{2.A}) = 40$, $V^{-}_{A}(T_{3.A}) = 75$, and $V^{-}_{A}(T_{4.A}) = 20$.

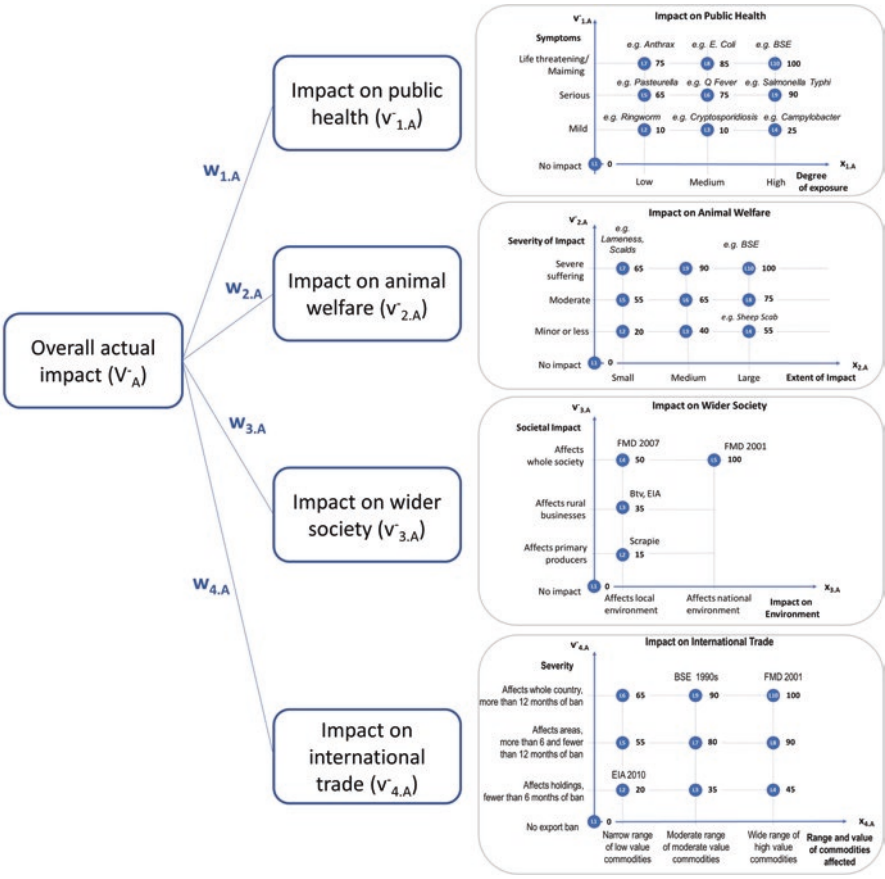

Fig. 8.21 Value model of the assessment of actual impacts from emerging animal health threats

Normalized attribute weights could then be calculated by dividing each value score by the sum total of the value scores:

$$w_{1.A} = V^-_A(T_{1.A}) / \begin{bmatrix} V^-_A(T_{1.A}) + V^-_A(T_{2.A}) \\ +V^-_A(T_{3.A}) + V^-_A(T_{4.A}) \end{bmatrix} = 100/235 = 42.6\%;$$

$$w_{2.A} = V^-_A(T_{2.A}) / \begin{bmatrix} V^-_A(T_{1.A}) + V^-_A(T_{2.A}) \\ +V^-_A(T_{3.A}) + V^-_A(T_{4.A}) \end{bmatrix} = 40/235 = 17.0\%;$$

$$w_{3.A} = V^-_A(T_{3.A}) / \begin{bmatrix} V^-_A(T_{1.A}) + V^-_A(T_{2.A}) \\ +V^-_A(T_{3.A}) + V^-_A(T_{4.A}) \end{bmatrix} = 75/235 = 31.9\%;$$



Fig. 8.22 Dummy threats for the elicitation of attribute weights: (**a**) Dummy threat with max impact on public health and no impact on the other attributes, (**b**) Dummy threat with max impact on animal welfare and no impact on the other attributes, (**c**) Dummy threat with max impact on wider society and no impact on the other attributes, (**d**) Dummy threat with max impact on international trade and no impact on the other attributes, (**e**) Dummy threat with no impact on all attributes

$$w_{4.A} = V^{-}_{A}(T_{4.A}) / \begin{bmatrix} V^{-}_{A}(T_{1.A}) + V^{-}_{A}(T_{2.A}) \\ + V^{-}_{A}(T_{3.A}) + V^{-}_{A}(T_{4.A}) \end{bmatrix} = 20/235 = 8.5\%.$$

The overall normalized impact $V^{-}_{A}(.)$ of each health threat T, measured on a dis-value scale, was assessed by a simple weighted sum (as the independence conditions hold for these four attributes):

$$V^{-}_{A}(T) = w_{1.A} v^{-}_{1.A}(T) + w_{2.A} v^{-}_{2.A}(T) + w_{3.A} v^{-}_{3.A}(T) + w_{4.A} v^{-}_{4.A}(T) \quad (8.2)$$

This model was then employed to evaluate and prioritize any emerging animal health threat through taking into account their actual impacts.

8.5.2 *Evaluating Perceived Impacts from Emerging Animal Health Threats*

Not only was DEFRA concerned about the actual impacts that emerging animal health threats could engender in Britain, but the organization was also concerned about the perceived impacts that health threats may generate. The extensive literature on the topics of risk perception (Slovic, 1987; Slovic et al., 2004) and the social amplification of risk (Kasperson et al., 1988) indicate the importance of measuring these perceived impacts, which are then able to be properly addressed. Contrastingly, most assessments of health threats typically neglect risk perception, whereby decision makers implicitly assume perceived risks to be irrelevant.

Consequently, a second multi-attribute value model was developed to evaluate perceived impacts. The value tree for the evaluation of perceived impacts (which decomposes the overall impact into three key impacts) is shown in Fig. 8.23. The tree represents the variables that assess the dis-value of animal health threats which are caused by perceived impacts. The evaluation of the overall perceived impact $V^{-}_{P}(.)$ of each health threat is decomposed into three impacts, each impact is accompanied by an associated variable $v^{-}_{P}(.)$: *impact on personal concern* ($v^{-}_{1.P}$), *impact on public concern* ($v^{-}_{2.P}$), and *impact on discontent* ($v^{-}_{3.P}$).

The three attributes for this value model are presented in Fig. 8.24 (as detailed in the fifth chapter). The health security team sought to evaluate the qualitative concerns that individuals and society may feel when learning about an emerging health threat in an unambiguous manner. Value functions over each attribute were also defined (as detailed in the sixth chapter). The dis-value scores from each of these functions are located on the left side of each impact level, which is also shown in the same figure.

The full value model to assess perceived impacts (with an associated attribute weight (w_P) allocated to each key impact and respective attribute) is shown in Fig. 8.25. The elicitation of weights also employed the *dummy alternatives* method

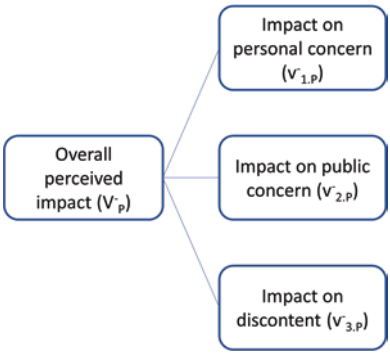

Fig. 8.23 Value tree for the assessment of perceived impacts from emerging animal health threats

the details of which have been previously described in this section. Four dummy threats have been presented ($T_{1.P}$, $T_{2.P}$, $T_{3.P}$, and $T_{4.0}$), as shown in Fig. 8.26. The first three threats (Fig. 8.26a-c) have a maximum impact on one attribute and no impact on the other two attributes, and the last threat (Fig. 8.26d) has no impact on the three attributes.

The DEFRA Veterinary Risk Group was then requested to rank and evaluate each dummy threat, with $V^-_P(T_{0.A}) = 0$ and the highest ranked threat received a score of 100 on the dis-value scale. The group defined the scores as: $V^-_P(T_{1.A}) = 100$, $V^-_P(T_{2.P}) = 40$, and $V^-_P(T_{3.P}) = 75$.

Normalized attribute weights could then be calculated by dividing each value score by the sum total of the value scores:

$$w_{1.P} = V^-_P(T_{1.P}) / \left[V^-_P(T_{1.P}) + V^-_P(T_{2.P}) + V^-_P(T_{3.P}) \right] = 100 / 215 = 46.5\%;$$

$$w_{2.P} = V^-_P(T_{2.P}) / \left[V^-_P(T_{1.P}) + V^-_P(T_{2.P}) + V^-_P(T_{3.P}) \right] = 40 / 215 = 18.6\%;$$

$$w_{3.P} = V^-_P(T_{3.P}) / \left[V^-_P(T_{1.P}) + V^-_P(T_{2.P}) + V^-_P(T_{3.P}) \right] = 75 / 215 = 34.9\%;$$

The overall normalized perceived impact $V^-_P(.)$ of each health threat T (which was measured on a dis-value scale) was assessed by a simple weighted sum, since the independence conditions hold for these three attributes:

$$V^-_P(T) = w_{1.P}\, v^-_{1.P}(T) + w_{2.P}\, v^-_{2.P}(T) + w_{3.P}\, v^-_{3.P}(T). \tag{8.3}$$

This model was employed to evaluate and prioritize any emerging or endemic animal health threat on their perceived impacts, as described next.

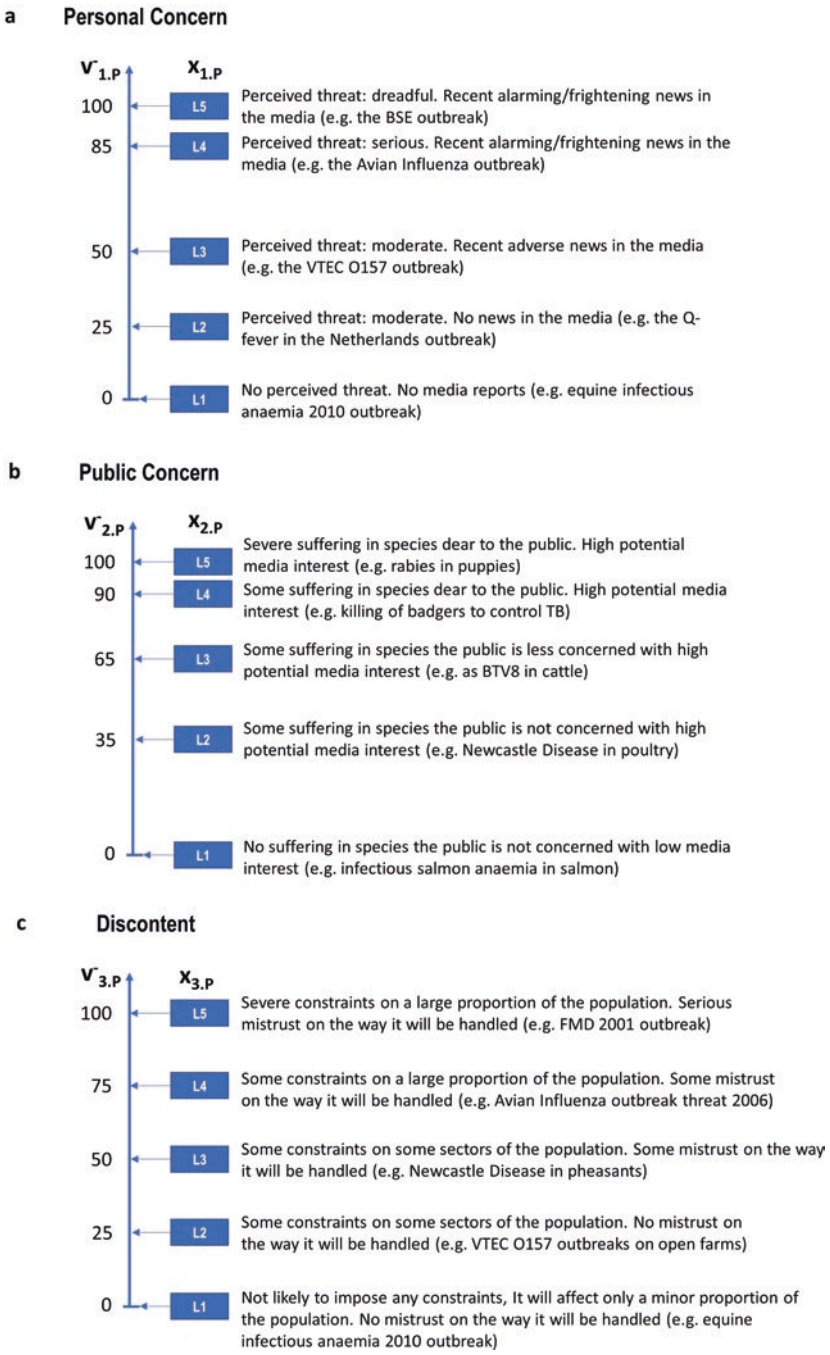

Fig. 8.24 Attributes for assessing perceived impacts from emerging animal health threats: (**a**) Personal concern impact, (**b**) Public concern impact, (**c**) Public discontent impact

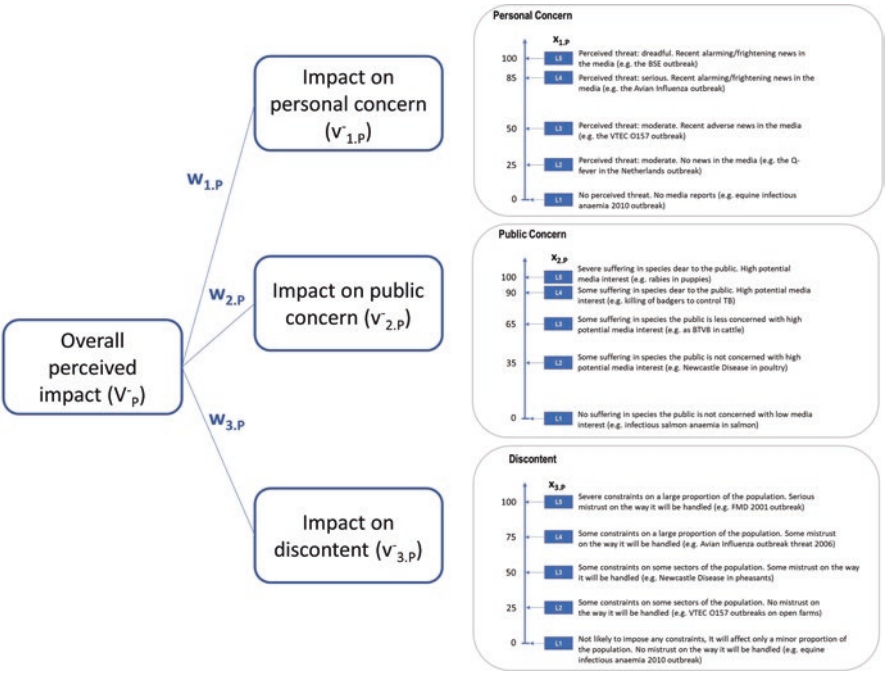

Fig. 8.25 Value model to assess the perceived impacts of emerging animal health threats

8.5.3 Evaluating Emerging Animal Health Threats

Each and every month, since the inception and implementation of the decision support system in 2009, the DEFRA Veterinary Risk Group employs these value models to evaluate and prioritize emerging health threats. The identification of the most pressing emerging animal health threats is crucial to guiding DEFRA decisions on impact mitigation and risk management.

During the monthly Veterinary Risk Group meetings, the DEFRA experts consider all the information gathered by portfolio managers and subsequently assess the actual impacts and perceived impacts for each emerging health threat. The use of expert judgment is employed, whereby both the hard evidence from surveillance systems and the soft evidence available about each threat is considered. Given the inherent uncertainty imposed by an emerging threat, the experts select the most probable impact from a reasonable worst-case scenario, following a precautionary principle (a single-point estimate as detailed in the fifth chapter).

First, let us illustrate the actual impact evaluation. Using Eq. 8.2 and with the attribute weights which had been defined by the decision makers, the overall normalized actual impact $V^-_A(.)$ of each threat T can be calculated to be:

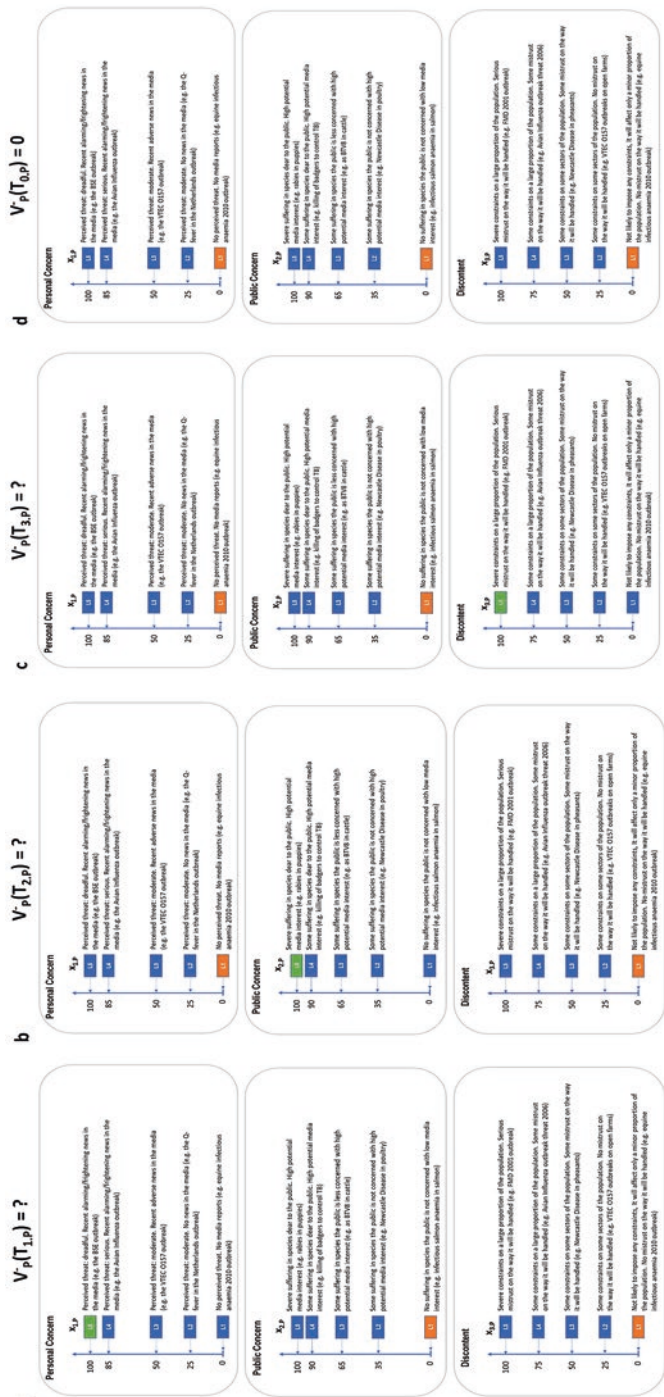

Fig. 8.26 Eliciting weights for the perceived impact value model with four hypothetical threats: (**a**) Highest impact on personal concern and no impact on the other attributes, (**b**) Highest impact on public concern and no impact on the other attributes, (**c**) Highest impact on public discontent and no impact on the other attributes, (**d**) No impact on the three attributes

$$V_A^-(T) = 0.426v_{1.A}^-(T) + 0.170v_{2.A}^-(T) + 0.319v_{3.A}^-(T) + 0.085v_{4.A}^-(T). \quad (8.4)$$

The information about the threats themselves is the property of DEFRA and remains confidential. As a result, here we shall illustrate the evaluation conducted by DEFRA with four hypothetical threats: T_1, T_2, T_3, and T_4. Assume that these threats would be accompanied by the actual impacts that have been identified in Fig. 8.27 Fig. 8.29.

For instance, for threat T_1, the normalized actual impact dis-value scores are: $v^-_{1.A}(T_1) = 85$ (see Fig. 8.27a), $v^-_{2.A}(T_1) = 40$ (see Fig. 8.27b), $v^-_{3.A}(T_1) = 100$ (see Fig. 8.27c), and $v^-_{4.A}(T_1) = 35$ (see Fig. 8.27d). In this case, the overall normalized actual impact (dis-value score) of this threat is:

$$V^-_A(T_1) = 0.426(85) + 0.17(40) + 0.319(100) + 0.085(35) = 36.3 + 6.8 + 31.9 + 3.0 = 77.9.$$

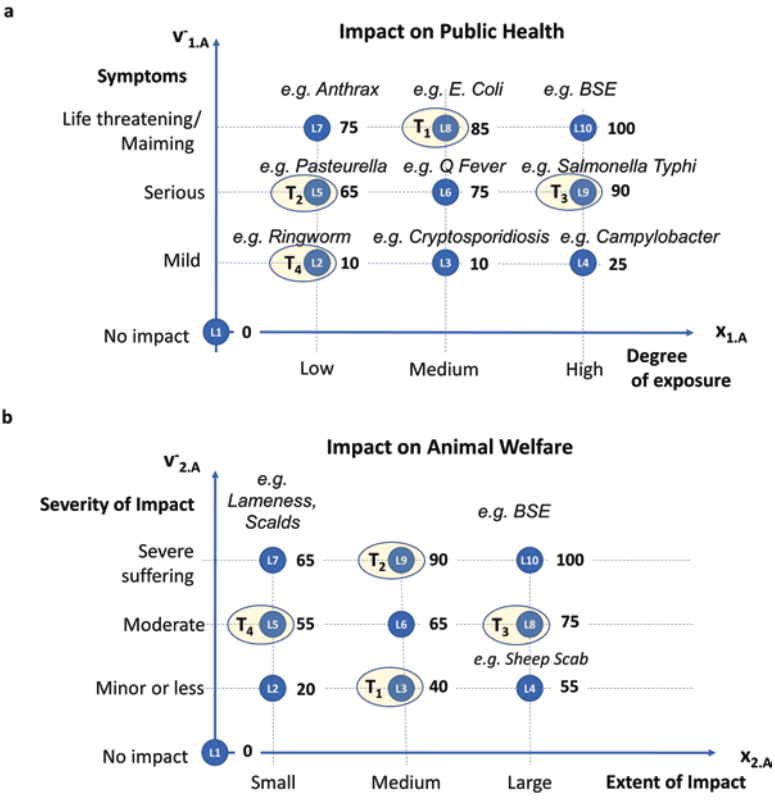

Fig. 8.27 Actual impacts of four hypothetical emerging animal health threats (T1, T2, T3, and T4) on: (**a**) Public health impact, (**b**) Animal welfare impact, (**c**) Wider society impact, (**d**) International trade impact

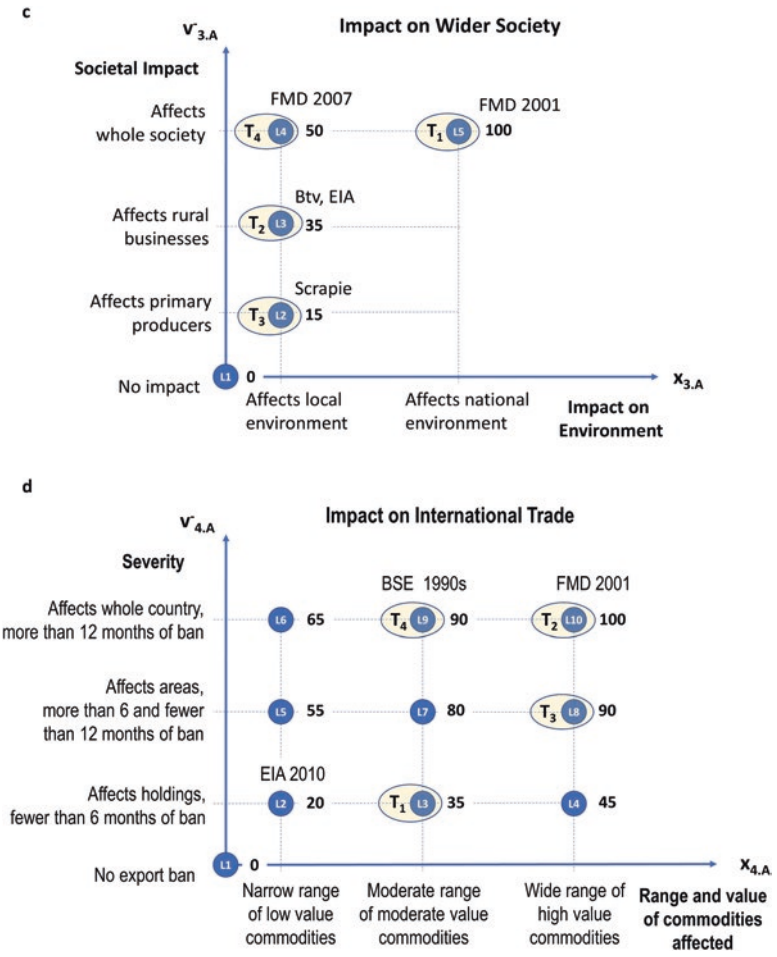

Fig. 8.27 (continued)

The same analysis can be executed for the other three threats. These results are shown in Fig. 8.28. Threat T_1 has the highest overall dis-value (77.9), followed by T_3 (63.5), T_2 (62.7), and then T_4 (37.2). The colored bars illustrate the contribution of each impact toward the overall valuation, provided by the weighted dis-value score of a threat on each attribute (as shown in the equation above for threat T_1).

Now, let us consider the perceived impact evaluation. Assume that the impacts caused by the four hypothetical threats are the ones represented in Fig. 8.29. Utilizing Eq. 8.3 alongside the attribute weights which have been defined by the decision makers, the overall normalized perceived impact $V^{-}_{P}(.)$ of each threat T can be calculated to be:

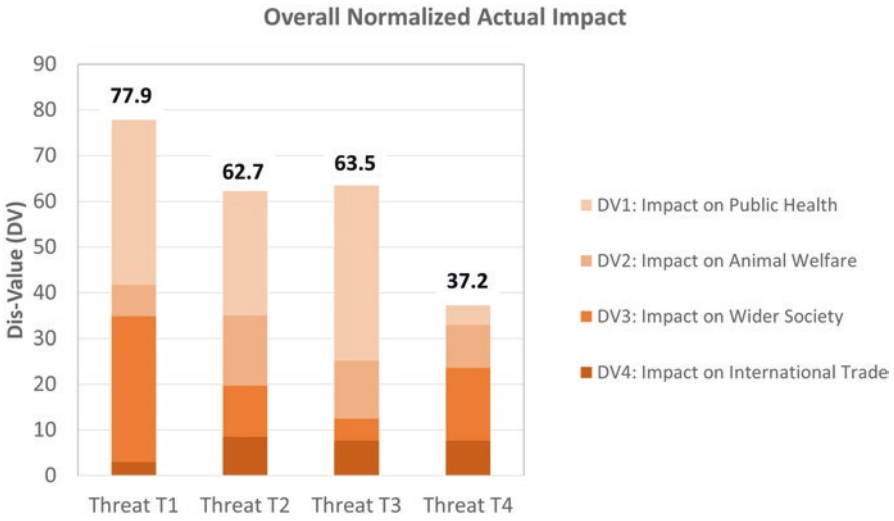

Fig. 8.28 Overall assessment of four hypothetical threats based on their actual normalized impact

$$V^{-}_{P}(T) = 0.465V^{-}_{1.P}(T) + 0.186V^{-}_{2.P}(T) + 0.349V^{-}_{3.P}(T).$$

For the same threat (T_1), the normalized perceived impacts (dis-value scores) are: $v^{-}_{1.P}(T_1) = 0$ (see Fig. 8.29a), $v^{-}_{2.P}(T_1) = 65$ (see Fig. 8.29b), $v^{-}_{3.P}(T_1) = 25$ (see Fig. 8.29c). The overall normalized perceived impact (dis-value score) of this threat is:

$$V^{-}_{P}(T_1) = 0.465(0) + 0.186(65) + 0.349(25) = 0.0 + 12.1 + 8.7 = 20.8.$$

The same analysis can be realized for the other three threats. These results are shown in Fig. 8.30. Threat T_4 has the highest overall dis-value (87.9), followed by T_3 (69.1), T_2 (28.4), and then T_1 (20.8).

These assessments aid DEFRA to better manage emerging animal health threats to the UK. Risk mitigating actions to manage high impact threats can be devised to reduce their impacts, as has been discussed in the previous chapter. The weighted dis-value scores can help to identify the areas wherein risk mitigating actions could exert greater influence. For instance, the hypothetical threat T_1 significantly impacts public health and wider society, as shown in Fig. 8.28. Were risk mitigating actions to be implemented in order to reduce these two impacts, a significant reduction in the overall impact of this threat could materialize. Furthermore, this reduction in overall dis-value could subsequently be quantified using the value model, as we have illustrated using the vaccination campaign case in the previous section. Additionally, this assessment is able to guide the planning of the capabilities that are available to DEFRA, such as evidence assessment, resources, and countermeasures.

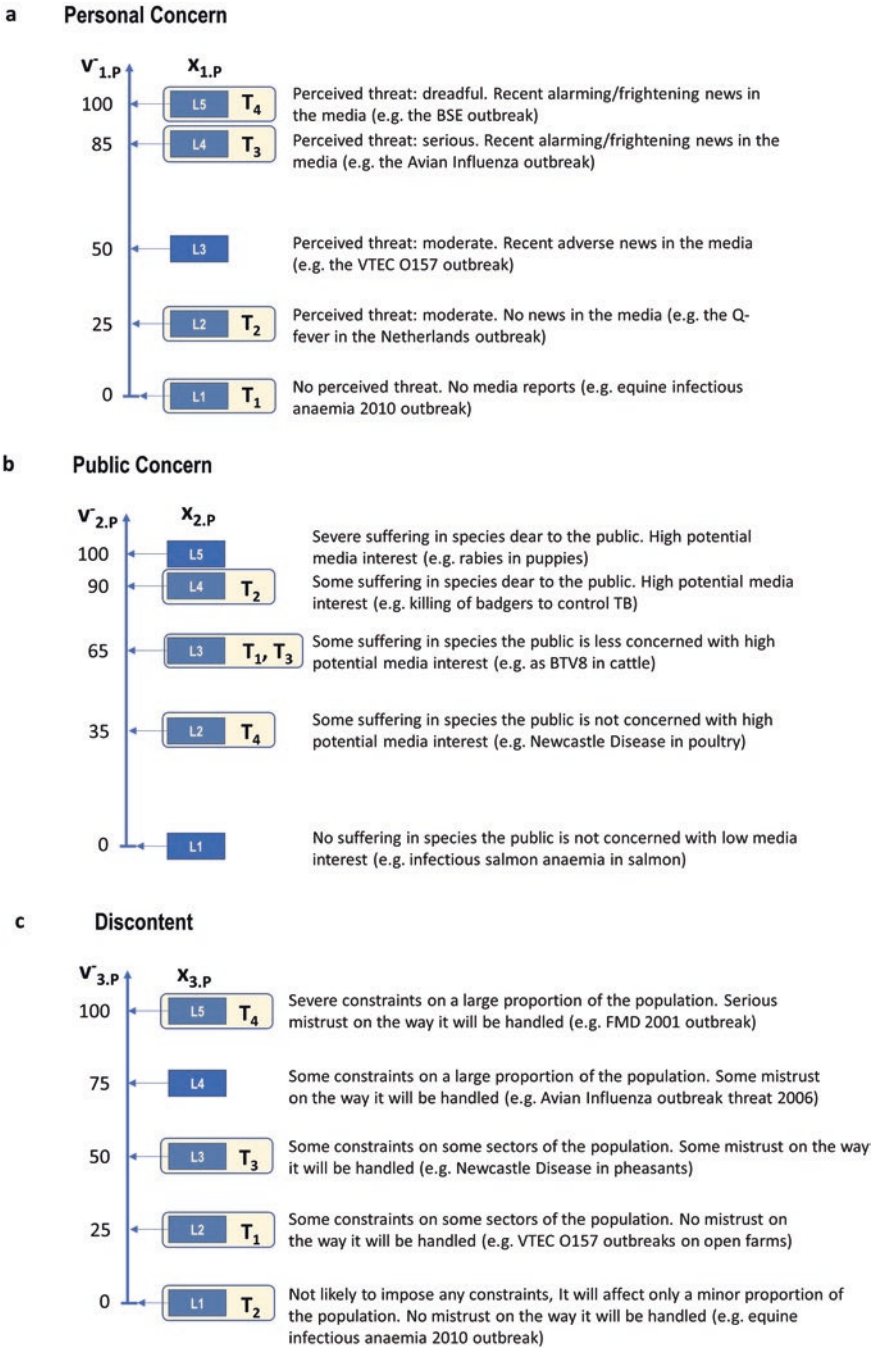

Fig. 8.29 Perceived impacts of four hypothetical emerging animal health threats (T1, T2, T3, and T4) on: (**a**) Personal concern, (**b**) Public concerns, (**c**) discontent

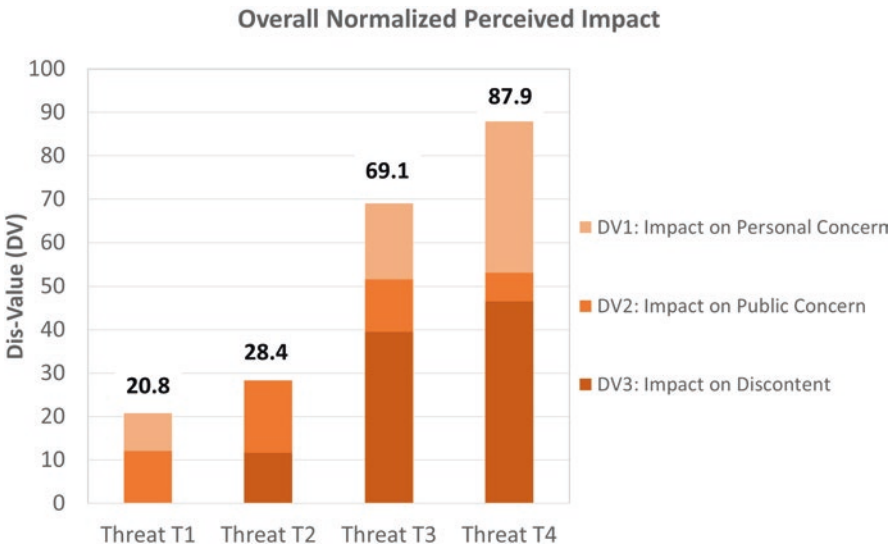

Fig. 8.30 Overall assessment of four hypothetical threats based on their perceived normalized impact

Should an outbreak occur, these organizational capabilities are able to be strengthened and extended for deployment when undertaking the highest ranked health threats (Del Rio Vilas et al., 2013).

On the other hand, undertaking perceived impacts requires that educational campaigns and other activities targeted at informing the public about actual risks be developed. For instance, while the hypothetical threat T_4 has a high perceived impact (see Fig. 8.30), the threat has a relatively low actual impact (see Fig. 8.28). This situation would necessitate that some educational activities, which could inform the public about the low actual impact of the threat despite the high perceived risks, be executed.

Since the development and implementation of these value models, more than 218 threats have been analyzed by the system (Montibeller, Franco, & Carreras, 2020a). In recent years, these threats have included: the COVID-19 virus, the Ebola virus, the Zika virus and the risks of African swine fever, among many other high-impact emerging animal threats which pose a risk to the UK. This decision support led to a better understanding of the risks threatening the country and strengthened the role of DEFRA in supporting the current UK Biological Security Strategy (UK Home Office, 2018).

8.6 Conclusions: Evaluating Health Threats and Health Security Actions with Multiple Consequences

In this chapter, we have presented as to how a health decision analysis can aid public health leaders when evaluating decision alternatives to enhance health security with multiple objectives. We have also demonstrated that this same type of evaluation can be adapted in such a way that the evaluation is rendered into a foundational structure which functions to support the prioritization of health threats with multiple consequences.

We have stressed the importance of carefully defining the screening criteria. These criteria filter out decision alternatives whose performance levels or impacts are deemed to be unacceptable. Subsequently, the comparative evaluation of options can be conducted, thereby considering only those decision alternatives whose impacts or performances fulfil a pre-established level of acceptability.

Subsequently, we have presented the evaluation of decision alternatives with two relevant consequences, thereby highlighting the prominent conceptual position that trade-offs should assume in choices with conflicting objectives. This analysis has also stressed the concept of value and the role of this concept in guiding choices, whereby the direction of improvement is defined by parallel indifference curves. A set of non-dominated alternatives lies on the Pareto front and, among these options, the option(s) with the highest value(s) should be selected.

For decision problems with more than two relevant consequences,the situation of which reflects most health security decisions, a multi-attribute value model can be developed, as has been also presented in this chapter. This type of model represents both the marginal values over attributes (represented by value functions) and the trade-offs (represented by attribute weights). Here, we have illustrated as to how these models can be developed for the subsequent assessment of decision alternatives, and how these models are also able to be adapted for the ranking of health threats.

The significance of maintaining a state of transparency during the evaluation process has formed a fundamental idea in this chapter, the presence of which provides a structure for a reasoned assessment, as well as a record of the evaluation process, so that the choices that have been made can be justified. Similarly, we have focused on and emphasized the qualities of comprehensiveness and rigor pertaining to the evaluation, both of which provide a means to compare the decision alternatives in a parallel manner while effectively managing the main complexities in the assessment.

In this chapter we have assumed that there has existed no requirement to model any major uncertainties, employing instead single-point estimates for the performance of alternatives and the impacts of health threats. The absence of this requirement has enabled an assessment of the *value* of decision alternatives and the *dis-value* of health threats. However, in many health security decision problems, uncertainty figures prominently, and, in those cases, the assessment should be based on *expected value* of decision alternatives or *expected dis-value* of health threats, the concepts of which shall constitute the topic of the next chapter.

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Chapter 9
Evaluating Health Threats and Health Security Actions Under Uncertainty



In the previous chapter we detailed as to how we are either able to thoroughly evaluate decision alternatives when multiple objectives must be achieved, or alternatively, how we are able to assess and prioritize health threats with multiple impacts. Within this previous chapter, the assessment of societal value for different decision alternatives under consideration, or, the assessment of societal dis-value for health threats under surveillance, assumed the most likely estimates pertaining to performances and impacts. In this chapter, we shall now extend this evaluation, thereby considering the role of uncertainty and the dispersion that uncertainties may trigger, which would affect the estimated performances of decision alternatives and the estimated impacts of health threats.

The field of behavioral decision making has given rise to a vast literature concerning unstructured decision making under uncertainty (Gilovich et al., 2002; Kahneman & Tversky, 2000). The findings of these studies have observed that decision makers consistently demonstrate biased decision making under uncertainty, whereby there frequently occurs both the miscalculation of probabilities of occurrences of events and the distortion of preferences (depending on the intuitive reference point that has been employed). Consequently, the occurrence of these biases necessitates that a systematic representation of uncertainties be executed in order to support experts and decision makers to debias their judgments and make reasoned choices, the process of which shall be detailed in this chapter (Montibeller & von Winterfeldt, 2015).

The chapter begins by discussing the least complex case of decisions under uncertainty, wherein only a single consequence of concern is represented and a limited number of discrete scenarios are considered in order to represent possible consequences of health security actions or health threats. This form of evaluation enables us to introduce important concepts to the discussion concerning the evaluation of decision alternatives under uncertainty. Subsequently, the evaluation is extended to include multiple consequences for the selection of decision alternatives or for the prioritization of health threats. This extension to multiple consequences is presented first under discrete scenarios and, subsequently, for continuous

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distributions that represent uncertainties about performances of decision alternatives and the impacts of health threats.

In the second chapter we presented a diagram that illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 9.1. The present decision stage: *evaluating health threats and health security actions and identifying best options* is now highlighted in this modified figure. This stage continues to be detailed both in this chapter and in the chapter that follows. In this chapter we focus on the evaluation of health security actions and health security threats *under uncertainty*. In a similar manner to the previous chapter, we shall assume that: (i) the problem has been adequately framed and agreed upon by the health security team, (ii) relevant objectives and consequences have been defined, (iii) a creative and diverse set of decision alternatives has been developed, (iv) key uncertainties, trade-offs, and risk limits have been established, and (v) the impacts of health threats and health security actions have been reliably estimated.

9.1 Assessing Expected Value with a Single Consequence

We shall begin the discussion on the ways in which decision alternatives should be evaluated under uncertainty by introducing the least complex case, wherein there exists a single consequence of concern and the uncertainty is subsequently discretized into a small number of scenarios. While this representation often proves too simplistic for the complex health security decision problems that must be made in practice, this decision setting functions to illustrate how a health decision analysis is performed. Additionally, this analysis reveals an arena wherein several important concepts for making decisions under uncertainty are introduced and presented.

9.1.1 Defining the Expected Value Rule

In decision situations under uncertainty, the evaluation of decision alternatives should be contingent on their expected societal value. This contingency arises from the impossibility of defining single-point estimates for the performances of the options under consideration on the relevant consequences (the case of which had been assumed in the previous chapter). We discuss the concept of *expected value* in this section.

First, let us describe *decision trees,* which form another way to represent decisions under uncertainty (Raiffa, 1968) and are equivalent to influence diagrams (Howard & Matheson, 2005a, b). However, unlike the influence diagrams, decision trees prove particularly effective when displaying the time sequence in a decision and when calculating expected values derived from a *small* number of discrete scenarios under consideration.

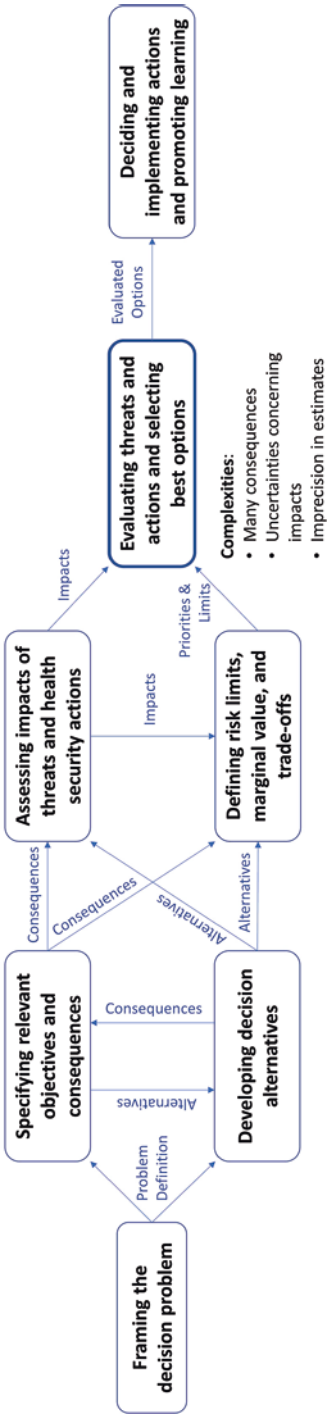

Fig. 9.1 Making reasoned health security decisions: a focus on evaluating health threats and health security actions under uncertainty

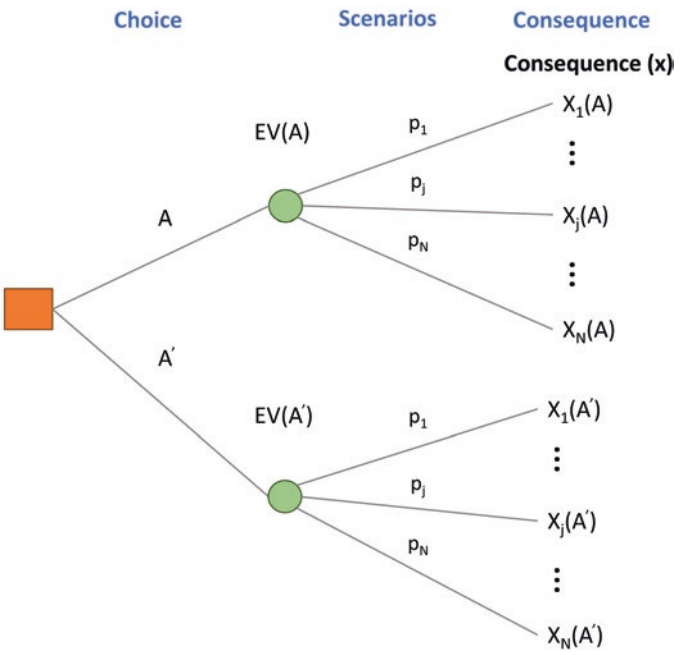

Fig. 9.2 Decision tree depicting the choice between two decision alternatives and N discrete scenarios

Let us illustrate this representation assuming that decision makers must choose between two alternatives (A and A′) that represent two choices under uncertainty, while considering the relevant consequence (measured by variable x), the scenario of which is represented by the decision tree shown in Fig. 9.2. The decision itself is represented by *decision nodes* (denoted by a square) in the tree and each arc emerging from a decision node represents a decision alternative. The decision alternatives should be *mutually exclusive*, and thus, only a single alternative should be selected. The representation of uncertainty adopts N discrete scenarios, which are represented as *chance nodes* (denoted by a circle), which have been described in the seventh chapter. In the tree, each arc that emerges from a chance node represents a future scenario whose associated probability of occurrence is p_j and whose possible consequence is X_j (.) under each j-th scenario. The scenarios represented from a chance node should be both *mutually exclusive* (only one outcome can happen) and *collectively exhaustive* (the set of scenarios should describe all the possible outcomes) (McNamee & Celona, 2005).

To introduce the concept of expected value, we shall discuss a simple case that represents each decision situation using an influence diagram and an equivalent decision tree. Let us posit that there emerges a health threat with the potential to cause 100,000 deaths within the time period and the region that is under consideration. The single fundamental objective of any risk mitigating action is to *maximize*

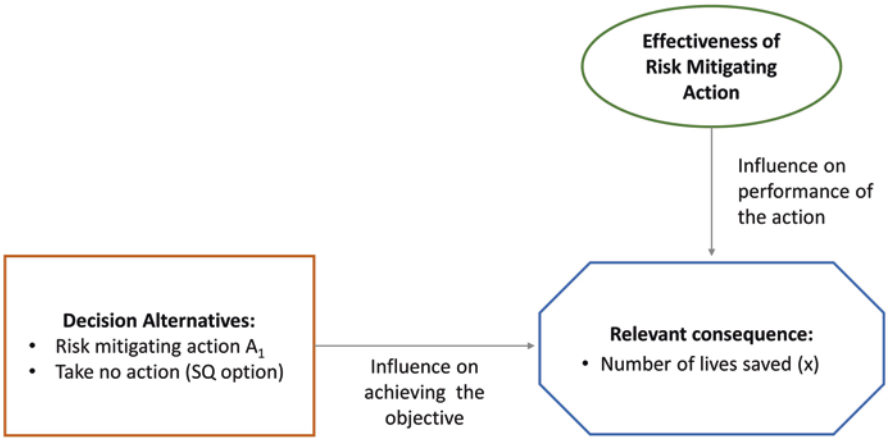

Fig. 9.3 Influence diagram of one risk mitigating actions against an emerging health threat

the number of lives saved and the attribute to measure this consequence is *the number of lives saved* (measured by variable x).

Single Mitigating Action Let us start by considering a single risk mitigating action (A_1), in addition to the alternative *take no action*, which forms the status quo (SQ) option. There exists uncertainty concerning the effectiveness of this risk mitigating action (i.e., how many lives could be saved were the action to be implemented). This decision situation is represented by the influence diagram shown in Fig. 9.3. The *decision* node influences the *consequences* node, as the choice made influences the number of lives saved. In addition, the *uncertainty* node influences the *consequences* node, as the effectiveness of the risk mitigation action influences the number of lives saved.

Let us represent the same situation with a decision tree, which is shown in Fig. 9.4. The *decision* node (square node in the tree) represents the choice between implementing A_1 or taking no action. Within this decision problem, we shall assume that the health security team has decided to only consider two discrete scenarios: one wherein the risk mitigating action brought about *low effectiveness* and the other wherein this same action brought about a *high effectiveness* (hence, this uncertainty is represented by a 2-point discrete distribution as we have detailed in fifth chapter).

If the decision makers were to implement the risk mitigating action A_1, the implementation would allow for the realization of one of the two scenarios, the event of which is represented by the *chance* node (circle node in the tree); the action either results in low effectiveness, or, the action results in high effectiveness. In the former case, the estimate stipulates that only $X_L(A_1) = 20{,}000$ lives would be saved, while in the latter case, the action would save $X_H(A_1) = 80{,}000$ lives. The probability of the low effectiveness scenario occurring has been estimated to be 20% ($p_L = 0.2$) and the probability of the high effectiveness scenario to be 80% ($p_H = 0.8$). On the other

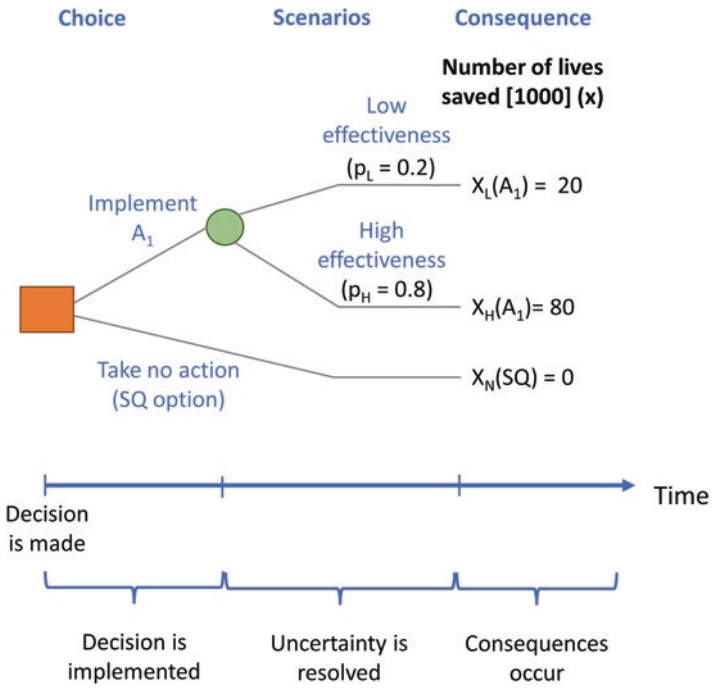

Fig. 9.4 Decision tree for a risk mitigating action (decision alternative) against a health threat with two effectiveness scenarios

hand, if the decision makers were to take no action (SQ option), no lives would be saved, i.e. $X_N = 0$ lives. Let us assume that, if the status quo were to be selected, there would exist no uncertainty about the consequence, and consequently, the inclusion of a chance node is not required on that particular branch of the decision tree.

The timeline for this decision is shown below the decision tree in the same figure. First, the *decision is implemented*, entailing either the implementation of A_1 or the maintenance of the SQ option, the decision of which represents the selection of an alternative. Assume that alternative A_1 were to be selected and implemented. Subsequently, the *uncertainty is resolved* concerning the effectiveness of this alternative, and *consequences occur* depending on the scenario in actuality; $X_L(A_1) = 20{,}000$ lives saved if the alternative were to demonstrate low effectiveness, or $X_H(A_1) = 80{,}000$ lives saved if the alternative were to demonstrate high effectiveness. The probability of each scenario occurring is given by their respective probabilities: $p_L = 0.2$ and $p_H = 0.8$. On the other hand, if the SQ were to be selected and implemented, the consequence must be $X_N(SQ) = 0$ lives saved, the result of which would be known immediately after if this choice were made, as we assumed an absence of uncertainty relating to the status quo option.

The situation that we have just described (wherein a single decision alternative is considered against the status quo option) proves common in practice. As long as

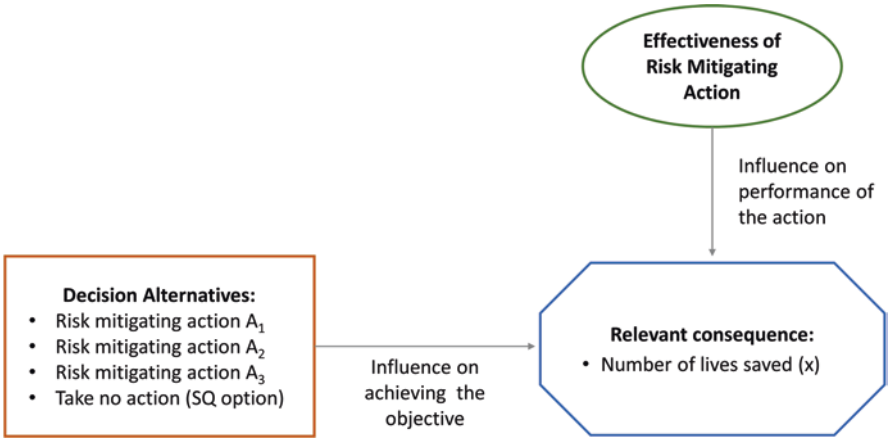

Fig. 9.5 Influence diagram of three risk mitigating actions against an emerging health threat

option A_1 remains within the available budget, this decision situation should prove to be a relatively easy choice. Even if there were to exist high levels of uncertainty concerning the effectiveness of this action, or if the decision alternative were to prove highly ineffective in saving lives under the scenarios that are being considered, the number of lives saved would prove higher than if no action were taken. Indeed, this health decision analysis, which compares alternatives against the SQ option can help us to take action and to avoid the status quo bias (Kahneman et al., 1991; Samuelson & Zeckhauser, 1988), whose presence results in a tendency to favor the *take no action* option. This comparison against the SQ option may also aid in reducing the organizational paralysis that may occur when decision makers are confronted with uncertainties.

Thus far, we have analyzed the choice of a single mitigating action under uncertainty. However, the most frequent situation encountered by decision makers is one wherein there exists more than one decision alternative under consideration, the situation of which we shall consider subsequently.

Multiple Mitigating Actions Let us extend the previous decision problem to discuss a slightly more realistic setting, wherein there exist three risk mitigating actions under consideration, A_1, A_2, and A_3, each of which enables multiple lives to be saved if the alternative were to be implemented, in addition to the *take no action* alternative (the SQ option). Again, we see that there exists uncertainty concerning the effectiveness of each risk mitigating action, i.e., how many lives the option would save. Assume that each decision alternative (risk mitigating action) would incur the same cost of implementation and due to budget restrictions, only a single alternative could be selected. This decision problem is shown in the influence diagram in Fig. 9.5.

Assume that the probabilities for high effectiveness (p_H) and low effectiveness (p_L) have been estimated for each option involved in this decision problem,

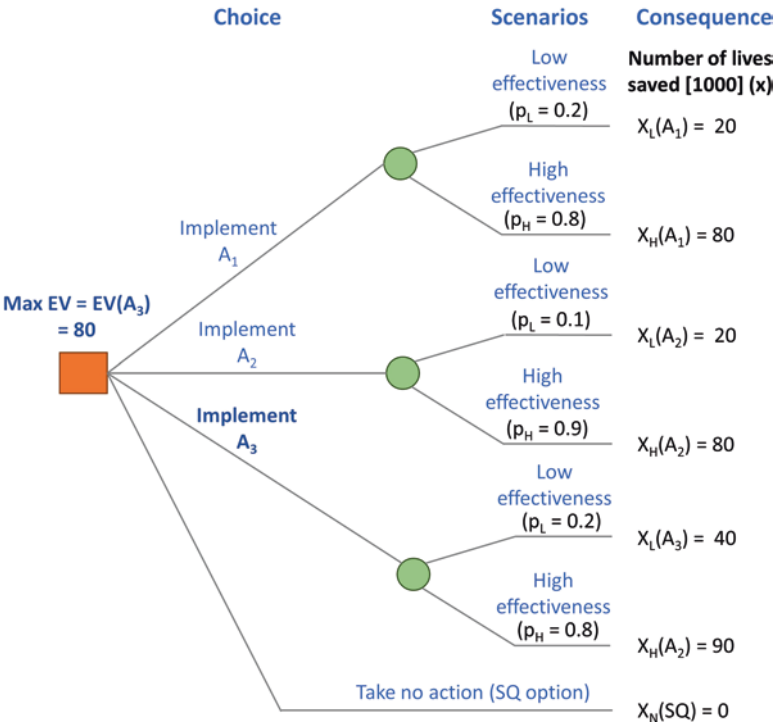

Fig. 9.6 Three risk mitigating decision alternatives against a health threat with two scenarios for their effectiveness

alongside an estimation as to the number of lives saved under each scenario for every option, as shown in the decision tree in Fig. 9.6. Let us compare the first two alternatives in this choice: risk mitigating action A_1 and risk mitigating action A_2. The estimated number of lives saved remains the same under each scenario for both alternatives, with $X_L(A_1) = X_L(A_2) = 20{,}000$ lives (under the low effectiveness scenario) and $X_H(A_1) = X_H(A_2) = 80{,}000$ lives (under the high effectiveness scenario). However, alternative A_2 is more likely to prove highly effective ($p_H = 0.9$) than alternative A_1 ($p_H = 0.8$). Therefore, alternative A_2 *dominates* alternative A_1 and should be selected in this pairwise comparison (this forms a logical conclusion and also fulfils the axiom 4a of Decision Theory, the concept of which has been discussed in the second chapter).

Now, let us compare alternative A_2 versus alternative A_3. While we wish to establish as to which alternative should be selected, we observe that neither alternative dominates the other, as alternative A_3 demonstrates a lower likelihood of high effectiveness ($p_H = 0.8$) than A_2 ($p_H = 0.9$), however, A_3 saves a greater number of lives under both scenarios ($X_L(A_3) = 40{,}000$ lives and $X_H(A_3) = 90{,}000$ lives) than A_2 ($X_L(A_2) = 20{,}000$ lives and $X_H(A_2) = 80{,}000$ lives). This forms a very common situation in practice, wherein there exist some non-dominated options under

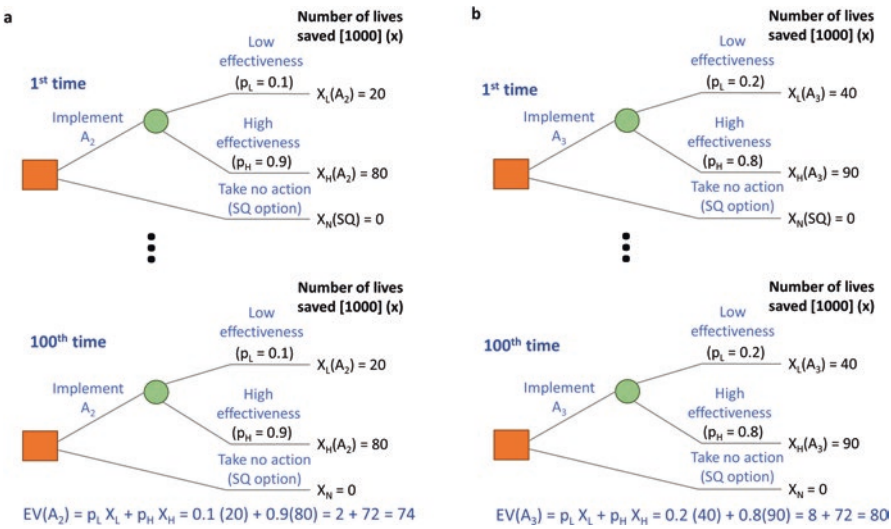

Fig. 9.7 Expected value of repetitive choices for two decision alternatives with two scenarios for their effectiveness (**a**) Expected value of alternative A_2, (**b**) Expected value of alternative A_3

consideration, and for this reason, we require a decision rule that is able to support the selection process in order to determine the best alternative.

Now, let us consider a hypothetical situation wherein there arises the opportunity to repeat the decision concerning the selection of either alternative A_2 or alternative A_3 100 times. Assume that each and every time, we opt to select alternative A_2 (these repetitive choices are illustrated in Fig. 9.7a). This process raises the question as to how many lives (on average) are expected to be saved after selecting A_2 100 times? In this case, we would arrive at the low effectiveness scenario (20,000 lives saved) ten times and we would arrive at the high effectiveness scenario (80,000 lives saved) ninety times, thereby repeating the process 100 times. Thus, the average number of lives saved would be given by the weighted sum of the probability of occurrence of each scenario multiplied by the number of lives saved within each scenario.

Formally, this decision rule is titled: the *expected value* (EV), and for the alternative A_2, said rule is calculated by:

$$EV\left(A_2\right) = p_L X_L\left(A_2\right) + p_H X_H\left(A_2\right) = 0.1\left(20{,}000\right) + 0.9\left(80{,}000\right)$$
$$= 74{,}000\ \left[\text{expected lives saved}\right].$$

If we repeat the same hypothetical situation for alternative A_3, and implement this alternative in 100 decisions (see Fig. 9.7b), the expected value of A_3 is calculated by:

$$EV\left(A_3\right) = p_L X_L\left(A_2\right) + p_H X_H\left(A_2\right) = 0.2\left(40{,}000\right) + 0.8\left(90{,}000\right)$$
$$= 80{,}000\ \left[\text{expected lives saved}\right].$$

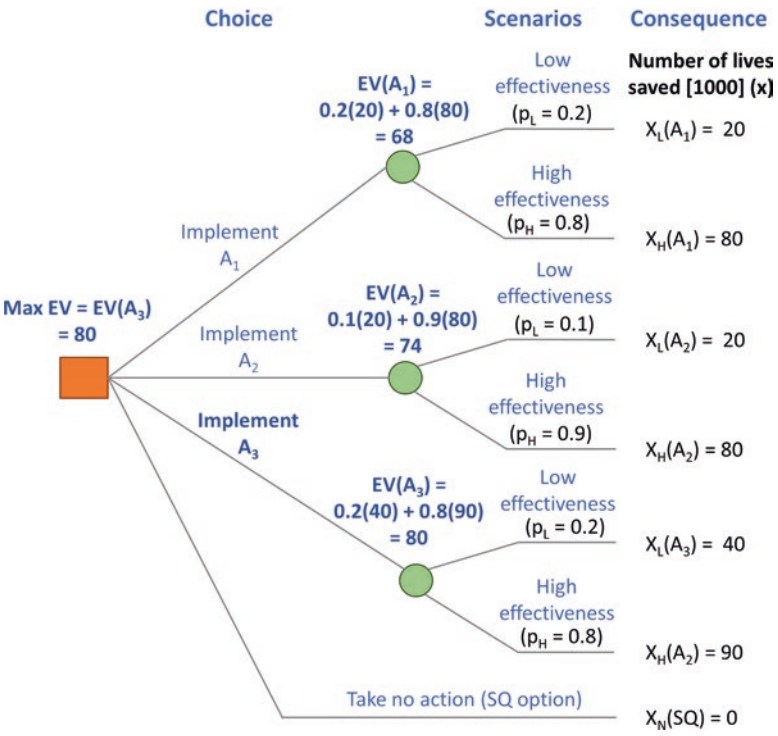

Fig. 9.8 Expected value of three risk mitigating decision alternatives against a health threat

Therefore, alternative A_3 maximizes *the expected number of lives saved* and should therefore be selected in this example. The hypothetical situation in Fig. 9.7 functions to illustrate that the process of repeated selection underpins the concept of expected value. The expected value of the three risk mitigating actions is shown in Fig. 9.8 wherein alternative A_3 has been highlighted, as the alternative provides the highest expected value: $EV(A_3) = 80{,}000$ expected number of lives saved.

The Expected Value Rule The expected value rule for a discrete set of scenarios can be formalized as follows: there emerges a decision alternative A with prospects under uncertainty, the condition of which is represented by a finite set of N scenarios, whereby each scenario is defined by both its respective probability of occurrence (p_j) and the estimate of the consequence under this respective scenario $x_j(A)$ for the decision alternative A (as shown previously in Fig. 9.2). The expected value (EV) of this alternative is calculated by:

$$EV(A) = \sum_j p_j x_j(A) \tag{9.1}$$

Notice that the decision rule under uncertainty entails maximizing *expected value*, which is provided by the multiplication of the probabilities and the consequences under the discrete scenarios that we just have discussed. This rule is in contrast with the previous chapter, wherein most likely performances of decision alternatives or impacts of health threats have been assumed, and the decision rule has been to maximize *value*.

9.1.2 Identifying the Benefits of the Expected Value Rule

There exist important reasons for adopting expected value as a decision rule to guide public choices under uncertainty and the adoption of this rule provides many major benefits for enhanced health security. This decision rule maximizes societal value in health security choices, prevents excessively risk averse or risk seeking behavior, and considers both the relevant consequences and the probabilities of occurrence of future scenarios. These benefits are discussed next.

The Maximizing of Societal Value If the expected value decision rule were to be consistently employed throughout a significant number of health security decisions, the decision rule shall maximize their societal value. This proves true despite there existing the possibility that some negative scenario could occur and give rise to poor or undesirable consequences.

Let us return to the repetitive decisions illustrated in Fig. 9.7. Decision makers may be tempted to select alternative A_2 instead of A_3, as the former risk mitigating action allows for a higher chance of being highly effective when compared with the latter action ($p_H = 0.9$ versus $p_H = 0.8$, respectively). However, if this rationale were to be appropriated and implemented for the process of selecting options, and therefore, the choice to select A_2 (instead of A_3) were to be made 100 times over, this process would very likely lead to a lesser number of lives saved, as the option whose expected value is lower is being repetitively selected ($EV(A_2) * 100 = 7{,}400{,}000$ expected lives saved instead of $EV(A_3) *100 = 8{,}000{,}000$ expected lives saved). On the other hand, if the option A_3 were to be continuously selected across those 100 decisions, a significant gain of 600,000 expected saved lives would be made (8,00 0,000 − 7,400,000 = 600,000 expected lives).

The Prevention of Excessively Risk Averse or Risk Seeking Behavior There exist strong reasons for arguing that the expected value rule should be used to guide public decisions (Fischhoff et al., 1993; Gregory et al., 2012). To explain why this proves to be the case, we should first understand the role of dispersion of consequences (due to uncertainty) and the link between dispersion and risk. Within Decision Analysis, a decision alternative that is characterized by significant dispersion brings about significant risks (this is in contrast with the commonly used risk metrics discussed in the sixth chapter).

This concept of risk functioning to measure dispersion becomes more comprehensible if one considers two options whose expected value is identical, while the

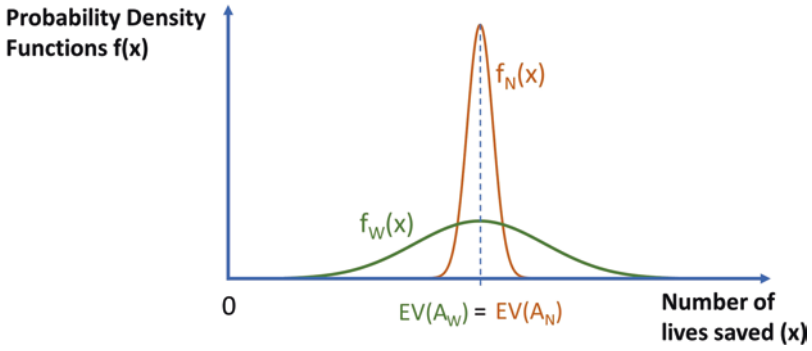

Fig. 9.9 Probability density functions of two decision alternatives against a health threat

consequences of the first alternative are less dispersed than those of the second alternative. For instance, let us imagine two risk mitigating actions (A_N and A_W) which can increase the *number of lives saved* (measured by variable x) from a health threat, as shown in Fig. 9.9. While there exists uncertainty about the effectiveness of these actions, alternative A_N entails a narrow possible spread of outcomes, the situation of which is represented by the probability density function $f_N(x)$ of this alternative (see the fifth chapter for details). On the other hand, alternative A_W entails a broader spread of outcomes, the situation of which is represented by the probability density function $f_W(x)$ of this alternative. Both decision alternatives have the same expected value: $EV(A_N) = EV(A_W)$. For this reason, decision makers would prefer A_N over A_W, as the former demonstrates less variability over the relevant consequence (number of lives saved), and therefore, alternative A_N proves less risky (if risk were to be conceptualized as a measurement of spread of outcomes).

Let us consider the consequences of adopting the expected value rule when we adopt this definition of risk as a measurement of spread of outcomes. The use of the expected value rule prevents policymakers from taking options that are excessively risk averse (which are accompanied by lesser dispersions), but, when these options are considered across a significant number of decisions, the options do not maximize societal value. The expected value rule also prevents decision makers from taking high-risk options (which are accompanied by greater dispersions) in health security decisions when confronted with undesirable outcomes.

An example can underpin the clarification as to why the expected value rule would prevent non-optimal choices like those that are mentioned above. Let us posit another health threat, whose setting is similar to the previous, whereby once again, there exists the potential that the threat could cause 100,000 deaths. Three risk mitigating actions have been devised (A'_1, A'_2 and A'_3), each with a 30% chance of demonstrating low effectiveness ($p_L = 0.3$) and a 70% chance of demonstrating high effectiveness ($p_H = 0.7$), with the objective of *maximizing the number of lives saved* and the associate attribute number of live saved (measured by variable x_S). The decision tree for this problem is shown in Fig. 9.10a. Alternative A'_1 has a low

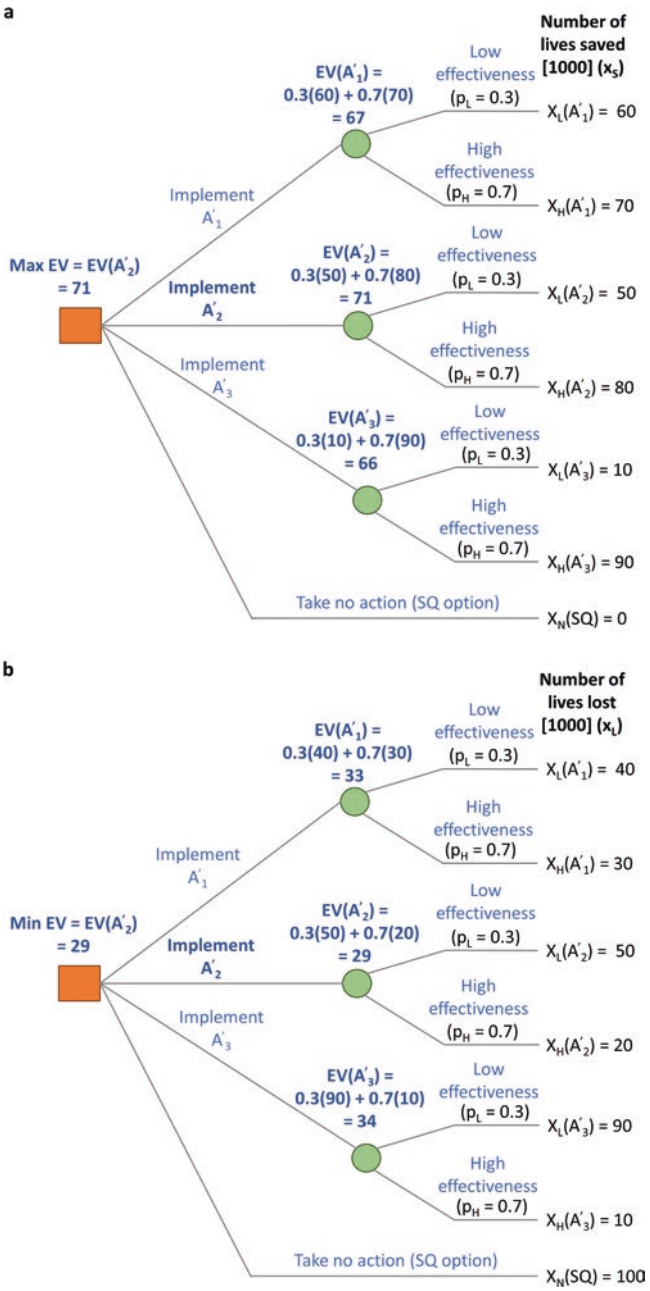

Fig. 9.10 Three decision alternatives represented equivalently as: (**a**) Gains (number of lives saved), (**b**) Losses (number of lives lost)

dispersion of consequences among these two scenarios with $X_L = 60{,}000$ lives saved (under the low effectiveness scenario) and $X_H = 70{,}000$ lives saved (under the high effectiveness scenario). Alternative A'_2 has a moderate dispersion of consequences among these two scenarios with $X_L = 50{,}000$ lives saved and $X_H = 80{,}000$ lives saved (under the two respective scenarios). Finally, alternative A'_3 has a broad dispersion, with $X_L = 10{,}000$ lives saved if the effectiveness of this alternative were to prove low and $X_H = 90{,}000$ lives saved if the effectiveness of this alternative were to prove high. Notice that this decision problem has been has been conceptualized to represent *gains*.

The expected value for these alternatives can be calculated (using Eq. 9.1) as:

$$EV\left(A'_1\right) = p_L X_L\left(A'_1\right) + p_H X_H\left(A'_1\right) = 0.3\left(60{,}000\right) + 0.7\left(70{,}000\right)$$
$$= 67{,}000\ \left[\text{expected lives saved}\right];$$

$$EV\left(A'_2\right) = p_L X_L\left(A'_2\right) + p_H X_H\left(A'_2\right) = 0.3\left(50{,}000\right) + 0.7\left(80{,}000\right)$$
$$= 71{,}000\ \left[\text{expected lives saved}\right];$$

$$EV\left(A'_3\right) = p_L X_L\left(A'_3\right) + p_H X_H\left(A'_3\right) = 0.3\left(10{,}000\right) + 0.7\left(90{,}000\right)$$
$$= 66{,}000\ \left[\text{expected lives saved}\right].$$

Following the expected value rule, alternative A'_2 should be selected, as this alternative maximizes the expected value: $EV(A'_2) = 71{,}000$ expected lives saved.

The expected value rule prevents decision makers from being affected by the gain-loss bias, the presence of which is common in unstructured decision making (Montibeller & von Winterfeldt, 2015). In this well-known cognitive bias, decision makers adapt their risk attitude based on the manner in which the choice has been framed, in that the choice is either perceived to be a gain or a loss (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). When a choice is framed as a gain, most individuals become risk averse and thus select options with narrow dispersion. That is, intuitively, decision makers would select option A'_1 in Fig. 9.10a, as the option is perceived to be the safest within the context of a decision that has been framed as a gain (number of lives saved). However, this choice fails to maximize the expected gain for this decision and, hence, proves to be sub-optimal.

Now, let us reframe this same decision problem as a loss, wherein we wish to *minimize the number of lives lost* with an associate attribute *number of lives lost* (measured by variable x_L) As the total number of deaths is 100,000, we are able to calculate the possible consequences of each alternative under every scenario by subtracting the number of lives saved (shown in Fig. 9.10a) from the total number of deaths. This new decision tree, which has been conceptualized to represent *losses* is demonstrated in Fig. 9.10b. Notice that from a Decision Theory point of view both the representations of gains *and* of losses are equivalent.

Let us calculate the expected value for these three reframed decision alternatives (see Fig. 9.10b):

$$EV\left(A_1'\right) = p_L X_L\left(A_1'\right) + p_H X_H\left(A_1'\right) = 0.3\left(40{,}000\right) + 0.7\left(30{,}000\right)$$
$$= 33{,}000\ \left[\text{expected lives lost}\right];$$

$$EV\left(A_2'\right) = p_L X_L\left(A_2'\right) + p_H X_H\left(A_2'\right) = 0.3\left(50{,}000\right) + 0.7\left(20{,}000\right)$$
$$= 29{,}000\ \left[\text{expected lives lost}\right];$$

$$EV\left(A_3'\right) = p_L X_L\left(A_3'\right) + p_H X_H\left(A_3'\right) = 0.3\left(90{,}000\right) + 0.7\left(10{,}000\right)$$
$$= 34{,}000\ \left[\text{expected lives lost}\right].$$

In this case, we wish to *minimize expected losses*. This expected value rule leads to the choice of A'_2, as this alternative has the lowest expected loss: $EV(A'_2) = 29{,}000$ expected lives lost. We are able to see that this choice is consistent with the previous analysis (see Fig. 9.10a), wherein the equivalent expected gains were being maximized and A'_2 had been selected, as $EV(A'_2) = 71{,}000$ expected lives saved.

However, in unstructured decision making, the gain-loss bias predicts that most individuals would be rendered risk seeking when considering losses (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Individuals are likely to adapt their preferences (in contrast to the gains framing), and in this second situation, prefer options with heavy dispersion. That is, intuitively, decision makers are now more likely to select option A'_3 in the decision tree shown in Fig. 9.10b, which has the highest dispersion. However, this choice does not minimize the expected loss for this decision and, therefore, proves sub-optimal.

As illustrated in the example above, the expected value rule prevents the occurrence of the gains-loss bias, whose presence can be triggered through the manner in which a decision is framed (either as a loss or as a gain). In addition, the rule consistently selects the option that optimizes societal value. In the long term, the consistent adoption of this decision rule (across a significant number of decisions) can provide significant societal gains in health security decisions and significantly reduce societal losses arising from health threats.

The Consideration as to Both the Relevant Consequences and the Probabilities of Occurrence Both the consequences and the probabilities of occurrence of future scenarios must be adequately considered when either evaluating decision alternatives, or, when prioritizing health threats, which is guaranteed if the expected value rule were adopted.

Behavioral studies on risk management and decision making have observed that managers often disregard events that would have a low probability of occurrence but high impacts (were they to occur) (Clearfield & Tilcsik, 2018; Krizan & Windschitl, 2007; March & Shapira, 1987). There also exists evidence that experts may attach lower probabilities to undesirable consequences due to the optimism bias, as these experts may hope that this scenario fails to occur(Chapin, 2001; Montibeller & von Winterfeldt, 2015). The calculation of expected value can help the health security

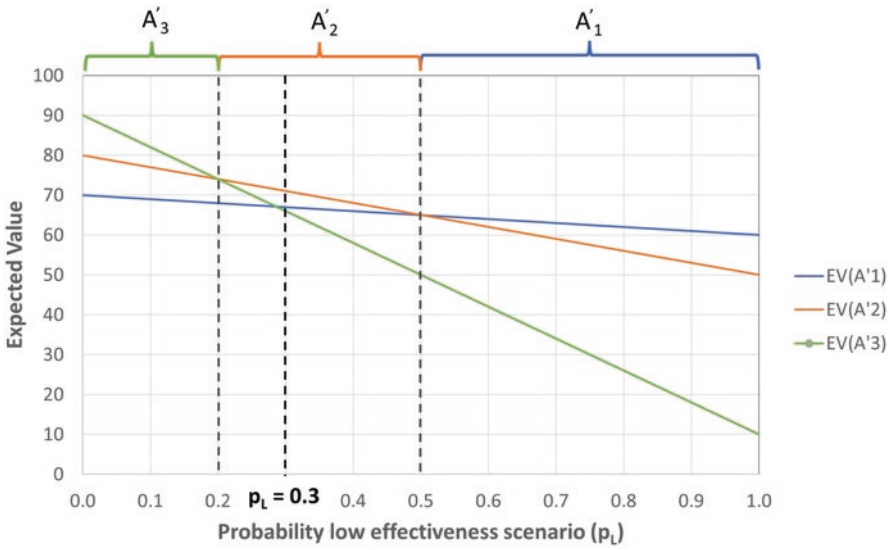

Fig. 9.11 Sensitivity of the expected value for each decision alternative affecting the probability of the low effectiveness scenario

team to grasp the extent to which the results of the analysis are sensitive to these probability estimates.

We are able to illustrate the sensitivity analysis on the estimations of probability using the problem considered in the decision tree shown in Fig. 9.10a. The decision alternative with the highest expected value has been identified as being A'_2, with $EV(A'_2) = 71{,}000$ expected lives saved. Were there to occur a scenario wherein the risk mitigating actions produced low effectiveness and this scenario had a higher probability of occurrence than originally estimated ($p_L = 0.3$), what would the consequences be in terms of choice?

The sensitivity analysis of the expected value of each decision alternative when the probability of the low effectiveness scenario (p_L) ranges from 0.0 to 1.0 is shown in Fig. 9.11. When we review the base-line probability ($p_L = 0.3$), the decision alternative A'_2 has the highest expected value ($EV(A'_2) = 71{,}000$ expected lives saved), as we have calculated previously, which is denoted in the graph by the horizontal line on this probability level. If p_L were to be increased above 0.3, the decrease of $EV(A'_2)$ is steeper than for $EV(A'_1)$. The intersection point of these two lines is when $p_L = 0.5$ (which has also been highlighted in the graph) and at this point $EV(A'_1) = EV(A'_2) = 65{,}000$ expected lives saved. If the probability of this low effectiveness scenario were to exceed this 0.5 probability threshold, alternative A'_1 should be selected, as A'_1 would have the highest expected value. On the other hand, if the probability p_L were to be reduced from the baseline level ($p_L = 0.3$), the intersection point between $EV(A'_2)$ and $EV(A'_3)$ is when $p_L = 0.2$, (also indicated in the

graph) with $EV(A'_2) = EV(A'_3) = 74{,}000$ expected lives saved. Below this $p_L = 0.2$ threshold, the alternative A'_3 should be selected instead of A'_2. Therefore, this sensitivity analysis demonstrates that, for this scenario, the solution (choice of A'_2) proves quite robust to changes affecting the original estimate of probability ($p_L = 0.3$) and option A'_2 would remain the alternative with the highest expected value (within the range $0.2 < p_L < 0.5$).

Similarly, a related issue arises when decision makers solely consider the impacts of emerging health threats while disregarding their probability of occurrence. We have observed this attitude in health security practices, which typically stems from adopting a precautionary principle (Keeney & Winterfeldt, 2001). Neglecting probabilities may prevent an adequate allocation of resources against emerging health threats from taking place, as two health threats whose impacts are identical would be considered to be equally relevant, even if one threat were to have a very low probability of occurrence while the other were to have a high probability (Jaspersen & Montibeller, 2015). Once again, the use of the expected value rule would prevent such over-simplifications and allow for the more adequate ranking of health threats.

There exists a single exception to this expected value rule, which occurs when an alternative that has the maximum expected value may result in catastrophic consequences that are unacceptable (Gregory et al., 2012). However, this issue can be adequately managed through the screening of alternatives a priori (before conducting any value assessment), as discussed in the previous chapter.

To summarize, the expected value rule presents three main benefits for public decisions in general and for health security decisions in particular. First, in the long term, if used consistently to select decision alternatives, the rule maximizes societal value. Second, the rule can prevent the presence of gain-loss biases, which may affect the risk attitude of decision makers due to the manner in which a decision is framed as a gain or as a loss. Third, the use of the expected value assists decision makers to avoid neglecting actions aimed at undertaking low-probability/high-impact adverse events or to avoid disregarding the likelihood of occurrence of events when ranking health threats.

9.2 Assessing Expected Value with Multiple Consequences and Discrete Distributions

We now extend the concept of expected value and employ it as a lens through which to view alternatives that have multiple relevant consequences, or health threats that have multiple impacts. Using the same approach that has been used above, in this section we consider uncertainties that have been modeled by a small number of scenarios.

9.2.1 Calculating Expected Value with Multiple Consequences

In the sixth chapter we have discussed as to how value functions can be developed to measure the marginal value of the impacts of health threats and the performances of decision alternatives. These functions are also able to normalize the value of each option on every relevant consequence. The overall value of each decision alternative can then be calculated by taking into account the attribute weights of the value model (Keeney & Raiffa, 1993; von Winterfeldt & Edwards, 1986).

In the previous chapter, we had assumed that decision alternatives could be assessed by single-point performances, or that health threats had been assessed on their most likely impact. Here, we extended these concepts to represent the uncertainty about performances of alternatives and impacts of threats, a feature of which proves significantly common in health security decisions, as discussed in the first chapter. In this section we consider distributions that are discrete and have a finite number of scenarios.

Expected Value of Decision Alternatives As we have seen in the previous chapter, the value of a decision alternative A can be assessed by a multi-attribute value model with each x_i attribute measuring the i-th relevant consequence linked with a decision objective. To each attribute we have associated a value function $v_i(.)$ and attribute weight w'_i. If independence preferences conditions were to hold, a simple weighted sum can be used to assess the overall value of each decision alternative. In situations wherein there exist a finite number of discrete scenarios, the overall value of this alternative $V_j(.)$ should be assessed under each j-th scenario:

$$V_j(A) = \sum_i w'_i v_i\left[x_i(A)\right] \tag{9.2}$$

Notice that in the formula above, the performance of alternative A (represented by $x_i(A)$) should be assessed on each i-th attribute and under each j-th scenario, i.e. $X_{ij}(A)$.

The expected value EV(.) of this alternative A is then calculated as the product of the value $V_j(A)$ under each scenario, multiplied by the probability of occurrence of each scenario p_j:

$$EV(A) = \sum_j p_j V_j(A) \tag{9.3}$$

This formulation allows for the consideration of both the multi-attribute value and the uncertain prospects of the decision alternatives. The evaluation can be represented by a decision tree, as shown in Fig. 9.12. The alternative A is evaluated under a set of N scenarios by a multi-attribute value model with M objectives (and respective attributes). The performances of this alternative are evaluated on each j-th scenario with the overall value $V_j(A)$ calculated by Eq. 9.2. The expected value for the alternative EV(A) is then calculated by Eq. 9.3. This same procedure is employed to

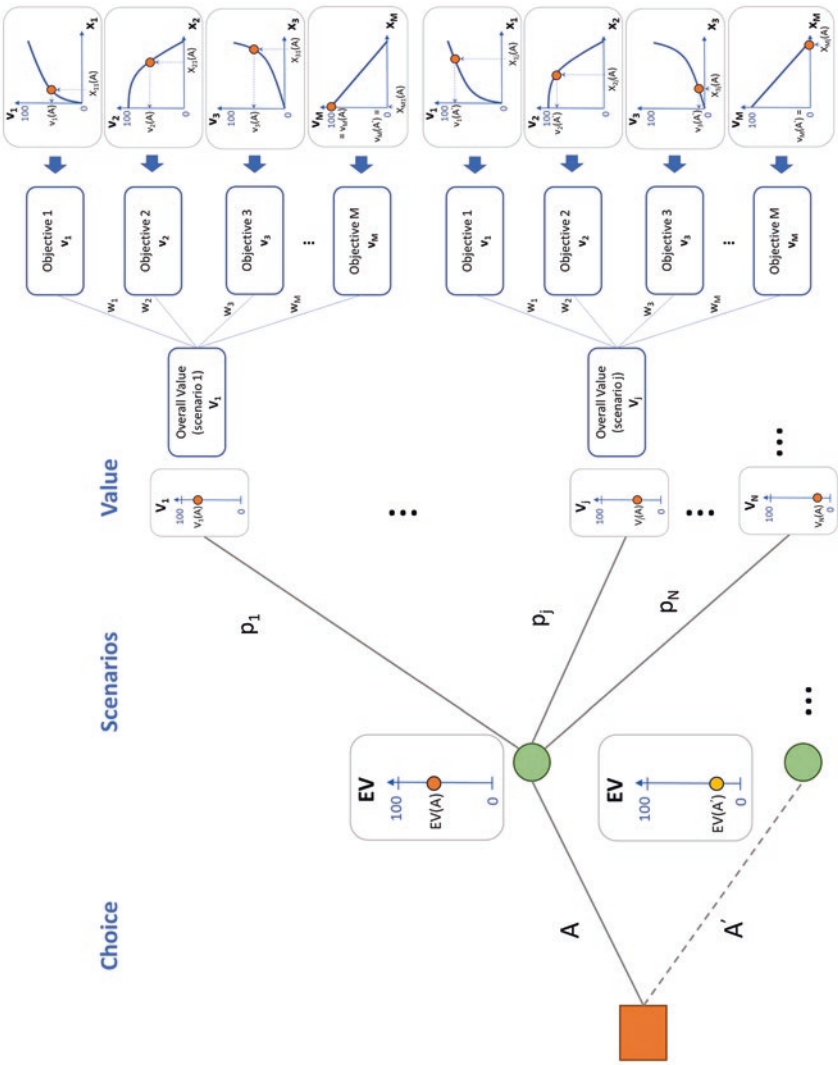

Fig. 9.12 Evaluation of alternatives with multiple impacts and a discrete set of scenarios

calculate the expected value of other decision alternatives, such as A′ in the same figure. The option with the highest *expected multi-attribute value* should be selected.

In Decision Analysis, we typically model the risk attitude of decision makers, whereby risk is defined as the dispersion of outcomes. There also exists a conceptual distinction between value and utility, with the former being employed to assess alternatives in riskless choices and the latter being employed in decisions under uncertainty (von Winterfeldt & Edwards, 1986). (For details, see Montibeller and Franco (2010, 2011), who provide a full conceptualization of decisions with multiple objectives under uncertainty, employing utility functions, as well as a critical appraisal of the key assumptions made in this type of decision analysis.)

However, in the context of this book, we opt to not make this distinction between value and utility and thus, we employ value even for the evaluation of decisions under uncertainty. The reasons for this methodological positioning are practical rather than theoretical, and are linked with the decision context under consideration: health security decision making.

The first reason stems from the fact that, in practice, the distinction between value and utility proves not so straightforward. Indeed, many decision analysts employ value functions even for decisions under uncertainty (Goodwin & Wright, 2009; von Winterfeldt & Edwards, 1986), particularly when there does not exist a need to model risk attitude (Keeney & von Winterfeldt, 2007).

Second, the elicitation of utility functions requires protocols that pose hypothetical gambles among prospects (Keeney & Raiffa, 1993; von Winterfeldt & Edwards, 1986). In our experience, health security experts and policymakers feel deeply uncomfortable posing these hypothetical questions,[1] often feeling as though they are being asked to contemplate risking the lives of individuals within a community (March & Shapira, 1987). Additionally, value functions prove easier to be defined (Keeney & von Winterfeldt, 2007) and are less likely to be affected by elicitation noise than utility functions (Hey et al., 2009; Keller, 1985; Smidts, 1997), i.e., proves to be more stable if elicited multiple times from the same decision makers (see Montibeller and von Winterfeldt (2015) for details).

Third, in the context of health security settings, the modeling of risk attitude over the dispersion of prospects (the process of which is required for the elicitation of utility) is a rather artificial process. Instead, decision makers often conceptualize risk in different ways, such as an undesirable consequence or as the probability of the occurrence of an undesirable consequence (Gregory et al., 2012; Morgan, 2017; Morgan & Henrion, 1992). Hence, decision makers may prefer to establish risk limits (Fischhoff et al., 1993), or to define priorities among undesirable consequences that they wish to minimize, as discussed in the sixth chapter), rather than modeling a societal risk attitude.

[1] These hypothetical questions require expressing preferences over prospects involving consequences and probabilities. For example, a policymaker could be asked if they would prefer a risk mitigating alternative with a 50% probability of saving 100,000 lives and a 50% probability of saving none, versus another risk mitigating alternative in which 50,000 lives are saved with certainty.

Expected Dis-Value of Health Threats Similar to the formulation of expected value that is specific to decision alternatives, the impacts of health threats can also be assessed by considering a small set of scenarios and their consequences under each scenario. Here, we formalize this type of evaluation for the assessment of *expected overall dis-value* of a threat.

The dis-value of a health threat T can be assessed by a multi-attribute value model with each x_i attribute measuring the i-th relevant consequence. Each attribute has an associated dis-value function $v^-_i(.)$ and attribute weight w'_i, as has been detailed in the previous chapter (see also Montibeller et al., 2020b). If preference independence conditions were to hold, a simple weighted sum can be used to assess the overall dis-value of the threat. In situations wherein a set of discrete scenarios is defined, the overall disvalue of this threat $V^-_j(T)$ can then be assessed under each j-th scenario:

$$V_j^-(T) = \sum_i w_i' v_i^-\left[x_i(T)\right] \tag{9.4}$$

Notice that in the formula above, the impact of threat T, $x_i(T)$, should be assessed on each i-th attribute and under each j-th scenario, i.e. $X_{ij}(T)$.

The expected overall dis-value EV(.) of the threat T is then calculated as the product of the dis-value of this threat in each scenario, $V_j^-(T)$, and the probability of occurrence of each scenario p_j:

$$EV^-(T) = \sum_j p_j V_j^-(T) \tag{9.5}$$

We illustrate as to how these expected multi-attribute value assessments (with a small number of scenarios) can be conducted in health security in the subsequent section. Despite the simple structures that underpin the modelling of these uncertainties, these assessments ultimately form a robust evaluation tool and are widely employed in health decision making (Hunink & Weinstein, 2014).

9.2.2 Calculating Expected Value with Multiple Consequences for the Prioritization of Low-Moisture Food Categories (FAO/WHO)

We return to the project for the prioritization of low-moisture food categories, which we conducted for the Food and Agriculture Organizations of the United Nations (FAO) and World Health Organization (WHO), the topic of which has been discussed in previous chapters to illustrate how expected multi-attribute value assessments can be conducted in health security practice.

Recall that a value model was developed for FAO/WHO to rank low-moisture food (LMF) categories, with linear value functions, and a simple weighted sum was

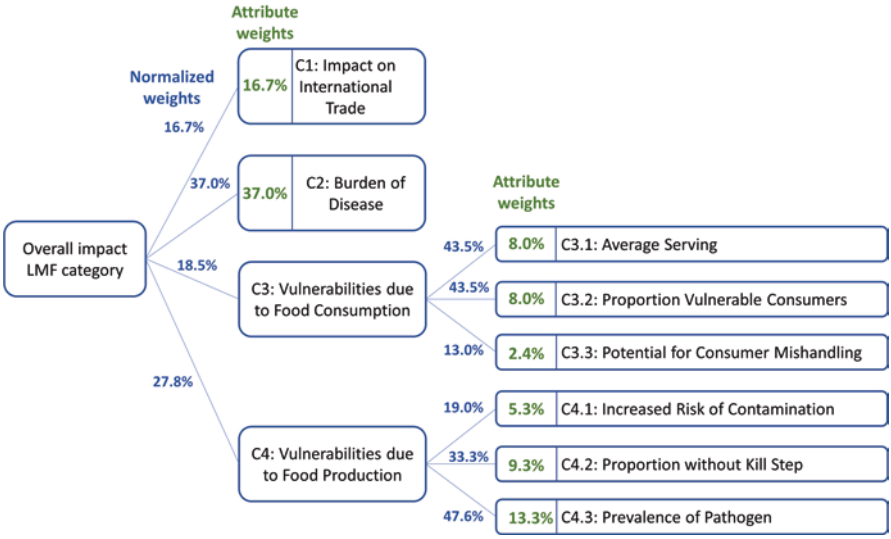

Fig. 9.13 Value tree with normalized and attribute weights for the value assessment of low-moisture food categories

utilized to aggregate the normalized overall impacts (FAO/WHO, 2014; Montibeller, 2018). In this section, we present the full evaluation of these food categories, demonstrate how a sensitivity analysis can be employed to consider the extent to which the model is robust against uncertainty in estimates, and discuss the ways in which the model could be extended to calculate expected overall impacts.

Value Model The value model for the assessment of LMF categories is demonstrated in Fig. 9.13. Weights were defined by the LMF experts following the dummy alternatives method explained in the sixth chapter. Normalized and attribute weights are presented in the same figure. The attributes employed to measure each impact are shown in Table 9.1, alongside the type of distribution employed to assess the impact each food category under consideration and the source of data utilized (see also the fifth chapter).

Estimates of Impacts and Normalized Valuation As we have previously mentioned in the sixth chapter, we defined linear value function over these attributes in order to value and normalize the impacts, with the lowest impact established at 0 and the highest impact established at 100.

For the first two impacts (C1 and C2), there existed no uncertainty, as the estimates were based on previous data on *international trade* (which was related to these food categories) and on the *burden of disease* for each LMF category that was reported in the literature. Therefore, single-point estimates based on this data were employed, which are shown in Tables 9.2 and 9.3. These tables also present the normalized impacts between 0 and 100, in the last column of each table.

Table 9.1 Attributes and distributions for assessing the impacts of low-moisture food categories (FAO/WHO, 2014)

Impact	Sub-impacts	Attribute	Distribution
C1: Impact on international trade	–	Export value in US$ billions/year	Single-point estimate (data)
C2: Burden of disease	–	Total DALYs in outbreak cases from 1990 onward	Single-point estimate (data)
C3: Vulnerabilities due to food consumption	C3.1: Average serving	Average g/day	Single-point estimate (data)
	C3.2: Proportion vulnerable consumers	Proportion (0–100%) consumed by vulnerable groups (toddlers and the elderly)	Single-point estimate (data)
	C3.3: Potential for consumer mishandling	Proportion (0–100%) of low-moisture food products in a given category with an increased risk as a result of mishandling/poor practices at any time between final retail and consumption.	Three-point estimate (expert judgment)
C4: Vulnerabilities due to food production	C4.1: Increased risk of contamination	Proportion (0–100%) of low-moisture food products in a given category with an increased risk of contamination post kill step.	Three-point estimate (expert judgment)
	C4.2: Proportion without kill step	Proportion (0–100%) of low-moisture food products in a given category without a kill step prior to retail and distribution.	Three-point estimate (expert judgment)
	C4.3: Prevalence of pathogen	Probability that a LMF is contaminated at a level with any pathogens with the potential to cause illness in consumers.	Single-point estimate (data)

Table 9.2 Impact estimates and normalized impacts for the low-moisture food categories on International Trade (FAO/WHO, 2014)

C1: International trade			
Code	Category name	Export value [US$ billions/year]	Normalized impact (v_i)
Cat 1	Cereals and grains	118.594	100.0
Cat 2	Confections and snacks	58.124	48.5
Cat 3	Dried fruits and vegetables	15.211	12.0
Cat 4	Dried protein products	22.800	18.4
Cat 5	Nuts and nut products	20.338	16.3
Cat 6	Seeds for consumption	1.150	0.0
Cat 7	Spices, dried herbs and tea	14.938	11.7

The impacts related to *vulnerabilities to food consumption* (C3) were decomposed into three sub-impacts. There existed available data about *average serving* (C3.1) and the *proportion of food consumed by vulnerable consumers* (C3.2), which were employed to estimate the impacts of the food categories. Once again, the impacts were normalized into 0-to-100 value scales.

Table 9.3 Impact estimates and normalized impacts for the low-moisture food categories on Burden of Disease (FAO/WHO, 2014)

C2: Burden of disease			
Code	Category name	Total DALYs in outbreak cases from 1990 on	Normalized impact (v_2)
Cat 1	Cereals and grains	72.53	45.9
Cat 2	Confections and snacks	60.26	35.4
Cat 3	Dried fruits and vegetables	32.78	12.2
Cat 4	Dried protein products	136.44	100.0
Cat 5	Nuts and nut products	118.51	84.8
Cat 6	Seeds for consumption	18.42	0.0
Cat 7	Spices, dried herbs and tea	80.71	52.8

Table 9.4 Estimates by individual low-moisture food international experts for the proportion of Consumer Mishandling (most likely proportions) (FAO/WHO, 2014)

C3.3 – Consumer mishandling									
Proportion (0–100%) of low-moisture food products in a given category with an increased risk as a result of mishandling/poor practices at any time between final retail and consumption (estimates of most likely proportions by individual LMF international experts).									
Code	Food name	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Lower estimate	Upper estimate	Median
Cat 1	Cereals and grain	10	30	20	5	30	5	30	20
Cat 2	Confections and snacks	1	8	10	5	2	1	10	5
Cat 3	Dried fruits and vegetables	1	15	15	5	5	1	15	5
Cat 4	Dried protein products	70	25	20	5	70	5	70	25
Cat 5	Nuts and nut products	0	15	10	5	1	0	15	5
Cat 6	Seeds for consumption	1	10	10	5	1	1	10	5
Cat 7	Spices, dried herbs and teas	60	15	20	5	10	5	60	15

However, data was not available, which could be used to estimate the third sub-impact *consumer mishandling* (C3.3), related to *vulnerabilities to food consumption*. As a result, we elicited expert estimates from five international LMF experts involved in the study. For each food category, each expert individually provided the most likely proportion of consumer mishandling, as well as the lower and upper bound of said proportions. The estimates for the *most likely* proportion from each individual expert are shown in Table 9.4. Subsequently, we employed the

Table 9.5 Impact estimates and normalized impacts for the low-moisture food categories on Consumer Mishandling (FAO/WHO, 2014)

C3.3 – Consumer mishandling			
Code	Category Name	Proportion (0–100%) of low-moisture food products in a given category with an increased risk as a result of mishandling/poor practices at any time between final retail and consumption	Normalized Impact ($v_{3.3}$)
Cat 1	Cereals and grains	20	75.0
Cat 2	Confections and snacks	5	0.0
Cat 3	Dried fruits and vegetables	5	0.0
Cat 4	Dried protein products	25	100.0
Cat 5	Nuts and nut products	5	0.0
Cat 6	Seeds for consumption	5	0.0
Cat 7	Spices, dried herbs and tea	15	50.0

median of these estimates to define the impact, as this operator is less sensitive to outliers than the mean, and normalized the impacts between 0 and 100, as shown in Table 9.5.

The impacts related to *vulnerabilities of food production* (C4) were also decomposed into three sub-impacts. The same use of expert judgment described above was adopted to estimate the *increased risk of contamination* (C4.1) and the *proportion of food within a category without a kill step* (C4.2), as data was also not available. The same experts were individually requested to provide most likely, upper bound and lower bound estimates for each category. The median and range of most likely estimates were calculated in a similar manner to that of consumer mishandling estimates. The median was then used to estimate the impact of each category, and this estimate was valued and normalized between 0 and 100. Finally, there existed available data about the presence of contamination (C4.3) for each food category, which was once again valued and normalized between 0 and 100.

Overall Ranking The overall normalized impact (value) of each food category could then be calculated by Eq. 8.1, which was presented in the previous chapter. The assessment considered the valuation of the category on every attribute (such as the valuation presented in Tables 9.2, 9.3, and 9.5) and employed the attribute weights from the value tree presented in Fig. 9.13. The results are shown in Fig. 9.14, with Category 1 ranked first (58.3 value points), followed by Category 4 (54.4 value points). The figure also illustrates the composition of weighted impacts for each food category, from the four impacts considered (C1, C2, C3, and C4).

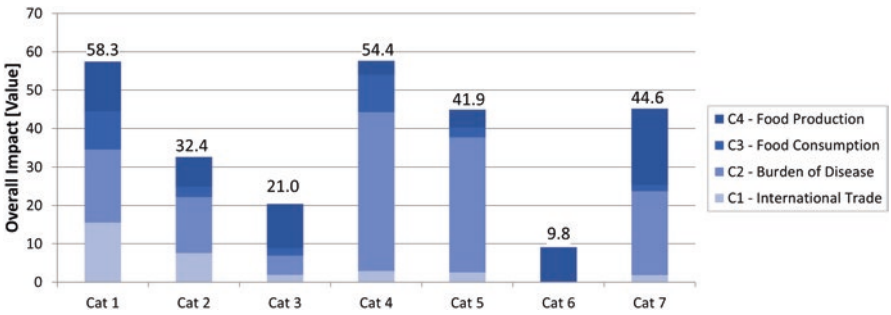

Fig. 9.14 Overall normalized impact (value) of low-moisture food categories (Montibeller, 2018)

In addition to overall results, we conducted a sensitivity analysis of these results, considering the competing priorities and the variability brought about by the assessments that employed expert estimates. These analyses may help to answer three important questions concerning the results of any decision analysis. First, how sensitive are the results to the priorities of the organization? Second, how sensitive are the results to impacts that have dispersion? And third, how sensitive are the results to the future scenarios that may happen? We describe how sensitivity analysis can be used to answer each of these questions.

Sensitivity Analysis on Attribute Weights By utilizing attribute weights as varied inputs, the influence of the attribute weights on the results can be assessed with a sensitivity analysis of the overall values for each food category. The logic that underpins this type of analysis, as introduced in the previous chapter, requires that each attribute weight ranges from 0% to 100%, and that the weights of the remaining attributes be proportionally adjusted given their baseline weights (see Montibeller and Franco (2007) for details).

Regarding the priorities of the decision makers in the LMF ranking project, a relatively heavy weight was allocated to the *burden of disease* ($w'_2 = 37.0\%$) in comparison with the weight allocated to *international trade* ($w'_1 = 16.7\%$), as represented in the value tree shown in Fig. 9.13. Let us analyze the sensitivity of the LMF overall ranking against these two attribute weights.

The sensitivity analysis on the weight of *international trade* is shown in Fig. 9.15a. Two points are easily identifiable, so that we are able to trace each line representing the overall impact of every LMF category. The first point is located at the baseline weight ($w'_1 = 16.7\%$) with the overall value for each LMF category shown in Fig. 9.14. For example, the overall value for LMF Category 1 is shown in the graph as V(Cat 1) = 58.3 value points at the baseline weight. The second point at which the line is defined occurs when the attribute weight is 100%. In this case, the overall value of each option is identical to the value of the option on the attribute. These normalized scores are shown in Table 9.2 for the attribute *international trade*. For instance, the overall value for LMF Category 1 is shown in the graph as

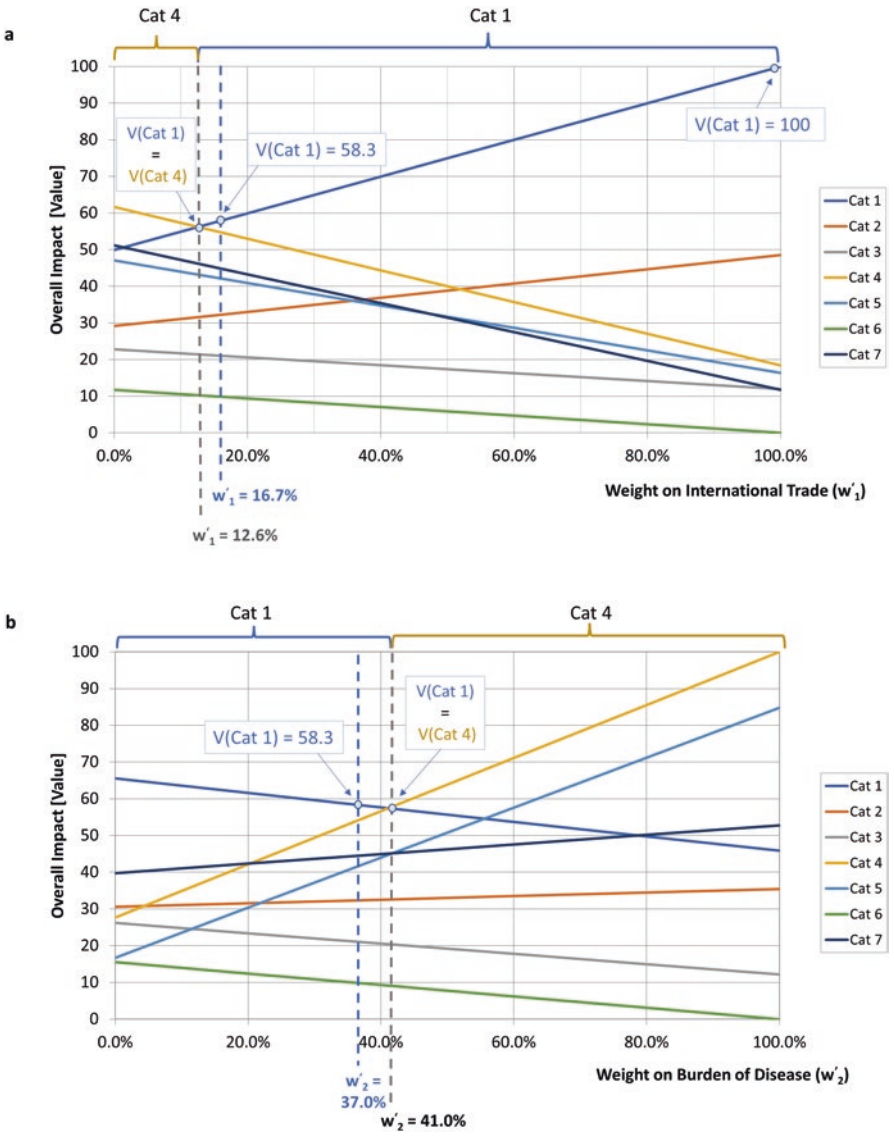

Fig. 9.15 Sensitivity analysis of overall value on attribute weights: (**a**) On International Trade, (**b**) On Burden of Disease

V(Cat 1) = 100 with the attribute weight set at $w'_1 = 100.0\%$. A line can be then traced between these two points, extending until the point at which $w'_1 = 0.0\%$.

As this sensitivity analysis on the weight of *international trade* graph shows, the highest ranked category (Cat 1) would remain the same even if this weight were to significantly exceed the baseline value ($w'_1 = 16.7\%$), as the overall normalized impact of this category would only increase. On the other hand, if this attribute

weight were to recede from the baseline level, an intersection between the two lines V(Cat 1) = V(Cat 4) would occur at $w'_1 = 12.6\%$, as indicated in the figure. Below the weight level (12.6%), Category 4 would have the highest overall value. However, in actuality, this low weight for international trade proved not realistic and hence the ranking was deemed as being robust.

The sensitivity analysis graph on *burden of disease* (which was plotted using the same logic as has been described above) is shown in the Fig. 9.15b. With the baseline weight ($w'_2 = 37.0\%$), Category 1 is the top ranked LMF category, with V(Cat 1) = 58.3 value points, the configurations of which are shown in the graph. This category would remain the highest ranked if the weight of this attribute were to recede from the baseline level ($w'_2 = 37.0\%$). On the other hand, if this weight were to further exceed the baseline level, the intersection point between the two lines V(Cat 1) = V(Cat 4) would occur at $w'_2 = 41.0\%$, as indicated in the same figure. Thus, Category 4 would only be rendered the category with the highest overall value if the weight on *burden of disease* were to exceed 41.0%. However, this weight level would probably represent a priority that is excessively high for such an impact in this decision problem, which had already been established at a high level ($w'_2 = 37.0\%$).

Hence, this sensitivity analysis on these attribute weights pertaining to the assessment of LMF categories illustrates that the model solutions prove robust against minor variations of these two baseline weights. This same type of sensitivity analysis should be executed for every attribute that pertains to a value model. These attribute-by-attribute assessments of robustness delineate the boundary conditions for the weight ranges, the range of which determines that the highest valued option remains the same. This process has been illustrated here using the two attributes above.

Sensitivity Analysis on Impact Estimates In order to conduct a sensitivity analysis of the impact estimates on the overall normalized impact for each LMF categories, we also considered the range of expert estimates for the most likely impacts. As we have mentioned previously, these expert estimates are exemplified in Table 9.4, for *consumer mishandling* (C3.3), and a similar set of estimates were elicited from experts for the attributes: *increased risk of contamination* (C4.1) and *proportion without kill step* (C4.2).

The results of this sensitivity analysis on estimates are presented in the bar graph shown in Fig. 9.16, with the overall scores for the *baseline* estimates (already presented in Fig. 9.14), as well as employing the *lower most likely* estimates from experts or the *upper most likely* estimates from experts (hence the uncertainty was modeled as a range following the taxonomy presented in Table 5.8 in the fifth chapter).

When looking at both the *lower most likely* and *upper most likely* conditions, Category 4 has the highest overall ranking (a value score of 59 with both the lower most likely estimates and the upper most likely estimates), followed by Category 1 (a value score of 55 with the lower most likely estimates and 58 with the upper most likely estimates). Given these uncertainties, with the overall value of Category 1

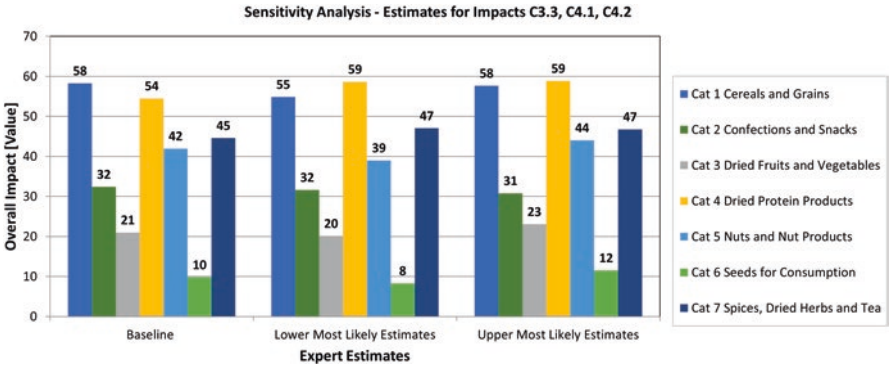

Fig. 9.16 Sensitivity analysis on expert estimates for the most likely impacts (Montibeller, 2018)

ranging from 55 to 58 value points, and the value of Category 4 ranging from 54 to 59 value points, it was recommended that Category 4 also be considered as a top-ranked LMF category in terms of its overall impact. In addition, further studies can attempt to better understand these impacts, which may reduce the variability of impact estimates on these three attributes.

Sensitivity Analysis on the Probability of Future Scenarios Thus far, the evaluation of LMF categories has been based on a single most likely scenario, and therefore, on the assessment of overall value for each food category. However, we can use this model to illustrate how the expected impact of each food category could be assessed if future scenarios were under consideration. This sensitivity analysis may help to assess the robustness of the results on future scenarios that may happen and incorporate this uncertainty in the health decision analysis.

Assume that, in addition to the baseline scenario originally considered above, two additional scenarios have been devised. One scenario is *negative*, with a probability $p_N = 20\%$, wherein impacts for each food category would *increase* as follows: Cat 1 by 10%, Cat 2 by 50%, Cat 3 by 40%, Cat 4 by 80%, Cat 5 by 80%, Cat 6 by 20%, and Cat 7 by 90%. The overall value of these higher impacts for each food category is shown in Fig. 9.17. The other scenario is *positive*, with a probability $p_P = 20\%$, wherein impacts for each food category would *decrease* as follows: Cat 1 by 30%, Cat 2 by 50%, Cat 3 by 40%, Cat 4 by 10%, Cat 5 by 10%, Cat 6 by 20%, and Cat 7 by 10%. The overall value of these lower impacts for each food category is shown in the same figure. The baseline scenario has been estimated with a probability $p_B = 60\%$ (as $p_N + p_P + p_B = 100\%$).

In this example, we use Eq. 9.2 to calculate the expected normalized impact (value) of each food category, as the leftward side of Fig. 9.17 demonstrates. The expected value of Category 1 (59.5 value scores) is the highest, followed by Category 4 (57.8 value points), and Category 7 (52.6 value points). The ranking of categories remains the same (in comparison with the previous overall value assessment), and so this uncertainty about impacts would not exert any significant influence on the

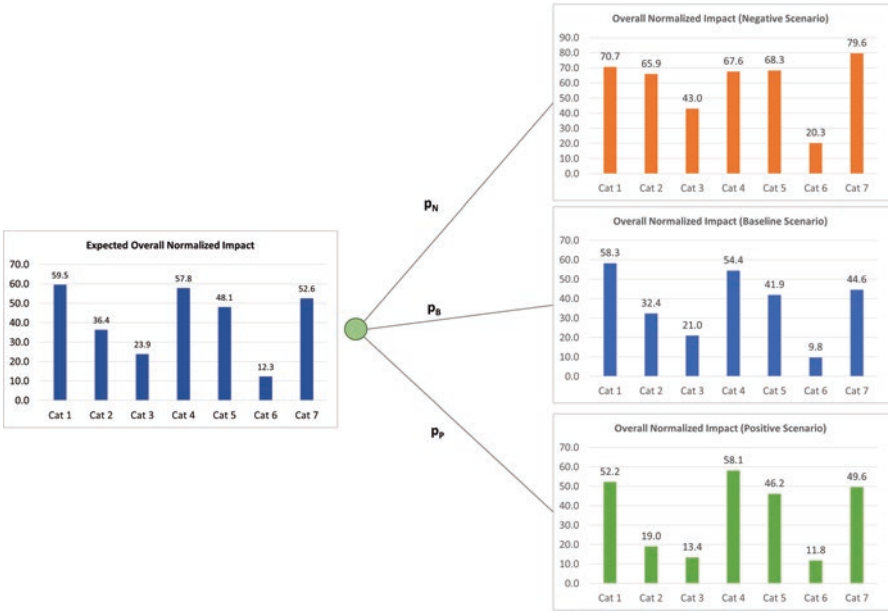

Fig. 9.17 Expected value analysis of the low-moisture food categories

recommendation as to which low-moisture food categories should be prioritized for improved risk control and further risk regulation.

We shall also perform a sensitivity analysis on the estimated probabilities of the scenarios defined above. This is illustrated in Fig. 9.18 for the probability of the baseline scenario (p_B), ranging from 0% to 100%. The analysis assumes that the probability of the two other scenarios would be equally adjusted if p_B were to exceed or recede from its baseline level ($p_B = 60\%$). Category 1 remains the LMF category whose expected value proves highest for the probability of the baseline scenario above 27%. Below this 27% level and above the 15% level, Category 4 becomes the highest ranked. Below this latter 15% level of probability, Category 7 becomes the highest ranked. This analysis therefore illustrates that the results prove robust against the estimated probabilities of these scenarios around the baseline level ($p_B = 60\%$). Hence, the uncertainty about the impacts of these LMF categories (the scenarios of which have been modeled by the scenarios), would fail to alter the recommendation that Category 1 be prioritized by FAO.

The same evaluation framework employed in this decision problem can be adapted to evaluate the expected dis-value of health threats. The project to prioritize emerging animal health threats (the topic of which has been introduced in previous chapters) is employed subsequently, in order to illustrate how this type of prioritization can be conducted in this context.

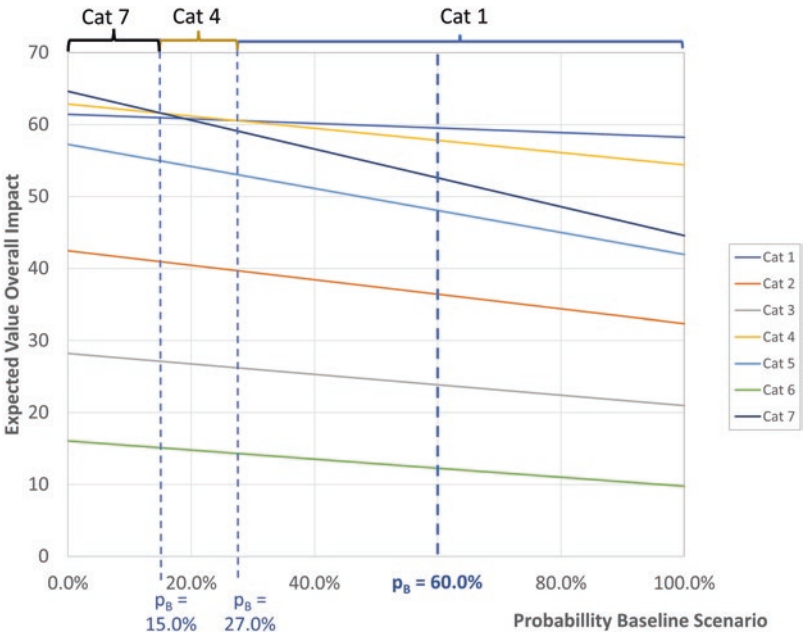

Fig. 9.18 Sensitivity analysis of the expected value of each low-moisture food category on the probability of the baseline scenario

9.2.3 Calculating Expected Dis-Value with Multiple Consequences of Emerging Animal Health Threats (DEFRA)

In the previous chapter, we had described the value model for ranking emerging animal health threats for the UK Department for Environment, Food and Rural Affairs (DEFRA) (Del Rio Vilas et al., 2013; Montibeller et al., 2020a). The model for actual impacts consisted of four attributes and the overall value was calculated with a multi-attribute value function consisting of a simple weighted sum.

In this same chapter, we had also demonstrated how the model is used to evaluate health threats, with the evaluation and calculation of the overall impact of four hypothetical emerging animal health threats. The dis-value of each health threat is reproduced in Fig. 9.19. However, that evaluation omits the probability of occurrence of each threat, and consequently, this omission has implicitly assumed that all threats have the same probability of occurrence, and yet, this condition is unlikely to be observed in practice (Jaspersen & Montibeller, 2015).

One simple way in which we are able to extend this evaluation entails the inclusion of the discrete probability of occurrence for each threat. This is exemplified in Fig. 9.20, whereby each threat (T_1, T_2, T_3, and T_4) is allocated a (single-point) probability of occurrence of a significant outbreak within a well-specified time-frame that

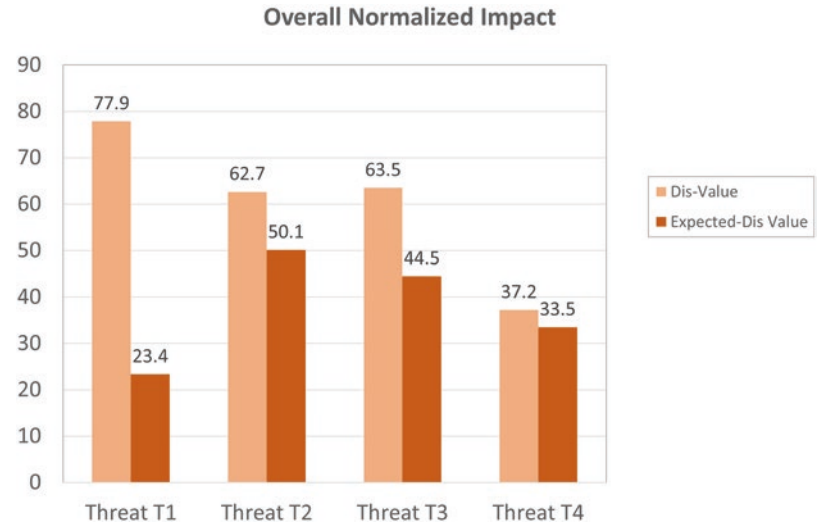

Fig. 9.19 Dis-value and expected dis-value of four hypothetical emerging animal health threats

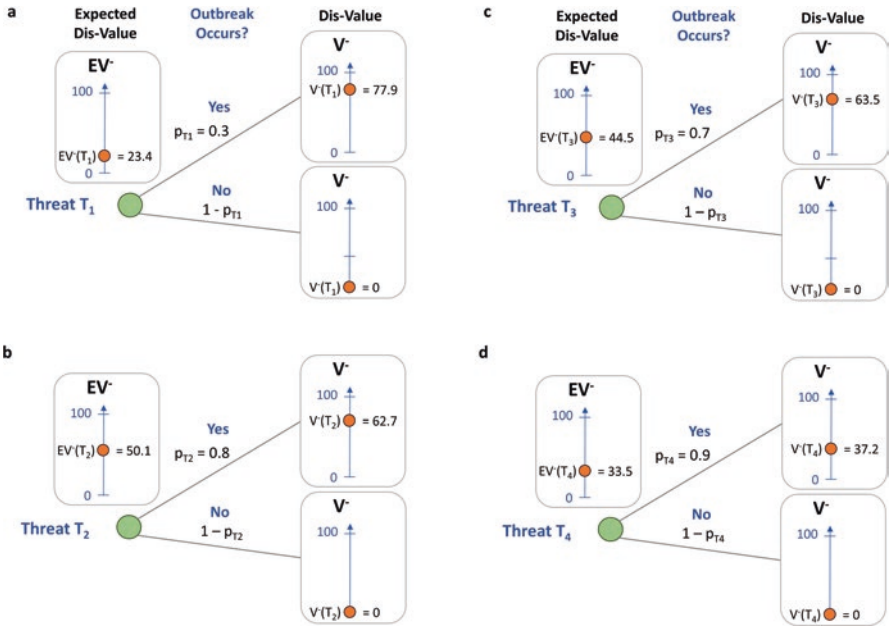

Fig. 9.20 Assessing the expected dis-value of emerging animal health threats: (**a**) Threat T_1, (**b**) Threat T_2, (**c**) Threat T_3, (**d**) Threat T_4

has been determined (p_{T1}, p_{T2}, p_{T3}, and p_{T4}, respectively). For instance, assume that $p_{T1} = 30\%$, $p_{T2} = 80\%$, $p_{T3} = 70\%$, and $p_{T4} = 90\%$ within the time frame under consideration. Therefore, the expected dis-value for Threat T_1 would be $EV^-(T_1) = p_{T1} V^-(T_1) = 0.3\ (77.9) = 23.4$ dis-value points (see Fig. 9.20a). Following this same logic, the expected dis-value for Threat T_2 would be $EV^-(T_2) = 50.1$ dis-value points (see Fig. 9.20b), for Threat T_3 would be $EV^-(T_3) = 44.5$ dis-value points (see Fig. 9.20c), and for Threat T_4 would be $EV^-(T_4) = 33.5$ dis-value points (see Fig. 9.20d).

The comparison between the deterministic dis-value and the expected dis-value of these four health threats (shown in Fig. 9.19) illustrates the significant influence that the probabilities exert on the ranking of health threats. If the ranking were to be contingent on expected dis-value, T_2 would be the first threat to be ranked (50.1 dis-value points), followed by T_3 (44.5 dis-value points).

A simulation employing actual emerging animal health threats (the exercise of which we conducted for this problem) demonstrated significant differences between these dis-value and expected dis-value rankings (Jaspersen & Montibeller, 2015). Therefore, it is advisable to include probability assessments in the rankings of health threats, the advice of which runs contrary to the current practice in health threat prioritization, which otherwise often neglects probabilities of occurrence (see Montibeller et al. (2020b) for a full critique of current practices).

Evidently, this expected dis-value assessment of health threats relies on the quality of probability estimates (as well as on the accuracy of the valuation model itself). These probability estimates can be inferred from previous data, from information that is gathered by surveillance systems, and from expert judgment. We shall return to this point which touches upon how to improve such estimates, in the next chapter.

9.3 Assessing Expected Value with Multiple Consequences and Continuous Distributions

Thus far, in this chapter, we have considered the ways in which a finite number of scenarios can be employed in the evaluation of expected value for health security actions, or in the evaluation of expected dis-value for health threats. These representations of uncertainty are a simplified, albeit, widely used and significantly beneficial way of evaluating actions and threats.

In this section[2] we extend this type of assessment to a more general case, wherein the uncertainties are represented by continuous distributions (discussed in the fifth chapter). We start by analyzing a case wherein there exists a single consequence under consideration, the situation of which allows for the introduction and

[2] This section requires a basic understanding of calculus and computational algorithms. Readers that feel both satisfied with using discrete distributions to characterize uncertainty and uninterested in conducting a more sophisticated risk analysis may proceed to the next section.

discussion of important concepts. Subsequently, we extend the evaluation, applying it to an assessment which deals with multiple consequences, the case of which proves to be most prevalent in health security decisions.

9.3.1 *Assessing Expected Value with Single Consequences and Continuous Distributions*

We consider two situations that require the calculation of expected value. The first situation occurs when decision alternatives for health security must be compared and there exists uncertainty about their performances. The second situation occurs when health threats must be assessed and there exists uncertainty about their impacts. In both of these cases, the uncertainties shall be assumed to be represented by continuous distributions.

Expected Value of Decision Alternatives Assume that the health security team wishes to evaluate the performance of a decision alternative (A) and is considering a single decision objective and associated relevant consequence. The attainment of this objective on the relevant consequence is measured by an attribute (measured by variable x) and the marginal value is measured by a value function v(.) over this attribute. There exists uncertainty about the performance of this decision alternative; this uncertainty is represented by a probability density function $f_A(x)$ over the attribute (measured by x). The expected value (EV) of alternative A is calculated by:

$$EV(A) = \int f_A(x) v\left[x(A)\right] dx \tag{9.6}$$

If we turn our attention toward the continuous distribution, we see that the integral in the equation above replaces the summation in Eq. 9.3, and the continuous probability density function $f_A(x)$ replaces the discrete distribution (with a finite number of scenarios and the associated probabilities) in the same equation.

The evaluation of expected value in Eq. 9.4 is illustrated in Fig. 9.21. The integral calculates the area under the probability density function $f_A(x)$, with the function representing the possible performance levels of alternative A. These performance levels are valued by the value function v(.) associated with attribute x (see Keeney (2014) for details and a more extensive coverage of this topic). Notice that, for the reasons we have discussed previously in this chapter, rather than using utility, we formulate this assessment assuming the measurement of *value*.

Let us illustrate the assessment of expected value by considering the vaccination campaign case, which has been introduced in previous chapters and consider the attribute *minimize vaccine hesitancy* ($x_{1.3}$). Recall that in the previous chapter, five decision alternatives had been evaluated on this attribute, based on their most likely performance. A linear value function had been defined over this attribute, whereby a level of resistance of 40% had been established as 0, and a level of resistance of

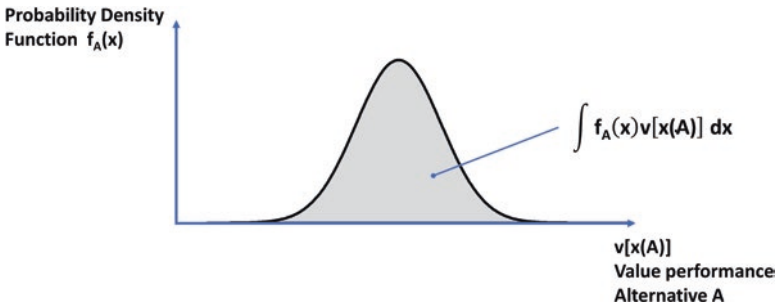

Fig. 9.21 Calculating the expected value of an alternative A, whose performance is evaluated by attribute x and valued by a value function v(.), and the dispersion of performance is represented by a probability density function $f_A(.)$

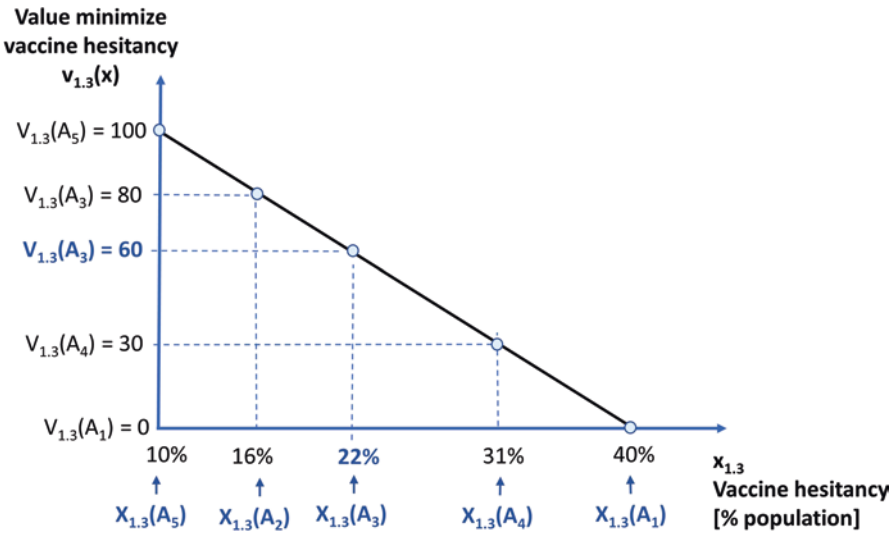

Fig. 9.22 Value function for the attribute vaccine hesitancy [% population] in the vaccination campaign case and most likely estimates of performance for the five decision alternatives

10% had been established as 100, as detailed in Fig. 9.22. In this value assessment, we shall consider the alternative A_3 (*hybrid centralized campaign*). The performance of this alternative had been valued as $v_{1.3}(A_3) = 60$, by considering the most likely level of resistance for this campaign ($x_{1.3}(A_3) = 22\%$ of the population exhibiting vaccine hesitancy). This *deterministic* assessment is highlighted in the same figure.

A probability density function $f_{A3}(.)$ had been defined to characterize the uncertainty about the performance of alternative A_3 (i.e. the % of the population exhibiting vaccine hesitancy if this vaccination campaign were to be implemented) over this attribute $x_{1.3}$, as shown in Fig. 9.23a (this figure should be read starting from the

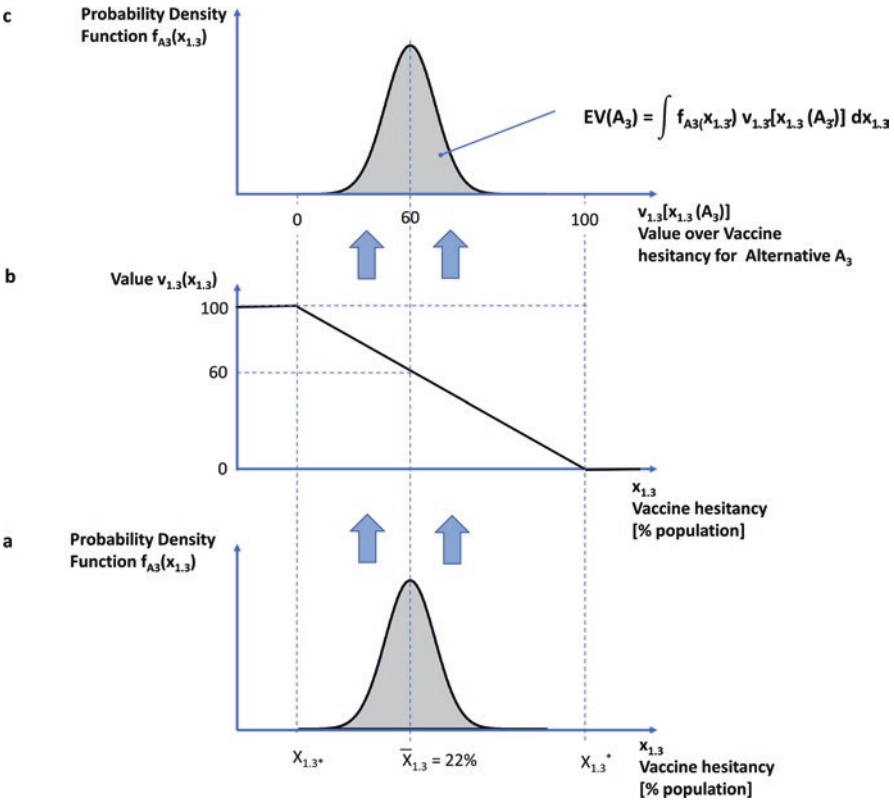

Fig. 9.23 Calculating the expected value of alternative A_3 in the vaccination case (this figure should be read starting from the lowermost element): (**a**) Probability density function $f_{A3}(.)$ of the performance on the attribute vaccine hesitancy [% population] (measured by variable $x_{1.3}$), (**b**) Normalization and valuation of performances by the value function $v_{1.3}(.)$, (**c**) Probability density function with normalized and valued performances (the area under the curve indicates the expected value of alternative A_3)

lowermost element). This distribution of performances is valued and normalized by the value function $v_{1.3}(.)$, with $v(X_{1.3*} = 40\%) = 0$ and $v(X_{1.3*} = 10\%) = 100$, as presented in Fig. 9.23b.

The area under $f_{A3}(.)$ in Fig. 9.23c, with its normalized and valued performances on the x-axis, provides the expected value $EV(A_3)$ of this decision alternative on the attribute $x_{1.3}$. If the probability density function were a Normal distribution, with a mean of 22% (proportion of the population), the expected value of this alternative is given by the normalized mean proportion, i.e. $EV(A_3) = 60$ value points. We now introduce a similar formulation to assess the impact of health threats, the scenarios of which are represented by continuous distributions.

Expected Dis-Value of Health Threats Let us assume that the health security team wishes to evaluate a single impact from a health threat T, whose consequence is measured by an attribute (measured by variable x), and the marginal dis-value is

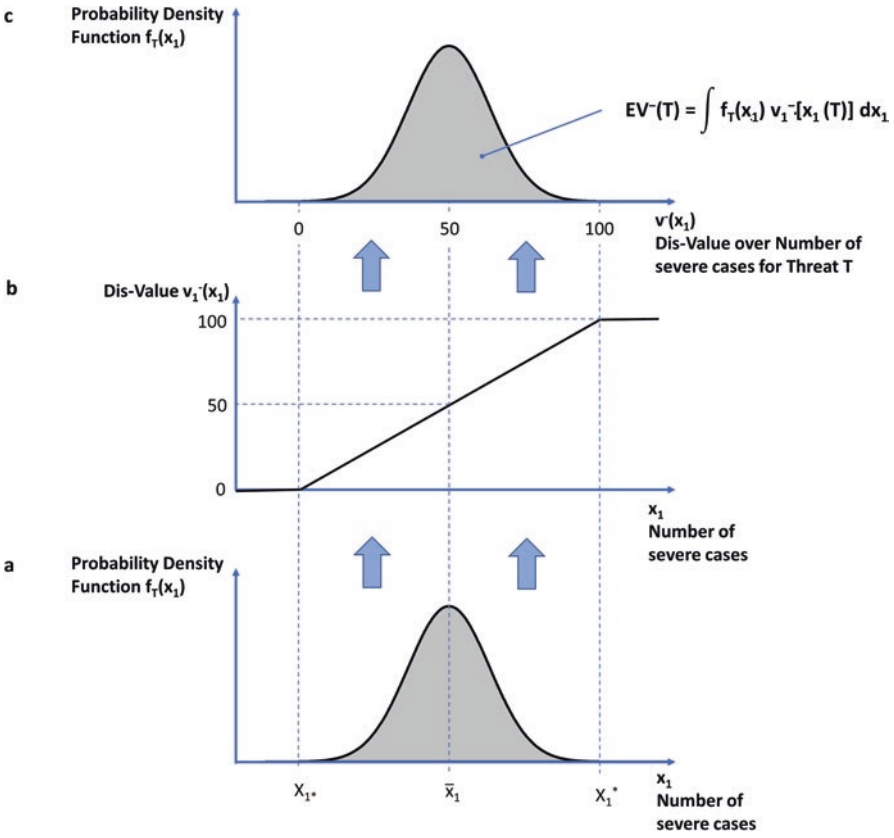

Fig. 9.24 Calculating the expected dis-value of Threat T on the attribute number of severe cases (this figure should be read starting from the lowermost element): (**a**) Probability density function $f_T(.)$ of the impact on the attribute number of severe cases (measured by variable x_1), (**b**) Normalization and valuation of impacts by the dis-value function $v^-_1(.)$, (**c**) Probability density function with normalized and valued impacts (the area under the curve indicates the expected dis-value of this threat on attribute x_1)

measured by a dis-value function $v^-(x)$ over this attribute (see Montibeller et al. (2020b) for details). There exists uncertainty about the impact of this health threat; this uncertainty is represented by a probability density function $f_T(x)$ over the attribute x. The expected dis-value (EV^-) of this threat can be calculated by:

$$EV^-(T) = \int f_T(x)\, v^-[x(T)]\, dx \tag{9.7}$$

Let us posit that a health threat that may cause a large number of severe cases if an outbreak were to occur, which is measured by the attribute *number of severe cases* (measured by variable x_1). The probability density function of this impact: $f_T(x_1)$ over this attribute is shown in Fig. 9.24a (this figure should be read starting from its

lowermost element). A linear dis-value function had been defined for this attribute, with the lowest possible level (X_{1*} = 10,000) receiving a score of 0 and the highest possible level (X_{1*} = 200,000) receiving a score of 100, as presented in Fig. 9.24b.

The area under $f_T(x_1)$ in Fig. 9.24c, with its normalized and valued attribute on the x-axis, provides the expected dis-value of this health threat ($EV^-(T)$) for the possible number of severe cases that the threat may cause. Were the probability density function to be a Normal distribution, with a mean of 90,000 severe cases, the expected dis-value of this health threat would be given by the normalized mean value, i.e. $EV^-(T) = 50$ dis-value points.

Let us posit that that a second impact must now be considered when assessing this health threat: the economic damage that the threat may cause to the economy. This impact is assessed by the attribute x_2: *economic damage* [in $million] measured by variable x_2. The probability density function for this impact, $f_T(x_2)$, is shown in Fig. 9.25a (this figure should be read starting from the lowermost element). As shown in Fig. 9.25b, the economic damage is normalized and valued by a dis-value function, with the minimum damage level (X_{2*} = $20 million) receiving a score of 0, the maximum damage level (X_{2*} = $800 million) receiving a score of 100, and $400 million of damage receiving a score of 70 dis-value points. This is a non-linear dis-value function, which allocates more marginal dis-value to the initial levels of economic damage as they may affect disadvantaged sectors of the population, the positions of which are proximate to the minimum impact level (X_{2*}).

The probability density function $f_T(x_2)$, with the dis-value for economic damage on the x-axis, is shown in Fig. 9.25c. The area under this curve provides the expected dis-value of this threat for the economic damage that the threat may cause. If the probability density function were a Normal distribution with a mean of $400 million, the expected dis-value is given by the normalized mean dis-value, i.e. $EV^-(T) = 70$.

The example above illustrates the assessment of expected dis-value for two independent impacts under uncertainty. However, in practice we wish to consider the multiple impacts simultaneously, in terms of the expected overall dis-value that the threat may cause. Analogously, when considering the performances of a health security decision alternative on multiple objectives, we wish to assess the overall expected value for each alternative by simultaneously considering the performance on the multiple attributes. This type of assessment, which is executed over multiple dimensions pertaining to the impacts of health threats or to the performances of health security actions, is discussed next.

9.3.2 Assessing Expected Value with Multiple Consequences and Continuous Distributions

The formulae for assessing the expected value of decision alternatives with uncertain performances, or, for assessing the expected dis-value of health threats with uncertain impacts, are similar to the formulae that consider a single attribute in the section above. However, the key difference between these formulae stems from the

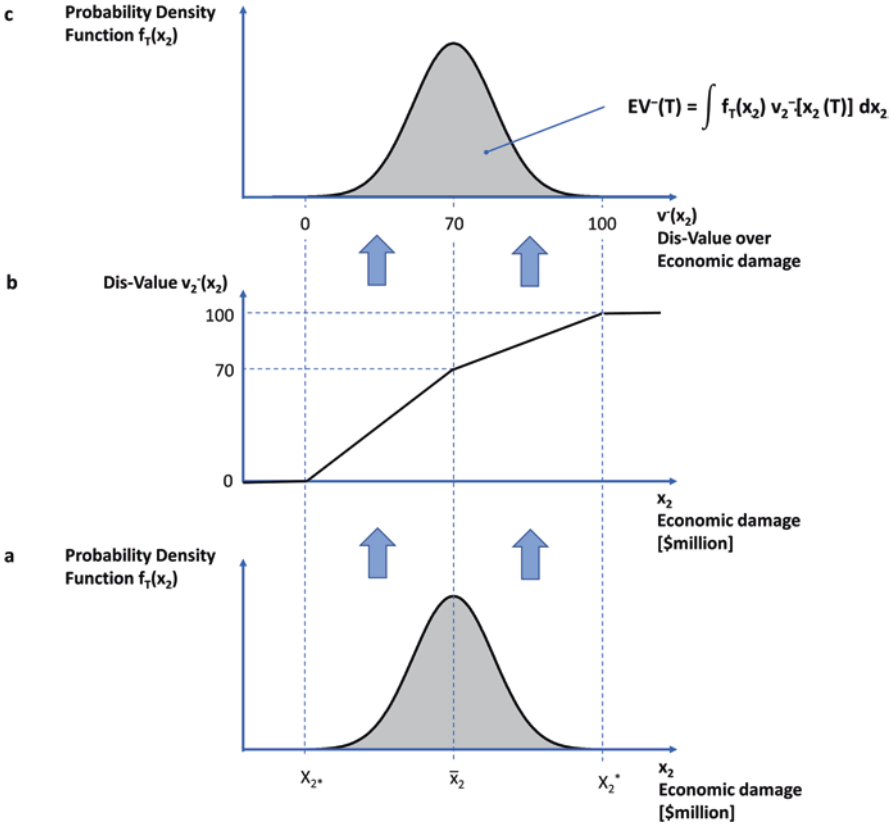

Fig. 9.25 Calculating the expected dis-value of Threat T on the attribute economic damage (this figure should be read starting from the lowermost element): (**a**) Probability density function $f_T(.)$ of this impact on the attribute economic damage (measured by variable x_2), (**b**) Normalization and valuation of impacts by the dis-value function $v^-_2(.)$, (**c**) Probability density function with normalized and valued impacts (the area under the curve indicates the expected dis-value of this threat on attribute x_2)

use of vectors of attributes, instead of a single attribute, in order to assess the performances of decision alternatives or the impacts of health threats. Let us formalize both types of evaluation below.

Expected Value of Decision Alternatives Let us assume that the health security team wishes to evaluate an alternative A by using a multi-attribute value function. There exist M decision objectives, which are linked to relevant consequences. The performances of this alternative are measured by a set of M attributes $\mathbf{x} = \{x_1, x_2, \ldots, x_M\}$ measuring the relevant consequences, which is associated with a set of respective value functions $\mathbf{v} = \{v_1(.), v_2(.), \ldots, v_M(.)\}$. There exists uncertainty about the performances of this alternative on the attributes, and these performances are represented by the vector $\mathbf{x}(A) = \{x_1(A), x_2(A), \ldots, x_M(A)\}$. This uncertainty pertaining

to the performances is represented by a probability density function $f_A(x)$ over this set of attributes **x**. The expected value (EV) of alternative A can be calculated by:

$$EV(A) = \int f_A(\mathbf{x})\mathbf{v}\left[\mathbf{x}(A)\right]dx \tag{9.8}$$

In contrast to Eq. 9.3, we now have a vector of attributes (**x**) (instead of a single attribute), as well as a vector of associated value functions (**v**) (instead of single value function). Additionally, the probability density function $f_A(\mathbf{x})$ is established over a set of attributes (**x**), instead of being established over a single attribute. A similar formulation can be employed to assess the dis-value of health threats.

Expected Dis-Value of Health Threats Let us postulate that the health security team wishes to evaluate the multiple impacts from a threat T. The possible consequences of this threat are measured by a set of attributes $\mathbf{x} = \{x_1, x_2, \ldots, x_M\}$ measuring the relevant consequences, which is associated with a set of respective dis-value functions $\mathbf{v}^- = \{v^-_1(.), v^-_2(.), \ldots, v^-_M(.)\}$. There exists uncertainty about the impacts of this health threat, and these impacts are represented by the vector $\mathbf{x}(A) = \{x_1(A), x_2(A), \ldots, x_M(A)\}$. This uncertainty pertaining to impacts is represented by the probability density function $f_T(\mathbf{x})$ over the set of attributes. The expected dis-value (EV^-)) of this threat can be calculated by:

$$EV^-(T) = \int f_T(\mathbf{x})\mathbf{v}^-\left[\mathbf{x}(T)\right]dx \tag{9.9}$$

In a similar manner to the conditions above, and in direct contrast to Eq. 9.5, we now have a vector of attributes (**x**), instead of a single attribute, as well as a vector of associated dis-value functions ($\mathbf{v}^-$), instead of single dis-value function. Moreover, the probability density function $f_T(\mathbf{x})$ is established over a set of attributes (**x**), instead of being established over a single attribute.

The overall assessment of expected dis-value of a threat, formulated in Eq. 9.9, would require summating the different probability density functions to find $f_T(\mathbf{x})$. For instance, this would entail computing the weighted sum of $f_T(x_1)$ from Fig. 9.24c and $f_T(x_2)$ from Fig. 9.25c in the example above (the process of which can only be conducted if independence conditions were to hold for an aggregation, as detailed in the previous chapter). The same holds true for the assessment of decision alternatives with multiple attributes described in Eq. 9.8, in that the assessment would require summating the different probability density functions to obtain $f_A(\mathbf{x})$. However, this summation of distributions is analytically difficult and often highly complex, as the process requires calculating their convolution (see Vose (2008) for details). Instead, in practice, Monte-Carlo simulation is typically employed to calculate the overall distribution and the expected value of decision alternatives, which shall be detailed subsequently.

9.3.3 Simulating the Performance of Decision Alternatives

The Monte-Carlo simulation is extensively employed in both Risk Analysis and Decision Analysis. In the former field, this simulation is used both to identify the distribution of the overall impacts and to establish the probabilities that these impacts shall reach a given level (see also the fifth and sixth chapters). There exists an extensive literature on this type of analysis, Vose (2008) provides a good coverage, while Morgan and Henrion (1992) discuss in great depth the main concepts of this type of simulation.

On the other hand, in Decision Analysis, Monte-Carlo simulation can be employed to calculate the expected value of decision alternatives and to understand their value spread. The rationale that underpins Monte-Carlo simulation is the same as that which underpins the hypothetical situation shown in Fig. 9.7, in that a decision is repetitively made over a large number of iterations and the value of the chosen alternative is recorded for each iteration. An approximation of the expected value is calculated to be the mean of the simulated values, which are obtained from each iteration. The histogram of values from the iteration provides an approximation of the distribution of value.

A Monte-Carlo simulation is composed of three main steps. First, the distribution functions of inputs should be defined in order to characterize the uncertainties inherent to the decision. Second, a pre-defined number of iterations is to be performed. With each iteration, the implementation of alternatives under uncertainty is simulated, the possible performances of every alternative are assessed, and the valued performances of the alternatives are recorded. Third, by estimating the simulated overall value of the alternative over the number of iterations, we are able to calculate the expected value of each decision alternative.

We illustrate this type of analysis using the vaccination campaign case. The simulation considers continuous distributions to represent the uncertainty pertaining to the performances of each vaccination strategy under consideration, as represented in the influence diagram in Fig. 9.26. The three steps of the simulation for this evaluation are described in the paragraphs that follow.

Defining Distribution Functions The first step in a Monte-Carlo simulation requires that we define the distributions that characterize the uncertainties influencing the performances of decision alternatives and the impacts of health security actions.

Consider decision alternatives A_1 (a *fully centralized vaccination campaign*) and A_2 (a *fully decentralized vaccination campaign*), which have been detailed in the seventh chapter and the value model for the assessment of these decision alternatives, detailed in the previous chapter. There exists uncertainty about actual performances of each possible campaign. To represent the uncertainty about the performance of each and every alternative, a distribution has been identified for representing the possible performance for each attribute of this model.

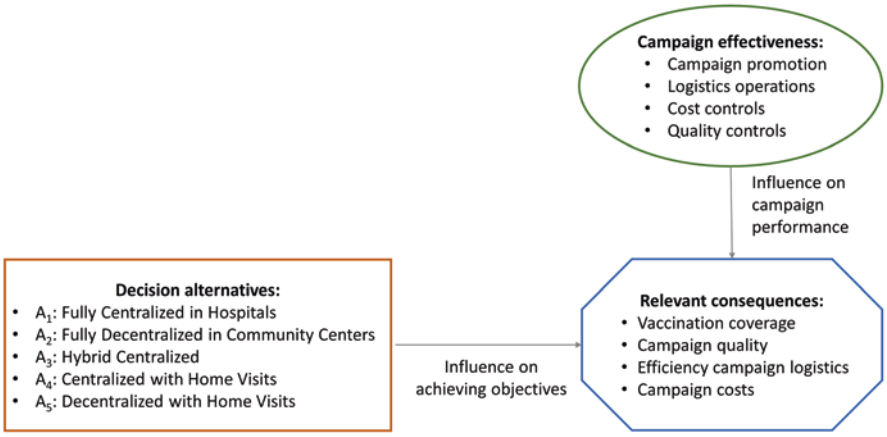

Fig. 9.26 Influence diagram for the vaccination campaign case, with the uncertainty about the effectiveness of each campaign affecting the performances of decision alternatives on relevant consequences

For example, for the attribute *proportion of the population vaccinated* [%] (measured by variable $x_{1.1}$) a Triangular distribution has been defined for modeling the performances of decision alternatives A_1 and A_2 as probability density functions, $f_{A1}(.)$ and $f_{A2}(.)$, respectively. These functions are shown in Fig. 9.27a, wherein each distribution represents the minimum possible proportion, the most likely proportion, and the maximum possible proportion for each vaccination campaign strategy. Triangular distributions are typically defined by experts, who provide estimates such as these ones indicated in the figure (see Vose (2008) for a detailed discussion about the choice and characteristics of distributions for a Monte-Carlo simulation).

Specifically, for the probability density function $f_{A1}(.)$ for alternative A_1, in Fig. 9.27a, the minimum proportion of the population that is vaccinated has been estimated to be 55%, the most likely to be 60%, and the maximum to be 65%. The area under the triangle $f_{A1}(x_{1.1})$ denotes the probability that a given performance shall occur. Hence, for this distribution, levels that are located just below or above 60% are deemed to be more likely than those levels which are close to the 55% or 65% thresholds. The range $\Delta v_{1.1}(A_1)$ in Fig. 9.27a represents the possible value scores that this alternative could reach, depending on its simulated performance. Notice that the value on this objective ($v_{1.1}$) would be zero if the simulated performance were to result in fewer than 60% of the population being vaccinated.[3]

[3] This assessment assumes that the screening criterion for including alternatives in the evaluation is based on the most likely performance (60%) and not on the minimal possible performance (55%). Were the minimal possible performance employed as screening criterion, alternative A_1 would have been eliminated a priori from the evaluation (the role of screening criteria is discussed in the previous chapter).

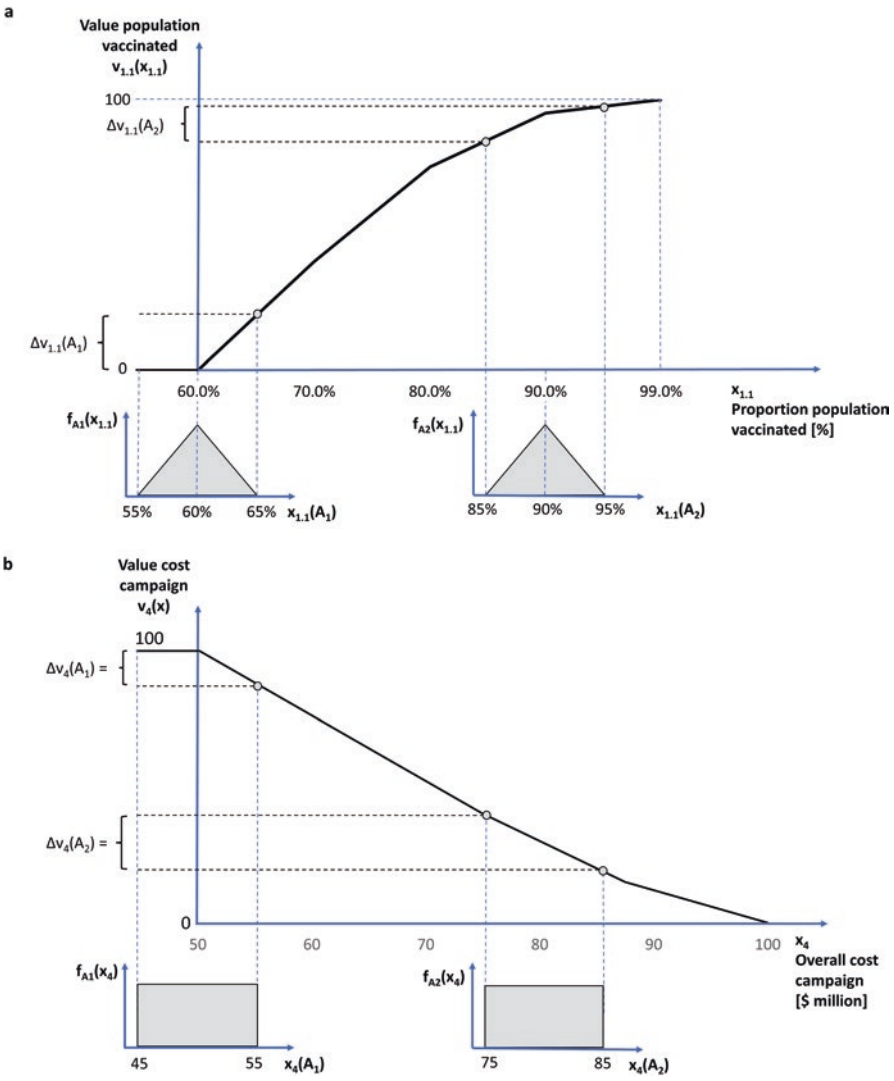

Fig. 9.27 Probability density functions for the performance of two alternatives A_1 and A_2 in the vaccination campaign case: (**a**) Functions for the attribute proportion of population vaccinated (measured by variable $x_{1.1}$), (**b**) Functions for the attribute cost of the campaign (measured by variable x_4)

In a similar way (as is also demonstrated in Fig. 9.27a), a probability density function $f_{A2}(x_{1.1})$, has been defined for alternative A_2, thereby allocating a minimum possible proportion of 85%, a most likely proportion of 90%, and a maximum possible proportion of 95% for this alternative. The range $\Delta v_{1.1}(A_2)$ represents the possible value scores that this alternative could reach, which are contingent on the simulated performance of said alternative.

Let us consider another attribute: the *overall cost of the campaign* (x_4). In this case, a Uniform distribution has been defined to represent the uncertainty about the actual costs of each decision alternative. The probability density functions, $f_{A1}(x_4)$ and $f_{A2}(x_4)$, for these two decision alternatives are shown in Fig. 9.27b. Uniform distributions assume the same probability for each level that lies within the performance range, and are typically used when additional information about the probability of occurrence does not exist. These distributions are typically defined by experts, who provide range estimates.

The overall costs for alternative A_1 could range from \$45 million to \$55 million, and is accompanied by the probability density function $f_{A1}(x_4)$, the situation of which is presented in Fig. 9.27b. The range $\Delta v_4(A_1)$ represents the possible value scores that this alternative could reach, depending on the simulated cost of said alternative. Notice that performances located below the \$50 million threshold would not bring about additional value to the alternative, and thus, would receive a score of 100 in the value model. The mean of this Uniform distribution is \$50 million. Similarly, the overall costs for alternative A_2 could range from \$75 million to \$85 million, and is represented by the probability density function $f_{A2}(x_4)$, with a mean of \$80 million (the situation of which is also presented in Fig. 9.27b). The range $\Delta v_4(A_2)$ represents the possible value scores that this alternative could reach, depending on the simulated cost of said alternative. The performances of these two alternatives over the other attributes of the value model have all been modeled using uniform distributions in the simulation.

Performing Iterations The second step in a Monte-Carlo simulation entails performing a set of iterations, so as to replicate the scenario wherein a decision is being made in a repetitive manner. The simulated performances of the alternatives are assessed and valued, followed by the recording of the overall value of every alternative for each iteration. This process is repeated over D iterations (d = 1, 2, …, D).

Let us posit a repetitive evaluation process, wherein there exists D iterations, and within each d-th iteration, there would occur the evaluation of alternative A_1. Let us simulate this decision alternative by detailing the process only for the first two iterations.

Consider the attribute: *proportion of population vaccinated* ($x_{1.1}$). In the first iteration (d = 1), a simulated performance $x^1_{1.1}(A_1)$ is selected at random as a function of the probability density function $f_{A1}(x_{1.1})$, as shown in Fig. 9.28a. This simulated performance is more likely to occur in areas with higher density within the triangle (the area of which is situated around the most likely performance of 60% rather than being proximate to either the upper or lower bounds). In the example, the simulated performance has been randomly selected to be: $x^1_{1.1}(A_1) = 63\%$. This performance level is then assessed by the value function, whose value score is: $v^1_{1.1}(A_1) = 12$ value points. This simulated value score is subsequently recorded.

Let us apply a similar process when approaching the attribute *overall cost of the campaign* (x_4), in the first iteration (d = 1). A simulated cost $x^1_4(A_1)$ is selected at random as a function of the probability density function $f_{A1}(x_{1.1})$, as shown in Fig. 9.28b. In this case, there exists the same probability of a given overall cost that

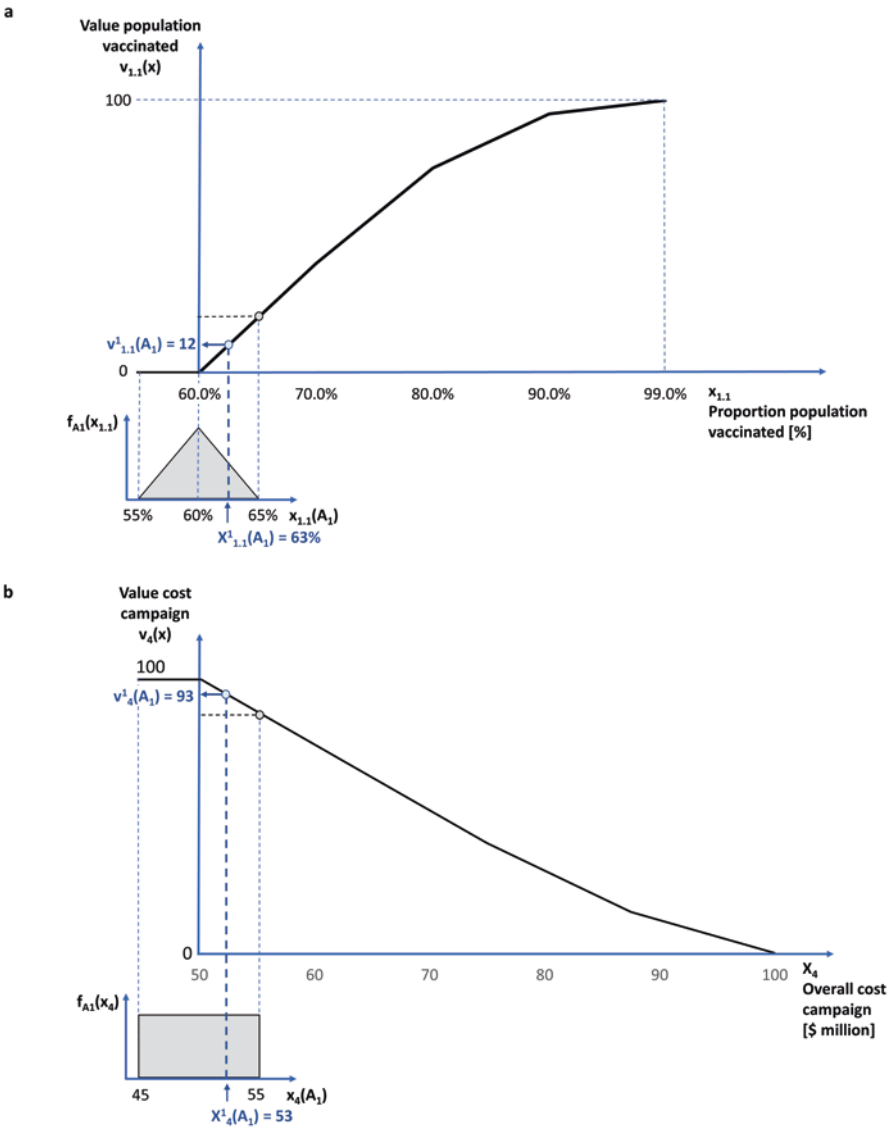

Fig. 9.28 Two iterations for the simulation of alternative A_1 in the vaccination campaign case: (**a**) First Iteration for the attribute proportion of population vaccinated (measured by $x_{1.1}$), (**b**) First iteration for the attribute overall cost of the campaign (measured by x_4), (**c**) Second Iteration for the attribute proportion of population vaccinated (measured by $x_{1.1}$), (**d**) Second iteration for the attribute overall cost of the campaign (measured by x_4)

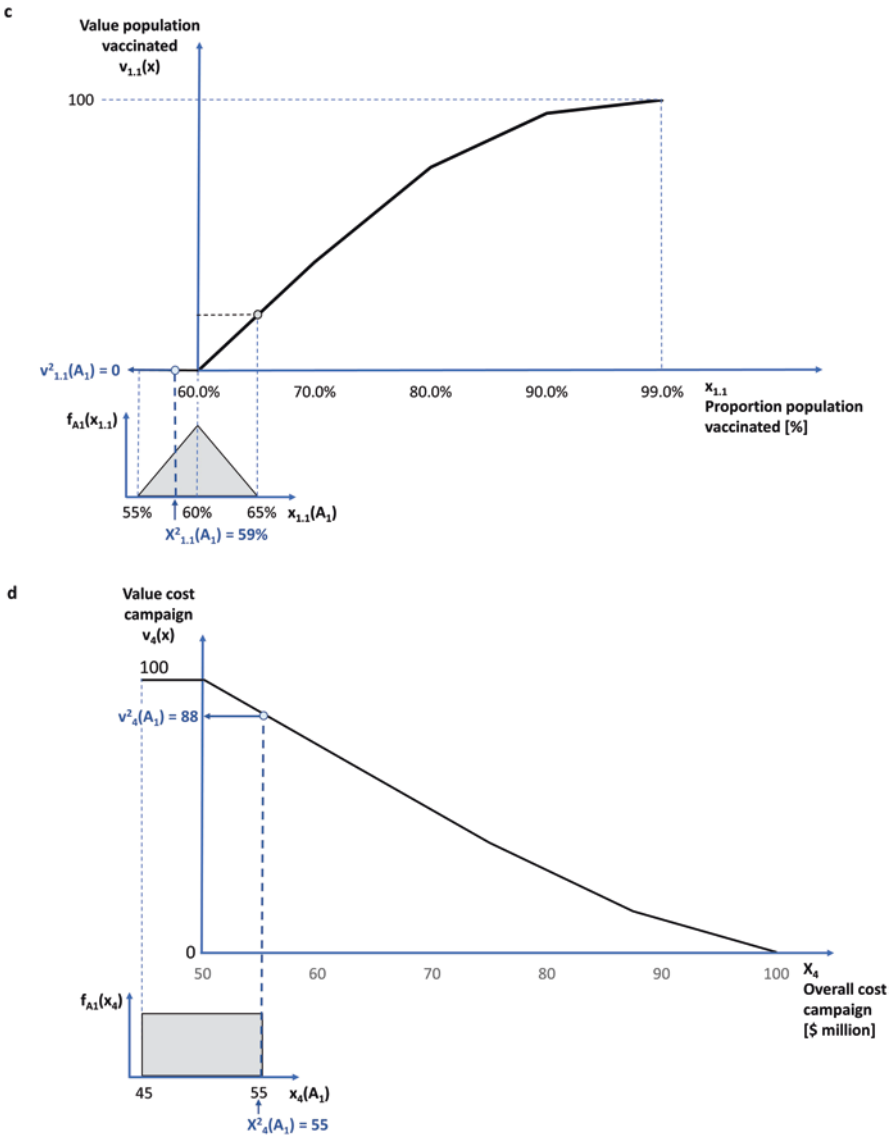

Fig. 9.28 (continued)

is located at any level within the \$45 million to \$55 million range. In the example, the simulated overall cost has been randomly selected to be: $x^1_4(A_1)$ = \$53 million. This performance level is then assessed by the value function, whose value score is: $v^1_4(A_1) = 93$ value points. This simulated value score is subsequently recorded.

A similar protocol is used to simulate and value this decision alternative with regards to the other attributes pertaining to the model of this first iteration. These

simulated value scores $v^1_i(A_1)$, are recorded for the first iteration, for each and every i-th attribute of the model.

We now shift our focus to the second iteration (d = 2) for Alternative A_1. The simulated performance on attribute $x_{1.1}$ is $x^2_{1.1}(A_1) = 59\%$, which has been selected at random as a function of $f_{A1}(x_{1.1})$ as shown in Fig. 9.28c. The value score of this simulated performance is: $v^2_{1.1}(A_1) = 0$ value points. The simulated cost on attribute x_4, which has been selected at random as a function of $f_{A1}(x_4)$, is $x^2_4(A_1) = \$55$ million, as shown in Fig. 9.28d. The value score of this simulated cost is $v^2_4(A_1) = 88$ value points.

A similar protocol is used to simulate and value this decision alternative with regards to the other attributes pertaining to the model of this second iteration. For this second iteration, these simulated value scores $v^2_i(A_1)$ are recorded, for each and every i-th attribute of the model. This same process is executed for all subsequent iterations up to (and including) iteration D.

We now repeat this process for alternative A_2 over D iterations. For the first iteration (d = 1), assume the simulated performances for attribute $x_{1.1}$ to be $x^1_{1.1}(A_2) = 87\%$ with $v^2_{1.1}(A_2) = 89$ value points, as shown in Fig. 9.29a, and for attribute x_4 to be $x^1_4(A_2) = \$78$ million with $v^1_4(A_2) = 34$ value points, as shown in Fig. 9.29b. A similar protocol is used to simulate and value this decision alternative with regards to the other attributes pertaining to the model of this first iteration. All of these simulated value scores for this first iteration $v^1_i(A_2)$ are recorded for each and every i-th attribute of the model.

For the second iteration, assume the simulated performances for attribute $x_{1.1}$ to be $x^2_{1.1}(A_2) = 94\%$ with $v^2_{1.1}(A_2) = 97$ value points, as shown in Fig. 9.29c, and for attribute x_4 to be $x^2_4(A_2) = \$81$ million with $v^2_4(A_2) = 28$ value points, as shown in Fig. 9.29d. A similar protocol is used to simulate and value this decision alternative with regards to the other attributes pertaining to the model of this second iteration. For this second iteration, these simulated value scores $v^2_i(A_2)$ are recorded, for each and every i-th attribute of the model. This same process is used for all subsequent iterations up to (and including) iteration D.

Calculating the Expected Value of Decision Alternatives The expected value of each decision alternative can be calculated once D iterations have been performed and the simulated overall value of the decision alternative has been recorded for every iteration. The expected value of an alternative is given by the mean of the simulated overall value from all iterations.

Specifically, for each decision alternative A, the simulated overall value of each d-th iteration $V^d(A)$ can be calculated by a multi-attribute value model using the simulated value score $v^d_i(A)$ accompanying each i-th attribute. This process is performed in the exact same manner as that of the most likely values in the previous chapter, wherein Eq. 8.1 had been used to calculate the overall value of each iteration.

The expected value of each alternative A is then calculated by the mean of the simulated overall value of each iteration $V^d(A)$:

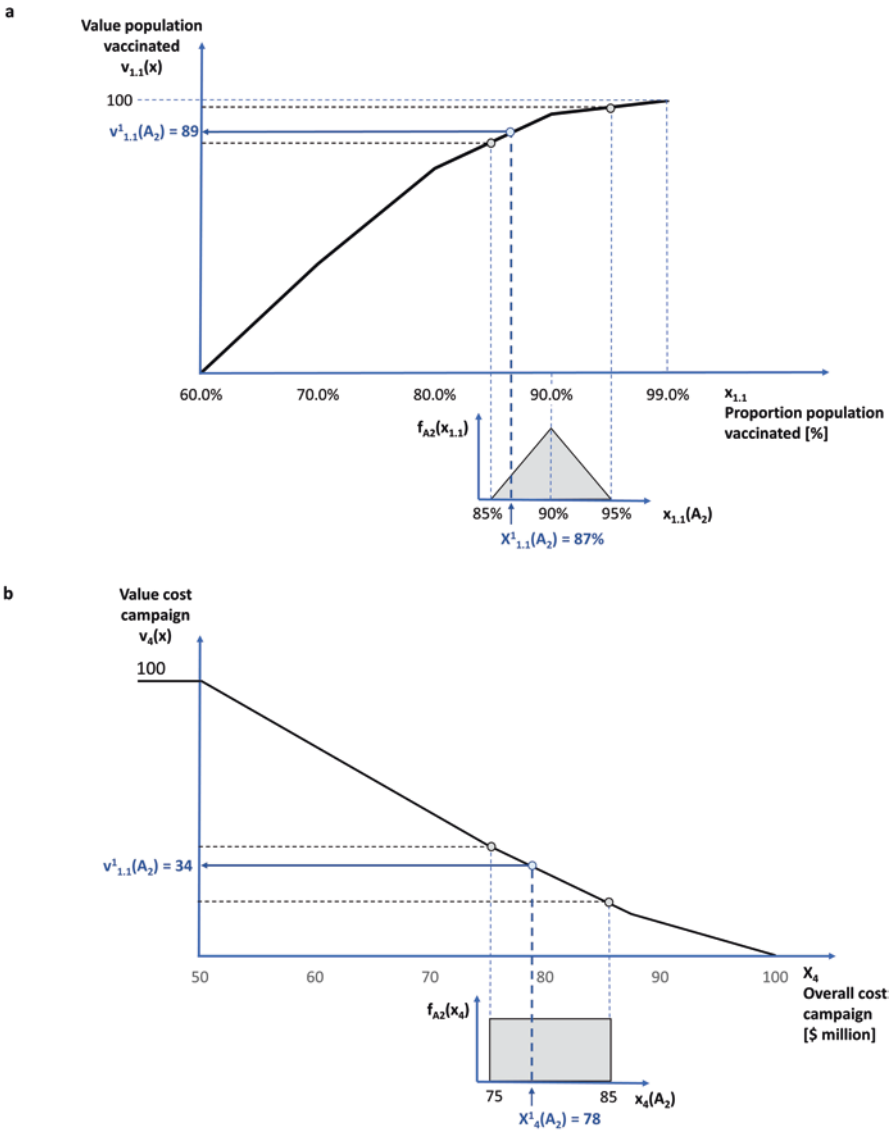

Fig. 9.29 Two iterations for the simulation of alternative A_2 in the vaccination campaign case: (**a**) First Iteration for the attribute proportion of population vaccinated (measured by $x_{1.1}$), (**b**) First iteration for the attribute overall cost of the campaign (measured by x_4), (**c**) Second Iteration for the attribute proportion of population vaccinated (measured by $x_{1.1}$), (**d**) Second iteration for the attribute overall cost of the campaign (measured by x_4)

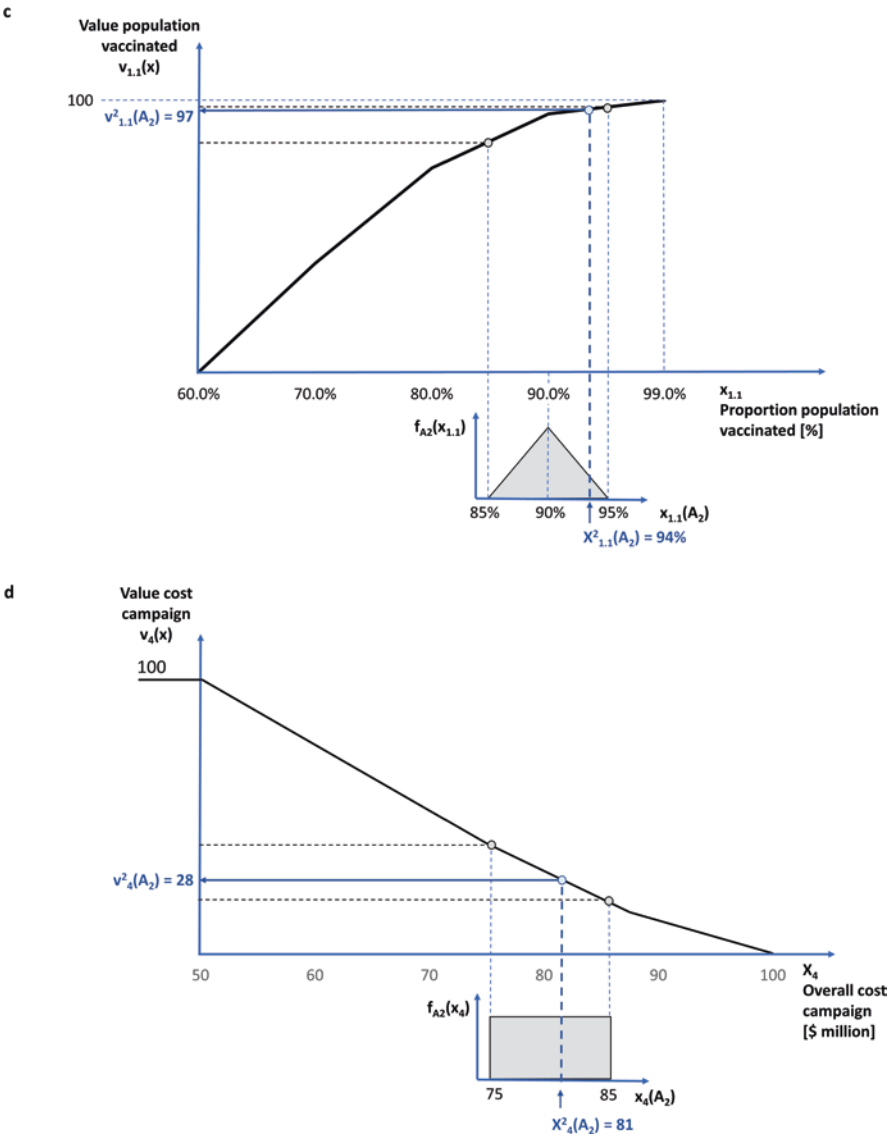

Fig. 9.29 (continued)

$$EV(A) = \frac{1}{D}\sum_{d=1}^{D} V^d(A) \tag{9.10}$$

For the vaccination campaign case, this simulation for alternatives A_1 and A_2 is illustrated in Fig. 9.30. The right-hand side presents the simulated value scores up

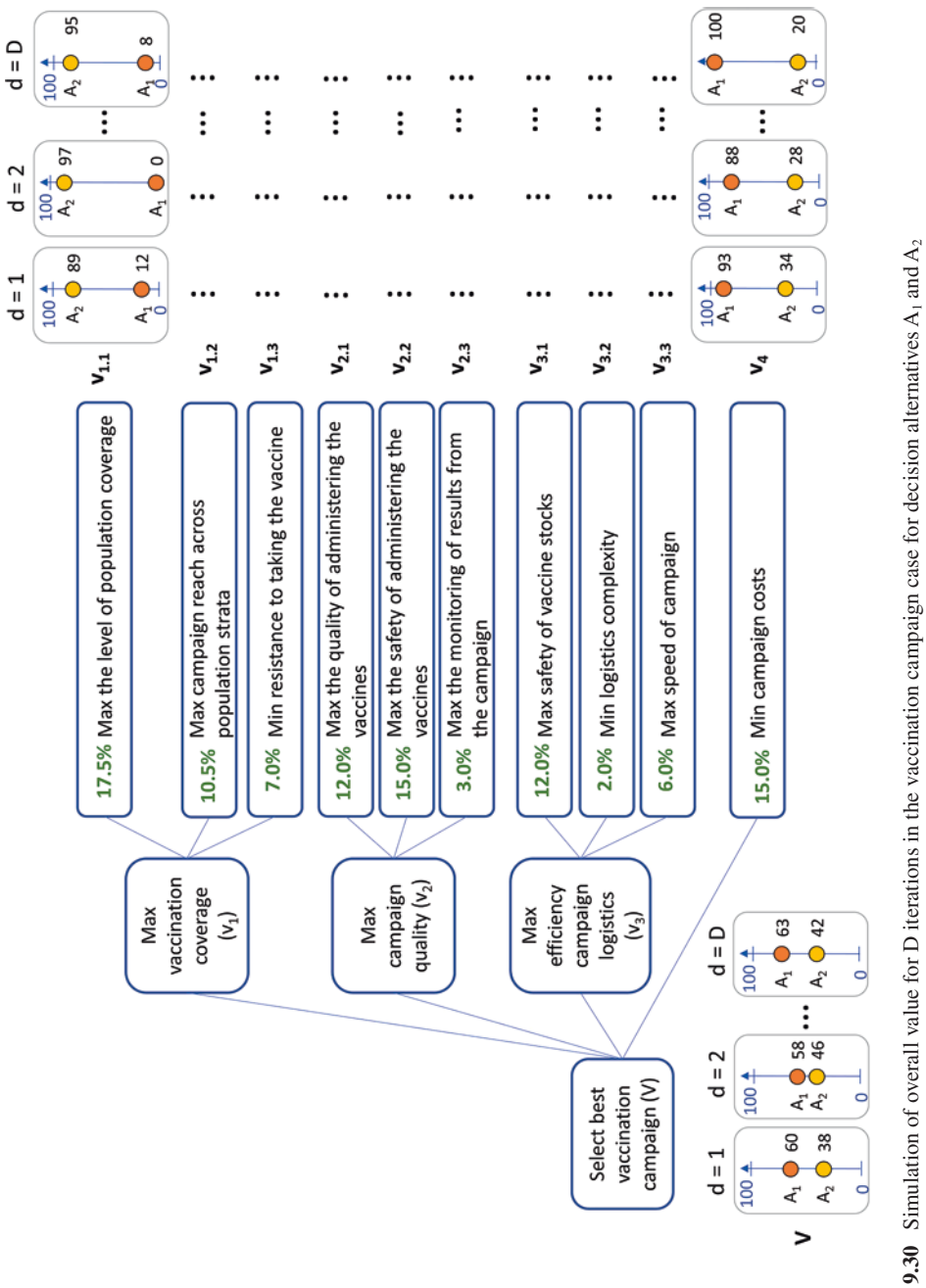

Fig. 9.30 Simulation of overall value for D iterations in the vaccination campaign case for decision alternatives A_1 and A_2

to D iterations on attributes measured by variables $x_{1.1}$ and x_4. For the *first* iteration, the diagram adopts the valuations for alternative A_1 presented in Fig. 9.28a ($v_{1.1}$) and Fig. 9.28b (v_4), and the valuations for alternative A_2 from Fig. 9.29a ($v_{1.1}$) and Fig. 9.29b. (v_4) Similarly, for the *second* iteration, the diagram adopts the valuations for alternative A_1 presented in Fig. 9.28c ($v_{1.1}$) and Fig. 9.28d (v_4), and the valuations for alternative A_2 from Fig. 9.29c ($v_{1.1}$) and Fig. 9.29d (v_4). The left-hand side of Fig. 9.30 presents the overall simulated value for the two alternatives, $V(A_1)$ and $V(A_2)$, which had been calculated by employing Eq. 8.1, for iterations d = 1, 2, …, D.

Executing this simulation for 1,000 iterations brings about an expected value for the first alternative of $EV(A_1) = 59.8$ value points, and for the second alternative of $EV(A_2) = 45.0$ value points, employing Eq. 9.10. When the simulation is extended in a similar manner in order to now encompass the other three decision alternatives (vaccination strategies), the expected values are: $EV(A_3) = 62.0$, $EV(A_4) = 55.9$, and $EV(A_5) = 37.6$.

These simulated expected overall values are very similar to the results that had been presented in the previous chapter, wherein most likely performance levels had been employed for each decision alternative. However, in this simulated analysis, there occurs dispersion of performance and therefore value, as is demonstrated by the histograms of the simulated overall value results for each decision alternative presented in Fig. 9.31. The broader the ranges, the more uncertain the actual overall value of a campaign strategy proves. For example, alternative A_3 demonstrates a broader spread than alternative A_1.

The overlapping areas in the histograms of each decision alternative (such as those that arise between alternatives A_1 and A_3) demonstrate that there have appeared iterations wherein the former alternative has produced a higher overall value than the latter alternative. A close inspection of the simulations results reveals that out of the 1,000 iterations, there have appeared 194 iterations wherein this has occurred. Consequently, these simulation results indicate that due to the uncertainty intrinsic to their performances, there exists a 19.4% chance that A_1 proves to be superior to A_3.

Calculating the Expected Dis-Value of Health Threats A similar procedure may be employed to estimate the expected dis-value of health threats, when there exist significant uncertainties about the impacts that these threats can cause. In such cases, the impacts of a health threat are modeled as distributions (in a similar manner to those decision alternatives in Fig. 9.27). The impacts are then simulated and valued over a D number of iterations (again in a manner similar to that which is detailed in Fig. 9.28 and in Fig. 9.29 for decision alternatives). The overall dis-value score of each threat is calculated for every iteration by employing a multi-attribute value model (such as the one that was developed for ranking emerging animal health threats, the process of which has been described in the previous chapter). For every health threat, the expected overall dis-value is given by the mean of the simulated overall dis-value for all iterations.

Specifically, for each health threat T, the simulated overall dis-value of each d-th iteration $V^{-d}(T)$ can be calculated by a multi-attribute value model using the

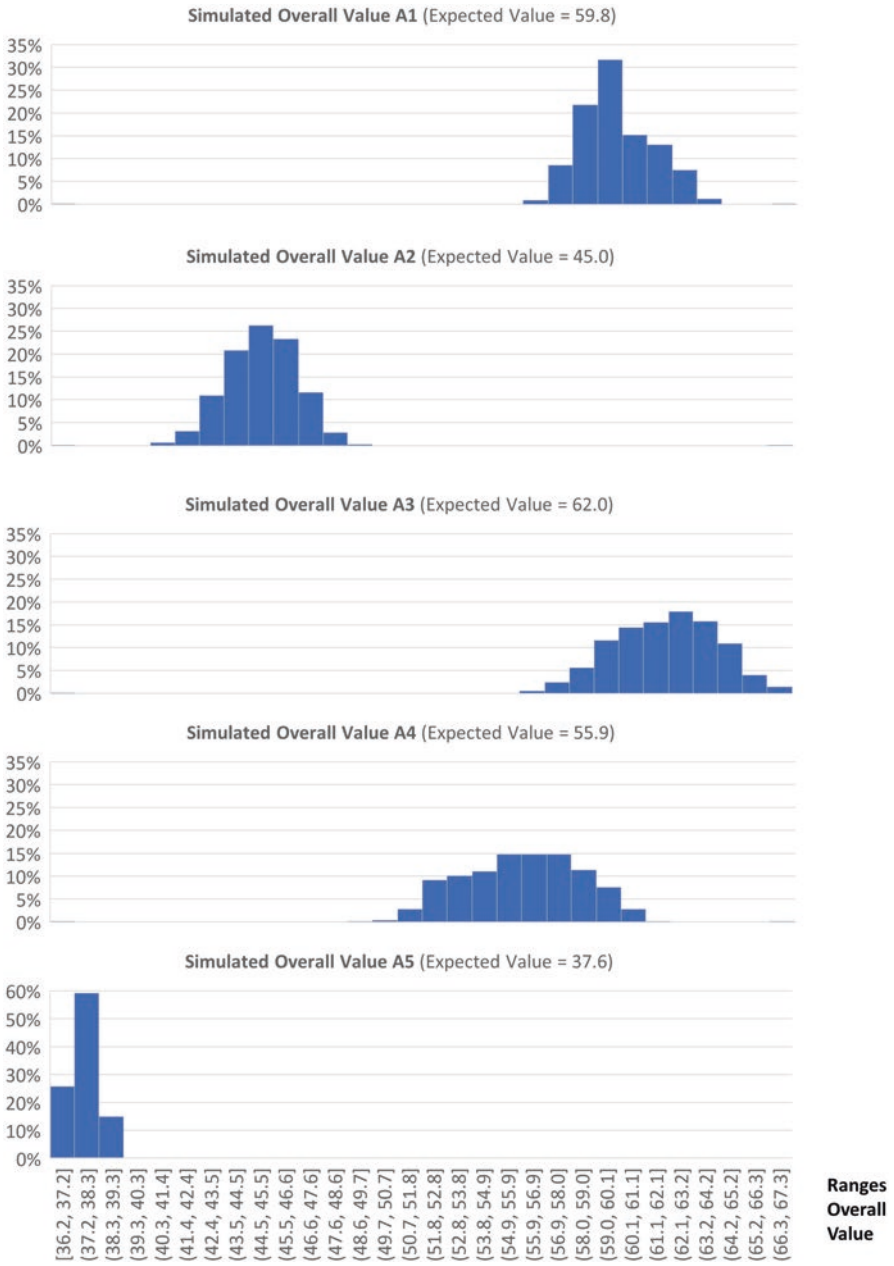

Fig. 9.31 Results from the simulation of the five decision alternatives considered in the vaccination campaign case (1000 iterations)

simulated dis-value score $v^{d}_{i}(T)$ accompanying each i-th attribute. The expected dis-value of each health threat T is then calculated using the mean of the simulated overall dis-value of each iteration $V^{-d}(T)$:

$$EV^{-}(T) = \frac{1}{D}\sum_{d=1}^{D} V^{-d}(T) \tag{9.11}$$

In this section we have presented a rather sophisticated analysis of expected value, involving continuous distributions and a Monte-Carlo simulation. In practice, this analysis requires some Risk Analysis expertise concerning both the development of simulation models and the analysis of the results produced by said models. While this expertise allows for an enrichment of the health decision analysis, the inclusion of these simulation models necessarily increases the complexity of the decision analysis. Consequently, unless there exists a team that either includes members that provide this decision modeling expertise, or, that is able to call upon an external decision analyst, it is recommended that simplified models such as those that have been presented in previous sections of this chapter be employed.

9.4 Conclusions: Evaluating Health Threats and Health Security Actions Under Uncertainty

Uncertainty forms a key complexity in any health security decision. Uncertainties arise when the evidence about impacts of health threats is either incomplete or lacking and also from the imprecisions in estimating the future performance of decision alternatives. If uncertainty were to be neglected in the evaluation of decision alternatives, there would occur the possibility that poor decisions or low-quality choices would be made. Disregarding the uncertainties when assessing the impacts of health threats may lead to misguided recommendations, avoidable risks, and sub-optimal allocation of resources.

In this chapter we have seen the ways in which we are able to incorporate uncertainty in the evaluation of decision alternatives and in the assessment of health threats. A conventional and uncomplicated way of describing uncertainties entails the use of discrete distributions to represent the uncertainty associated with impacts of health threats and performances of decision alternatives. In this type of health decision analysis, a small number of scenarios and their associated probabilities is defined. A more sophisticated analysis involves the consideration of continuous distribution for impacts and performances.

Regardless as to the representation that is adopted to consider uncertainty, we have argued that the expected value proves to be the best way of ranking and selecting alternatives under uncertainty in a health decision analysis. This decision rule ensures that, in the long-term, were many health security decisions to be made following said rule, societal expected value would be maximized. The rule also hinders the gain-loss bias, whose presence would otherwise give rise to a distortion, which may lead to both excessively risky choices when selecting decision alternatives (the

choice of which would be predicated on the negative impacts that the options may trigger), and to choices that are excessively risk averse (when selecting decision alternatives on the basis of the benefits that these alternatives may generate). Here, we have also argued that if multiple objectives prove to be relevant to a decision (the case of which represents the vast majority of health security situations), then decision alternatives can be chosen based on their expected overall value.

Conversely, we have suggested that health threats be ranked based on their expected overall dis-value. This assessment takes into account both the aggregate dis-value of impacts along the dimensions that are relevant within a specific decision context (health impacts, social impacts, economic impacts, etc.), and the probability that the threat shall occur within the time horizon under consideration.

Since there exist uncertainties about impacts from both health threats and health security actions, and imprecisions about judgments, it is important that we understand the extent to which the results are sensitive to these input parameters of a health decision analysis. Ideally, we wish to identify or develop robust options that prove less sensitive to said parameters. Additionally, we may gather further information (such as evidence from randomized experiments), which is able to reduce the uncertainties associated with relevant impacts. The sensitivity analysis of a decision model can help us to identify as to which pieces of additional data would prove more relevant to the decision, thereby forming an important element that underpins and guides research efforts.

Once alternatives have been adequately evaluated, they are ready to be employed in order to support the choices that must be made by health security teams. These evaluations can employ either overall value or expected overall value. Evaluations are based on *overall value* for situations wherein the level of uncertainty is low, or, when most likely values can be adequately employed, as has been described in the previous chapter. Conversely, evaluations are based on *expected overall value* when uncertainties are high and thus must be represented, the situation of which is described in this chapter. The manner in which the evaluation of decision alternatives and the assessment of health threats is able to better support the choices of health security teams shall be the topic of the next chapter.

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Chapter 10
Selecting the Best Options for Enhanced Health Security



The previous two chapters have presented the ways in which a health decision analysis can be conducted to systematically and thoroughly evaluate health security actions and health threats. Evaluations such as these constitute a prelude, thereby providing an input so that we are able to identify the best options to enhance health security, target the most relevant health threats, and select actions that mitigate risks. This chapter focuses on how high-value options can be selected in health security decision processes, the topic of which concludes this decision stage.

We begin the chapter by presenting a discussion concerning the sources of evidence that can be employed to assess the impacts of health threats and the performances of health security actions. Importantly, this evidence provides the inputs required for the evaluation that is conducted by any health decision analysis. The decision to address this topic in this current chapter (as opposed to the previous chapters) stems from the desire to emphasize that estimates form a critical element of assessing the impacts of health threats and health security actions and the performances of decision alternatives, the assessments of which are utilized as *inputs* in the value models that had been presented in the previous two chapters. Moreover, by structuring the chapters in such a manner, we highlight the role of an objectives-driven decision process, which is oriented toward attaining the fundamental objectives that decision makers seek to achieve or detrimental impacts that they wish to minimize. Thus, it becomes clearly indicated that either the gathering of evidence for the evaluation of decision alternatives, or, for the assessment of health threats, is a *means* to support evidence-based decision making, instead of an end per se, as is often observed in health security situations.

The second section of this chapter discusses the different types of decision situations and the different ways in which we can approach these situations in order to improve health security or to manage health threats. These decision situations can be classified as either: the choice of a single option, the ranking of options, the categorization of options, the recursive choice of an option, or the selection of a

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portfolio of health security projects. A similar classification can be applied to assess and rank health threats: the choice of a single threat to target, the ranking of threats, the recursive choice of a threat to target, or a regular ranking of threats. We subsequently discuss how the assessment of either the decision alternatives, or, of health threats, serves as a foundation to support each type of decision situation, and how a health decision analysis can be adapted to meet specific requirements of each type of decision situation.

In the second chapter we had presented a diagram that illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 10.1. The present decision stage, *evaluating health threats and health security actions and selecting the best options*, is now highlighted in this modified figure. This stage has been discussed in the two previous chapters and is concluded in this chapter. Here, we adopt a lens whose focus is on *selecting the best options for enhanced health security*. We shall assume that the adequate evaluation models have been developed in order to assess either the (expected) value of health security actions, or, the (expected) dis-value of health threats.

10.1 Gathering Evidence About Impacts and Performances

The previous two chapters have detailed the ways in which health security decision alternatives can be comprehensively evaluated against multiple objectives and under uncertainty. This evaluation model is reproduced in Fig. 10.2, wherein an alternative A is evaluated on M objectives and against N scenarios. This same type of evaluation is performed for alternative A` and the overall expected value of each alternative, EV(A) and EV(A′), can then be calculated and compared.

We recommend that value models be constructed first, before decision alternatives are considered in the evaluation model. Subsequently, decision alternatives can be evaluated by utilizing this model, which entails the gathering of realistic estimates about their performances. A similar recommendation can also be applied to the ranking of health threats, wherein a model that considers the weighted relevant consequences is developed first. Consequently, said model can be employed to estimate the potential impacts of emerging health threats.

One key aspect of a thorough evaluation is formed by the quality of the evidence about the performances of decision alternatives for enhancing health security, represented in Fig. 10.2 by $X_{ij}(A)$ for the performance of alternative A on the i-th attribute and under the j-th scenario. Similarly, reliable impacts of health threats must be defined for the evaluation of health threats. In this section, we shall discuss both how evidence can be gathered in the context of a health decision analysis and the biases that should be avoided when making estimates pertaining to the future performances of decision alternatives and the possible impacts of health threats.

As we have previously mentioned, a major advantage of conducting a health decision analysis stems from the decomposition of performance and impact assessments (Keeney, 1982). Decomposition enables the health security team to engage

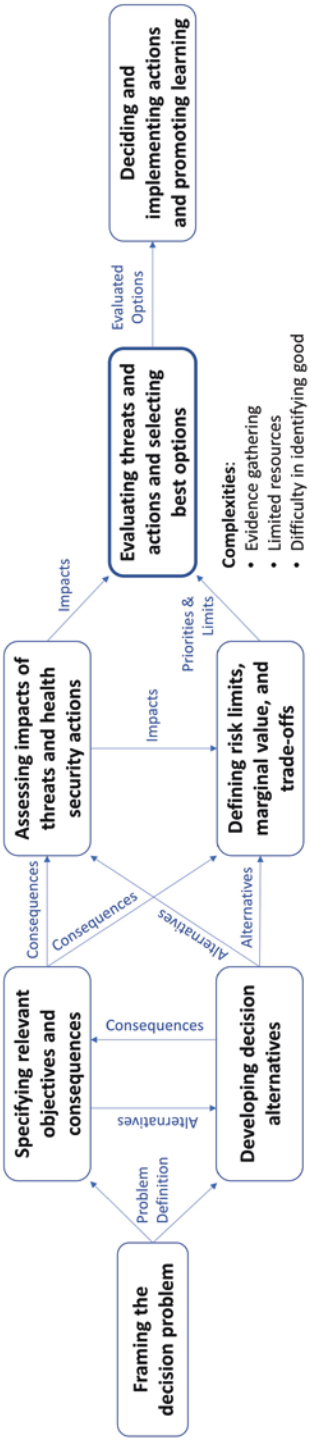

Fig. 10.1 Making reasoned health security decisions: A focus on selecting the best options for enhanced health security

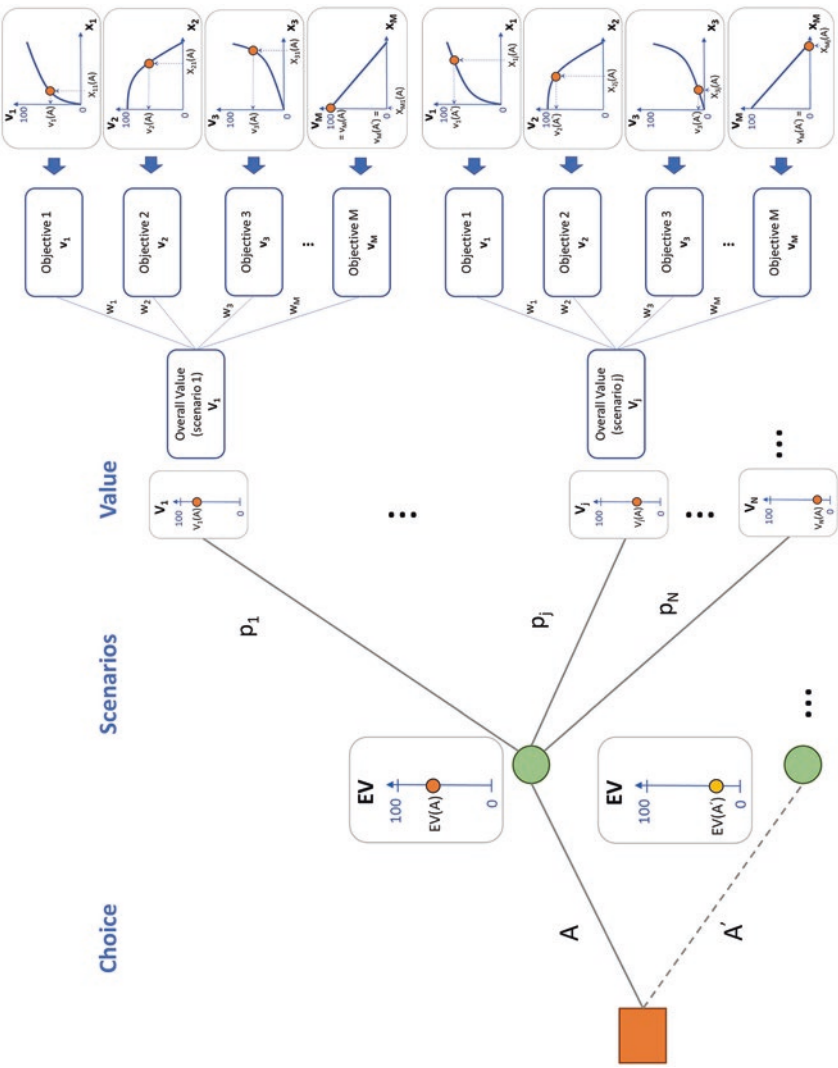

Fig. 10.2 Data gathering for the evaluation of decision alternatives – estimating performances and probabilities of scenarios

different experts in order to provide evidence and estimates for the different aspects of the decision model within their respective field of expertise. Moreover, this targeted use of experts allows for high-quality evidence to be employed throughout the decision analysis and maximizes the expertise that is employed in the evaluation of decision alternatives or of health threats. Processes that have been well-designed for expert engagement can also efficiently use scarce expertise and adjust to the limited availability of predictive modeling resources.

For example, let us posit a situation wherein a European country is considering the imposition of a quarantine mandate on arrival at national airports for all travelers arriving from another continent (which is being affected by an outbreak of a contagious disease). Policymakers may be concerned about the reduction in international visitors, the occurrence of which would affect the tourism, travel, service and retail industries. One of their objectives, beyond *minimizing the risk of disease spread*, could be to *minimize the loss of income from overseas visitors*. An assessment of the impacts related to this latter consequence could measure the loss of income experienced by the tourism industry, the loss of direct business opportunities (e.g. duty-free sales, revenues for the airlines, airport hotels revenues), as well as the loss of indirect business opportunities (e.g. business deals that cannot be completed, services that cannot be sold). While the definition of this objective falls within the remit of the decision makers responsible for this decision, the assessment of the impacts should involve experts from specific fields, which in this example would be represented by economists specialized in the national economy and those that are specialized in international trade.

Notice that this decomposition of impacts neither implies that impacts be uncorrelated, nor that they be necessarily isolated (and without any complex interrelationships). The huge economic damage that pandemics inflict are often consequences of health-related impacts across economically active sectors of society, as well as a populational response of fear which is elicited by the health threat. Recent examples of economic disruptions are exemplified by the Ebola outbreaks in Western Africa (CDC, 2020; World Bank, 2014) and the COVID-19 global pandemic that started in 2020 (World Bank, 2020). Hence, the spillover effects from health impacts to economic impacts must be considered in the appraisal of overall impacts caused by health threats, as well as in the assessment pertaining to the benefits of risk mitigating actions.

There exist three main sources of evidence that can be used to assess the impacts of health threats and the performances of decision alternatives in health security decisions. The first source consists of evidence from studies and from surveillance systems. The second source stems from outputs produced by predictive models, such as epidemiological simulations and economic impact analyses. The third source consists of estimates provided by experts, which are based on the available data and their expert judgments.

By focusing on decision making, there arises a key distinction in the manner in which evidence and data are used in Health Decision Analysis. Descriptive data must be used as a basis to predict: the impact of health threats, of health security actions, and the possible performance of decision alternatives. Quantitative models

can be developed to predict: the health impacts, economic impacts, and social impacts of health threats. These models can also help to predict the benefits and costs of decision alternatives or of different policies. Expert judgment can be used to predict hard to measure impacts or those with limited amount of hard data and evidence.

Decisions are always taken for the future. While this seems a rather obvious statement, its consideration brings about a shift in the way in which evidence is approached in health security decisions. Solely employing an adequate descriptive understanding of the phenomena fails to suffice, instead, the aim of decision-focused data analyses is, to provide accurate, reliable, and unbiased estimates concerning the possible impacts of *future* events, as well as those concerning the performances of decision alternatives if they were indeed to be implemented in the *future*. High-quality estimates can support policymakers as to how best to proceed, despite the irreducible uncertainties that they are confronted with (Hammond, 1996). Let us discuss the ways in which each type of source of evidence can be employed, while adopting a decision-making focus.

10.1.1 Employing Evidence from Surveillance Systems and from Scientific Studies

Sources of evidence about emerging health threats at their earliest stages of development are typically provided by health surveillance systems. Indeed, effective surveillance systems are essential for health security, and they must track health threats that follow both a human-human transmission pattern and a zoonotic transmission pattern within the One Health initiative (Kelly et al., 2017). These systems provide the inputs for a number of surveillance objectives, such as supporting the early detection of emerging health threats, measuring the burden of disease over time for a given pathogen, monitoring the effectiveness of a health policy, and so on (Groseclose & Buckeridge, 2017; Morse, 2012). Evidently, data from surveillance systems also serves as crucial inputs for epidemiological predictive models (Brauer et al., 2019) and can aid the early assessments of emerging disease severity.

In the context of health security decisions, evidence from surveillance systems can provide relevant information and inputs for a health decision analysis on four main fronts as follows: provide early warnings concerning an emerging health threat, aid in estimating the frequency of occurrence of re-emerging health threats, support the assessment of the effectiveness of previous health security interventions, and highlight potential problems in the health systems. We comment below as to how health surveillance system can support a health decision analysis for the prioritization of health threats or the evaluation of health security actions.

First, health surveillance systems can warn policymakers as to any emerging health threats in the early stages after emergence and before scientific studies and predictive models are developed. The estimated impacts of these threats can then be assessed with an amalgamation of expert judgment and early data from surveillance

systems, like the decision support system that we developed for the UK Department for Environment, Food and Rural Affairs (DEFRA) for ranking emerging animal health threats illustrates (Del Rio Vilas et al., 2013; Montibeller et al., 2020a). This use of health surveillance data as input to inform the systematic prioritization of health threats avoids the drawbacks of unstructured decision processes (the topic of which has been discussed in the first chapter), which may lead the health security team to prioritize threats that are highly salient, but ultimately, low impact.

Second, health surveillance systems can aid in estimating the probability of occurrence of re-emerging health threats. Sophisticated surveillance systems can record data about each and every previous disease outbreak, in terms of occurrence, spread, and severity. Consequently, historic frequency data may provide an indication as to the probability of a future outbreak within a given time horizon, the information of which can support more reliable expert estimates for these relatively rare events (Jaspersen & Montibeller, 2015).

Third, data from health surveillance systems can provide evidence relating to the effectiveness of previous health security interventions. This information may then be used to guide the estimation of the performances pertaining to decision alternatives that have been implemented in the past, which can in turn be contemplated in health security actions affecting the future. However, an assessment concerning the effectiveness of previous interventions as a means to estimate the performance of present and future health security actions would only prove meaningful provided that the previous and future settings be comparable, both in terms of constituting a similar intervention and an equivalent population characteristic (Hunink & Weinstein, 2014).

Fourth, health surveillance systems allow for the provision of an updated assessment of the health security events, thereby highlighting potential problems that may arise within the health systems. As we have discussed in the third chapter, the signaling of an unsatisfactory event by a health surveillance system may foster an agreement among the health security team that there does indeed exist a relevant health security problem to be analyzed and undertaken, thus aiding the team to identify vulnerabilities and deficiencies of the health system that must be appropriately addressed. Subsequently, a capability assessment (using the concepts that have been described in the seventh chapter) may be employed to generate actions that seek to improve health and mitigate risks.

The knowledge about emerging health threats can then be fostered by utilizing the early signals that are supplied by health surveillance systems, alongside the use of rigorous scientific studies. Specifically, randomized control trials represent the gold standard for healthcare studies and for supporting medical decision making. A systematic review of primary studies can provide strong evidence concerning the effectiveness of a medicine or treatment (Hunink & Weinstein, 2014). In health security decisions, this type of evidence can inform, for instance, the assessment as to the severity of an emerging disease or the effectiveness of a given vaccine type.

Increasingly, randomized control trials are also being used to test different development policies within Economics (Banerjee et al., 2019). Correspondingly, this idea can be extended to conduct pilot trials for health policies (Newhouse &

Normand, 2017), the results of which may inform the assessment pertaining to the performances of the various health security actions under consideration. Thus, a more intensive usage of randomized control trials in the context of health security decisions is recommended, so that there be more reliable estimates concerning the performances of decision alternatives and a reduction in any ineffective allocation of scarce resources.

To better illustrate as to how randomized control trials could be employed to improve the quality of a health decision analysis, we shall once again utilize the vaccination campaign case, which has been discussed in previous chapters. In the context of this health decision analysis, the various vaccination campaign strategies that are under consideration could be tested in a confined (yet relevant and representative) area of the affected country. Subsequently, in this pilot intervention, the performance of each strategy could then be assessed on the relevant consequences. Consequently, the performance of each piloted alternative strategy functions as foundation on which to develop more realistic estimates for each vaccination strategy, which in turn could be employed in the evaluation and comparison of decision alternatives, thereby allowing for the best option to be selected and deployed nationwide.

10.1.2 Employing Outputs from Predictive Models

Predictive models form an important source of evidence for a health decision analysis and are able to support the estimates of the performances of decision alternatives or of the impacts that health threats may bring about. Models for predicting the transmission of an infectious disease are widely employed in health security decisions (see Brauer et al. (2019) for a detailed coverage). The output from these models is typically a given response, such as the number of infected individuals or deaths as a function of time.

One challenge for public health leaders stems from the fact that predictive outputs from disease transmission models are typically only *inputs* for the relevant consequences in health security decisions. Correspondingly, Health Decision Analysis allows for the possibility of a nexus to be formed between these simulated predictions and the appraisal of different alternatives to manage a given health threat, thereby providing a decision-focused perspective that may support a more structured decision making process.

For instance, let us postulate that a health security team is concerned with the health impact of a disease outbreak. There arise four main objectives that they wish to minimize. First, *minimize the duration of the outbreak*, as the outbreak itself places the health system, the economy, and society under strain. Second, *reduce the daily rate of severe cases*, as the number of cases creates a daily demand for intensive care hospital beds and medical personnel. Third, *reduce the peak number of severe cases*, given the limited overall availability of intensive care hospital beds. Fourth, *reduce the total number of severe cases*, given the health burden that the outbreak may cause.

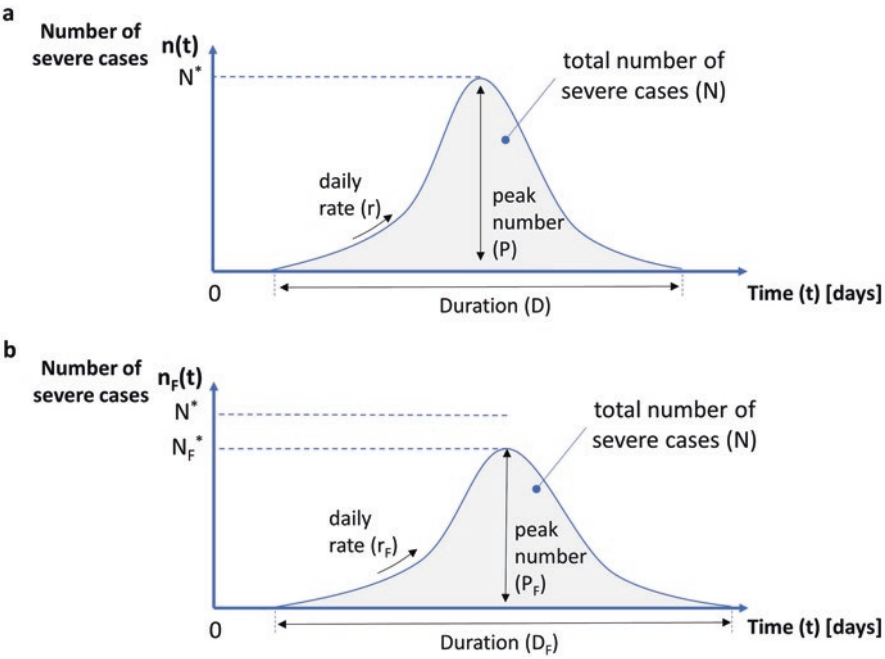

Fig. 10.3 Outputs from a transmission model predicting: (**a**) The number of severe cases and (**b**) The flattened number of severe cases after implementing a risk mitigating action

Now, let us assume that a transmission model has generated the prediction for function n(t) (the number of severe cases caused by a disease outbreak), wherein time (t) is given in days, as shown in Fig. 10.3a. This prediction can inform as to the impact of this health threat on the four relevant consequences, the situation of which is shown in the same figure, as follows: the *duration of the outbreak* D [in days], the *daily rate of severe cases* r [cases per day], the *peak number of severe cases* N^* [number of cases], and the *total number of severe cases* N [number of cases].

The decision-focused perspective, which is geared toward minimizing the four objectives that are listed above, can support decision makers in two ways. First, this perspective can form a robust nexus between the outputs from the transmission models and the relevant consequences for the decision. Second, a decision-focused perspective can support the identification of health security actions and aid the health security team to better understand the beneficial and detrimental impacts of said actions on the relevant consequences.

Let us return to the same case and posit that the estimated peak number of severe cases have exceeded the number of available intensive care hospital beds. This excess could drive the health security team to design risk mitigating actions that seek to flatten the curve, such as social distancing measures. Subsequently, policies such as this could be simulated in the transmission model like that which Fig. 10.3b illustrates. This new flatter function, $n_F(t)$, would generate an outbreak whose duration is longer ($D_F > D$), whose daily rate of severe cases is lower ($r_F < r$), but whose

peak number of severe cases is lower ($N_F^* < N^*$), while the total number of severe cases N remains the same (given by the area under the function $n_F(t)$ in the same figure).

In this same case, other risk mitigating actions could be designed and simulated in a similar manner to that which is illustrated in Fig. 10.3b. Subsequently, the performance of each policy on the four objectives would be estimated. A value model could then be used to prioritize the four objectives, the topic of which has been discussed in the eight chapter. This valuation of each and every health security action could be employed to compare the different options (as well as comparing these alternative to taking no action, which is illustrated in Fig. 10.3a) and to indicate the risk mitigating action(s) with the highest societal value.

This nexus that arises between the results from transmission models and the decision making process often remains absent in health security decisions. Epidemiologists produce sophisticated models that are able to simulate different risk mitigating policies. However, policymakers usually interpret these results holistically in the appraisal of the decision consequences, and in turn, fail to adopt a clear decision-focus that is concerned with the objectives whose attainment is being sought. In addition, it proves difficult to keep track of multiple impacts of several alternative risk mitigating policies, as it was illustrated in Fig. 10.3. Given both the complexity of health security decision problems, and the cognitive limitations inherent to humans that negatively affects unstructured decision making (Payne et al., 1992, 1993), it is unlikely that this informal approach prove capable of guiding high quality decision processes (Spetzler et al., 2016).

The perspectives of Health-Effectiveness Analysis and Health Cost-Benefit Analysis are accompanied by the established tradition of utilizing predictive models when assessing healthcare outcomes (Brent, 2016; Hunink & Weinstein, 2014). Additionally, the economic impacts of epidemics have also been extensively explored, both when assessing impacts retrospectively as well as when seeking to predict future impacts. The World Bank impact assessment as a result of the 2014 Ebola epidemic in West Africa forms a good example that represents this type of Economic Impact Analysis (World Bank, 2014). An economic impact analysis can also be used to inform the assessment of performances of the decision alternatives and the impacts for health threats. However, this book highlights that, unlike Cost-Benefit Analysis, Decision Analysis focuses on assessing and comparing multiple decision alternatives, the perspective of which is in direct contrast to the former, wherein typically, a single course of action is considered (Gregory et al., 2012).

The estimation of the long-term consequences of decision alternatives forms another dimension wherein predictive models significantly support the decision making process. Examples of this type of prediction include the total number of deaths, which is established by a transmission model, or the total economic impact caused by a health threat, which is established by an economic impact analysis. The estimated costs of each decision alternative can be appraised with standard net present monetary valuation models, which discount future costs using a fixed discount rate (Brent, 2016; Hunink & Weinstein, 2014). This same type of standard discounting, which represents the time value of money, can be used to calculate the net present value of the economic and the other monetized impacts.

Studies in Health Policy Analysis often attempt to monetize the value of a human life, so that these analyzes are able to be compared with the cost of health policies. When considering long-term horizons, this monetization process typically calculates the net present monetary value of long-term consequences. However, behavioral evidence has demonstrated that subjects value lives both at present and in the future equally (Guyse et al., 2020), the evidence of which suggests that value-of-life monetization and standard discounting for this type of impact may not adequately represent societal values. Hence, it is advisable that the number of lives impacted by a health threat, or, saved by risk mitigating actions be maintained as an independent consequence instead of monetizing them.

In addition to tangible consequences, an outbreak of a disease may bring about social disruption (Kasperson et al., 1988), the occurrence of which may further trigger intangible impacts. Consequently, the modeling of other varieties of intangible impacts (such as fear) may prove more difficult when employing a predictive model, (Setbon et al., 2005). Moreover, health security teams may lack sufficient time to develop predictive models prior to the moment wherein health security decisions must be made. In such instances, the use of expert judgment may inform and complement the evaluation of health security actions and the assessment of health security threats, as described next.

10.1.3 Employing Estimates from Experts

Expert estimates prove valuable in situations wherein there exists no reliable hard evidence, or, when there exists a lack of adequate predictive models (Morgan, 2014, 2017; Morgan & Henrion, 1992). In the context of health security decisions, expert judgment is particularly useful when providing two types of estimates, which are: the assessments of impacts of health threats and health security actions and the estimations of probability of occurrence for possible disease outbreaks. Let us briefly describe these two types of estimates subsequently.

The first type of expert estimate entails providing assessments of the potential impacts of emerging health threats. This type of expert judgment is particularly useful during the early stages of the health decision analysis, prior to the execution of randomized control trials and the development of reliable predictive models. For example, the decision support system that we developed for DEFRA, which supports the ranking of emerging animal health threats in the UK, enables the use of expert judgment to identify levels of impacts (as has been described in the eighth chapter), despite the rather limited hard data when the assessments must be made (Del Rio Vilas et al., 2013; Montibeller, Franco, & Carreras, 2020a).

When levels of uncertainty are high (which often proves to be the case for emerging health threats), it is not always possible to provide reliable single point estimates. In these cases, experts may be able to estimate the distributions of impacts, or, alternatively, at least the ranges of the possible impacts. This latter situation proved to be the case for the prioritization of low-moisture food categories, the task

of which was conducted for the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO). In this project, the low-moisture food experts identified ranges for some of the impacts of each food category as well as establishing the most likely level of impact, the execution of which was due to the lack of hard evidence, which would otherwise have been required for estimating the whole distribution of impacts (Montibeller, 2018), as has been described in the ninth chapter.

Experts may also find themselves able to estimate the possible performances of health security actions based on individual experience undertaking previous health security initiatives and expertise in their field. However, there exists one important caveat concerning this use of expert judgment in such cases. Experts who are promoting a given health security action must not provide estimates about the performance of said action, as these experts may suffer from motivational biases and provide estimates that favor the action (Montibeller & von Winterfeldt, 2015). Instead, independent and reliable experts should be appointed, who are tasked with providing realistic and unbiased estimates.

The second type of expert estimate involves providing the probability of occurrence for possible disease outbreaks. In such cases, experts may make initial estimates concerning the probability of outbreaks based on the health surveillance data and on other sources of soft evidence. This type of estimate is particularly useful when managing rare events, as proves to be the case for many emerging health threats. Consequently, given the challenges associated in providing precise probability estimates in these situations, we developed methods to enable experts to provide qualitative information about the likelihood of occurrence of emerging health threats, which can then be meaningfully converted into quantitative probability estimates (Jaspersen & Montibeller, 2015).

There exists an extensive literature on the subject of expert judgment elicitation (Dias et al., 2018; Hanea et al., 2021; Morgan, 2014) alongside well-developed protocols for eliciting estimates. However, a series of biases are known to affect such estimates, thus, adequate elicitation protocols must be used and debiasing tools should always be employed (Montibeller & von Winterfeldt, 2015). We shall subsequently detail the elicitation protocol and possible biases pertaining to the two main types of estimates that often employ expert judgment: the estimation of the impacts of health threats or health security actions, and the estimation of the probabilities of occurrence for disease outbreaks.

Estimation of the Impacts of Health Threats and Health Security Actions In this type of estimation, experts provide estimates of the impact over a consequence of interest. These estimates could take the form of a small number of points of a discrete distribution, or, a continuous probability distribution (see the fifth chapter for the various types of representations of impact). For instance, in the early stages of an emerging health threat, at the point wherein transmission models are not yet available, an expert could be requested to estimate the number of deaths that the disease could cause if an outbreak were to occur.

The fixed variable method forms a useful protocol for the elicitation of cumulative distribution functions (CDFs) from experts (Abbas et al., 2008; Morgan &

Henrion, 1992). At the first stage of this protocol, a realistic range pertaining to the consequence of interest is estimated by the expert, the estimation of which ranges from the minimum (X_0) to the maximum (X_{100}) level of impact. The subsequent stage entails dividing this range into a small number of intermediate equidistant points (e.g., X_{20}, X_{40}, X_{60}, and X_{80}) as well as identifying the mid-point (X_{50}). For each X_l-th point of the variable, the expert is tasked with estimating the probability that the true value of the variable either lies below or at the level X_l, i.e., $P(x \leq X_l)$. Once the probabilities of these intermediate points have been estimated, a CDF can then be drawn by interpolating these point estimates.

For an example of this elicitation protocol, here, let us consider the *number of severe cases* (measured by variable x) that could be caused by an emerging health threat forms the consequence of interest, and consequently, that experts must estimate as to this number prior to the development of any reliable prediction models. For these estimates to be meaningful and reliable, it would be necessary to define a clear scenario, with a precise time frame and region of occurrence. In this example, let us assume the time horizon to be 12 months and that the estimates shall be made for a specific country.

Let us assume that the expert has defined a possible range for this variable to be between X_0 = 2,000 cases and X_0 = 18,000 cases. A small number of intermediate and equidistant points have been defined, as shown in Fig. 10.4a: X_{20} = 6,000; X_{40} = 8,000; X_{60} = 12,000; X_{80} = 16,000 cases. In addition, the mid-point has been identified: X_{50} = 10,000 cases, as shown in Fig. 10.4a. For each point of the consequence (measured by variable x), the expert is tasked with estimating the probability that the number of cases would be located at or below that level. Hence, for X_{20} = 6,000 cases, the question ($P(x \leq X_{20}) = ?$) could be posed as: "if an outbreak of this disease were to occur in this country within the next 12 months, what is the probability that this emerging health threat would cause at least 6,000 cases?" If the expert were to answer this question by providing a 7% estimation, then $P(x \leq X_{20}) = P(x \leq 6{,}000) = 0.07$. Repeating the protocol for the other selected points of the distribution in Fig. 10.4a would provide the estimates for each level of the consequence, as exemplified in Fig. 10.4b. These point-estimates can then be interpolated for a continuous CDF, as shown in the same figure.

Some relevant cognitive and motivational biases may affect this type of estimate, the presence of which can be reduced or avoided by adequate debiasing techniques (Montibeller & von Winterfeldt, 2015, 2018). As we have mentioned in the second chapter, cognitive biases occur due to faulty reasoning processes (Gilovich et al., 2002; Kahneman et al., 1982), which distort judgments in comparison with rationality standards. Motivational biases occur due to motivated reasoning (Kunda, 1990), thereby inducing estimates toward a preferred direction. The relevant biases for the estimation of impacts and performances, as well as debiasing tools to minimize them are listed below:

- *Affect-influenced bias (motivational bias)*: An emotional predisposition for, or against, a specific outcome or option, which taints judgments (Finucane et al., 2000; Slovic et al., 2004). Several studies have reported this bias, assessing the

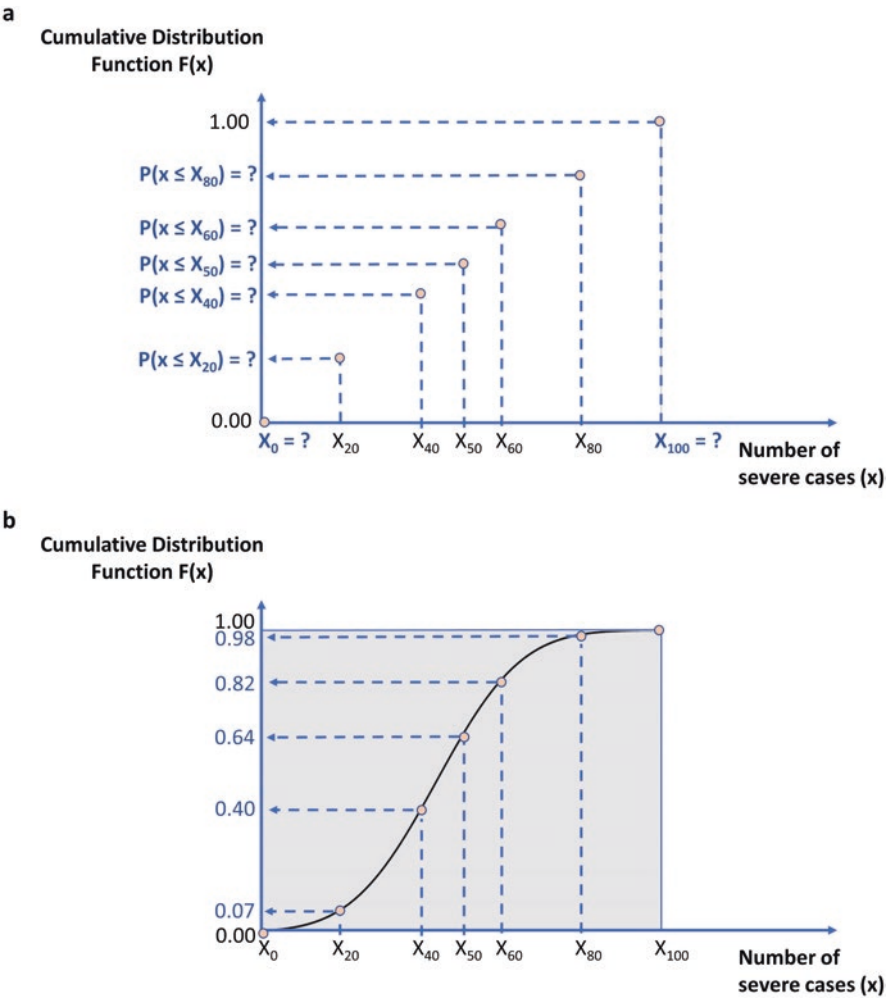

Fig. 10.4 Elicitation of a cumulative distribution function (CDF) from an expert for the number of severe cases that could be caused by a health threat: (**a**) The fixed variable method, (**b**) Interpolating the point estimates for a continuous CDF

role of affect in causing an inverse perceived relationship between the positive and the negative consequences related to pandemics and human-caused hazards (Siegrist & Sütterlin, 2014). Debiasing techniques include: avoiding loaded descriptions[1] of consequences in the attributes, verifying judgments with alternative elicitation protocols when eliciting probabilities (see Morgan and Henrion (1992) for details), and using multiple experts whose perspectives are varied.

[1] A loaded description influences the expert in providing an answer that is aligned with a presupposed assumption. This assumption is implicitly conveyed by the manner in which the question is being asked.

- *Anchoring bias (cognitive bias)*: The estimation of a numerical value is predicated on an initial value (anchor), which is then insufficiently adjusted to provide a final result (Tversky & Kahneman, 1974). Debiasing techniques include avoiding anchors, providing multiple and counter-anchors, and using different experts who employ various different anchors.
- *Desirability of a positive event or consequence (motivational bias)*: The desirability of an outcome leads to an increase in the extent to which this outcome is expected to occur (Krizan & Windschitl, 2007, p. 96). It is also called the *wishful thinking* bias (Seybert & Bloomfield, 2009) or the *optimism bias* (Weinstein, 1980). This bias occurs in estimates of costs (Dillon-Merrill et al., 2002) and duration (Connolly & Dean, 1997) in project planning. Debiasing techniques include using multiple experts with various different perspectives, using a scoring rule that incentivizes judgment accuracy (Carvalho, 2016; Winkler, 1996), and placing hypothetical bets against the estimated consequence.
- *Undesirability of a negative event or consequence (motivational bias)*: The desire to be cautious, prudent, or conservative in estimates that may be related to harmful consequences (Chapin, 2001; Dolinski et al., 1987). Most evidence concerning this bias is related to probabilities of life events (Chapin, 2001; Dolinski et al., 1987) and some risk assessments that are intentionally biased toward conservative estimates (as discussed by the Institute of Medicine, 2013). Debiasing techniques are identical to the techniques of the above bias.
- *Overconfidence (cognitive bias)*: For a given parameter, experts provide estimates that are located above the actual performance (overestimation) (Lichtenstein & Fischhoff, 1977; Lichtenstein et al., 1982) or provide a range of variation that is excessively narrow (overprecision) (Moore & Healy, 2008). Debiasing techniques include providing probability training and demonstrations of overconfidence, starting elicitations with extreme estimates (low and high), avoiding central tendency anchors, using counterfactuals (Roese, 1999; Woo, 2016) to challenge extremes, using fixed variable elicitation protocols, and automatically expanding the initial range provided by a factor of two or three (Ferretti et al., 2022).
- Scaling biases (cognitive bias): The manner in which the consequence is measured, or the attribute is defined, may affect estimates made by experts due to this family of stimulus-response biases (Poulton, 1982, 1989) Debiasing techniques include selecting appropriate scaling techniques for the required measurements.

Estimation of Probabilities of Events In this type of estimation, experts provide the probabilities of the occurrence of events. For instance, experts may provide an estimate as to the probability that an emerging health threat shall cause an outbreak in a given region and within a given time frame. In a more detailed assessment, experts may provide probabilities for the scenarios represented in a decision tree, which is comparing health security decision alternatives (see the ninth chapter for further details).

The *probability wheel* forms a useful tool for the estimation of the probability of the occurrence of events (see Henrion and Morgan (1992) for details). Consider an

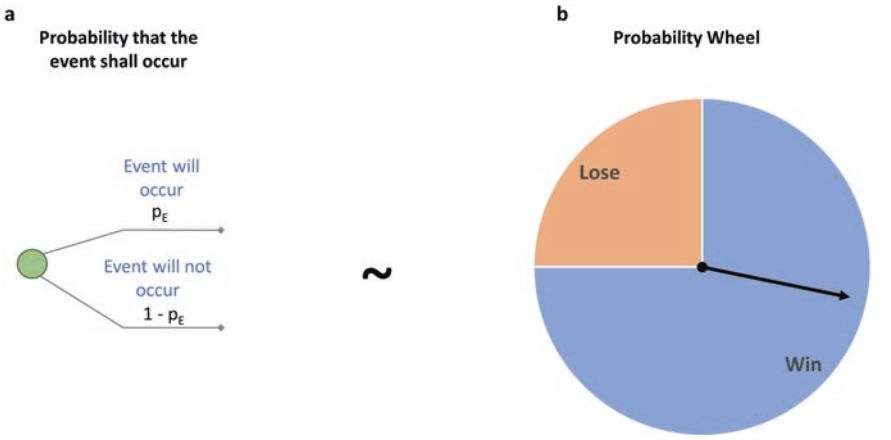

Fig. 10.5 Elicitation of the probabilities of events occurring with a probability wheel: (**a**) Prospects for the event under consideration, (**b**) Probability wheel with adjusTable Win area. The area of the probability wheel is adjusted until the expert is rendered indifferent toward the prospects of the event and the wheel

expert estimating the probability of the occurrence of an outbreak (p_E) of an emerging health threat, as shown in Fig. 10.5a. In a probability wheel, such as the one that is presented in Fig. 10.5b, if we were to spin the wheel, the pointer may stop either on the *Win* area or the *Lose* area. The task requires that the *Win* area be adjusted until the expert is rendered indifferent (symbolized by ~ in the same figure) toward betting on whether the event shall indeed occur against the odds in the probability wheel. At this point in the process, when an indifference judgment has been reached, the *Win* area of the wheel is the same as that of the probability of the event occurring (p_E). For instance, in the same figure, if the expert were indifferent toward both the prospects on the left and the probability wheel on the right, this condition would indicate that the estimate of the outbreak occurring within the considered time frame and region is $p_E = 0.75$.

We have used this type of elicitation tool successfully in health security projects. For instance, in a project executed for the UK Department for Environment, Food and Rural Affairs (DEFRA) on the prioritization of bio-security threats, we employed a probability wheel to elicit the probability of invasive species extending across Britain during the time horizon under consideration from DEFRA experts (Montibeller et al., 2020a). The probabilities were more reasoned when using this method in comparison to the method that employed initial direct estimates provided by the experts.

This type of estimate may also suffer from some relevant cognitive and motivational biases. Experts may suffer from the affect-influence, anchoring, and desirability biases detailed above. In addition, some other biases may affect such judgments, the presence of which may also be reduced by adequate debiasing techniques (Montibeller & von Winterfeldt, 2015, 2018). These additional biases, and debiasing tools, are listed below:

- *Availability/Ease of recall (cognitive bias)*: The probability of an event that is easily recalled is overstated (Bazerman & Moore, 2013; Tversky & Kahneman, 1973). Debiasing techniques include conducting probability training, providing counter examples, and providing statistics to experts.
- *Confirmation bias (motivational bias)*: The desire to confirm a belief, leading to unconscious selectivity in the acquisition and use of evidence (Nickerson, 1998). This bias has been reported in medical diagnostics and scientific thinking. Debiasing techniques include using multiple experts with different points of view about hypotheses, challenging probability assessments with counterfactuals, and probing for evidence for alternative hypotheses.
- *Equalizing Bias (cognitive bias)*: Decision makers may allocate similar probabilities to all the events or scenarios that are featured in a decision tree (Fox et al., 2005; Fox & Clemen, 2005). Debiasing techniques include first ranking these events, followed by the subsequent assigning of ratio probabilities and the eliciting of probabilities along the decision tree in a hierarchical manner.
- *Gain-Loss Bias (cognitive bias)*: Alternative descriptions of a choice and its outcomes (Tversky & Kahneman, 1981), either as gains or as losses, may lead to different results and distort the estimation of probabilities of events (Frisch, 1993; Levin et al., 1998; Tversky & Kahneman, 1981). Debiasing techniques include clearly identifying the status quo, as well as adjusting probabilities for rare events and very likely events to compensate for any distortions.
- *Splitting bias (cognitive bias)*: The manner in which events are organized and grouped in a decision tree may affect the estimation of their probabilities of occurrence (Fischhoff et al., 1978; Ofir, 2000). Debiasing techniques include separating events that are allocated high probabilities and not separating events that are allocated lower probabilities, using a hierarchical estimation of probabilities, and using ratio judgments instead of direct estimation of points.
- *Underestimation of rare events (cognitive bias)*: When decision makers or experts experience uncertainties, by encountering occasional adverse events, they tend to underestimate the possibility of rare events (Hertwig, 2012; Hertwig et al., 2004). Debiasing techniques involve considering the probability of this class of events and adjusting probability estimates to compensate for the underestimation, as well as decomposing the probability elicitation into the sub-events that compose the event.

Often, a case occurs wherein a group of experts is involved in the estimation of a variable. In these instances, it is recommendable that experts first provide their estimates individually, in order to avoid group pressures and group judgment biases (Kerr & Tindale, 2011). There exists a large body of literature concerning the ways in which to aggregate expert estimates, using *mathematical aggregation methods* that somehow combine individual estimates or *behavioral aggregation methods* wherein the group of expert discusses individual estimates and agrees upon joint estimates. Simple combination rules, e.g., calculating the average of individual estimates, typically perform well against more sophisticated mathematical or behavioral aggregation methods (see Clemen and Winkler (1999, 2007) for details).

10.1.4 Designing the Involvement of Experts

This book promotes a clear distinction between assessing multiple impacts of health threats and health security actions as *a means to decide* between conflicting health security objectives. Said distinction can help to clearly delineate the roles and responsibilities of experts and that of policymakers. Experts should be responsible for providing the evidence and expert opinion in the assessment of impacts and the probabilities of occurrence of outbreaks while decision makers should be responsible for making difficult trade-offs and policy choices.

Any ambiguous divisions of responsibility between experts and policymakers may bring about problems, which some countries have experienced during the early stages of the COVID-19 pandemic in 2020, as reported by Haddon et al. (2020) and Calvert and Arbuthnott (2021). Specifically, experts may be required to make difficult trade-offs that lie outside their job remits and may subsequently receive the blame for policy choices for which they had ultimately not been responsible.

Whatever the source of evidence employed, a key consideration for a reasoned decision process involves minimizing motivational biases (Montibeller, 2018; Montibeller & von Winterfeldt, 2015) which are listed above. Experts who conduct data analyses or develop predictive models may have their own agendas, which could otherwise interfere with the assumptions that have been made and negatively impact the quality of the models produced. Experts may also suffer, even unconsciously, from confirmation bias (Klayman, 1995; Nickerson, 1998), wherein the analysis is used to support pre-conceived preferable results.

Hence, there arises the importance of involving credible and independent experts, as well as the requirement of a full set of explicit assumptions derived from descriptive and predictive models. It is also recommendable to establish an expert group that is characterized by variety, in order to support the health security team when appraising the issue from various different perspectives. Equally, it is advisable to draw from sound but distinctive descriptive analysis tools and predictive modeling techniques. This triangulation of data can provide a more robust illustration of the issue than would be the case were this issue to be analyzed from a single analytical standpoint.

Furthermore, there exists a more insidious problem related to motivational biases, in that there occurs the selective involvement of experts in consultation processes which directly inform decision making. In such cases, only experts that favor a decision alternative that has been pre-selected by policymakers are involved in the consultation, to further the choices that have already been made by decision makers in such a manner that postures that these choices have been "underpinned by scientific evidence". For example, the desirability of option bias (Montibeller & von Winterfeldt, 2015) may have influenced the decision of the UK government as to whether to impose a second lockdown during the COVID-19 global pandemic in 2020. According to the report by Calvert and Arbuthnott (2021), some health experts that had been in favor of the herd immunity strategy, or that had assessed the health impacts of the disease as being not so severe, had been involved in the government consultation meetings. The opinions of these experts were given more weight than

the majority of scientists whose models predicted a significant number of severe cases and thus the latter group had recommended an immediate lockdown.

Once adequate evidence has been gathered about impacts from health threats and health security actions, the expected value of decision alternatives can be assessed, or the expected dis-value of health threats can be estimated, the processes of which have been detailed in the previous two chapters. We now assume that said evaluation has been completed and therefore, in the remaining sections of this chapter we shall discuss the different types of decision situations that can be supported by this systematic and thorough evaluation, leading to the selection of the best option(s) to improve health security or the selection of health threat(s) to be targeted.

10.2 Identifying the Type of Health Security Decision Situation

The evaluation of decision alternatives, or of health threats, is a means to support reasoned choices. While most of the Decision Analysis literature is focused on the selection of the best alternative, there exist other types of decision problem (Roy, 1996) which can be supported in health security situations. In this section we detail these distinctive decision situations, through adopting first a focus on decision alternatives to enhance health security, and subsequently, on health threats. We demonstrate how the evaluations, which have been detailed in the two previous chapters, can be used and adapted to support reasoned choices for each type of decision situation.

10.2.1 Identifying the Type of Decision Situation: Health Security Actions

There exist five types of decisions in health security situations concerning decision alternatives that encompass health security actions (see also Gregory et al. (2012) for a discussion in the context of environmental decisions). Each type of decision situation is described and exemplified briefly next.

Selection of a Single Health Security Option The first type of decision situation entails selecting a single preferable alternative with the highest expected value. For example, the health security team may wish to identify the best strategy for vaccinating a population against an infectious disease.

Ranking of Health Security Options The second type of decision situation entails the ranking of decision alternatives on a given metric. For instance, to enhance health surveillance, the health security team may wish to conduct a ranking of projects in terms of their expected value.

Categorization of Health Security Options The third type of decision situation involves the classification of decision alternatives into an exhaustive set of categories. For example, different types of vaccine for a given disease may be classified into either high-effectiveness or low-effectiveness groups.

Execution of Recursive Selection of Health Security Options The fourth type of decision situation involves the development of a decision support system for the recursive evaluation and selection of option(s). For instance, the health security team may wish to develop a system that periodically identifies the best risk mitigating actions against current health threats.

Selection of a Portfolio of Health Security Projects The fifth type of decision situation involves the selection of a portfolio of projects that maximizes the efficiency of resource allocation for enhancing health security. For example, the decision as to which projects should be funded among a great number of options to increase the preparedness of the health system being considered, such as: vaccination campaigns, educational campaigns, hospital expansions, new health clinics, etc.

The identification of the type of decision situation is important, as the characteristics of the situation shall partly inform the selection of fundamental objectives and the relevant consequences to be employed in the evaluation. To illustrate this point, let us consider a problem wherein an organization is assembling a health security team that must be composed of five people and thus, participants must be selected. If the decision situation were characterized as a ranking, the available candidates would be ranked on their health security expertise and the candidates with the five highest scores would be selected for the team. On the other hand, if the decision situation were conceptualized as a categorization of options, a different evaluation process would take place. In this latter process, a set of categories would be defined, for instance in terms of different expertise (epidemiology, health policy, risk management, economic analysis, healthcare, etc.). Each candidate would then be allocated to a category based on their expertise. Within each category, candidates could then be ranked in terms of their specific expertise and the best candidates would be selected as participants. In this example, notice that the classification of alternatives into categories is likely to foster greater variety among group than the ranking of candidates, as the latter is focused on health security expertise. Moreover, the attributes that shall be used in the first type of evaluation are likely to be different than those in the second type.

While this discussion concerning the various types of decision situation has been positioned at this stage of the book for the sake of expository clarity, in practice, it is recommended that the type of decision situation and a plan detailing the execution of the evaluation precede the definition of fundamental objectives. In Table 10.1, the five types of decision situations and the requirements for the evaluation of decision alternatives are specified, based on the benefits of a high-quality health decision analysis, the topic of which has been discussed in the second chapter. Once the type of decision situation has been identified, this Table can be used to assess the

Table 10.1 Types of decision situations and their evaluation requirements for health security actions

Type of decision situation	Requirements for the evaluation
Selection of a single health security option	A comprehensive assessment of all the relevant consequences, which enables a like-for-like comparison between the decision alternatives. A transparent valuation of both the evidence in favor of and against each decision alternative, and, of the priorities in reaching conflicting objectives. An unbiased evaluation of each alternative, which employs: high quality evidence, a clear distinction between judgments and facts, and debiased estimates. A highly justifiable choice, which details: the benefits and drawbacks of the chosen alternative against the other options, the rationale for selecting the option, and the assumptions made in the assessment.
Ranking of health security options	A comprehensive assessment of all the relevant consequences, which enables the ranking of decision alternatives. A transparent valuation of the evidence in favor and against each decision alternative and of the priorities in reaching conflicting objectives. Additionally, there exists a clear metric for ranking the options. An unbiased evaluation of each alternative, which employs: high quality evidence, a clear distinction between judgments and facts, and debiased estimates. A highly justifiable ranking, which details: the benefits and drawbacks of each option, the rationale for their ordering, and the assumptions made in the assessment.
Categorization of health security options	An exhaustive set of categories that are aligned with the decision framing of the specific decision situation. A comprehensive assessment of all the relevant consequences, which enables the allocation of each option to one specific category. A transparent valuation of the evidence for each decision alternative and of the priorities connected with the categories. An unbiased evaluation of the fit of each alternative for every category, which employs: high quality evidence, a clear distinction between judgments and facts, and debiased estimates. A highly justifiable categorization, which details: the fit of each option for every category, the rationale for their classification, and the assumptions made in the assessment.
Execution of recursive selections of health security options	A systematic assessment of all the relevant consequences, which enables a like-for-like comparison between the decision alternatives and periodic updates with new data. A decision support system that transparently values the evidence in favor and against each decision alternative and records the priorities among conflicting objectives. A decision support system that performs an unbiased assessment of the options, is based on debiased judgments, and promotes high quality expert estimates. A highly justifiable recommendation, which details the benefits and drawbacks of the chosen alternative against the other options. A decision support system that is transparent concerning the rationale the system uses to provide recommendations.

(continued)

Table 10.1 (continued)

Type of decision situation	Requirements for the evaluation
Selection of a portfolio of health security projects	A comprehensive assessment of all the relevant consequences, which enables a like-for-like comparison between the projects. A transparent valuation of the evidence in favor and against each project and of the priorities in reaching conflicting objectives. An unbiased evaluation of each project, which employs: high quality evidence, a clear distinction between judgments and facts, and debiased estimates. An unbiased assessment of synergies, contingencies and frictions among projects. A highly justifiable portfolio of selected projects, which details: the benefits and drawbacks of the chosen options against the excluded options, the rationale for the inclusion or exclusion of each option into the portfolio, and the assumptions made in the assessment.

requirements of the respective evaluation. A similar classification of the types of decision situation can be made for the second category of health security decisions, health threats, as discussed next.

10.2.2 Identifying the Types of Decision Situations: Health Threats

For the first four types of decision situations for decision alternatives, an analogous classification of the types of decision situations can be made for the evaluation and prioritization of health threats. Each type is described and exemplified briefly below:

Selecting the Health Threat to Target The first type of decision situation entails the choice as to which threat should be targeted. An example of this type of decision problem is formed by the project that we developed for the FAO and WHO, for the prioritization of low-moisture food categories, considering their health and economic impacts as well as vulnerabilities in food production and in food consumption (FAO/WHO, 2014; Montibeller, 2018).

Ranking of Health Threats The second type of decision situation entails the ranking of health threats. There exists a growing number of these rankings being reported in the literature, albeit many of the evaluation models lack the properties necessitated by a proper health decision analysis. Indeed, we conducted a detailed critical review and a simulation study that has highlighted the conceptual and practical shortcomings brought about by many of these applications (Montibeller et al., 2020b), despite the promising nature of the process of ranking health threats, which can support the enhancement of health security (Del Rio Vilas et al., 2011).

Categorization of Health Threats The third type of decision situation entails the classification of health threats into categories. A health decision analysis provides a strong framework for such a decision evaluation, the robustness of which well exceeds the simplistic risk matrices (Cox Jr., 2008; Thomas et al., 2014). The threats can be evaluated on multiple attributes, and risk levels can be established in order to classify health threats by considering both multiple impacts and competing priorities. This type of analysis is illustrated later on in this chapter.

Execution of Recursive Evaluations of Health Threats The fourth type of decision situation involves the development of decision support systems for the regular prioritization of health threats. We have been heavily involved in the development of these systems, such as that which was developed for DEFRA for the regular assessment and ranking of emerging animal health threats (Del Rio Vilas et al., 2013; Jaspersen & Montibeller, 2015) and for the regular assessment and prioritization of bio-security threats (Montibeller, 2018; Montibeller et al., 2020a).

In Table 10.2 we specify the four types of decision situations and the requirements for the evaluation of health threats, based on the benefits of a high-quality health decision analysis, which has been discussed in second chapter. Once the type of decision situation has been identified, this Table can be used to assess the requirements for the respective evaluation.

The classification presented in this section may support the identification of the type of decision situation that is being confronted by the health security team. Furthermore, this classification may also guide the development of evaluation models that can achieve the requirements listed in Table 10.1 (for the assessment of health security actions) and in Table 10.2 (for the evaluation of health threats). In the next section, we detail the ways in which a health decision analysis can be used and adapted to support each type of decision situation.

10.3 Conducting a Health Decision Analysis for Each Type of Decision Situation

In this section, we demonstrate how each type of health security decision situation can be adequately supported by the evaluation of options to improve health security or by the assessment of health threats in a health decision analysis. We assume that the health security actions, or the health security threats, have been thoroughly evaluated and valued. Specifically, in conditions of low uncertainty, that the value of every health security action or the dis-value of every health threat has been measured. Likewise, in conditions of high uncertainty, we assume that the expected value of every health security action or the expected dis-value of every health threat has been assessed.

Table 10.2 Types of decision situations and their evaluation requirements for health threat management

Type of decision situation	Requirements for the evaluation
Selecting the health threat to target	A comprehensive assessment of all the relevant impacts, which enables a like-for-like comparison between the threats. A transparent valuation of both the evidence about each threat and of the priorities in minimizing different consequences. An unbiased evaluation of each threat, which employs: high quality evidence, a clear distinction between judgments and facts, and debiased estimates. A highly justifiable choice of the targeted threat, which details: the multiple impacts of the chosen threat against the other threats under consideration, the rationale for choosing the threat to be targeted, and the assumptions made in the assessment.
Ranking of health threats	A comprehensive assessment of all the relevant impacts, which enables the ranking of threats. A transparent valuation of the evidence pertaining to each threat and of the priorities in minimizing different impacts. Additionally, there exists a clear metric for ranking the threats. An evaluation that performs an unbiased assessment and ranking of the threats, is based on debiased judgments, and promotes high quality expert estimates. A highly justifiable ranking of the threats, which details: their multiple impacts, the rationale for their ranking, and the assumptions made in the assessment.
Categorization of health threats	An exhaustive set of categories that are aligned with the decision framing and clear risk levels. A comprehensive assessment of all the relevant impacts caused by the threats, which enables the allocation of each threat to one specific category. A transparent valuation of the evidence for each health threat and of the priorities for minimizing consequences, both of which relate to the categories. An unbiased evaluation of the fit of each health threat for every category, employing high quality evidence, a clear distinction between judgments and facts, and debiased estimates. A highly justifiable categorization, which details: the fit of each threat for every category, the rationale for their classification, and the assumptions made in the assessment.
Execution of recursive evaluations of health threats	A systematic assessment of all the relevant consequences, which enables a like-for-like comparison between the threats and periodic updates with new data. A decision support system that transparently values the evidence for each threat and records the different impacts that each threat may cause. A decision support system that performs an unbiased assessment of the threats, is based on debiased judgments, and promotes high quality expert estimates. A highly justifiable recommendation, which details: the impacts of each threat and the rationale for the choice of a targeted threat, or, for the ranking of threats. A decision support system that is transparent about the rationale the system uses to provide recommendations.

10.3.1 Selecting a Single Health Security Option or Targeting a Single Threat

The selection of a single option in decisions regarding health security actions, or the selection as to which single health threat to target are both supported by a similar type of evaluation. Here, we consider the two situations in sequence and provide an example as to how an evaluation of overall value can support the selection of a single option, followed by an illustration as to how an assessment of overall dis-value can support the selection of a health threat to target.

Selecting a Single Health Security Option Selecting a single decision alternative can be directly supported by a multi-attribute value analysis, which considers the performance of each decision alternative on every fundamental objective, as we have detailed in the eighth chapter. If uncertainties were to be relevant, then the distributions of performance could be estimated over a small number of scenarios in a decision tree, or instead, continuous distributions can be defined for a more precise modeling of dispersion, as we have described in the ninth chapter. The expected value can then be calculated for each decision alternative.

The vaccination campaign case can be used to illustrate the way in which this value analysis may support the choice of a single option. The results of the overall analysis (which have been presented in the eighth chapter) are reproduced in Fig. 10.6a, with Alternative A_3 providing the highest overall value, with $V(A_3) = 62.3$ value points. A sensitivity analysis pertaining to the attribute weights can reveal the extent to which the solution proves robust against changes in health security priorities, such as those which affect *campaign cost* weight, which is shown in Fig. 10.6b. If slight variations from the baseline weight ($w'_4 = 15.0\%$) are able to change the best solution (such as shifting the weight allocated to campaign cost above the threshold $w'_4 = 19.6\%$ in the same figure, which would lead to A_1 becoming the preferable option), then the health security team must carefully consider their priorities. On the other hand, if the model is insensitive to slight recessions from the baseline weights, then the team experiences to reach an agreement as to the precise weights.

In the ninth chapter, the evaluation of these alternative vaccination strategies has been enriched with the consideration of dispersion of performances. There, we have detailed the process of a Monte-Carlo simulation in order to estimate the expected value of each option with 1,000 iterations. The boxplot of the simulation results is shown in Fig. 10.6c, with alternative A_3 having the highest expected value ($EV(A_3) = 62.0$) followed by A_1 ($EV(A_1) = 59.8$).

The dispersions in the simulation results in Fig. 10.6c indicate some overlap between the expected value of the two leading options: A_3 and A_1. Hence, there exists some risk of selecting A_3, the decision of which must be contemplated by the health security team. Indeed, an analysis of these results reveals that in 194 iterations (out of a total of 1,000 iterations), A_1 had a higher overall value than alternative A_3. Therefore, the risk of selecting A_3 despite the possibility that A_1 could turn out to be a better alternative is 19.4%.

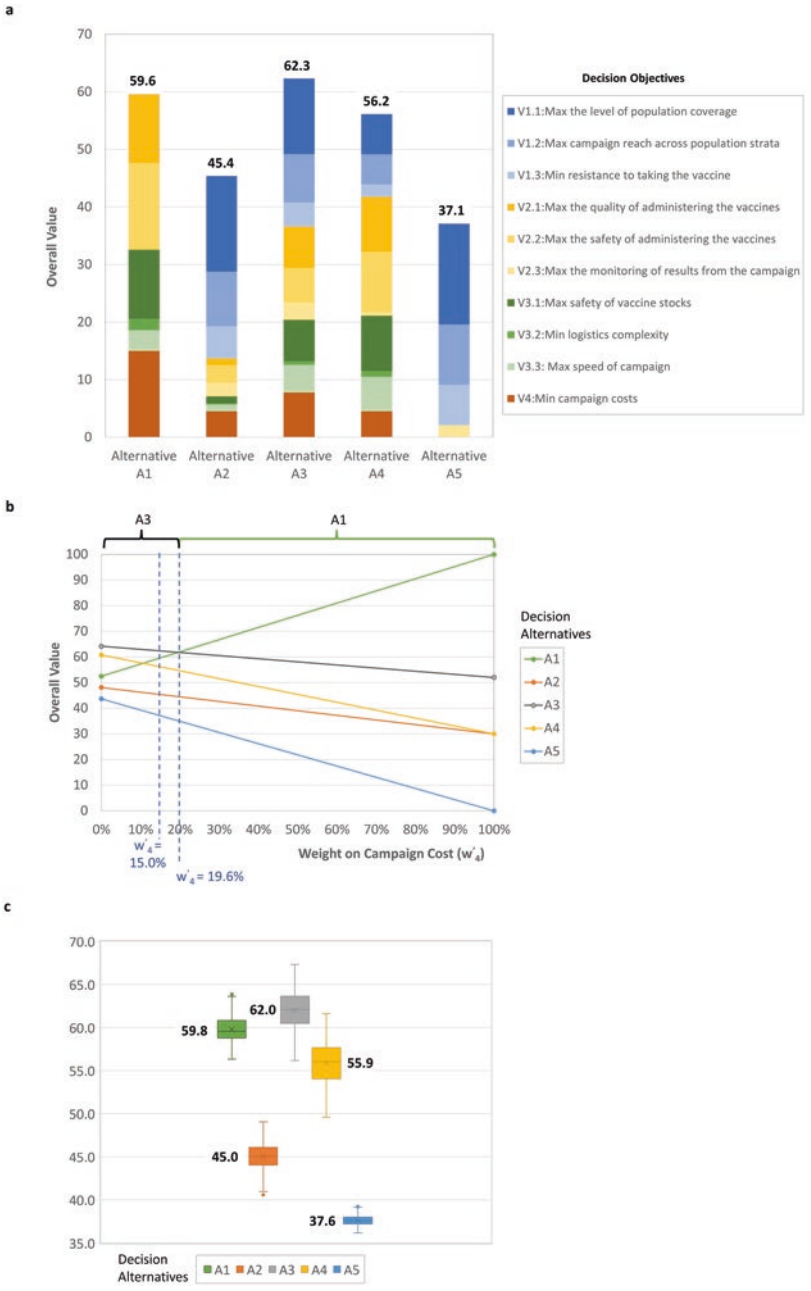

Fig. 10.6 Health decision analysis of the vaccination campaign case: (**a**) Overall value of vaccination strategies, (**b**) Sensitivity analysis on the campaign cost weight, (**c**) Results from the Monte-Carlo simulation

Selecting a Health Threat to Target A similar evaluation to that which is described above can be used to assess health threats, so that the top threat can be targeted. One example wherein this type of evaluation was conducted is formed by the project that we developed for FAO/WHO, for the prioritization of low-moisture food categories, through considering their health and economic impacts and vulnerabilities (FAO/WHO, 2014; Montibeller, 2018). Here, the decision entailed selecting as to which single low moisture food category (among seven categories) should be recommended to CODEX Alimentarius for more stringent risk regulations.

The value assessment of these low-moisture food categories has been detailed in the ninth chapter. Figure 10.7a reproduces that Category 1 (*cereals and grains*) had the highest overall normalized impact (58.3 points) followed by Category 4 (*dried protein products*), with a value of 54.5 points. A sensitivity analysis can help to establish the extent to which the results prove robust against changes in priority. For instance, as presented in Fig. 10.7b, an increase in the *international trade* impact weight, from its baseline level (16.7%), would not alter the selection of Category 1, the category of which is ranked the highest. On the other hand, a reduction from the baseline level is not realistic, given the size of these markets in billions of dollars.

The uncertainty in this evaluation of low-moisture food categories arose from the absence of data for the estimation of some impacts (C3.3, C4.1, and C4.2) for each food category. These estimates were provided instead by expert judgment. We conducted a sensitivity analysis on their lower most likely (ML) estimates and upper most likely estimates from the experts, as shown in Fig. 10.7c; Category 4 has the highest overall normalized impact under these two sets of estimates, followed by Category 1. These results suggest caution is required when selecting the top category and indicate that further data analysis may be necessitated to reduce the dispersions of these impact assessments, the occurrence of which is due to the limited availability of data.

10.3.2 Ranking of Health Security Options or Health Threats

The ranking of health security options, or, of health threats, can be supported by a similar evaluation structure that has been suggested for the previous decision situation. The assessment of the overall value provides a full ranking of decision alternatives, and the ranking of overall dis-value provides a full ranking of health threats. The main distinction in this health decision analysis, in comparison with the selection of a single option, arises from a concern about the stability of the ranking. The ranking may be subject to changes if different priorities are to be considered for the multiple impacts in the value model (Montibeller et al., 2020b), or if the probability of occurrence of threats were different to baseline estimates of probabilities (Jaspersen & Montibeller, 2015). In the subsequent text, we illustrate the use of this evaluation structure for the ranking of decision alternatives, which is then followed by the ranking of health threats.

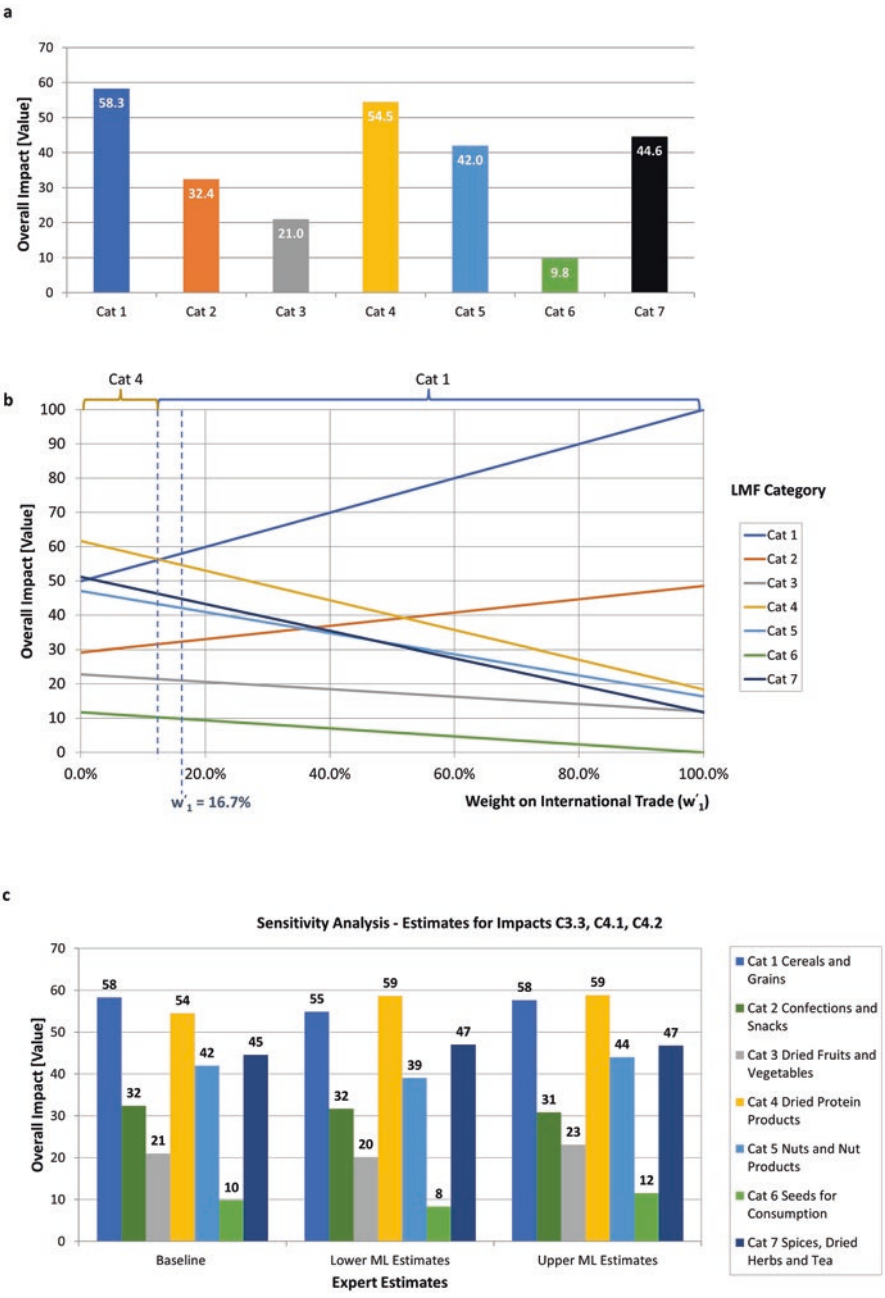

Fig. 10.7 Health decision analysis for the low moisture food category ranking (Montibeller, 2018): (**a**) Overall impact of the food categories, (**b**) Sensitivity analysis of the results on the international trade impact weight, (**c**) Sensitivity analysis of the expert estimates of impacts

Ranking of Health Security Options The value assessment employed to support the selection process of a decision alternative can be illustrated by the vaccination campaign case. The overall value of each decision alternative (shown in Fig. 10.6a) provides a ranking of the vaccination campaign strategies. The extent to which the ranking proves sTable could also be assessed for these results for two types of model parameters: attribute weights and dispersion of performances of the decision alternatives.

The extent to which this ranking proves sensitive to different priorities can be explored through realizing a sensitivity analysis on attribute weights, as Fig. 10.6b illustrates. For example, as the graph shows, the ranking remains sTable for any weight that is lower than the threshold weight ($w'_4 \geq 19.6\%$). The sensitivity of this ranking to the uncertainties pertaining to the performances of decision alternatives can be explored by a Monte Carlo simulation, which provides a possible dispersion of performances as shown in Fig. 10.6c. Overlaps between the box plots of two decision alternatives indicate the probability of alterations in their ranking. For example, there exists a 19.4% chance that the overall value of alternative A_1 surpasses the overall value of alternative A_3 in this analysis.

Ranking of Health Threats The model for ranking emerging animal health threats that we developed for DEFRA can illustrate as to how the dis-value assessment of impacts may support the ranking of health threats. In the ninth chapter, we have detailed the four hypothetical threats (T_1, T_2, T_3, and T_4) that were evaluated using this evaluation model, which considers four main impacts (*impact on public health*, *impact on animal welfare*, *impact on wider society*, and *impact on international trade*), and subsequently, the overall dis-value of each health threat was calculated. The results are reproduced in Fig. 10.8a. Moreover, the probabilities of occurrence of each threat were estimated ($p_1 = 0.3$, $p_2 = 0.8$, $p_3 = 0.7$, and $p_4 = 0.9$, respectively) and their overall expected dis-value was also calculated, as presented in the same figure. The overall dis-value provided a full ranking of the threats.

The same case can also be used to demonstrate the extent to which the ranking of the threats proves sTable. A sensitivity analysis on the attribute weights of the four impacts enables decision makers to verify the extent to which this ranking proves to be robust to different health security priorities. This analysis, which is similar to that which has been detailed in the eighth chapter, is shown in Fig. 10.9 for the *expected* dis-value of each health threat. The baseline weights of the value model are also shown as dashed lines in those graphs (42.6% for the *impact on public health*, 17.0% for the *impact on animal welfare*, 31.9% for the *impact on wider society*, and 8.5% for the *impact on international trade*). Vertical dashed lines also indicate the weight thresholds were the ranking of threats would change.

For the *impact on public health*, this impact would necessitate that the weight exceeds the baseline level (42.5%) and extend beyond 63% in order for there to occur an alteration to the ranking (the point at which Threat T_3 becomes the highest ranked impact, instead of Threat T_2), the occurrence of which proves to be a substantial increase to this priority. For the *impact on animal welfare*, the ranking remains unaltered regardless as

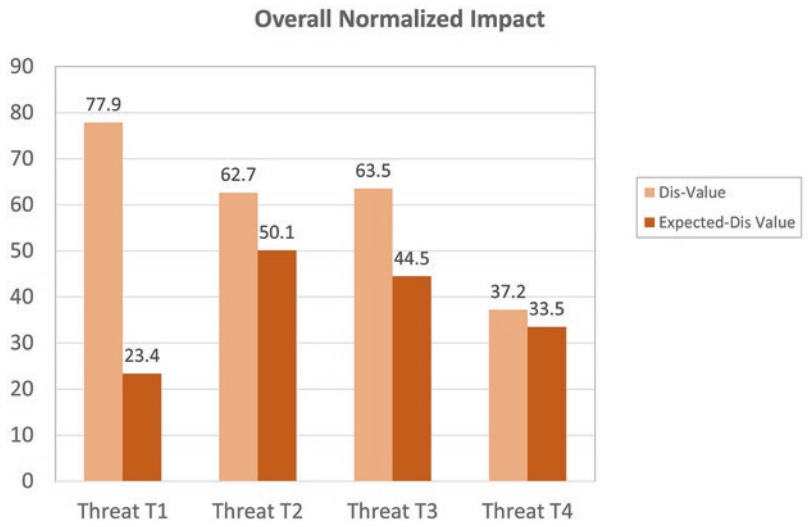

Fig. 10.8 Evaluation of four hypothetical emerging animal health threats (dis-value and expected dis-value of each threat)

to the weight allocated to this impact, and thus, Threat T_2 remains the highest ranked impact. If we consider the *impact on wider society*, once again, we see that this attribute weight would require that the weight substantially exceed the baseline level of 31.9% and extend beyond 66% for there to occur an alteration to the ranking (the point at which Threat T_4 is rendered the highest ranked impact). Finally, when we consider the *impact on international trade*, an alteration to the ranking would occur only if this attribute weight were to exceed 95%, the level of which proves to be well above the baseline level of 8.5%. Therefore, this sensitivity analysis makes clear that the ranking proves very robust to any minor imprecisions pertaining to the health security priorities.

We could also assess the extent to which this ranking proves robust to uncertainty pertaining to the actual probability of the occurrence of each threat. Evidently, these probabilities area difficult parameter to estimate in practice, given that the evidence available is limited and that, for many diseases, outbreaks seldom occur. Hence, it proves important that a sensitivity analysis be performed to assess the stability of the ranking. One common way to explore this robustness entails the use of a Monte Carlo simulation, the process of which has been detailed in ninth chapter.

Let us consider the ranking of emerging animal health threats based on expected dis-value, which is shown in Fig. 10.8. Let us assume that there exist uniform distributions for each probability estimate, wherein the mean is provided by the baseline probability and the bounds are defined as ±0.1. In this scenario, the probability of occurrence for the first threat (T_1), whose baseline probability is $p_1 = 0.3$, is simulated within the range: $0.2 \leq p_1 \leq 0.4$, the pattern of which proves similar for the other threats from their respective baseline probabilities. The simulated expected dis-value for the four threats for 1,000 iterations is shown in Fig. 10.10. The overlaps between the distributions of two alternatives indicate that there occur

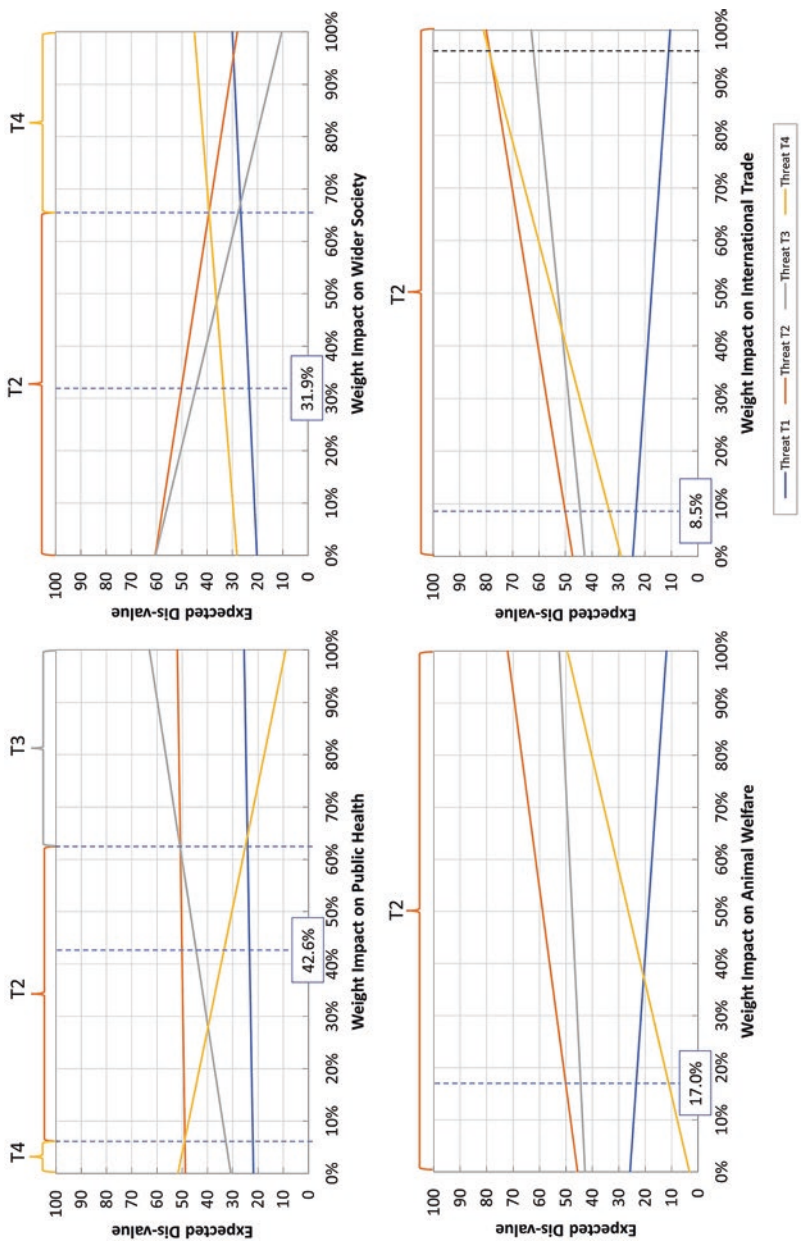

Fig. 10.9 Sensitivity analysis on each impact weight for the emerging animal health threat ranking (vertical dashed lines indicate the baseline weight of the impact and weight thresholds where the ranking of threats would change)

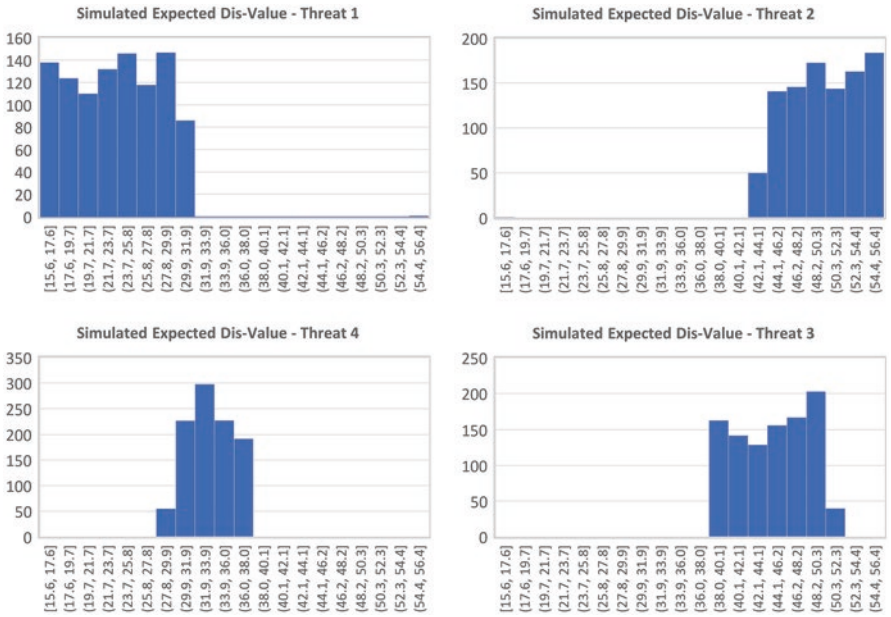

Fig. 10.10 Monte-Carlo simulation results (1000 iterations) for the overall impact of each hypothetical emerging animal health threat

alterations to the ranking. For instance, notice that there exists an overlap of overall impact (expected dis-value) between Threat T_2 and Threat T_3. Indeed, in 171 iterations, the latter threat receives a higher overall value score than the former, therefore, given these levels of uncertainty pertaining to the probability of occurrence, there exists a 17.1% chance that T_3 would be ranked first.

10.3.3 Categorizing Health Security Options or Health Threats

Value models can inform sophisticated classifications of decision alternatives or health threats. The allocation of items to specific categories proves a less common, but highly relevant type of decision analysis (Roy, 1996) for health security problems, particularly for health threats. In health security evaluations, such classifications are often based on qualitative labels ("high risk" or "low risk") or semi-qualitative risk matrices. As we have previously discussed in the first chapter, these evaluations prove to be simplistic classifications of threats, and may fail to adequately identify risks, and as a consequence, may underpin misleading recommendations for policymakers to follow. In this section, we reverse the order of discussion, covering first the categorization of health threats, which is then followed by the categorization of health security options.

Classification of Health Threats into Categories Let us revisit the value model for ranking emerging animal health threats for DEFRAand demonstrate as to how risk categories can be defined for this model. The first step entails identifying, with the health security team and health experts, *reference levels* on each attribute that characterizes the boundaries of impact. For instance, for *the impact on public health* attribute shown in Fig. 10.11a, any impact that reaches or exceeds reference level L8 (high risk level) would be considered to be very high risk, any impact that reaches or exceeds reference level L5 (medium risk level) would be considered to be high risk, any impact that reaches or exceeds reference level L3 (low risk level) would be considered to be medium risk, and any impact below this latter level would be considered to be low risk. A similar classification has been employed for the

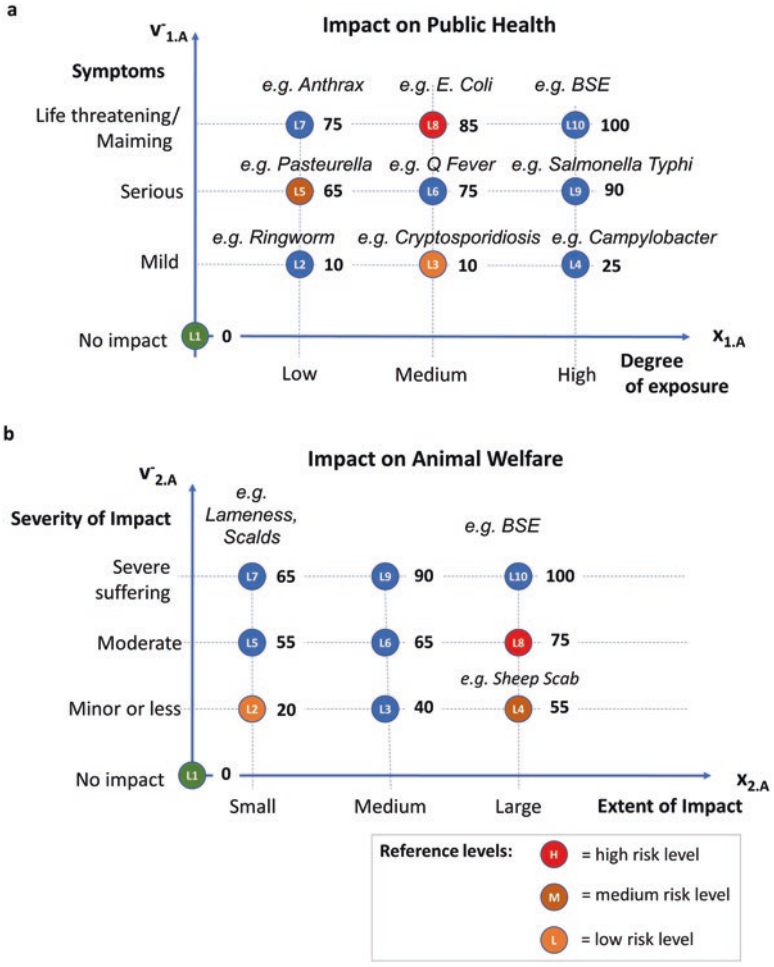

Fig. 10.11 Reference levels for the four types of impact in the value model to assess emerging animal health threats: (**a**) Impact on public health, (**b**) Impact on animal welfare

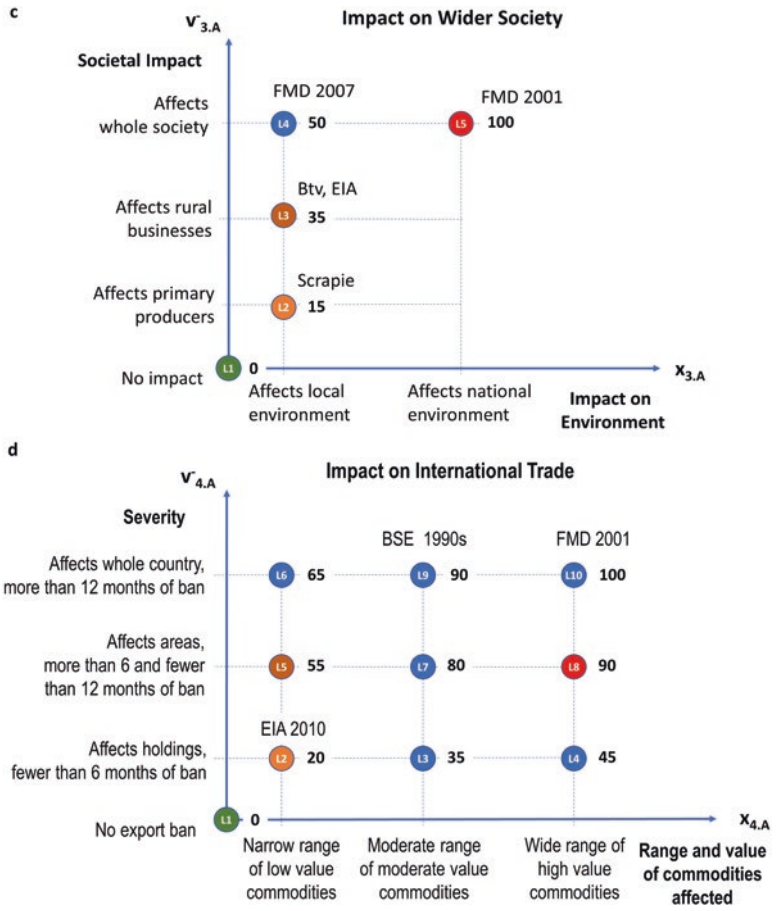

Fig. 10.11 (continued) Reference levels for the four types of impact in the value model to assess emerging animal health threats: (**c**) Impact on wider society, (**d**) Impact on international trade

other three attributes, as displayed in Fig. 10.11b (*impact on animal welfare*), Fig. 10.11c (*impact on wider society*), and in Fig 10.11d (*impact on international trade*).

The combination of these reference levels for the four attributes provides a *risk profile*. This risk profile indicates the impacts of a hypothetical health threat which would trigger those impacts were an outbreak to occur. For instance, for the high risk reference level, this threat (T_{HR}) would trigger a level L8 impact on the first attribute ($v^{-}_{1.A}(L8) = 85$, see Fig. 10.11a), level L8 on the second attribute ($v^{-}_{2.A}(L8) = 75$, see Fig. 10.11b), level L5 on the third attribute ($v^{-}_{3.A}(L5) = 100$, see Fig. 10.11c), and level L8 on the fourth attribute ($v^{-}_{4.A}(L8) = 90$, see Fig. 10.11d). The overall dis-value of this threat can be calculated using Eq. 8.4 from the eighth chapter by employing these dis-value scores and the baseline weights of the model:

$$V^{-}\left(T_{HR}\right) = 0.426v^{-}_{1.A}\left(T_{HR}\right) + 0.170v^{-}_{2.A}\left(T_{HR}\right) + 0.319v^{-}_{3.A}\left(T_{HR}\right) + 0.085v^{-}_{4.A}\left(T_{HR}\right);$$

$$V^{-}_{A}\left(T_{HR}\right) = 0.426\,(85) + 0.170\,(75) + 0.319\,(100) + 0.085\,(90) = 88.9.$$

The overall dis-value of the other risk profiles have been calculated in the same manner.

These four risk profiles are displayed along the evaluation of the four health threats in Fig. 10.12. Notice that the expected dis-value for all four emerging animal health threats exceed the low risk threshold (14.1 points). Indeed, two health threats are located close to the high-risk threshold (52.9 points), and, if their probability of occurrence were to increase marginally, these two threats would be classified as high risk.

Regarding the case of an imminent outbreak of one of these threats, also notice that the probability of a threat would shift from the baseline probability level to 100% (since at this point, the threat is undoubtedly occurring) Hence, in this case, the expected dis-value of this threat would be identical to its actual dis-value. For example, for threat T_1, this scenario would occur were the baseline to shift from $p_1 = 0.3$ to $p_1 = 1.0$ and, thus the expected dis-value of this threat is: $EV^{-}_{A}(T_1) = p_1 V^{-}_{A}(T_1) = 1.0\,(77.9) = V^{-}_{A}(T_1) = 77.9$. In such a scenario, this threat would be classified as high risk, the event of which is demonstrated by the dis-value analysis in Fig. 10.12. The same effect would occur for threats T_2 and T_3, if each were to

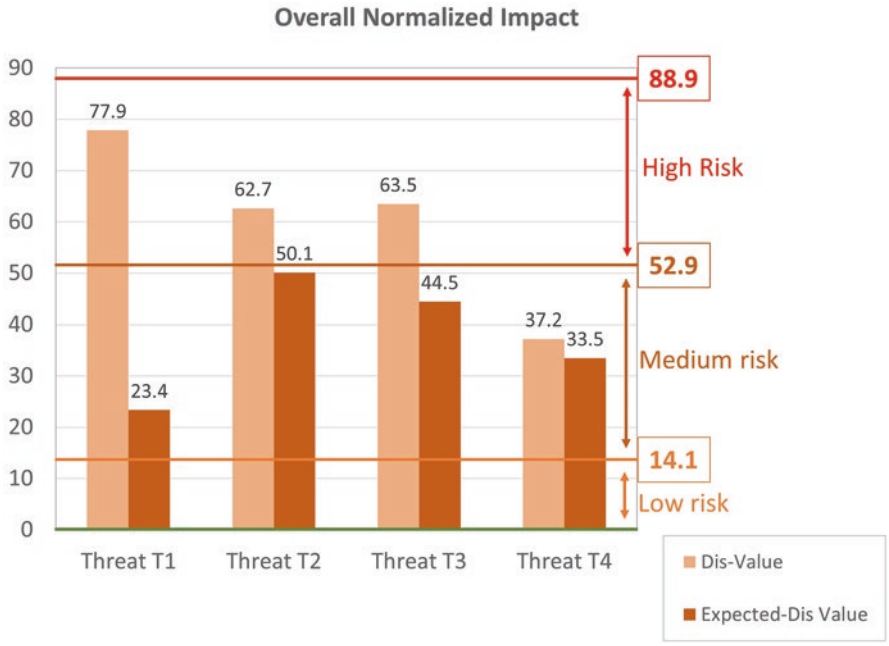

Fig. 10.12 Risk categories and the evaluation of four emerging animal health threats

imminently occur, as these threats would exceed the high-risk threshold: $EV^{-}_{A}(T_2) = p_2\, V^{-}_{A}(T_2) = 1.0\ (62.7) = 62.7$ dis-value points and $EV^{-}_{A}(T_3) = p_3\, V^{-}_{A}(T_3) = 1.0\ (63.5) = 63.5$ dis-value points. This last example illustrates the dynamic use of a categorization model, which can be particularly useful if the model were implemented as a decision support system for recurrent evaluation and ranking of threats, as well as for underlining imminent outbreaks whose consequences are severe, and therefore require urgent actions to be taken.

This case involving the categorization of emerging animal health threats illustrates a robust way of classifying health threats. The classification is able to: take into account the health security priorities, consider risk levels in relation to multiple impacts, enable the use of probabilistic information, and reduce the ambiguity of impact assessment. These benefits stand in stark contrast to the ambiguously defined qualitative risk labels (Budescu & Wallsten, 1985; Wallsten et al., 1986) or the poorly conceptualized assessments of impacts and likelihoods, which utilize 1-to-5 scales in risk matrices (Cox Jr., 2008; Thomas et al., 2014).

Categorization of Health Security Options into Categories A similar categorization scheme to that which is employed above for categorizing health threats can be used for categorizing decision alternatives (Bana e Costa & Oliveira, 2002). In this case, *performance profiles* should be defined, in a manner similar to that which defines risk profiles for health threats, which has been exemplified in Fig. 10.11. These performance profiles, with reference levels on each attribute, can be used to demarcate the different categories to which each option is allocated to, which we again see is a process that functions in a similar manner to that which demarcates low/medium/high risk categories shown in Fig. 10.12 for health threats.

For example, options that seek to improve health security could be categorized in this way as either being of high/medium/low priority, based on the multi-attribute performance profiles that establish the overall value of each category and on the overall value of each decision alternative. This type of categorization allows for a greater degree of transparency and quality of the evaluation in comparison with the loosely defined qualitative labels, which are employed at times to classify health security actions and projects.

10.3.4 Conducting Recurrent Health Security Evaluations with Decision Support Systems

The three types of decision situations covered so far in this section all constitute processes that occur once, in that either a choice must be made among the possible alternatives to improve health security, or a single health threat must be selected to be targeted. Likewise, either the ranking of options or of health threats is required, and decision alternatives must be categorized or health threats must be adequately classified. However, in many decision processes, choices are recurrent, in that these selection processes must be repeated more than once, for instance, a quarterly

selection of a decision alternative, a monthly ranking of risk mitigating options, or the periodic categorization of health threats and so on.

Consequently, when undertaking cases wherein repetitive choices must be made, decision analysis models can be developed the one time and later implemented as decision support systems (DSSs) (Barcus & Montibeller, 2008; Kou et al., 2011; Montibeller et al., 2020a). We have used this type of approach frequently to support health security teams and have found them to be highly beneficial in increasing the quality of assessment and improving decision making processes, while simultaneously reducing the time and effort that is required for developing single-use decision models, as the same decision model can be used each and every time.

This type of application is exemplified by the decision support system that we developed for DEFRA, for the recurrent ranking of emerging animal health threats (Del Rio Vilas et al., 2013; Montibeller et al., 2020a). The value models for assessing actual impacts and perceived impacts (which have been described in the eighth chapter), as well as a similar model to assess the DEFRA capabilities against each threat, were all implemented, thereby forming a decision support system. The system enables the input of evidence from various different risk manager portfolios (for example cattle, exotic species, global animal health, etc.) for each emerging health threat. The system also functions as a platform on which to execute the expert assessment of impacts that each threat may cause, alongside a capability assessment as to how prepared DEFRA is against each threat. Threats are ranked in terms of their overall impacts and their perceived impacts against capability levels. The system is used monthly to analyze the current threats and provide recommendations to the Chief Veterinary Officer. As mentioned previously, since implementation in 2009 and further development and improvements during 2011–2016, the decision support system has supported DEFRA in analyzing more than 218 emerging animal health threats to the UK (Montibeller et al., 2020a).

There exist several benefits of employing a decision support system for guiding recurrent health security decisions. First, the systems allow for less time and effort to be allocated to certain processes as the development of a health decision analysis model is a single-time event Second, decision support systems enable consistency, the characteristic of which positively affects the decisions made, as the system is partly formed by standardized assessments of impacts and performances, and coherent valuations of decision alternatives or health threats. Third, said systems provide records as to previous decisions which have been made, and historical records of the assessments, both of which can be used to further improve the decision processes and assessments.

10.3.5 Selecting Portfolios of Health Security Projects

Thus far, in this book, we have considered choices that are contained in a single project, for instance the selection of the best vaccination strategy or of the best risk mitigating action against a health threat. Consequently, we have seen the ways in

which a health decision analysis can aid health security teams to identify the option(s) with the highest expected value. To extend this framework, we should consider a *portfolio* of projects to enhance health security, which must be funded from a limited overall investment budget among all the projects being considered for improving health preparedness. Indeed, this type of decision is highlighted in a World Health Organization framework specific to health systems for health security, which stresses the importance of prioritizing actions and investments for enhancing health security at a country level (WHO, 2021).

The allocation of resources among a number of possible projects has been extensively researched for Research & Development project selection (Heidenberger & Stummer, 1999; Verbano & Nosella, 2010). In public decisions, Portfolio Decision Analysis (Montibeller et al., 2009; Montibeller & Franco, 2011; Salo et al., 2011) has been extensively employed to select projects with multiple impacts in a manner that seeks to maximize the value-for-money of the portfolio of selected projects. In health assessments, this type of evaluation has been frequently used for supporting pharmaceutical companies evaluate and select their drug development portfolio (e.g. Phillips & Bana e Costa (2007)).

An example can illustrate as to how a portfolio decision analysis can support the prioritization and the selection of projects. Let us posit that there exist 11 possible projects for improving health security, involving projects such as vaccination campaigns, investments to expand ICU capacity, health education campaigns, track-and-trace systems, and so on. A value model has been developed to assess the expected benefits of each project, as described in the eighth chapter.

Utilizing this value model, and under conditions of uncertainty, the overall expected benefit for each project has been calculated and has been measured on expected value, as shown in Table 10.3. This same Table also presents the estimate of the implementation cost for each project Notice that in portfolio decision problems, we do *not* include the implementation cost in the evaluation of overall value. Were all the projects to be implemented, the total cost of this implementation would amount to $185 million, which would bring about a total expected benefit of 278 value points. However, let us assume that there were to be only $75 million available for funding these projects. Consequently, given these constrained resources, which projects should be selected to maximize societal value?

A practical solution to this decision problem involves calculating the expected benefit/cost ratio of each project. Having derived results from these calculations, we are subsequently able to rank the projects in descending order according to this value-for-money metric, as shown in Table 10.4. Cumulative costs are also calculated, and projects that lie within the budget are sequentially included in the portfolio, and these projects are classified according to their position among the highest to the lowest value-for-money ratio: Project 03, Project 07, Project 10, Project 06, Project 04, and Project 05. When the cumulative cost reaches the budget limit ($75 million), the inclusion of projects is halted. The cumulative expected benefit of this portfolio is 136 expected value points. Using this prioritization rule, we know that several projects cannot be funded and are excluded from the portfolio, as they

Table 10.3 Projects to improve health security for portfolio selection

Project	Implementation Cost (C_k) [$million]	Expected Benefit (B_k) [expected value]
Project 01	20	30
Project 02	40	50
Project 03	1	5
Project 04	5	10
Project 05	60	100
Project 06	1	3
Project 07	2	8
Project 08	30	40
Project 09	20	20
Project 10	3	10
Project 11	3	2
Total cost	**185**	**278**

Table 10.4 Prioritization of health security projects according to their value-for-money (descending order)

Project	Implementation Cost [$million]	Expected Benefit [expected value]	Value-for-Money Ratio [expected value/$million]	Cumulative Costs [$mi]	Cumulative Expected Benefit [expected value]	Included in the Portfolio Value-for-Money ratio (Yes/No)?	Included in the Portfolio Knapsack Optimization (Yes/No)?
Project 03	1	5	5.0	1	5	Yes	Yes
Project 07	2	8	4.0	3	13	Yes	Yes
Project 10	3	10	3.3	6	23	Yes	Yes
Project 06	1	3	3.0	7	26	Yes	Yes
Project 04	5	10	2.0	12	36	Yes	Yes
Project 05	60	100	1.7	72	136	Yes	Yes
Project 01	20	30	1.5	92	166	No	No
Project 08	30	40	1.3	122	206	No	No
Project 02	40	50	1.3	162	256	No	No
Project 09	20	20	1.0	182	276	No	No
Project 11	3	2	0.67	185	278	No	Yes

exceed the required budget, as shown in the same Table: Project 01, Project 08, Project 02, Project 09, and Project 11.

While this value-for-money ratio analysis proves simple and straightforward to perform and explain, this decision rule fails to guarantee an optimal allocation of resources. For instance, if we look closely at Table 10.4, after the inclusion of the last project (Project 05), we see that $3 million in the budget are left unused. However, despite the fact that Project 11 occupies the last position in terms of the ranking of value-for-money projects, this Project 11 could also be funded as this option proves to be affordable and could thus be included within the portfolio. Conducting this manual insertion is relatively easy when managing a small number of projects but ultimately proves difficult to be performed if a great number of projects were being considered, the latter case of which occurs frequently in health security decision situations.

A more generalizable approach involves formulating this evaluation as a knapsack optimization problem. Let us consider the expected benefit (B_k) of each project and the implementation cost (C_k) for each k-th project, the values of which are shown in Table 10.3. The overall budget is given by C. A binary variable x_k is associated with each project, which would either be set as 1 if the project were to be selected and included within the optimal portfolio, or, which would be set as 0 were the project to be excluded. The total benefit function B is then calculated by:

$$\max B = \sum_k B_k x_k$$

$$\text{Subject to: } \sum_k C_k x_k \leq C.$$

Solving this linear programming model with a computer optimization package would enable the identification as to which projects could be funded by the budget: Project 03, Project 07, Project 10, Project 06, Project 04, Project 05, and Project 11. This optimization guarantees the maximum and most efficient use of the available budget (£75 million) and delivers the portfolio with the maximum cumulative expected benefit (138 expected value points), the assurance of which contrasts directly with the value-for-money ranking rule employed in Table 10.4 (Kleinmuntz, 2007).

When making health security decisions in a joint project with the LSE Department of Health Policy, we have used a portfolio decision analysis for determining as to which essential medicines the UK Department of Health and Social Care should include in their medicinal buffer stocks against pandemics and supply chain disruptions . The value assessment takes into account the demand of each drug and the impact that the drug shortage could cause on patients that require specific medicines. A portfolio model identifies the best portfolio of medicines that could be composed given the £66 million budget limit.

This type of portfolio decision analysis can significantly support initiatives to increase the value-for-money of public choices, thereby maximizing the efficiency of inevitably limited public resources for health preparedness and enhanced health security. One major benefit that arises from utilizing Portfolio Decision Analysis stems from the condition that value can be systematically assessed with a

multi-attribute value model, thereby avoiding the ambiguity often encountered in the assessment of value in value-for-money studies. Another benefit stems from the ability to compare the detrimental effects from the inefficient allocation of resources (which promotes low-value projects for political reasons for instance) to the total value of the optimal portfolio.

In Table 10.5, we summarize the ways in which a health decision analysis can be developed for each type of decision situation that has been discussed in this section. Once a specific decision situation is recognized and the level of uncertainty assessed, the specific cell of the Table can be used to guide the development of the evaluation of health security actions or of health threats, as well as an evaluation of the sensitivity analysis against organizational priorities and/or against estimations of future prospects.

Table 10.5 Health decision analysis for each type of decision situation

Type of decision situation	Uncertainty is relatively low and thus the most likely impact levels can be accurately determined	Uncertainty is relatively high and thus the distribution of impacts must be determined
Selecting a single health security option or targeting a single health threat	Conduct a multi-attribute value analysis to identify the option with the highest overall value, or the health threat with the highest overall dis-value. Conduct a sensitivity analysis on the attribute weights to assess as to whether the chosen option (or targeted threat) remains the highest scorer against different variations of organizational priorities.	Conduct an expected value analysis to identify the option with the highest expected value, or the threat with the highest expected dis-value. Conduct a sensitivity analysis on the attribute weights to assess as to whether the chosen option (or targeted threat) remains the highest scorer against different variations of organizational priorities. Conduct a sensitivity analysis on the estimates for the probability of scenarios to assess as to whether the chosen option (or targeted threat) remains the highest scorer against variations of future prospects.
Ranking of health security options or ranking of health threats	Conduct a multi-attribute value analysis to rank the options based on their overall value, or to rank health threats based on their overall dis-value. Conduct a sensitivity analysis on the attribute weights to establish the robustness of the ranking of options, or of the ranking of threats, against variations of organizational priorities.	Conduct an expected value analysis to rank the options based on their expected value, or to rank the threats based on their expected dis-value. Conduct a sensitivity analysis on the attribute weights to establish the robustness of the ranking of options, or of the ranking of threats, against variations of organizational priorities. Conduct a sensitivity analysis on the estimates for the probability of scenarios to establish the robustness of the ranking of options, or of the ranking of threats, against variations of future prospects.

(continued)

Table 10.5 (continued)

Type of decision situation	Uncertainty is relatively low and thus the most likely impact levels can be accurately determined	Uncertainty is relatively high and thus the distribution of impacts must be determined
Categorizing health security options or categorizing health threats	Conduct a multi-attribute value analysis to evaluate the options and identify performance profiles to classify the options into categories. Similarly, conduct a multi-attribute value analysis to evaluate the threats and identify risk profiles in order to classify the threats into categories. Conduct a sensitivity analysis on the attribute weights to establish the robustness of the categorization of options, or of the categorization of threats, against variations of organizational priorities.	Conduct an expected value analysis to evaluate the options and identify performance profiles to classify options into categories. Similarly, conduct an expected value analysis to evaluate the threats and identify risk profiles in order to classify the threats into categories. Conduct a sensitivity analysis on the attribute weights to establish the robustness of the categorization of options, or of the categorization of threats, against variations of organizational priorities. Conduct a sensitivity analysis on the estimates for the probability of scenarios to establish the robustness of the categorization of options, or of the categorization of threats, against variations of future prospects.
Conducting recurrent health security evaluations with a decision support system	Implement the multi-attribute value analysis as a decision support system, so that recurrent choices/rankings/categorizations can be periodically made. Automate the sensitivity analysis on attribute weights into the decision support system.	Implement the expected value analysis as a decision support system, so that recurrent choices/rankings/categorizations can be periodically made. Automate the sensitivity analysis on attribute weights into the decision support system. Automate the sensitivity analysis on the estimates for the probability of scenarios into the decision support system.
Selecting portfolios of health security projects	Conduct a multi-attribute value analysis to evaluate the projects, estimate the implementation costs of each project, and identify the optimal portfolio of projects. Conduct a sensitivity analysis on the attribute weights to establish the robustness of the portfolio of options against variations of organizational priorities.	Conduct an expected value analysis to evaluate the projects, estimate the implementation costs of each project, and identify the optimal portfolio of projects. Conduct a sensitivity analysis on the attribute weights to establish the robustness of ranking of options against variations of organizational priorities. Conduct a sensitivity analysis on the estimates for the probability of scenarios to establish the robustness of the portfolio of options against variations of future prospects.

10.4 Conclusions: Selecting the Best Options for Enhanced Health Security

This chapter has discussed two topics that had been touched upon in the previous two chapters but ultimately deserved to be discussed in greater detail at this point of the book. First, a thorough evaluation requires inputs, which are formed by the gathering of realistic and reliable evidence about the impacts of health threats and health security actions, as well as by gathering data concerning the performance of options to improve health security. Second, there exist several types of decision situations, and the evaluation process must be adequately adjusted to support each of these situations.

The quality of evidence is crucial for supporting choices in health security decisions, the case of which we have argued in this chapter. There exist three main sources of evidence: studies and surveillance systems, predictive models, and expert opinion. If available, hard evidence should be employed to estimate the possible impacts of health threats and health security actions, as well as the performance of decision alternatives. Since decisions must cope with future events, predictive models play a central role in estimating impacts, and can be used to conduct processes such as epidemiological simulations of disease spread among the population and assessments of the impacts of risk mitigating actions. In many instances, expert opinion can complement or inform such estimates, particularly those which pertain to novel situations, such as emerging health threats, or for impacts wherein only intangible evidence is available. Regardless of the evidence employed, it is crucial that estimates be realistic and reliable, without the interference of motivational and cognitive biases. These requirements necessitate that we employ repuTable expertise, well-designed consultation processes that avoid conflicts of interest or the use of distorted data analyses, and adequate debiasing tools to improve the quality of expert judgment.

The second section of the chapter has highlighted the need to identify the type of decision situation under consideration, as the type influences the defining of fundamental objectives (and associated relevant consequences), as well as the type of evaluation that must be developed in the health decision analysis. With regards to health security actions, there exist five different types of decision situations: (i) the selection of a single option, (ii) the ranking of options, (iii) the categorization of options, (iv) the development of decision support systems to support periodic selection of options, or (v) the selection of a portfolio of projects to improve health security. A similar classification has been suggested to classify decision situations regarding health threats, comprised of four different types of decision situations: (i) the target of a single threat, (ii) the ranking of threats, iii) the categorization of threats into categories, and iv) the development of decision support systems to support recurrent evaluations of health threats.

The three chapters that have elucidated the evaluation, and the subsequent choice of threats and actions have mainly focused on the content of the evaluation models. However, these choices are not taken in an organizational vacuum. Instead,

typically, they are made by groups, the health security team, which is either located within a single organization, or, which has a multi-organizational composition. Furthermore, these choices must be effectively implemented if they are to improve health preparedness and enhance health security. Finally, if we wish to further improve these decision processes and the societal value of our choices then organizational learning proves to be a crucial element of said processes. These group and organizational aspects of deciding upon and implementing the selected decision, as well as systematic learning during decision processes, shall form the subject of the subsequent and final chapter.

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Chapter 11
Deciding and Implementing Health Security Actions and Promoting Systematic Learning



Decision making in health security decisions brings about both technical and social complexities. The three previous chapters have mainly detailed technical aspects that pertain to the evaluation and choice of health security actions and health threats to target. In this chapter, we focus on the social complexities inherent to these choice processes, the discussion of which ranges from the selecting of options to the implementation of health security actions, which is then followed by the fostering of an environment wherein systematic learning (which is associated with high quality decision processes) can take place. If policymakers wish to select decision alternatives in a reasoned manner, these complexities must be fully addressed. In this case, addressing social complexities takes on the form of following high quality choice processes, effectively implementing the chosen actions to enhance health security, and improving current and future decision processes.

The overwhelming majority of health security decisions are made by teams, which are often composed of health experts, risk managers, and policymakers. Hence, we focus on the ways in which health security *teams* can be more effective when making health security decisions. There exists ample behavioral evidence demonstrating that groups may present dysfunctional behaviors, consequently, a key element for more effective decision processes involves knowing how to facilitate teams, the process of which can reduce such behaviors, while simultaneously fostering knowledge exchanges, group productivity, and team motivation.

Even in the case of high-quality decision processes, the ability to effectuate effective and positive changes is rendered unfeasible in situations wherein the best alternatives have not been successfully implemented. Hence, in this chapter, we provide some recommendations as to how to maximize the chances of a successful implementation of health security actions, the subject of which is often neglected in the Decision Analysis literature. Here, we shall argue that addressing these

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implementation challenges necessitates that we improve implementation planning and carefully manage group dynamics.

Throughout the book, we have continued to underscore the importance of achieving high-quality decision processes and reasoned choices in health security situations. The attainment of these two factors should support decision makers to select high-value decision alternatives for enhancing health security, which are able to maximize societal value and minimize negative societal and individual impacts. These decision processes should also foster improved learning about important facets of a decision: a better understanding of the decision situation, an elucidated conceptualization of both the decision objectives and the more prominent relevant consequences, a deeper understanding about the key uncertainties that influence outcomes, and a broader perspective concerning the possible alternatives to improve health security. The ways in which health security teams can learn more effectively and systematically is also discussed in this chapter.

In the second chapter we have presented a diagram that illustrates the decision stages required for making reasoned health security decisions, which is reproduced in Fig. 11.1. The present decision stage, *deciding and implementing choices, and promoting systematic learning*, is now highlighted in this modified figure. We shall assume that the health decision analysis has already been conducted, which has evaluated the (expected) value of health security actions or the (expected) dis-value of health threats.

11.1 Facilitating Choices in Health Security Teams

Most health security decisions are made in groups, typically composed of policymakers, health experts, risk managers, and other relevant stakeholders, such as local authorities, health services leaders, and emergency planning personnel. There exists strong behavioral evidence from Social Psychology demonstrating that many of the choices taken by groups may be affected by dysfunctional group dynamics. We have already mentioned this literature in the third chapter, providing some suggestions as to how group decision making can be improved. In this section we revisit this topic in greater depth, by adopting a specific focus which seeks to address how to reduce dysfunctional group behaviors and minimize group judgment biases in choice processes. These group-related challenges require group work that has been effectively facilitated and group decision processes that have been carefully designed, the combination of which can allow for greater levels of team productivity and an environment that is conducive to high quality decision making. We offer suggestions as to how such goals can be achieved in this section, arguing that a health security team leader take on a more pro-active role to foster reasoned decision processes.

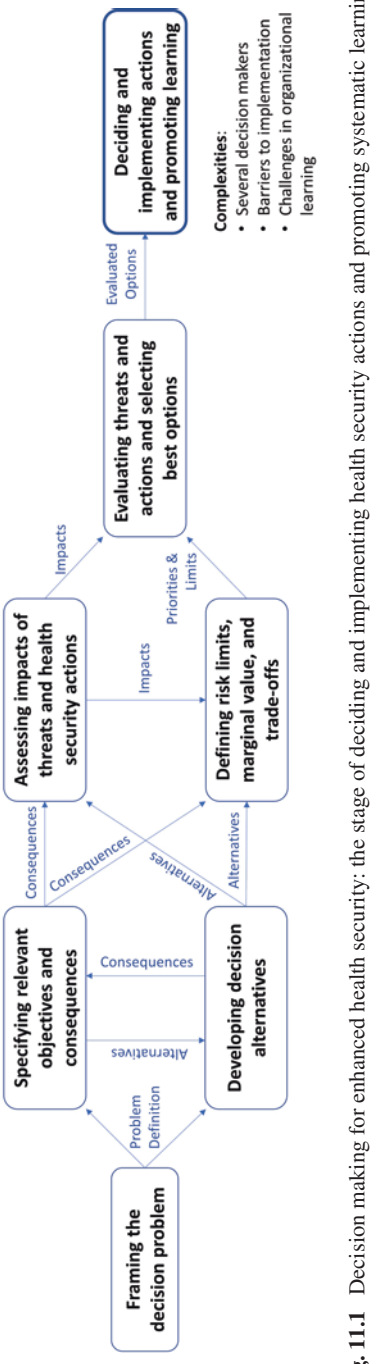

Fig. 11.1 Decision making for enhanced health security: the stage of deciding and implementing health security actions and promoting systematic learning

11.1.1 Observing Dysfunctional Group Dynamics and Biases in Health Security Decisions

There exists ample evidence from Social Psychology demonstrating that group dynamics may bring about many dysfunctional behaviors in decision making as well as assessing the detrimental effects of these behaviors. Relevant dysfunctional behaviors (Kerr & Tindale, 2004, 2011; Wittenbaum & Moreland, 2008) can take the form of: (i) group pressure on individual members to conform to the majority view, (ii) groups that are dominated by a strong, influential, leader, (iii) group inattention to novel or undisclosed information, (iv) dysfunctional shared myopic representations of the decision problem, (v) group motivation losses due to inefficiencies in the group decision process and the disengagement of some members, (vi) and group coordination losses due to the strains inherent to group work when compared with individual-oriented tasks.

In the case of contagious diseases, the many instances wherein medical doctors and scientists have faced resistance regarding novel treatments that have clear benefits exemplifies the detrimental influence that group pressure may exert on health security decision making (Harrison, 2004). Due to a myopic problem representation by the establishment, such resistance retards scientific understanding, and prevents the implementation of health security actions that could otherwise eliminate the disease, or, reduce its transmission. For instance, consider the inoculation campaign against smallpox in Continental Europe, following the successful implementation in England in the 1750s. In France, the treatment was strongly supported by the Royal Academy of Sciences and some pioneering figures such as the physician, Theodore Tronchin. However, the Catholic Church and conservative factions of the medical profession demonstrated resistance to inoculation, the process of which remained erratic in the country until 1902, at which time inoculation became compulsory.

More recently, the detailed account by Calvert and Arbuthnott (2021) chronicles the decision making process and response by the UK government to the COVID-19 global pandemic in early 2020 and illustrates the many group dysfunctionalities that arose. The government was supported by a committee of expert health scientists, which formed the Scientific Advisory Group for Emergencies (SAGE). However, the initial advice pertaining to the seriousness of the threat in early 2020 that was provided by SAGE was allegedly ignored by members of the government, who showed inattention to novel information about the virus and the distressing situation that was unfolding in Italy, as the government considered the health threat to be a "theoretical risk". Following the account of the authors, this disregard for qualified scientific advice, coupled with selective and motivated use of individual experts that espoused the "take no action" solution (which was the solution that was initially preferred by the government) led to delays in acting decisively. This protracted lack of response was reversed only at a time wherein the number of cases and deaths was rendered unacceptable, and the requisite that the first national lockdown be implemented occurred.

Relevant group judgment biases must be minimized, as there exists evidence that they affect group judgments. Montibeller and von Winterfeldt (2018) list five main biases, based on the reviews of forecasting elicitation (Kerr & Tindale, 2011) and of team-based decision making (Jones & Roelofsma, 2000). The first bias is *false consensus*, occurring when individual members of the group overestimate the similarities between their own judgment and that of the other members, leading to judgments that employ incorrect assumptions about the decision problem (Ross et al., 1977). The second bias is *groupthink* (Janis, 1983) occurring when members of very cohesive groups are focused on attaining a consensus on the agreed solution, which is attained by limiting information search and by disregarding other decision alternatives and objectives (Jones & Roelofsma, 2000). The third bias is *group polarization* (Lamm, 1988), occurring when group discussions make prominent the initial individual position or opinion of the majority of its members. This bias may affect the selection of options, particularly if the group were to be initially inclined toward a given option. Group polarization may also affect the risk attitude of groups, rendering the group as a whole more risk-seeking/risk-averse than the individual members as discussions progress (Isenberg, 1986). Another bias is *group escalation of commitment*, occurring when a group supports a course of action that is clearly inadequate, the support of which is exacerbated by groupthink and group polarization. Finally, groups may suffer from *group overconfidence*, which occurs when the judgements of confidence of the group exceeds that of the judgments of confidence of individual group members (Plous, 1995).

Once again, the account provided by Calvert and Arbuthnott (2021) illustrates the ways in which these biases may have arisen during the decision making process of the UK government during their initial response to the COVID-19 global pandemic in February 2020. According to the authors, among the politicians leading the government, there existed a culture of mistrust of external experts, which could be explained by groupthink. The alleged reluctance to consider the scientific advice about the seriousness of the pandemic may be explained by wishful thinking (Chapin & Coleman, 2009; Vosgerau, 2010), which led to group polarization (Jones & Roelofsma, 2000).

These group judgment biases and dysfunctional behaviors may exacerbate individual biases and exert detrimental influences on the quality of the decision processes (Kerr & Tindale, 2004, 2011; Wittenbaum & Moreland, 2008). Groups that are excessively homogenous, or that are led by an influential figure, may define the problem in a very narrow fashion (Legrenzi et al., 1993; Legrezni & Girotto, 1996). Such groups may also ignore relevant decision objectives or consequences (Bond et al., 2008; Keeney, 1992) for the specific decision context, as well as key uncertainties that affect the outcomes (Jargowsky, 2005; Wänke et al., 1995). Even more concerning is the ample behavioral evidence that exists demonstrating that groups often struggle to generate creative decision alternatives (Paulus et al., 2002; Siebert & Keeney, 2015) and, instead, converge in favor of a simplistic solution too quickly. Group polarization, groupthink, and escalation of commitment may also negatively affect a sound definition of trade-offs (Keeney, 2002) and the establishment of reasonable risk limits (Fischhoff et al., 1993).

More specifically, dysfunctionalities in group behavior and group judgment biases exert a strong negative impact on the quality of the decision making. Dysfunctional and biased groups may produce a narrow problem frame (see the third chapter), create an incomplete list of fundamental objectives and relevant consequences (see the fourth chapter), disregard key uncertainties and scenarios (see the fifth chapter), distort the definition of risk limits and trade-offs (see the sixth chapter), promote a limited exploration of decision alternatives (see the seventh chapter), distort the evaluation of health security actions and health threats (see the eighth and ninth chapters), and incorrectly define the type of decision to be made and decision analysis to be employed (see the tenth chapter).

Despite the potential drawbacks in group decision making that are described above, when making difficult choices in health security situations, decision making groups bring about several advantages when compared with individual decision makers. These advantages are particularly true when the group composition favors a variation of perspectives and representativeness of different interests at stake in the decision process. Groups may: (i) enhance the pooling of relevant and distinctive information, (ii) aid in the verification and correction of errors, (iii) enhance individual task motivation and improve satisfaction among members (Kerr & Tindale, 2011), as well as (iv) foster a sense of commitment toward the best course of action to take (Phillips, 2007).

Hence, if we wish to improve the efficacy of health security teams in making decisions, and, to maximize the quality of health security decision processes, group dysfunctional dynamics must be addressed and group judgment biases must be minimized. There exist several initiatives that aim to improve the efficiency and efficacy of the health security teams. First, there exists the necessity to establish clear rules and decision-making responsibilities that guide group interactions. Second, we are able to design group decision making processes in such a way as to enable a reduction in behavioral dysfunctionalities and minimization of biases in group judgments. Third, the use of either an internal or external group facilitator, who can support group discussions, convergences, and agreements on how best to proceed also forms an option to effectuate positive changes on group decision making. Suggestions for said improvements are detailed next.

11.1.2 Establishing Rules and Responsibilities for Group Interactions

Groups that have failed to establish group interaction rules and decision making responsibilities in a clear manner may struggle to reach an adequate (or any) conclusion. *Interaction rules* define the manner in which the individual opinions are expressed, the debates among group members are conducted, the disagreements are managed, and the agreement is reached by the team. Decision making *responsibilities* serve to indicate the extent to which each and every individual member of the

group bears the responsibility for the decision, as well as to provide a clear indication as to which individual is ultimately responsible for making the decision.

Consequences of these dysfunctionalities can be observed in situations wherein excessive time is spent appraising ideas and viewpoints, without a requirement for convergence, decision and action (Russo & Schoemaker, 1989). Another common feature of these dysfunctional groups, particularly if they are composed mostly by scientists and health experts, is "paralysis by analysis" (Lenz & Lyles, 1985), wherein there occurs a demand for increasingly more sources of evidence and an unrealistic requirement that all uncertainties be resolved prior to any action being taken (Hammond, 1996).

Hence, the health security team should establish a clear definition of the *decision task*, which should involve a *process outcome* and a *process purpose* that is attainable (Weaver & Farrell, 1997). For example, should the team systematically rank health threats (group decision task), so that the top-ranked threats be targeted (process outcome) for better preparedness and risk mitigation planning (process purpose)? Or, instead should the group task involve the identification of possible alternatives for a vaccination campaign (group decision task) and the best vaccination campaign (process outcome), and select the alternative that maximizes the benefits while minimizing risks and maintaining the costs within budget (process purpose)?

This recommendation that the decision task be clearly defined and agreed upon when commencing the decision making process sounds rather obvious, and yet, in practice, we have observed many instances wherein the task itself remains unclear in strategic decision making and policy choices. Without a well-defined group task, establishing an adequate decision frame (Spetzler et al., 2016), identifying the type of decision and evaluation to be made (Gregory et al., 2012; Roy, 1996), defining the fundamental objectives for the specific decision context (Barcus & Montibeller, 2008; Keeney, 1992, 2013), and developing a creative set of decision alternatives is rendered impossible (Keller & Ho, 1988; Siebert & Keeney, 2015).

It is also important that the *aims* and *roles* of members who compose the health security team be well-specified. The distinction between experts and decision makers proves a crucial one in health security settings. Experts should provide reliable and unbiased advice, which should be limited to their field of expertise and be absent of any conflicts of interest. Their expert judgments should be based on evidence and high-quality descriptive and predictive models (Morgan, 2014). On the other hand, decision makers should provide the judgments that are required for selecting decision alternatives, or for targeting specific health threats. In particular, they must negotiate the difficult trade-offs that often are required in policymaking (Keeney, 2002) and decision makers may be required to establish risk limits and risk tolerance levels (Fischhoff et al., 1993).

There also exists a need to establish *rules of behavior* for group work. The literature on group performance (Kerr & Tindale, 2004; Wittenbaum & Moreland, 2008) makes suggestions as to some of the rules that are prescribed in practice to increase group performance. First, the group should openly test the assumptions and the inferences of its members. Second, team members should share all the relevant

information. Third, in communicating with each other during meetings, members should use clear and concise language and clarify meaning. Fourth, members should explain their reasoning and intent. Fifth, the focus should be on perspectives and not fixed and intransigent positions. Sixth, the discussions should be constructive and collaborative and not adversarial. Seventh, the decision making process should encourage participation and lead to engagement and commitment (see Schwarz (2002), Garvin and Roberto (2001), and Phillips (2007) for details).

11.1.3 Minimizing Group Dysfunctionalities and Judgment Biases

Group interactions that are carefully designed and properly managed can reduce the behavioral dysfunctionalities that are often observed in group decision making (Kerr & Tindale, 2004, 2011; Wittenbaum & Moreland, 2008). Group judgment biases should be minimized as much as possible in a health decision analysis (Montibeller & von Winterfeldt, 2018). Specific solutions that seek to minimize group dysfunctional behavior and group judgment biases involve a combination of group *process facilitation* and *content management*. Below, we detail the central issues affecting teamwork and provide some suggestions as to how to alleviate each issue during the decision making process.

Group Pressuring Individuals to Follow the Majority A major issue that arises during group decision making involves the pressure to conform to the majority view. Additionally, the perception that the majority is correct can lead to minority group members failing to challenge the position of the majority. Group pressures on individual members to conform to the majority view can have a very detrimental effect on the quality of group decision making, stemming from a limited understanding of a decision situation, which can lead to a narrow set of solutions.

In terms of group decision processes, three ways of reducing the majority pressures on individual group members involve including experts with varied perspectives, identifying decision makers that represent the different stakes in the health security situation, and encouraging participants to express their opinions and reduce pressures to conform. The quality of the content employed in a health decision analysis can also be improved against pressures exerted by the majority on individuals, by representing the different perspectives pertaining to the issue at stake using a decision model and by encouraging an extensive representation of the decision problem.

More specifically, the group pressure may be addressed by carefully configuring the manner in which opinions and judgments are expressed in group discussions. The evaluation of ideas and viewpoints should be curbed at the point at which they are being expressed, with a clear separation between idea generation and idea evaluation, which can reduce evaluation apprehension (Paulus et al., 2002). Another

useful strategy to reduce group pressure entails requesting that participants write their ideas first, prior to divulging them with the group. Anonymity may also help in settings wherein there exists extreme group pressure, as opinions and ideas remain unanchored to particular individuals when shared with the group (Kerr & Tindale, 2011). The anonymous sharing of ideas and judgments can be facilitated by the use of digital collaboration platforms (see Montibeller (2018) for an example of the use of such platform in a health security context).

Group Reporting to an Influential Leader Behavioral evidence has demonstrated that influential and high-status group members have a tendency to believe that their ideas are correct and often disregard members that disagree with these positions, thereby dominating the discussion (Kerr & Tindale, 2011). Authoritarian-style leaders can significantly influence the quality of decision making in a negative manner, through their attempts to impose the option that they believe to be the best on the group, without any due consultation with experts or policymakers. This option may have been chosen after an early individual deliberation or, alternatively, as a "pet option" which has been driven by motivational biases (Montibeller & von Winterfeldt, 2015). In the latter situation, it is common for the choice to be posteriorly rationalized, i.e., arguments are constructed to justify the pre-chosen option to the health security team.

Two strategies to reduce the influence exerted by a dominant leader on group decision processes involve attempting to equalize power among the health security team members and designing participation processes that reduce the imbalances of power between members of the health security team. In terms of the content of a health decision analysis, we can only avoid representing the views of strong leaders or influential members in the decision model and, instead, encourage a representation of the decision problem that has been informed by multiple, varied perspectives. Obviously, these solutions assume some willingness by the influential leader to cede their power and foster debate.

However, if a health security team were reporting to a figure with an authoritarian leadership style and such strategies prove to be unfeasible, tactics of diplomacy and persuasion (Cialdini, 2021) are required for helping to promote good choices. In such cases, one piece of advice entails designing and pre-selecting a set of robust options, which can then be presented to the decision maker, who has been tasked with selecting. In this case, regardless as to the actual choice made and the quality of the selection process that is employed by the decision maker, the health security team can ensure that a good option shall be selected.

Group Disregarding Novel or Undisclosed Information Cohesive groups may disregard novel information, particularly in instances wherein this information contradicts the espoused assessment or opinion that is held by the majority (Janis, 1983). Additionally, information that could be critical for a reasoned decision may not be disclosed to the group, either due to a lack of opportunity or self-censuring stemming from evaluation apprehension (Paulus et al., 2002).

The lack of attention to novel information, or, to critical information that remains undisclosed at a group level may impact the quality of the choice in a significantly detrimental manner. The absence of adequate information may prevent a full, evidence-based appraisal of decision alternatives and a comprehensive assessment into all of their impacts from being conducted. Additionally, a general disregard toward absent information may prevent some potentially strong decision alternatives from being included within the selection process.

Two strategies to reduce this dysfunctional group behavior involve designing participatory processes that enable the divulging of individual information and the constraining of attempts to suppress or neglect new information by group members. In terms of content, we should seek to provide an extensive and detailed representation of all the relevant information available and organize the information in a way that supports reasoned decision making, thereby enabling a well-conceptualized and fully developed health decision analysis to be conducted.

Indeed, a major benefit of a decision analysis for supporting health security decision making stems from the transparency of the information used, as well as from the targeted gathering of information to support the evaluation of decision alternatives and to guide decision making. If properly managed, a health decision analysis can aid experts in effectively sharing relevant and useful information and the assumptions that underpin their respective opinions and judgments.

Additionally, the same suggestions for reducing the degree of group pressure that is exerted on individuals to conform may help to shift the attention of the group toward novel information and aid participants in sharing their individual information points. Ensuring that the unbiased expert opinion be divulged and seriously considered by policymakers forms a particularly important issue. Thus, public accountability and transparency can certainly be of value. The release of the transcripts pertaining to the Scientific Advisory Group for Emergencies (SAGE) meetings public in the UK in 2020, during the COVID-19 pandemic, constitutes a positive example of making more transparent the expert opinion that was being provided to the UK government.

Groups Producing Dysfunctional Shared Representations About the Decision Problem Groups whose composition is homogenous may develop a rather narrow and limited representation of the decision problem. This issue is exacerbated in highly cohesive groups, which may curb dissent and suppress distinctive perspectives (Janis, 1983). These narrow problem definitions are very likely to lead to simplistic solutions that do not fully address the decision situation. Similarly, this group dysfunctional behavior may impact the quality of the decision alternatives under consideration, the situation of which may result in the problem at stake not being adequately addressed, thus severely reducing the quality of the choice.

Group decision processes can be designed, or, be re-designed to reduce this behavioral dysfunctionality. Here, it is recommended that a varied set of experts be engaged, a broader problem definition be encouraged, and that an excessively restrictive or distorted assumptions be challenged. When addressing issues relating to the content itself, it is recommended that the decision consequences (from the key

assumptions made in the analysis of the decision situation) be identified, the evidence underpinning key assumptions be gathered and assessed and all the assumptions employed in the health decision analysis be made explicit.

Moreover, there exist powerful modeling tools to support groups during the process of structuring complex decision problems (Mingers & Rosenhead, 2001). Said tools enable the external representation of decision problems and can help groups to expand the decision frame and develop a more comprehensive understanding of the decision situation (Franco & Montibeller, 2011b). Causal maps are frequently employed in our practice, as these form a particularly useful tool (Eden, 2004; Montibeller & Belton, 2006), as has been detailed in the fourth chapter. These problem structuring tools, when used jointly alongside strategies for reducing group conformity pressures, may significantly increase the quality of the problem definition.

Groups Presenting Motivational and Coordination Losses Individuals working in groups may experience demotivational elements, particularly in cases wherein the contributions of group members cannot be personally identified, when members perceive their contribution to be irrelevant for team success, or when other members are perceived to not be making adequate contributions (Kerr & Tindale, 2011, p. 20). Coordination losses also frequently occur in group work, particularly in groups that are larger and in groups whose participants have undefined roles. The consequences of these difficulties involve the sub-optimal use of participant expertise and time, thereby creating a situation wherein the information and judgements that have been provided may be of a lower quality than had initially been possible. These lower quality inputs are likely to affect the evaluation of decision alternatives and, consequently, distort the choices made by the group (Montibeller & von Winterfeldt, 2015).

Coordination and motivational losses may be reduced by developing well-planned decision processes, thereby establishing an efficient way to conduct expert consultations, and an efficient and effective participatory procedure involving the decision makers. Additionally, a health decision analysis can support the adequate management of the content employed in the decision, with the use of adequate representations of the decision situation and also provide the requisites and stages for the involvement of experts and decision makers during the construction of the decision model.

Furthermore, establishing clear rules and responsibilities to mediate group interactions, the topic of which has been previously discussed, can function to reduce motivational and coordination losses. While successes should be attributed to the team, it is the role of the team leader to stress the contributions of the individual team member and to foster an environment wherein the team feels motivated and coordinated. In decision making processes, working with a smaller number of group members is always less complicated, with five to fourteen participants forming an ideal number of participants (Shaw et al., 2004). For very large task forces, it is recommended that they be subdivided into smaller working parties, thereby facilitating the delineation of a clear remit and responsibilities. These task forces may

then inform the core team and convey their findings and viewpoints. Once again, a well-structured health decision analysis can help in organizing the role and content of the working parties and provide coherence and consistency in the appraisal of decision alternatives.

Groups Suffering from Judgment Biases As we have mentioned previously, groups may suffer from several group judgment biases (Montibeller & von Winterfeldt, 2018). These biases include false consensus (Ross et al., 1977), groupthink (Janis, 1983), group polarization (Lamm, 1988), group escalation of commitment, and group overconfidence (Plous, 1995).

There exist some useful debiasing tools against group judgment biases (Montibeller & von Winterfeldt, 2018) that involve designing, or re-designing, decision processes. First, we can assemble a group of decision makers that represents the perspectives of all the relevant stakeholders (as detailed in the third chapter). Second, we should select experts with different perspectives with regards to the decision situation. Third, we can design participation processes that enable the sharing of individual information. Fourth, we should encourage participants to express their opinions and reduce any existing pressures to conform. Furthermore, in terms of the content itself, we must develop a broad representation of the decision situation (as detailed in the third chapter) and employ structured elicitation protocols for the elicitation of judgments (as discussed in the sixth chapter).

We summarize the suggestions as to how we can improve group decision making, both in terms of improving group processes and enhancing the quality of decision-related content, in Table 11.1. Next, we suggest one manner of deploying these strategies in practice, with the use of Facilitated Decision Analysis.

11.1.4 Facilitating Group Decision Making with Decision Analysis

Fostering a sense of awareness toward the presence of any dysfunctional group behaviors and group judgment biases proves to be a significant challenge for any team. Consequently, the *implementation* of the advice that has been put forth thus far, which seeks to increase the effectiveness of decision making processes and to reduce group dysfunctionalities and judgment biases, also forms a key obstacle. Hence, the nomination of internal facilitators, or the hiring of external facilitators, can prove to be an effective tactic to support health security teams as these facilitators can promote high-quality decision making practices and support the health security teams in becoming more efficient and effective.

We have supported many organizational decision making processes, by adopting simultaneously the role of a decision analyst and that of an external facilitator. In these interventions, the responsibilities of the facilitator is two-fold, in that they must support the health decision analysis while facilitating the decision-making

Table 11.1 Potential weaknesses and remedies to improve group decision making

Potential weaknesses	Remedies to improve Group decision making
Group pressure to conform to the majority view	**Process**: Identify decision makers that represent the different stakes. Involve experts whose perspectives are varied. Encourage participants to express their opinions and reduce existing pressures to conform. **Content**: Represent the different perspectives about the issue. Encourage an extensive and detailed representation of the decision problem.
Groups dominated by a strong leader or influential member	**Process**: Equalize power among the health security team members. Design participation processes that reduce power imbalances. **Content**: Avoid representing only the views of strong leaders/ influential members. Encourage an extensive and detailed representation of the decision problem.
Inattention to undisclosed novel information	**Process**: Design participation processes that enable the sharing of individual information. Constrain attempts by group members to suppress or neglect new information. **Content**: Provide an extensive and detailed representation of the relevant information available. Organize the information in a manner that supports reasoned decision making.
Groups suffering from dysfunctional shared representations	**Process**: Involve a varied set of experts. Encourage a broader problem definition. Challenge assumptions that are excessively restrictive or distorted. **Content**: Identify as to which decision consequences have been made from the key assumptions. Gather and assess the evidence behind key assumptions. Make explicit all the assumptions in the health decision analysis.

(continued)

Table 11.1 (continued)

Potential weaknesses	Remedies to improve Group decision making
Groups suffering from motivational and coordination losses	**Process**: Ensure efficient processes for expert consultation. Ensure efficient and effective decision processes. **Content**: Employ adequate representations to depict the decision situation. Mediate and structure the involvement of experts and decision makers during the decision model building.
Group work is time consuming and resource intensive	**Process**: Ensure efficient processes for expert consultation. Ensure efficient and effective decision processes. **Content**: Employ adequate representations to depict the decision problem. Mediate and structure the involvement of experts and decision makers during the decision model building.
Group judgment biases	**Process**: Identify decision makers that represent the different stakes. Involve experts whose perspectives are varied. Design participation processes that enable the sharing of individual information. Encourage participants to express their opinions and reduce any existing pressures to conform. **Content**: Develop a broad representation of the decision situation. Employ structured elicitation protocols for the elicitation of information and judgments.

group. An internal and neutral facilitator that has a robust understanding of the content that is described in this book may adopt a similar role, thereby supporting their team to improve the quality of the decision processes and to increase the efficacy of the teamwork in deliberating and making decisions.

Taken as a whole, we have entitled these decision aiding processes as *Facilitated Decision Analysis* (Franco & Montibeller, 2010), as illustrated in Fig. 11.2. In the *decision modeling space*, the facilitator supports the group in modeling the decision situation, using the concepts that have been detailed in the previous chapters. In the *group process space*, this individual facilitates the group, following the advice detailed in this chapter. Here, the decision model represents information from the health security team, such as uncertainties, relevant consequences, decision alternatives, risk limits, and trade-offs. Subsequently, the results derived from the model, such as the expected value of health security actions and dis-value of health threats, are used to inform group discussions and team interactions. Both spaces possess respective outcomes. The *group* outcomes are comprised of the agreed solution by the team, the commitment to action of the group, and group learning. Contrastingly,

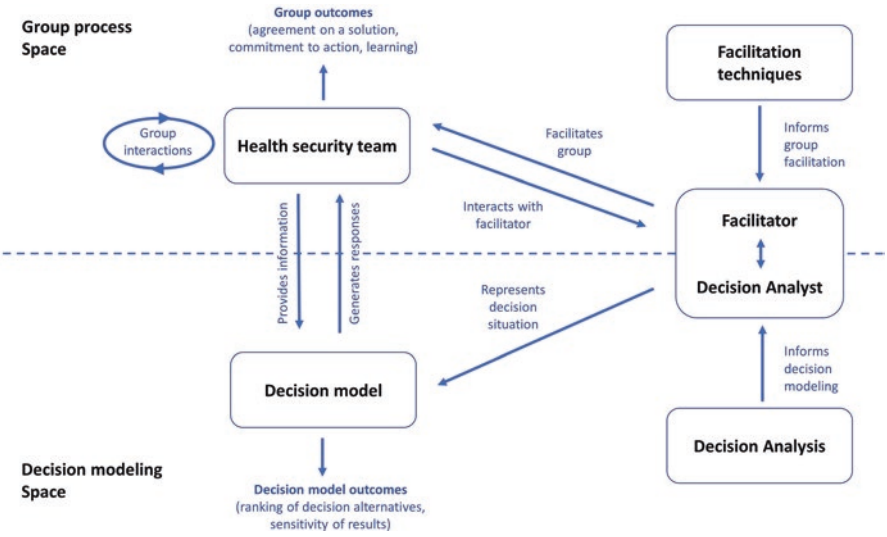

Fig. 11.2 Facilitated decision analysis. (Adapted from Franco & Montibeller, 2010, p. 495)

the decision model outcomes are typically comprised of a ranking of decision alternatives and sensitivity analyses of the results against the input parameters of the decision model. A successful facilitation shall improve the chances of positive group outcomes, and a successful health decision analysis shall increase the chances of a high quality choice (see also Franco and Montibeller (2011a) for details).

A facilitated decision analysis brings about several key benefits for supporting health security decisions (Montibeller, 2018). First, this mode of intervention provides the opportunity for the group to comprehensively disclose information concerning the health security options (Rouwette & Vennix, 2007) and the varied perspectives about relevant decision objectives (Eden & Ackermann, 2013). Second, a facilitated decision analysis provides a platform on which to stage the negotiation of different positions (Eden & Ackermann, 2001). Third, this type of group decision process functions to foster a joint commitment among the group, the presence of which is paramount to the successful implementation of a chosen option (Franco et al., 2016; Franco & Montibeller, 2010; Phillips, 2007).

Present in prediction problems, such as the epidemiological models for the prediction of disease transmission and the number of cases, is the concept of a *true value*, which is obtained about the uncertainties are resolved and the consequences occur under a given scenario. Contrastingly, this *true value* is absent in valuation tasks, the condition of which forms an important distinction between the two categories of decision problems. Accordingly, what a decision analysis seeks to develop are the *requisite models* (Phillips, 1984), which are not, in a sense, "perfect" but are sufficiently extensive and detailed to aid the group in undertaking the decision situation that has been presented and identify the options with the highest expected value. Additionally, rather than being discovered, preferences and judgments are

constructed, i.e., they are externally-internally developed during the decision aiding process, instead of being pre-defined internal concepts in the minds of individual decision makers (Roy, 1993; Slovic, 1995). Requisite modeling requires that decision-making processes be managed effectively, thereby promoting the sharing of information among members of the group, supporting the negotiation of different perspectives and stakes, and enabling the group to reach a joint agreement as to the best solution for the health security situation.

The project for the Malaria Consortium/USAID that we conducted in collaboration with the MIT Humanitarian Supply Chain Lab, the case of which has been introduced in the seventh chapter, illustrates the use of a facilitated decision analysis in a health security context. The project was focused on improving supply chains for rapid malaria test (RMT) kits in Uganda, and, specifically, in identifying and designing high-value RMT kits for the agents that composed the supply chains (see Carland et al. (2018) for details). The project also highlights the importance of understanding the different perspectives that stakeholders hold and the relevance of acknowledging their values in order to create high-value policy options (Gregory & Keeney, 1994; Keeney, 1992; Siebert & Keeney, 2015).

In this project, we used a low technology workshop and worked as both facilitators *and* as decision analysts for the expert group involved in the project. Multi-attribute value models were developed for understanding the preferences and the priorities of the agents involved in these supply chains, which were comprised of first-line buyers (FLB), distributors, and retailers. Specifically, a multi-attribute value model was developed for representing the preferences of each agent in the supply chain. The objectives for the supply chain agents were defined from the literature and were enriched by inputs from the participants during the workshops. We elicited marginal value functions and attribute weights from each agent of the supply chain (see also Keller et al. (2009) on the development of individual decision models for group decision making).

The value models were developed with the expert group during workshops in an interactive manner, that is, using flip charts and simple visual representations. We facilitated the group discussions and elicited the expert judgments (marginal value functions, attribute weights) from the group using the elicitation protocols that have been discussed in the sixth chapter. These facilitated workshops helped participants in better understanding the decision problem and the objectives of the different agents in the supply chain.

Each malaria kit (option) was a bundle combining the device itself as well as the subsidy, training, advertising, biohazard disposal and barcoding. We employed the value model of each agent to evaluate pre-existing malaria kits (A, B, C and E) and developed new options (D, F-M). The value scores were defined between 1 and 5 (instead of between 0 and 100 as has been used in previous chapters of this book) for each agent of the supply chain. Figure 11.3 demonstrates the setting of the workshop (on the right) and the overall results of the health decision analysis (on the left).

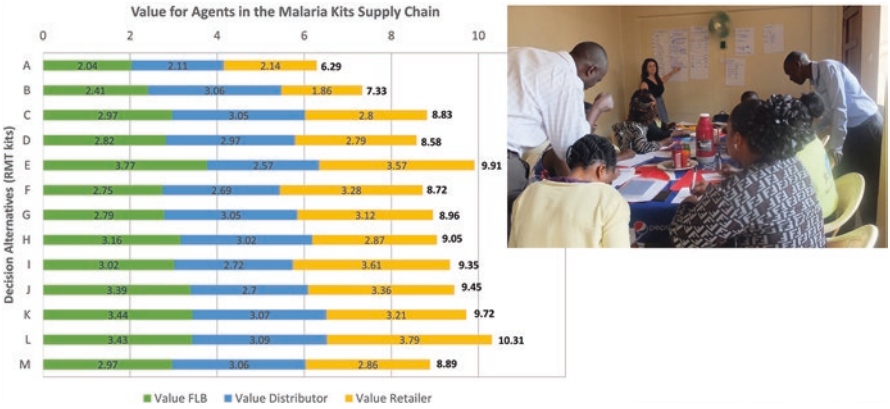

Fig. 11.3 Value of malaria kits for different agents in the supply chain for the Malaria Consortium/USAID. (Carland et al., 2018; Montibeller, 2018)

In addition to the overall value of each option for each agent of the supply chain, we considered the three agents to be equally important. Hence, the overall value of each option for the whole supply chain was calculated by summating the overall value scores for each agent. For example, in the same figure, the overall value of the bundle A for the supply chain (6.29 value points) was calculated by summating the overall value from the FLB (2.04 value points), the Distributor (2.11 value points), and the Retailer (2.14 value points). Option L had a higher value for the supply chain than the existing options (10.31 value points). The results from this decision analysis proved robust against variations of the relative importance of the agents.

Typically, in these facilitated decision analysis interventions, we would explore the results interactively with the health security team, as the model forms a structure which allows for the attainment of the group outcomes, which are shown in Fig. 11.2. The decision model in such instances is a means for the group to agree upon a solution, to commit to action, and to learn more about the decision situation and the organizational priorities.

Often, instead of face-to-face workshops, we have conducted this interactive exploration of the solutions with the team using digital platforms as a mode of communication, which have proved to be very effective. However, in the case of this specific project, this interactive exploration of results was not feasible, given the limited internet infrastructure in Uganda. Instead, we disseminated the health decision analysis via an article published in the Malaria Initiative newsletter of the US President (PMI, 2018), the publication of which is read by thousands of health policymakers and public health experts that have engaged with, or that have been responsible for developing policies for malaria prevention and treatment.

11.2 Implementing Successfully Selected Options

Thus far in the stages of the health security decision process that have been described, the health security team shall have made a decision and shall have selected options for implementation. Following the suggestions covered in this book for how these decision processes should be conducted and how the decision alternatives should be appraised and chosen, the decision process should lead to the selection of high-value options for enhanced health security, or to the selection of risk mitigating and health security actions that can effectively address the most serious health threats.

However, regardless as to whether the decision process has been of a high-quality, or as to whether a thoughtful and reasoned choice has been made, there can occur no accruement of benefits or mitigation of risks if the selected options fail to be implemented successfully. This section discusses this thorny issue of decision implementation and provides some suggestions as to how to make the implementation of options more likely to be successful.

Decision implementation is a topic that remains largely absent from the Decision Analysis literature, with some laudable exceptions, such as Spetzler et al. (2016) and Gregory et al. (2012). In this literature, there often exists the hidden assumption that, once a reasoned choice has been made, a successful implementation shall naturally follow. However, this implementation issue has been thoroughly studied by the Strategy Implementation literature (see Hakonsson et al. (2012), Merkus et al. (2019) and Noble (1999) for details) and these findings show evidence of multiple barriers that hinder the implementation of chosen strategies and, rather frequently, unsuccessful implementation attempts.

The most frequent barriers against successful implementation involve (Nutt, 2002; Spetzler et al., 2016): (i) difficulties in moving from a planning mode to an action mode, (ii) hesitation to act due to the uncertainties and risks involved, (iii) incapacity to allocate appropriate levels of resources for implementation, (iv) opposition from key figures in charge of implementing actions, or (v) misuse of resources allocated to implementation activities. We make suggestions as to the solutions that seek to confront each of these barriers in this section.

Difficulties in Shifting from Planning to Action A reasoned decision process is inherently conceptual and abstract, even if the core components of the decision problem were to be adequately represented in a decision model, as has been suggested in this book. The conceptual nature of said process may favor members of the health security team that have a natural tendency toward analyzing hypothetical situations or considering more abstract concepts. Additionally, diverse perspectives and an inclusive and open space wherein opinions are shared (Kerr & Tindale, 2004, 2011), and an understanding of the role of irreducible uncertainties (Hammond, 1996) form the main components of high-quality decision processes.

However, the point at which there occurs the need to take action, a different mindset is required, which is in contrast with the mindset that is required during decision deliberations that preceded the selection of options (Spetzler et al., 2016).

During the implementation phase, there exists a need for the alignment of purpose and a collective commitment toward the solution selected from all the relevant stakeholders. For these reasons, implementers should replace uncertainty with the certitude of both purpose and clear mission. This shift from divergence to convergence (Russo & Schoemaker, 1989) must be carefully managed, and may require different members of the team to lead the implementation phase: planners for the decision process phase and action-oriented executives for the implantation phase.

Hesitations to Act In a reasoned decision process, a hesitation to act at the stage wherein either the selection of options is imminent or the selection of options has already taken place is occasionally observed. This situation is particularly common in public decisions that rely on extensive scientific evidence, such as health security situations. A major source of inaction in such instances is formed by the presence of irreducible uncertainties, which cannot solely be resolved by gathering more data or evidence (Hammond, 1996). Irreducible uncertainties may provoke feelings of discomfort in health experts and health policymakers, who, quite rightly, wish to follow an evidence-based decision process, even during the later stages of the decision process, at which point a decision must be made. As a consequence, public health leaders may be impeded by a protracted effort to continuously gather more evidence prior to finally actioning a decision, leading to "paralysis by analysis" (Lenz & Lyles, 1985).

Another major source of hesitation to act is formed by excessive risk avoidance. Any health security action shall involve some negative aspects, such as implementation costs that may be higher than original estimates or actions that may, in actual fact, prove to be less effective than had been originally assumed. Additionally, actions often may bring about some unexpected consequences, especially when undertaking emerging health threats, whose scientific knowledge is still evolving. This risk avoidance attitude may create severe inaction on the part of the health experts and policymakers. This type of excessive risk avoidance attitude is particularly observable in societies that suffer from hindsight bias (Blank et al., 2007; Roese & Vohs, 2012). In such cultures, policymakers are held responsible if an element of an implemented solution either fails, or, brings about negative consequences, even if the information that could prevent these setbacks were to be unavailable at the time at which the decision would have been made.

The solutions to address these hesitations to act are threefold, and are to be implemented during the decision making processes. First, decision makers must come to terms with the nature of irreducible uncertainties and the limits of evidence gathering in decision making (Hammond, 1996). Second, decision makers should recognize the outcome bias (Mazzocco et al., 2004) and understand that decisions are always made about an uncertain future, which cannot be fully controlled. Third, decision makers should also consider inaction while decision deliberations continue to be an action in and of itself (Samuelson & Zeckhauser, 1988), such as the number of casualties and critical cases that may come about were there to occur a failure to implement risk mitigating actions in response to a disease outbreak.

Incapacity to Allocate Resources A decision is only actioned at a stage wherein resources have been irrevocably allocated to the execution of the action (Spetzler et al., 2016). These resources are comprised not only of capital, but also personnel, equipment, and facilities. In health security situations, it is common to observe instances wherein decisions are made, and yet, there occurs an incapacity to allocate resources to their implementation. Commonly, this problem stems from the lack of adequate resource levels, from necessarily limited health budgets, alongside a demand to improve multiple areas of health security and mitigate multiple health threats.

If there occurs the situation wherein no additional resources are able to be obtained for the health security field, then the solution to this barrier entails a realistic prioritization of projects. The portfolio decision analysis that has been presented in the tenth chapter may support policymakers in identifying the health security projects that should be funded (given the available budget), i.e. selecting the projects with the highest (expected) value-for-money. Following this rationale, if large-scale projects, with large but costly benefits, prove to be unfeasible given the budget constraints, these large-scale projects may be replaced by a set of small-scale projects, whose benefits are limited but whose costs are relatively inexpensive. Indeed, this set of small-scale projects may, overall, provide more benefits than a single large-scale project, at a lower overall cost than the single, large-scale project.

Let us illustrate this point with the portfolio decision analysis that has been described in the previous chapter. The results of this analysis are graphically reproduced in Fig. 11.4. Recall that there exists a $75 million budget and total of eleven

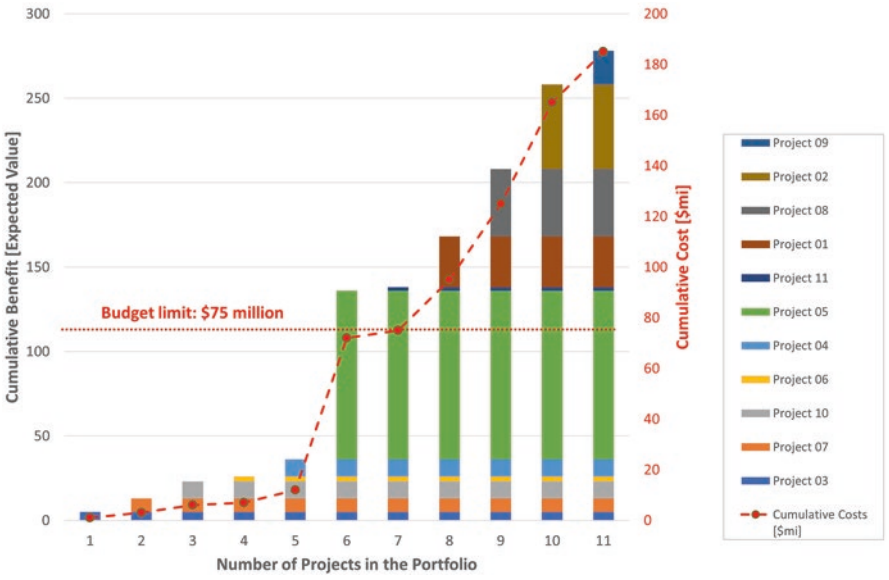

Fig. 11.4 Portfolio decision analysis for the optimal allocation of resources

health security projects, and each project is accompanied by an estimation of benefits (measured by expected value) and an implementation cost. The value-for-money figure of each project is used to prioritize projects for the portfolio, and benefits are maximized given the budget constraint. The stacked bars in the graph demonstrate the cumulative benefit of including projects in the portfolio (in descending value-for-money order) on the left y-axis, and the line in the same graph shows the cumulative cost of inserting projects in the portfolio. Seven projects can be included in the optimal portfolio that accede this budget: Project 03, Project 07, Project 10, Project 06, Project 04, Project 05, and Project 11. The last project (Project 11) that was included in the portfolio provides relatively low value-for-money (expected value = 2 value points and implementation cost = $3 million) in comparison with the other four projects that are not included in the portfolio (Project 01, Project 08, Project 02, and Project 09), as shown in the same figure, but this project can be inserted into the optimal portfolio to achieve maximum benefit.

Opposition from Implementers Key figures that are responsible for the implementation of the selected options may prevent or detract implementation efforts if the figures were either to be ill-informed about the benefits of the solution or unsupportive toward the chosen solution. Hence, two major drivers can significantly improve the chances of a successful implementation and can render the implementation more effective (Floyd & Wooldridge, 1992; Phillips, 2007). First, the health security team must have a *shared understanding* of the decision situation, the key uncertainties, the fundamental objectives, the decision alternatives, and of the selected options. Second, the health security team should feel a *commitment* to the solution chosen and to implement the selected options.

Both a shared understanding of the decision situation and a commitment to the solution chosen, each of which are drivers, must be addressed during the earlier stages of health security decision processes, as has been suggested in the third chapter. If key stakeholders were to have an adequate level of participation in the decision process and if the process itself were designed in such a way as to encourage the engagement and involvement of the health security team members, then the establishing of these factors may help to increase both drivers.

Additionally, it is also recommendable that the health security team include representatives of those stakeholders that shall be responsible for executing the decision. For example, these representatives may take the form of health managers that preside over hospitals and care facilities, policymakers that manage health services, and, if appropriate to the specific decision context, representatives from private companies that provide health services and related goods.

These implementers may contribute valuable suggestions to the decision table (Spetzler et al., 2016), such as identifying relevant decision objectives for the implementation stage, suggesting new alternatives, supporting the gathering of information and evidence for the appraisal of options, providing insights and information about the challenges that arise during the execution phase, and identifying the practical viability and potential failures of specific health security options. Engaging these individuals may also contribute to: (i) fostering a shared understanding

concerning the matters at stake, (ii) acknowledging the notion of why the decision is important, (iii) agreeing upon the fundamental objectives whose attainment is being pursued in the decision, (iv) specifying the trade-offs and risk limits that have been defined, (v) and recognizing what is expected in terms of decision implementation.

A facilitated decision analysis can be used as a significant enabler of both drivers, functioning not only to create an arena wherein to foster an improved shared understanding of the decision situation, but also a commitment among the health security team toward the chosen solution (Franco & Montibeller, 2010; Phillips, 2007). Once again, we stress the close relationship between a well-designed decision process, which aims not only to identify options with high societal value but also to achieve group outcomes and an implementation stage with few obstacles.

Misuse of Resources for Implementation

The vast budgets required for implementing large-scale health security actions renders these actions an easy target for the misuse of resources that had initially been allocated toward implementation. This misuse ranges from unwise choices made by officials concerning how to implement the decision to malfeasant behavior wherein resources are deviated or stolen.

The solution to this problem requires that there exist a sense of accountability and control over the implementation activities, involving a clear plan for deployment as well as milestones for intermediate achievements (Bossidy & Charan, 2009). A health decision analysis can aid in developing metrics for success evaluation, which is attained by ensuring that the relevant consequences inform the performance metrics and that the value model assesses the distance between the actual performance to the planned performance.

The vaccination campaign case that has been introduced in the previous chapters can function to illustrate the use of a value model to assess the performance of the implemented alternative, identify gaps in performance, and support the planning for further adjustment activities. Recall that five vaccination strategies have been contemplated for this case, as detailed in seventh chapter: *fully centralized in hospitals* (A_1), *fully decentralized in community centers* (A_2), *hybrid centralized* (A_3), *centralized with home visits* (A_4), and *decentralized with home visits* (A_5). The assessment of value, which has been described in the eighth chapter, has indicated that alternative A_3 provides the highest overall value of $V(A_3) = 62.3$ points.

Let us assume that this vaccination strategy (A_3) has been chosen by the health security team and is subsequently implemented. The profile of the estimated valued performances of A_3 is shown on the right-hand side of Fig. 11.5 (from Table 8.1 in the eighth chapter). The estimated overall value $V(A_3)$ can be calculated as a weighted sum of attribute weights and the value scores, using Eq. 8.1 from the eighth chapter, and is shown on the left-hand side of the same figure.

Now, let us imagine that the vaccination strategy has been implemented, and the actual performances that have been evaluated after the implementation phase has taken place, the situation of which is represented by the implemented alternative A^I_3. For example, the performance of the implemented alternative with regards to

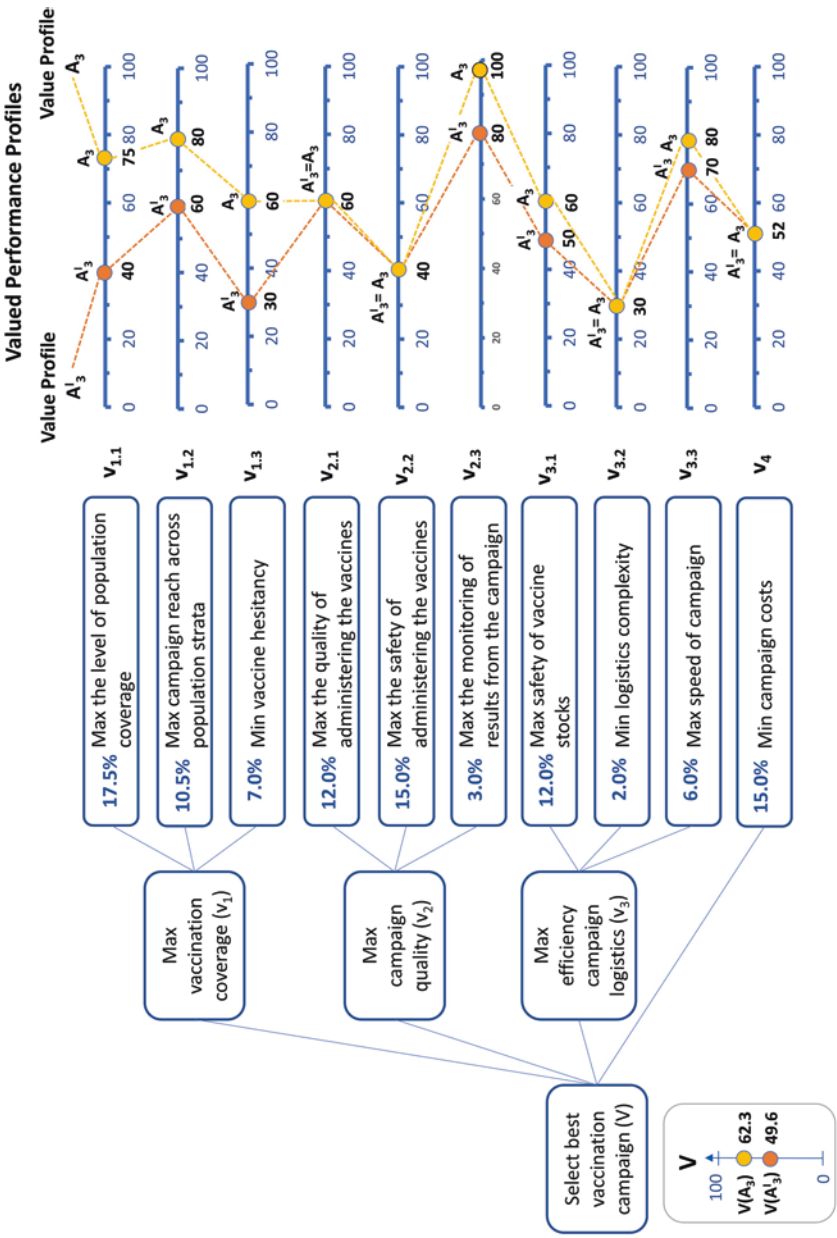

Fig. 11.5 Evaluation and value gap analysis of the planned (A_3) and implemented (A'_3) vaccination campaign

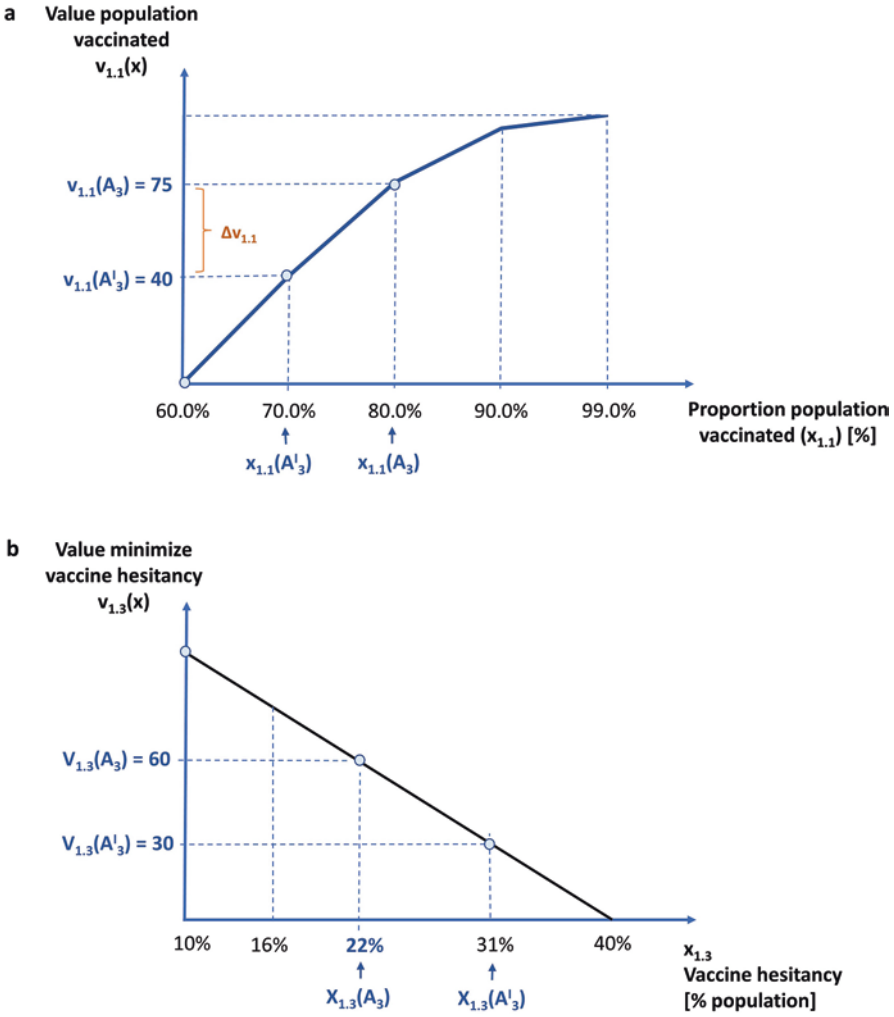

Fig. 11.6 Evaluation of the planned (A_3) and implemented (A^I_3) vaccination campaign on two attributes: (**a**) Proportion of population vaccinated, (**b**) Vaccine hesitancy

the proportion of the population vaccinated is $x_{1.1}(A^I_3) = 70\%$ on this attribute, with a value score of $v_{1.1}(A^I_3) = 40$ points, as shown in Fig. 11.6a. This is in contrast with the original estimated performance of $x_{1.1}(A_3) = 80\%$ with a value $v_{1.1}(A_3) = 75$ points. Similarly, the actual vaccine hesitancy is $x_{1.3}(A^I_3) = 31\%$ of the population, with a respective value score $v_{1.3}(A^I_3) = 30$ on this attribute, instead of the estimated original performance $x_{1.3}(A_3) = 22\%$, with a value $v_{1.3}(A_3) = 60$ points, as shown in Fig. 11.6b.

We can define the valued performance profile of the implemented strategy, by performing the same type of value assessment that is described above for the other

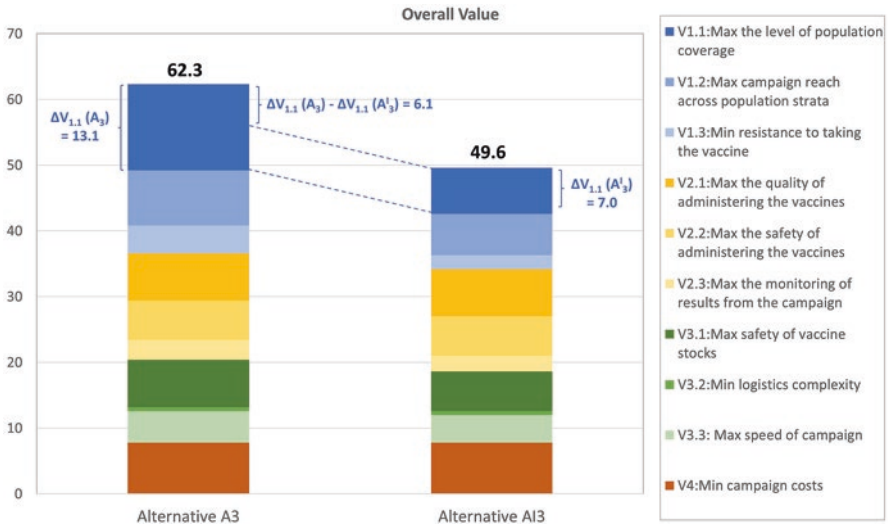

Fig. 11.7 Value gap analysis for the planned (A_3) and implemented (A^I_3) vaccination campaign

attributes of the value model. This value profile of the implemented vaccination strategy is shown on the right-hand side of Fig. 11.5. The overall value of the implemented alternative, using the value scores and the attribute weights from Eq. 8.1 (presented in the Eighth chapter), is only $V(A^I_3) = 49.6$ points, in contrast with the original estimated value of this strategy $V(A_3) = 62.3$ points, as shown on the left-hand side of the same figure.

The value profile of the estimated alternative (A_3) when compared with the value profile of the implemented alternative (A^I_3), presented in Fig. 11.5, shows the *value gap* between planning and implementation. On some dimensions, the estimates are reliable, such as for the logistic complexity ($v_{3.2}(A_3) = v_{3.2}(A^I_3) = 30$ value points) and for the cost of the campaign ($v_4(A_3) = v_4(A^I_3) = 52$ value points), for example. On other dimensions, the actual performance lies below the estimates, such as for the campaign reach across the population strata ($v_{1.2}(A_3) = 80$ value points and $v_{1.2}(A^I_3) = 60$ value points) and the ability to monitor the results of the campaign ($v_{2.3}(A_3) = 100$ value points and $v_{2.3}(A^I_3) = 80$ value points), for instance.

The comparison of this value gap between the two value profiles, shown in Fig. 11.7, can help the health security team in identifying remedial actions that may improve the value of the implemented option. Let us consider the value gap for attribute $x_{1.1}$, *maximize the level of population coverage*. The weight of this attribute is $w'_{1.1} = 17.5\%$, as shown in the value tree depicted in Fig. 11.5, and the estimated valued performance of the vaccination campaign on this attribute is $v_{1.1}(A_3) = 75$ value points, as shown in Fig. 11.6a. Hence, the value added from alternative A_3 on this attribute is given by $\Delta V_{1.1}(A_3) = w'_{1.1}\, v_{1.1}(A_3) = 0.175(75) = 13.1$ value points, as is shown on the left-hand side of Fig. 11.7. However, once implemented, the

performance of this vaccination strategy proves inferior when compared with the original estimate that had been made, with $v_{1.1}(A^I_3) = 40$, as shown in Fig. 11.6a. Hence, the value contribution on this attribute from the actual strategy is only $\Delta V_{1.1}(A^I_3) = w'_{1.1}\ v_{1.1}(A^I_3) = 0.175(40) = 7.0$, with a value reduction of $\Delta V_{1.1}(A_3) - \Delta V_{1.1}(A^I_3) = 13.1 - 7.0 = 6.1$, as highlighted in Fig. 11.7.

Let us assume that remedial actions could be devised to shift the proportion of the population that is vaccinated from 70% toward the planned 80%. We could calculate the value that is added through the execution of said actions. In this case, the remedial action would increase the value by 35 value points on this attribute (see Fig. 11.6a): $\Delta v_{1.1} = v_{1.1}(A_3) - v_{1.1}(A^I_3) = 75 - 40 = 35$ points. Hence, the increase in added value of said action on this attribute would be $\Delta V_{1.1} = w'_{1.1}\ \Delta v_{1.1} = 0.175(35) = 6.1$ value points, as depicted in Fig. 11.7, which would shift the overall value on this attribute toward the originally estimated value of $\Delta V_{1.1}(A_3) = 13.1$ value points. If these remedial actions were to incur additional costs, these extra costs should also be estimated. The value-for-money of these remedial actions could then be calculated against other remedial actions to support the successful implementation of the chosen vaccination strategy, with the selection of the most effective options if additional resources for implementation were made available.

This rigorous performance evaluation of the implemented decision alternative brings about many benefits in comparison with the ad hoc assessments that are often conducted after public policy implementations have taken place. First, the assessment fully aligns the performance evaluation with both the decision-making objectives and the relevant consequences that have been employed in the health decision analysis. Second, the evaluation enables a detailed and quantitative assessment of performance, attribute-by-attribute, instead of a mere checklist of achievements that function on a *yes* or *no* scale. Third, the value assessment provides the means to calculate an overall value score for the implemented alternative and to identify value gaps. Fourth, the assessment permits the valuation of value gaps and the identification of the most critical gaps so as to prioritize their narrowing. Fifth, this performance evaluation provides a template for incentivizing the implementers and for monitoring their performance so that their attention is turned toward achieving the societal value that is sought by the chosen health security options. A more formal assessment and greater control over the implementation performance may also help to reduce the misuse of resources during this critical stage of any health security project.

In addition to the importance of an implementation strategy and of overcoming implementation barriers, at this point of health security decision processes, systematic learning forms another key aspect. While this aspect is also rather neglected in Decision Analysis, systematic learning proves to be very relevant and is discussed in the subsequent section.

11.3 Systematic Learning in Decision Making Processes

The literature on Organizational Learning underpins the importance of promoting systematic learning, that is, both single-loop and double-loop learning (Argyris, 1999). The former is associated with learning about the current problem, devising ways of better solving this problem and implementing a solution in order to solve it. The latter type of learning is concerned with reframing the problem at stake, and delineating a broader definition of the decision problem and of the purpose of the decision (Checkland & Scholes, 1999). This double-loop process then lends to the design and the implementation of a solution for this reframed, broader problem.

For instance, if the problem were to be framed in terms of how many intensive care units (ICUs) are required to increase the preparedness of a health system against a severe health threat, the solution could be refined so that the solution identifies requirements and selects high quality ICUs that provide excellent value-for-money (single-loop learning). If we were to appropriate and reframe this original problem, this broadening could take the form of inquiring as to which are the most important health capabilities to increase preparedness against a health threat. In this latter case, the solution could be a combination of increasing the number of ICUs, and developing a vaccination campaign and an education campaign about preventative health measures. This latter approach would constitute the process of double-loop learning.

Despite the importance of learning in decision making, it proves extremely difficult to do so systematically, particularly during decision processes whose decision model is not transparent and comprehensive and whose structure is not well-organized. Unstructured decision processes typically do not maintain a formal record of what has been considered and what has been disregarded, nor do these processes record the judgments and assumptions made, or how the options have been evaluated and subsequently selected.

One of the main benefits of establishing structured processes for making health security decisions and for conducting health decision analyses is that these processes allow for the ability to systematically learn from any successes and any failures that have come about. Indeed, learning should be a key aim in Decision Analysis (Roy, 1993), and every stage of a decision process should be a means to: better understand the intricacies of the decision problem, clearly agree upon the objectives and priorities that must be considered, realistically identify the costs and benefits of each decision option, and reflect upon the key uncertainties that may affect their performance.

Thus, decision models should be employed as learning tools (de Geus, 1988) instead of being seen as structures that provide the "optimal" solution (Franco & Montibeller, 2010). This focus on decision analysis for learning is an important conceptual distinction in Operations Research (Montibeller, 2018). A learning-focused analysis places the emphasis on decision modeling for supporting reasoned decision making and learning, instead of prescribing an optimal solution that must be implemented by the decision makers (Roy, 1987, 1993). Decision models should adequately support reasoned decisions, but decision makers are the ultimately the individuals that

must decide; high-stakes decision making is a human endeavor and should remain so despite all the advances that artificial intelligence has been providing for pattern recognition and for the automation of repetitive choices whose goal is clear and singular.

While organizations can (and should) enable and promote learning, learning is always an individual-focused and group-based activity (Argyris, 1999). The concepts and suggestions made in this book may help health security teams to learn in a more effective manner and further improve their choices, both within a single decision process and across a series of decision processes. In this section we suggest some feedback loops in the decision process, which may help health security teams in conducting more deliberate and systematic opportunities for learning and for refining solutions.

11.3.1 Learning from the Identification of Objectives and the Development of Alternatives

Two decision stages can help the health security team to recursively reframe and improve the definition of the decision problem (see the learning loops in Fig. 11.8). First, the identification of any additional fundamental objectives and relevant consequences may assist the expansion of the decision frame. Second, the development of new alternatives may also expand the decision frame. When taken as a whole, these two reflective activities may substantially improve the understanding of the decision objectives that the health security team wishes to achieve and of the solution space wherein solutions may be found.

Identifying Additional Objectives and Consequences The specification of additional fundamental objectives and relevant consequences shall expand the decision frame, as discussed in the third chapter. This specification process may indicate that a greater number of concerns should be considered in the health security decision than had originally been thought by the health security team. Expanding the set of objectives (Bond et al., 2010; Keeney, 1992, 2013) may stem from considering further concerns that are held by key stakeholder, the inclusion of the concerns of a stakeholder that had been initially disregarded, the addition of any relevant consequences that require inclusion, any additional benefits that must be considered, and any additional costs that are required by elements of the decision. The fourth chapter has provided a detailed discussion as to how to identify the fundamental objectives, the strategies of which can be used to identify any additional objectives throughout the learning loop.

Identifying New Decision Alternatives The inclusion of new alternatives shall also expand the decision frame, the topic of which has also been discussed in the third chapter. These new alternatives may result from the inclusion of any additional fundamental objectives. In such cases, said alternatives could be providing solutions to objectives that had initially been disregarded. New alternatives may also be devised to address any weaknesses involved in the initial set of alternatives, or, may

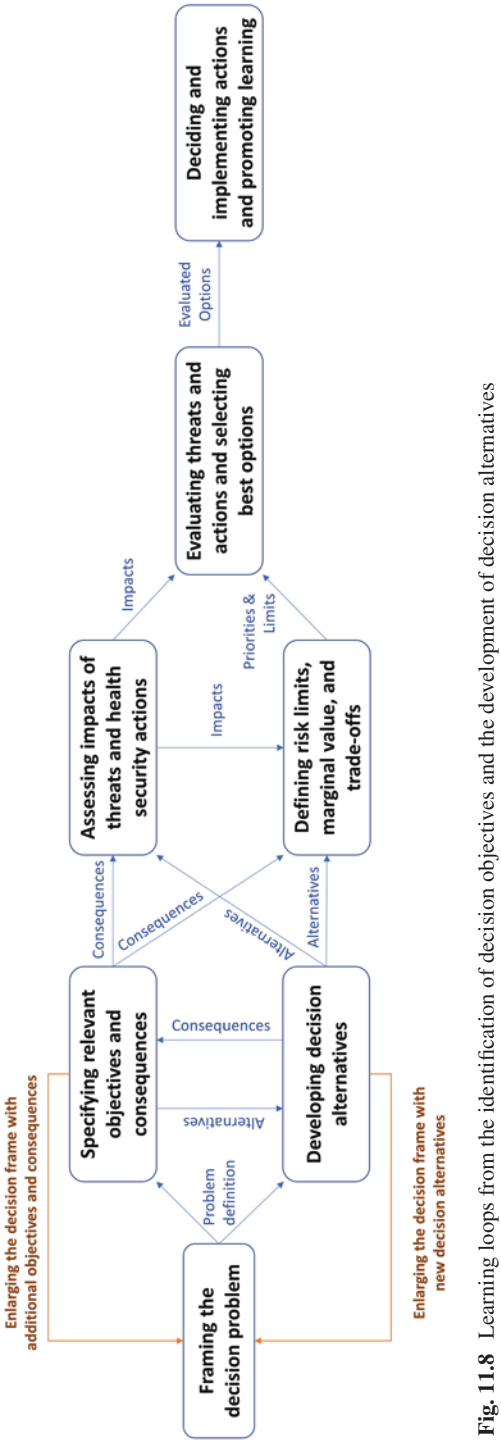

Fig. 11.8 Learning loops from the identification of decision objectives and the development of decision alternatives

be redesigned utilizing this original set as a foundation, to reduce any weaknesses and improve the strengths of the pre-conceived alternatives (Keller & Ho, 1988; Siebert & Keeney, 2015). The seventh chapter has suggested several ways of developing more alternatives and these same strategies can be employed to further expand the option set during the learning loop.

Let us revisit the decision frame for managing a health threat that has been triggered by a virus, the case of which has been presented in the third chapter. Let us now consider this case in a dynamic manner, so that we are able to better illustrate the recursive process of expanding the decision frame through the use of a learning loop. Let us posit that, initially, to manage this health threat, the health security team has defined the objective to be *minimize viral presence*. In this case, the option set has been designed so that the options *reduce viral presence*, and involve actions such as isolating infected people or suppressing disease vectors (see Fig. 11.9a).

Subsequently, let us now assume that the team has decided to revisit the original decision objective and expand the objective, opting to render the original objective as a means to *minimize viral exposure*. In turn, this broader objective shall expand the option set, which now not only includes options to *reduce viral presence* but also options to *reduce viral exposure*, such as the compulsory wearing of protective equipment and recommended hygienic procedures (see Fig. 11.9b).

Finally, let us turn to another feedback loop in this case, and let us imagine that, once again, the team wishes to revisit the previous decision objective, agreeing upon the notion that the objective *minimize viral exposure* is a means to *minimize health effects*. Again, the expansion of the objective that has been set, for the second time, would lead to a subsequent expansion of the option set, which would allow for the inclusion of options to *reduce viral presence*, options to *reduce viral exposure*, as well as options to *reduce health effects*, such as vaccination and post-exposure treatments (see Fig. 11.9c). As this example illustrates, expanding objectives, in recursive learning loops, systematically expands the problem frame and encompasses a greater number of decision alternatives of different types.

It is important to note that the learning loop that is derived from the identification of decision objectives and the identification of decision alternatives does *not* always have the expansion of the scope of the decision frame as the ultimate aim of said loop, as the example in Fig. 11.9 illustrates. Instead, the aim of the loop entails the identification of a decision frame that is *adequate* for the specific health security decision situation, and includes objectives that are both essential and controllable and options that lie within the specific decision context, as has been discussed in the fourth chapter (see also Keeney (1992, 2013) for further details). Consequently, this aim necessarily involves a recursive process of the delineation and refinement of both the definition of the decision objectives and the specification of the decision alternatives.

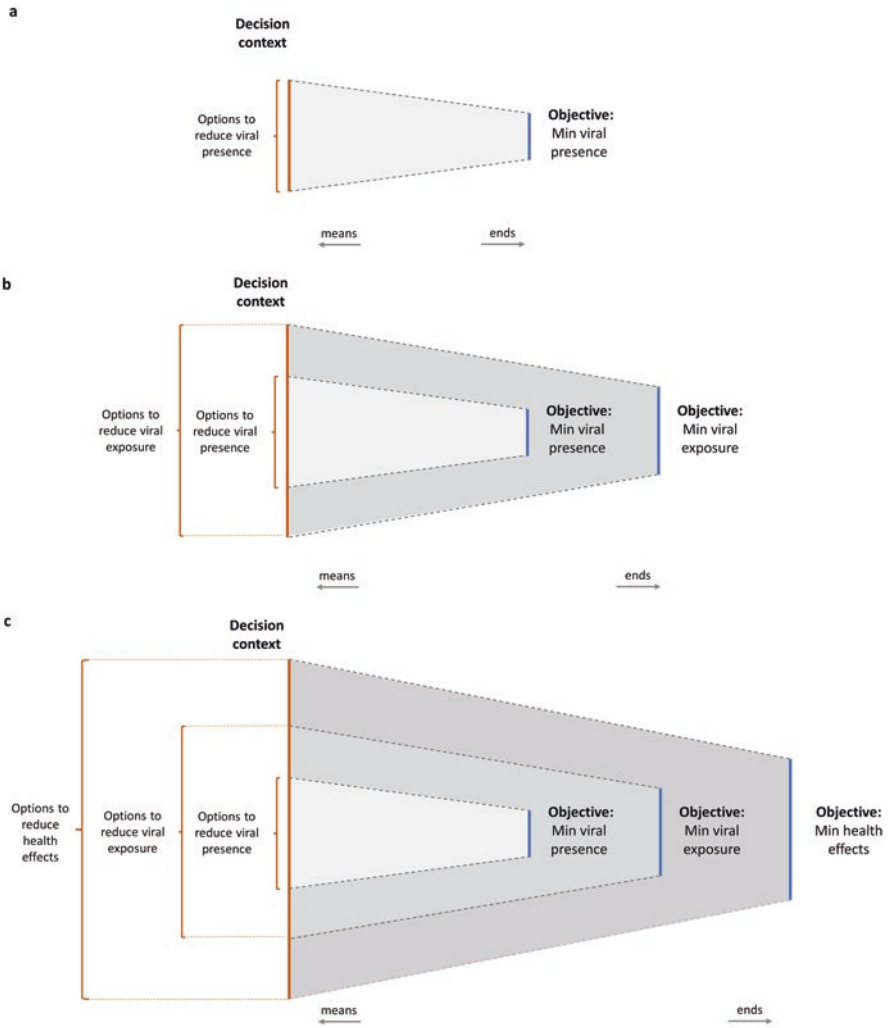

Fig. 11.9 Recursively expanding the decision frame: (**a**) Objective is to minimize viral presence, (**b**) Objective is to minimize viral exposure and viral presence, (**c**) Objective is to minimize health effects, viral exposure, and viral presence

11.3.2 Learning from the Assessment of Impacts and the Definition of Risk Limits

Two decision stages can improve the specification of objectives and relevant consequences, as well as the development of new decision alternatives in a recursive manner (see learning loops in Fig. 11.10). First, the assessment of the impacts of health threats and health security actions may support a more precise specification

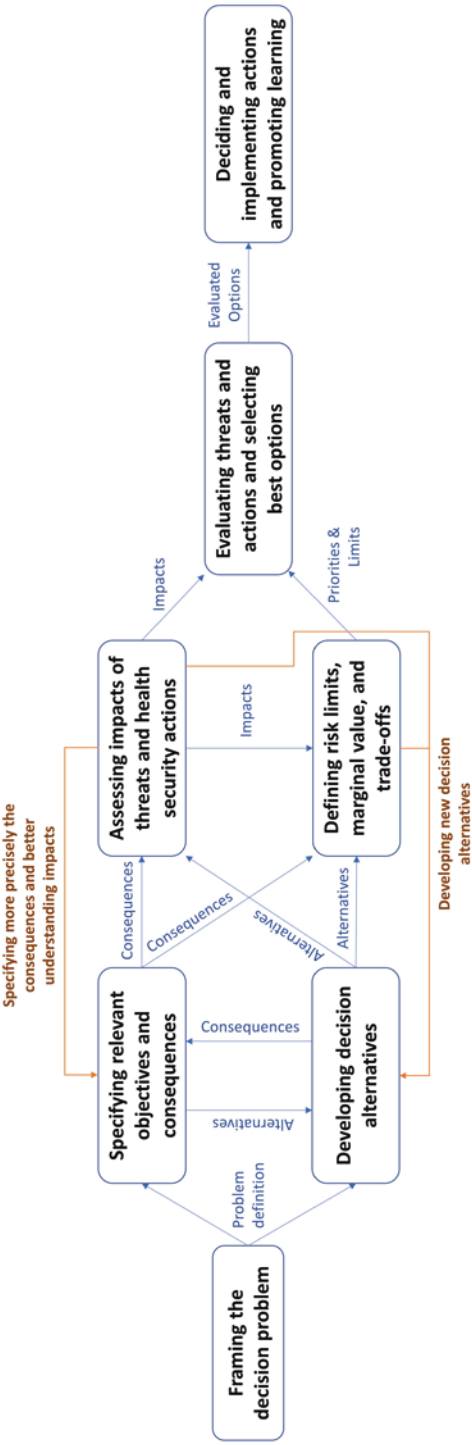

Fig. 11.10 Learning loops from the assessment of impacts and the definition of risk limits and trade-offs

of the consequences, and, may provide a better understanding of the possible impacts of health security actions and health threats. This assessment can also support the development of new and better decision alternatives. Additionally, the definition of risk limits may help in the identification or the development of better decision alternatives.

Refining the Specification of Objectives and Consequences The assessment of impacts of health threats and health security actions may indicate that the objectives that had originally been defined had not been specified to an adequate standard. These assessments may also highlight that the originally stated objectives have held different meanings for different stakeholders, an issue which only becomes apparent once there occurs an attempt to measure the impacts of health security actions and health threats. In cases such as these, the health security team should return to the drawing board, and specify the decision objectives and attributes more precisely (Keeney, 1992; Keeney & Gregory, 2005). The properties of the objectives, as well as the properties of attributes, the topics of which have been discussed in the fourth chapter and fifth chapters respectively, may help to further improve the definition of objectives and consequences during this learning loop.

Developing New Decision Alternatives A better understanding as to the uncertainties and scenarios that form part of this decision stage may also generate ideas for further developing decision alternatives and for initiatives to gather more information during this learning loop. In the seventh chapter, we have put forth some suggestions as to the tools that can be employed to increase the expected value of decision alternatives when making decisions under uncertainty. Two additional tools are particularly useful for the re-design of the decision alternatives that may provide higher societal value: the calculation of the expected value of perfect information and the development of tornado charts. Furthermore, the redefinition of risk limits may expand the solution space and, thus, foster new options that can be brought to the decision table. These three tools are described next.

Expected Value of Perfect Information Let us imagine that, in a decision under uncertainty, we have been imbued with the ability to foretell as to which scenario would occur after every uncertainty has been resolved. In this case, wherein we are conscious of the perfect information about the future, we are always able to select the scenario whose outcome proves to be the best. The expected value of this decision is called the *expected value of perfect information* (EVPI) (Raiffa, 1968).

In order to illustrate this type of expected value of perfect information analysis, let us revisit an example from the ninth chapter. Let us posit that a health threat has the potential to cause 100,000 deaths within the time period and the region under consideration. The sole fundamental objective of any risk mitigating action is to *maximize the number of lives saved*, and the attribute to measure this consequence is *the number of lives saved* (x). There exist three risk mitigating actions under consideration, A'_1, A'_2, and A'_3, and each action could save a number of lives were it to be implemented. However, there exists uncertainty regarding the effectiveness of

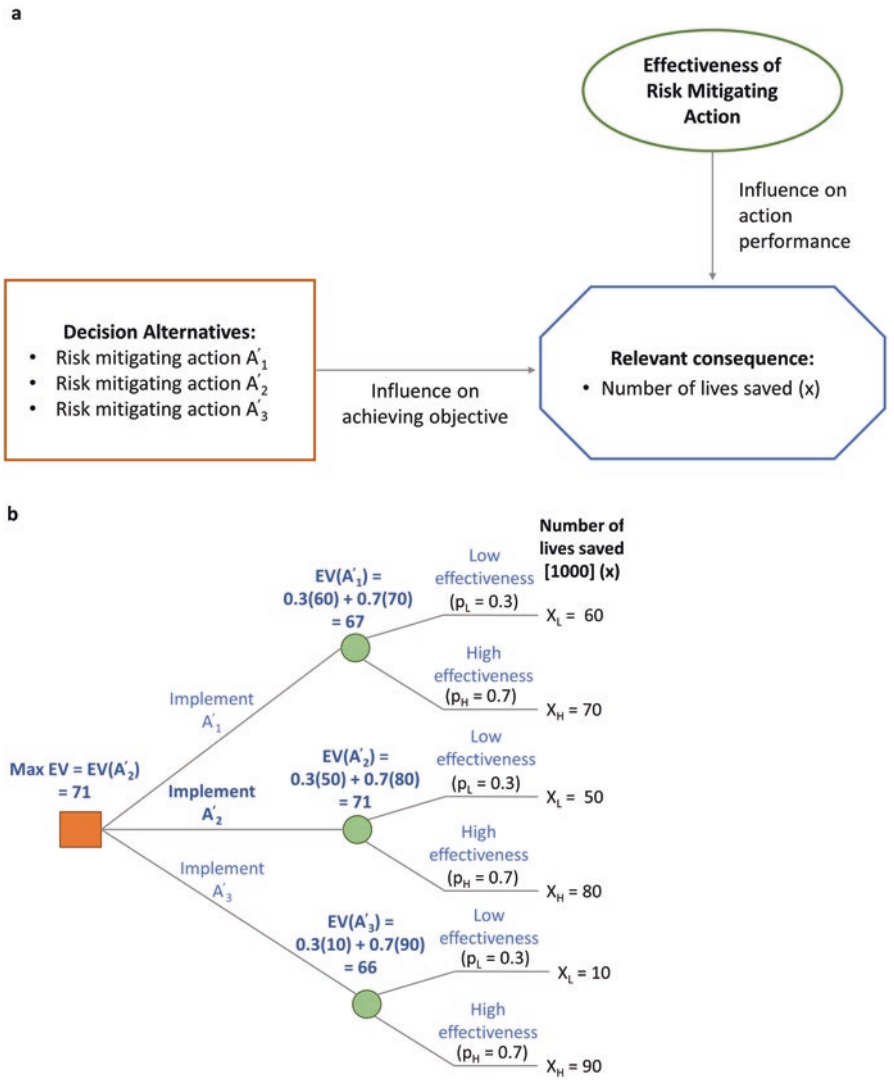

Fig. 11.11 Selecting among the three risk mitigating options: (**a**) Influence diagram representation, (**b**) Decision tree representation

each risk mitigating action; each of these decision alternatives would incur the same cost of implementation and only action can be selected due to budget restrictions.

This decision problem is shown in the influence diagram in Fig. 11.11a, wherein the uncertainty about the effectiveness of the risk mitigating action influences the performance of this action. There exists a $p_L = 30\%$ probability that the actions demonstrate low effectiveness and a $p_H = 70\%$ probability that they demonstrate high effectiveness. The number of lives saved for each action and under each

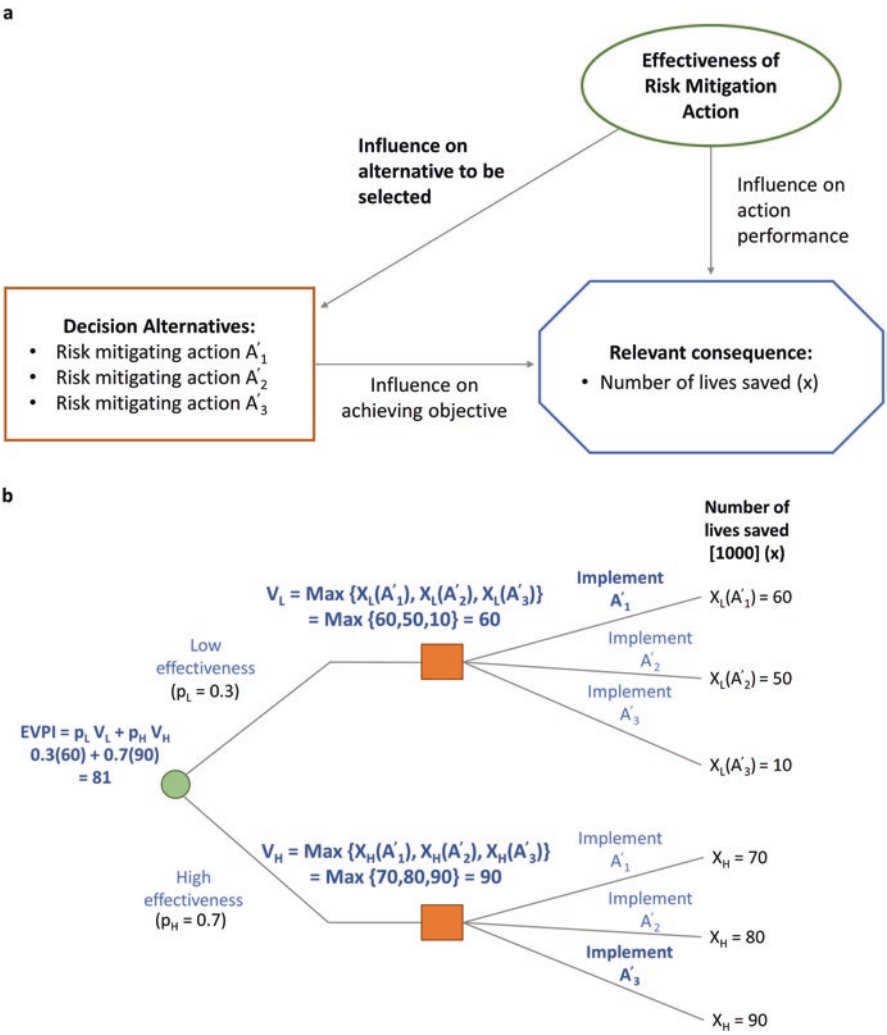

Fig. 11.12 Conducting a value of perfect information analysis: (**a**) Influence diagram, (**b**) Decision tree

scenario is shown in the decision tree that is displayed in Fig. 11.11b, which details the decision problem depicted by the influence diagram. The option that maximizes the number of lives saved is A'_2, with $EV(A'_2) = 71{,}000$ lives saved.

How many lives could be saved if we were to have perfect information concerning the future? In this case, prior to selecting an action, the decision makers could first learn about the uncertainty resolution. This sequence of information is illustrated in the influence diagram in Fig. 11.12a, wherein the *uncertainty* node shall influence the alternative to be selected in the *decision* node. In a decision tree, this

sequence of information-decision is represented by the *chance* node, which is then followed by *decision* nodes, as shown in Fig. 11.12b. Under the scenario of low effectiveness, the best choice is A'_1 with $EV(A'_1) = 60{,}000$ lives saved. On the other hand, under the scenario of high effectiveness, the best choice is A'_3 with $EV(A'_3) = 90{,}000$ lives saved. The *expected value of perfect information* for this problem is thus: $EVPI = p_L\ V_L + p_H\ V_H = 0.3(60{,}000) + 0.7(90{,}000) = 81{,}000$ lives saved.

In this example, if the health security team were able to obtain perfect information, they would save an additional 10,000 lives in relation to the original decision under uncertainty. ($EVPI - EV(A'_2) = 81{,}000 - 71{,}000 = 10{,}000$ lives): Obviously, this proves unfeasible as perfect information is impossible to be obtained, however, the EVPI provides an upper bound, which establishes that up to 10,000 additional lives could be saved if there were to exist more information about the actual effectiveness of the risk mitigating actions.[1] If the potential gains in acquiring more information are significant, the expected value of perfect information can function as a motor, driving initiatives for improving information gathering on the influence that key uncertainties have on the performances of decision alternatives in the learning loop.

Tornado Charts Not every uncertainty exerts the same degree of influence on the results of a decision model. A tornado diagram represents the swing of the outputs, for instance, the expected value of each decision alternative, given the range of uncertain inputs.

Let us revisit the analysis of the uncertainties of the performances in the vaccination campaign options that have been described in the ninth chapter, using the baseline values that have been calculated in the eighth chapter. Recall that the option with the highest overall value was alternative A_3 with $V(A_3) = 62.3$ value points. Imagine that the health security team is considering the selection of this option but would like to understand the degree to which A_3 is sensitive to the uncertainties pertaining to the estimated performances of this decision alternative.

There exist several ways of drawing a tornado chart (see Vose (2008) and McNamee and Celona (2005) for details). A simple manner of plotting the chart entails both identifying a lower threshold, which establishes that there exists a 10% chance that the performance shall either be lie at or below this lower threshold, and identifying an upper threshold, which establishes that there exists a 10% chance that the performance shall either lie at or above this upper threshold.

Let us consider the attribute *proportion of population vaccinated* (measured by variable $x_{1.1}$) in the vaccination campaign case. For alternative A_3, a triangular distribution $f_{A3}(x_{1.1})$ has been defined to represent the uncertainty of the performance of this alternative (see Fig. 11.13a), as detailed in the nineth chapter. As shown in the same figure, the lower-level performance threshold for this triangular function is

[1] It is also possible to calculate the parameter of the expected value of *imperfect* information, however, the computation proves slightly more complicated than that of the expected value of perfect information; see McNamee and Celona (2005) for details.

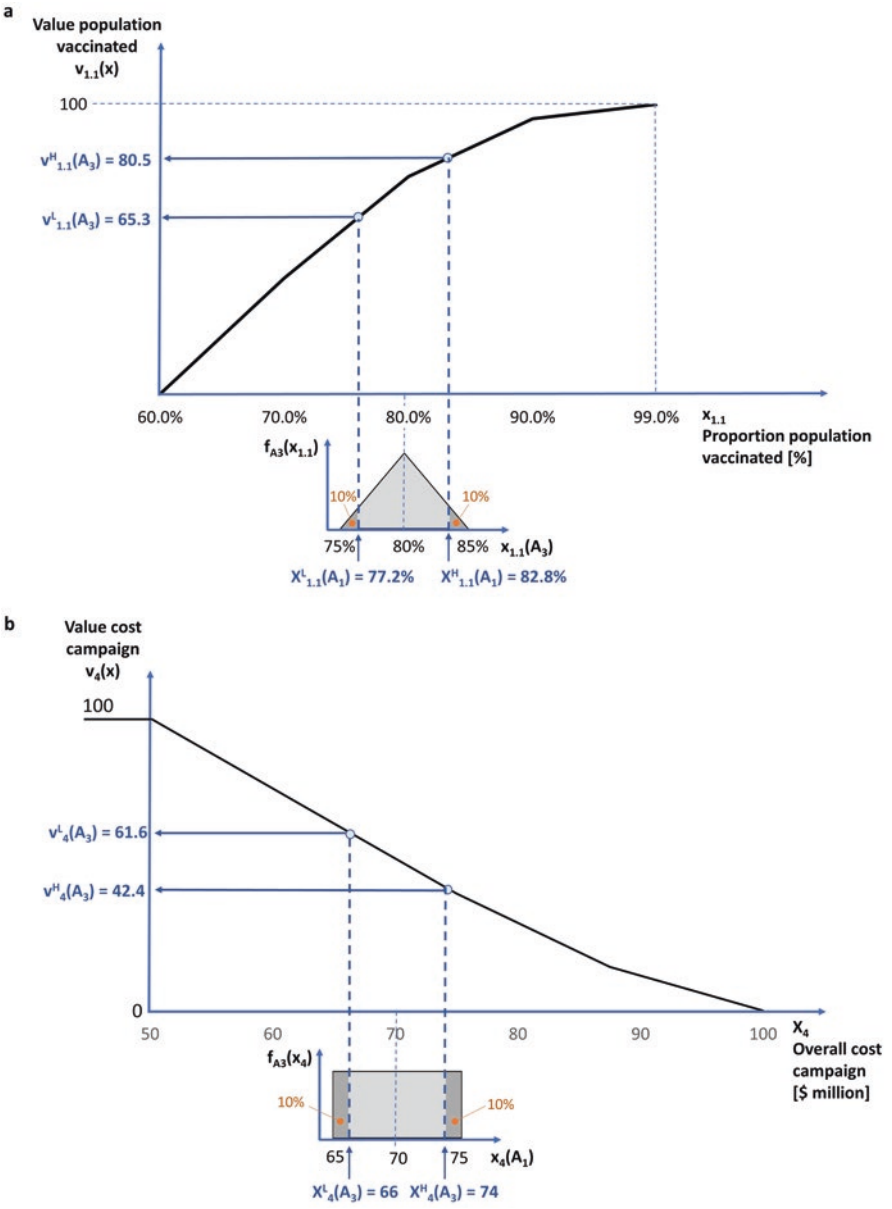

Fig. 11.13 Identifying lower and upper bounds for a tornado chart analysis (for decision alternative A_3): (**a**) Proportion of population vaccinated attribute, (**b**) Overall cost of campaign attribute

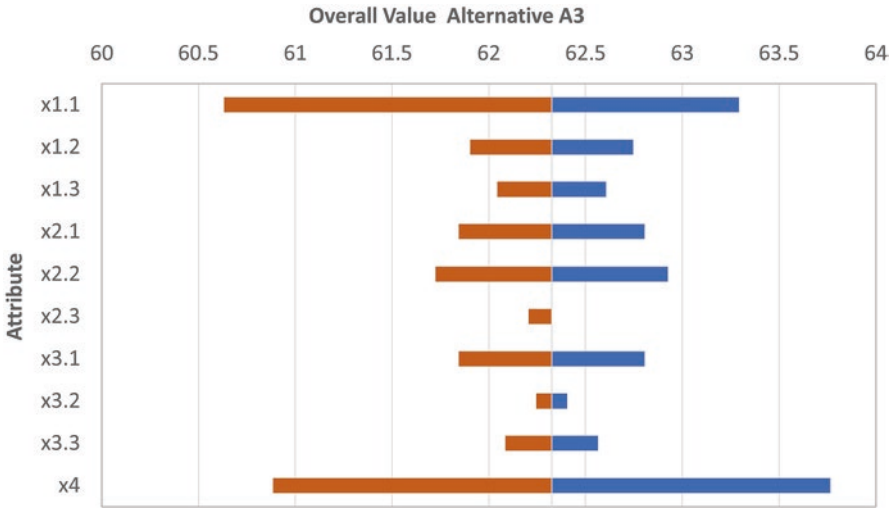

Fig. 11.14 Tornado chart for alternative A_3 in the vaccination campaign case

$X^{L}_{1.1}(A_1) = 77.2\%$ and the higher-level performance threshold is $X^{H}_{1.1}(A_1) = 82.8\%$. The value scores for these two levels on this attribute are $v^{L}_{1.1}(A_3) = 65.3$ and $v^{H}_{1.1}(A_3) = 80.5$ respectively.

Recall that for the other attributes of this value model, we have assumed uniform distributions to characterize the uncertainty about the performances of each alternative. For example, for the attribute *overall cost of the campaign* (x_4), the uniform distribution for the same alternative is $f_{A3}(x_4)$, as shown in Fig. 11.13b. The lower-level performance threshold for this uniform distribution is $X^{L}_{4}(A_3) = \$66$ million and the higher-level performance threshold is $X^{H}_{4}(A_3) = \$74$ million. The value score for these two thresholds on this attribute are $v^{L}_{4}(A_3) = 61.6$ and $v^{H}_{4}(A_3) = 42.4$ respectively. The same lower and upper thresholds have been defined for the other attributes in the value model.

The tornado chart is drawn by emplacing a single performance of an attribute at the two performance thresholds (a lower-threshold and an upper-thresholds) while maintaining all the other performances at baseline levels (presented in Table 8.1 in the eighth chapter). The chart for alternative A_3 is shown in Fig. 11.14. Notice that the wider variations are for the attributes *proportion of population vaccinated* ($x_{1.1}$) and *overall cost of the campaign* (x_4). This analysis indicates that the initiatives for gathering more information that could reduce these two uncertainties, thereby tightening the distributions $f_{A3}(x_{1.1})$ and $f_{A3}(x_4)$ shown in Fig. 11.13, would reduce the possibility of there occurring decreases in the overall value of this alternative. A similar tornado chart could be developed for the other decision alternatives in this vaccination campaign case. This analysis may support the identification of improvement actions which reduce the variability of performances and enhance the quality of the decision options in this learning loop.

Risk Limits and Constraints Defining risk limits and constraints delineates the solution space, thereby allocating that which is unacceptable and that which is acceptable (in terms of performances) into separate spheres within the single space. Consequently, the effect of this delineation is that it enables the inclusion of feasible options and the exclusion of their unfeasible counterparts, as we have detailed in the sixth chapter. Therefore, the reconsideration of risk limits or constraints could have an expansive effect upon the solution space. For instance, if effective and inexpensive treatments against an emerging disease were to be discovered, the earlier, more stringent risk limits that had sought to contain the number of cases, and had been established at a time when no such treatment had been available could, at this stage, be relaxed, as treatment would now be readily available to treat infected patients.

One area wherein this recursive learning cycle in the decision process proves particularly useful is in the reconsideration of the investment budget. Often, it is possible to increase the budget using contributions from external donors or from private donations. If that were to be the case, it may be possible to select (and fund) a superior alternative, with a higher societal value, than the alternative that had otherwise been selected at a time at which the budget had been lower.

Let us revisit the example in the sixth chapter, wherein four risk mitigating alternatives against a health threat have been considered (A_1, A_2, A_3, and A_4) on two consequences to be minimized: *number of severe cases* (measured by variable x) and *total cost of mitigation* ($). Were no risk mitigating action to be implemented, the health threat would cause X^* severe cases. As shown in Fig. 11.15a, each alternative incurs a given cost C_l and a remaining number of severe case X_l after being implemented. Two limits had been defined in this decision problem, a maximum acceptable number of severe cases (X_L) and a maximum available budget (C_L). The gray area in the same figure indicates the region of feasible solution.

Recall that A_4, despite being the most effective alternative in minimizing the number of severe cases, had been excluded, as this option had proven too expensive to be funded ($C_4 > C_L$). However, if the budget were increased, from C_L to C^*_L, this action would expand the feasible region to such a degree as to include alternative A_4, as shown in Fig. 11.15b. The selection of this option would be the most beneficial in terms of risk reduction, in comparison to selecting A_3 and A_2 (as $X_4 < X_3 < X_2$).

The three tools that are described above, that is, the expected value of perfect information, the tornado charts, and the redefinition of risk limits may support the health security team in systematic learning about the decision situation. The expected value of perfect information can indicate the additional value of seeking more sources of information about the possible prospects of each health security option. Furthermore, tornado charts can help to identify the uncertainties that most affect the value of decision alternatives. Lastly, redefining risk limits and other constraints may increase the number of options that can be brought to the decision table, and expand the search space for the design of new health security options with additional benefits.

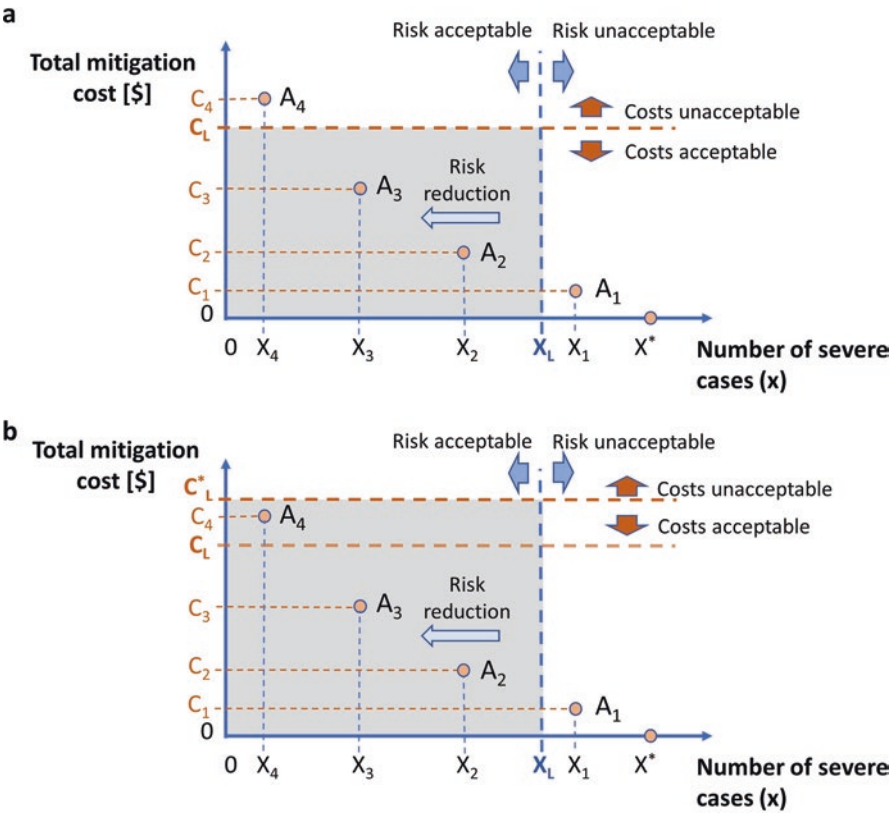

Fig. 11.15 Expanding the solution space by relaxing a constraint: (**a**) Original cost constraint (C_L) with alternative A_4 excluded, (**b**) Increased cost constraint (C^*_L) which makes alternative A_4 feasible

11.3.3 Learning from the Evaluation of Threats and of Health Security Actions

The evaluation of health threats or of health security actions may, recursively, improve and refine the four previous decision stages (see the learning loops in Fig. 11.16). First, impact assessments may be refined once a first evaluation has been conducted. Second, hidden fundamental objectives, or neglected relevant consequences, may be discovered during the evaluation phase. Third, new decision alternatives may be created to address shortcomings of the current options, which have been highlighted by the evaluation. Fourth, risk limits and trade-offs may be more clearly defined and further agreed upon by the health security team during the evaluation of health security actions stage.

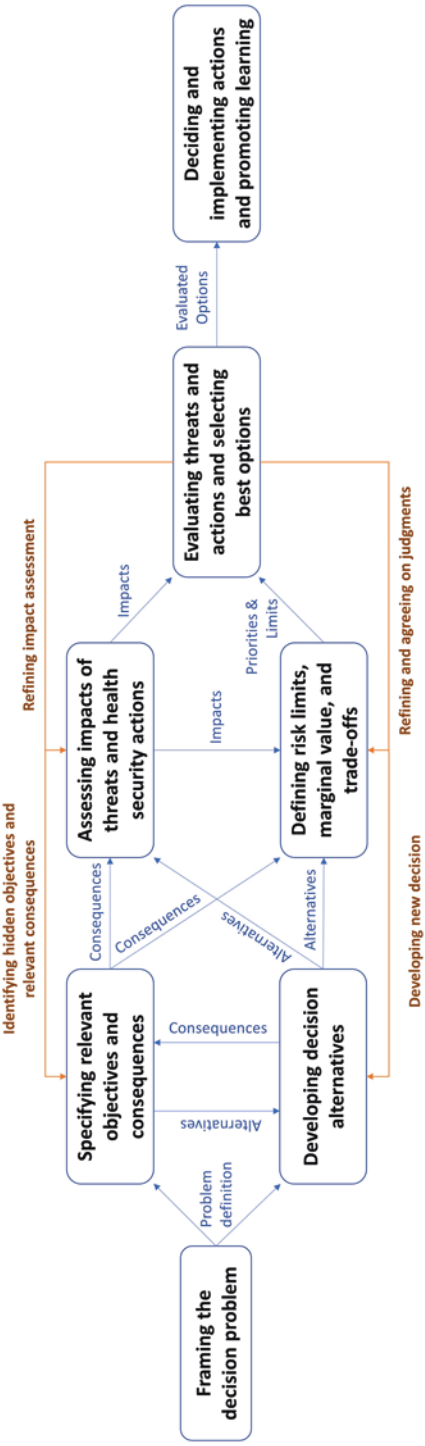

Fig. 11.16 Learning loops from the evaluation of threats and health security actions

Identifying Hidden Objectives and Relevant Consequences The evaluation of decision alternatives may highlight that some fundamental objectives are absent, or that some relevant consequences have been neglected. Similarly, in the prioritization of health threats, this evaluation may also indicate that relevant impacts have not been considered in the analysis. In these cases, the relevant objectives or consequences should be included within the model, evidence should be gathered about the possible impacts, and the decision alternatives should be re-evaluated using this more comprehensive model. Similarly, in the evaluation of health security actions, the absence of some relevant decision objectives may become apparent once the options have been evaluated, and should be considered in this learning loop.

For instance, let us consider a health security team that is deciding between two types of vaccine for a contagious disease. Imagine that both options (A_x and A_y) have the same efficacy and health risks, and the cost per dose of each vaccine is also very similar. These factors would lead to a similar value in the assessment phase, which would signal that there exists an indifference toward the two options. Consequently, a useful question to ask in such cases is whether the team would still prefer one vaccine over the other (either A_x or A_y), and, if so, what is the underlying reason for this preference? Let us imagine that the team would prefer A_x, as this vaccine is produced nationally, while A_y would require importation, and as a consequence, incurs risks in terms of supply and foreign exchange rates. The existence of this preference and the information that underpins it would indicate the absence of an important objective: *maximize stability of supply of the vaccine stocks*. This learning loop would also indicate that there exists a concern about a relevant consequence: *price volatility of vaccine stocks*.

Developing New Decision Alternatives The evaluation of decision alternatives proves to be an effective manner of generating further options. At times, it is possible to combine two pre-existing alternatives to form a new alternative, thereby generating more additional value than the two pre-existing alternatives would have provided individually. This same redesigning process may be used to reduce the drawbacks of the original alternatives and to increase the value of the new alternative. Additionally, under uncertainty, scenarios that provide low expected value may be addressed with planned risk mitigating actions, thereby increasing the resilience of alternatives against negative situations, as has been discussed in the seventh chapter.

For example, consider the evaluation of the five vaccination strategies, which have been described in the eighth chapter, and are reproduced in Fig. 11.17. The third alternative has the highest overall value: $V(A_3) = 62.3$ value points. However, notice that the performance of this option on the attributes *maximize the quality of administering the vaccine* ($v_{2.1}$) and *maximize the safety of administering the vaccine* ($v_{2.2}$) are relatively low in comparison to the performance of alternative A_1 on these same attributes, as indicated in the figure: $v_{2.1}(A_3) = 7.2$ value points and $v_{2.2}(A_3) = 6.0$ value points *versus* $v_{2.1}(A_1) = 12.0$ value points and $v_{2.2}(A_3) = 15.0$ value points. Hence, if alternative A_3 were able to appropriate some of the actions of

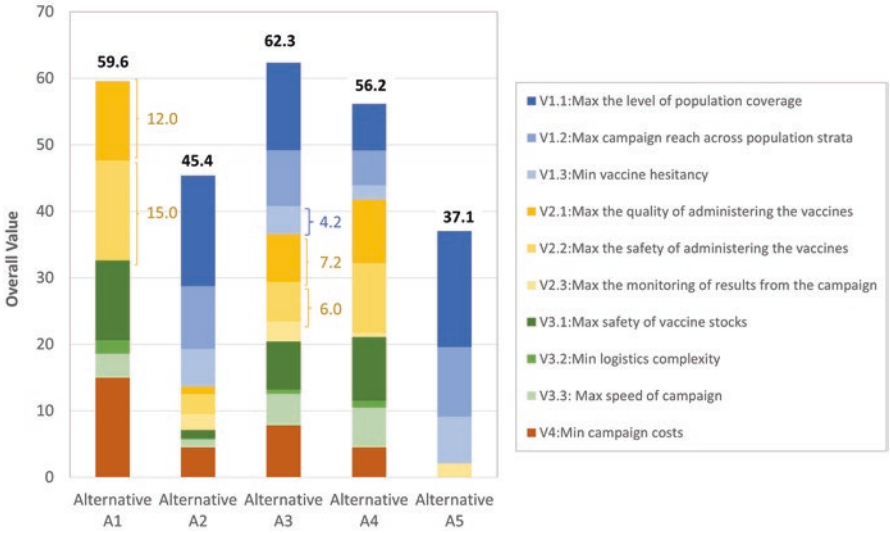

Fig. 11.17 Overall value of the five vaccination campaign strategies and the design of mixed vaccination strategies

alternative A_1 on these two attributes, without incurring any additional costs, this redesigned alternative A'_3 would increase the overall value of the best option by 13.8 value points: from $v_{2.1}(A_3) = 7.2$ to $v_{2.1}(A'_3) = 12.0$ and from $v_{2.2}(A_3) = 6.0$ to $v_{2.2}(A'_3) = 15.0$.

The evaluation of decision alternatives under uncertainty may also help to identify actions for improving the expected value of these alternatives, as detailed in the nineth chapter. For instance, consider again the evaluation of three risk mitigating actions (A'_1, A'_2, and A'_3), which have been depicted in the decision tree in Fig. 11.11b. The second alternative proves to be the best, with an expected value of $EV(A'_2) = 71{,}000$ lives saved. The expected value of this option could be further improved if actions were implemented in order to increase the number of lives saved under the low effectiveness scenario. For instance, if, under the low effectiveness scenario, the number of lives saved could be increased by $\Delta X_L = 10{,}000$ lives, from $X_L(A'_2) = 50{,}000$ lives to $X_L(A'_2) = 60{,}000$ lives, this increase would in turn increase the expected value of alternative A'_2 by 3,000 saved lives ($p_L \Delta X_L = 0.3 \times 10{,}000 = 3{,}000$ expected saved lives).

Another way of increasing the expected value of this decision alternative (A'_2) in the problem depicted in Fig. 11.11b would entail redesigning the risk mitigating action, in such a manner as to reduce the probability of low effectiveness. For instance, imagine that this probability could be reduced from $p_L = 0.3$ to $p'_L = 0.1$ (an thus from $p_H = 0.7$ to $p'_H = 0.9$). In this case, the expected value of A'_2 would be increased by 5,000 saved lives ($EV(A'_2) = p'_L\ X_L(A'_2) + p'_H\ X_H(A'_2) = 0.1\ (50{,}000) + 0.9\ (80{,}000) = 76{,}000$ expected saved lives). Thus, this

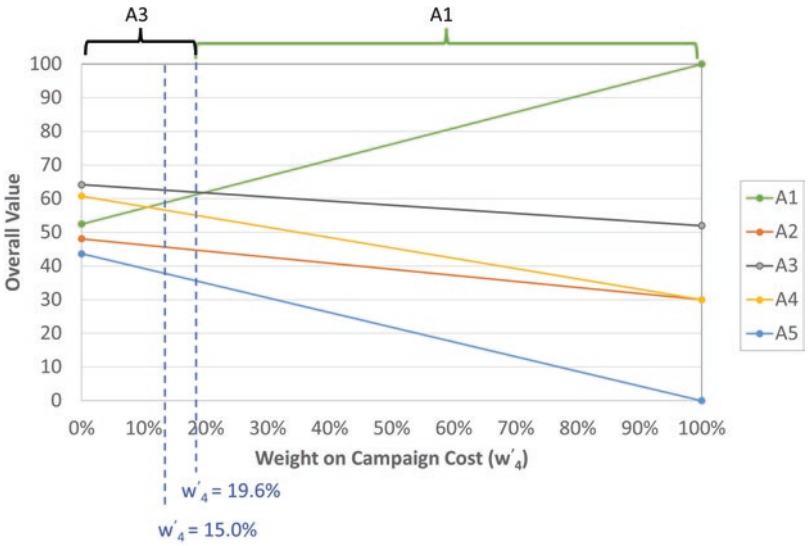

Fig. 11.18 Sensitivity analysis on the attribute weight cost of the campaign for the vaccination campaign case

learning loop could help to identify ways of increasing the expected value of decision alternatives.

Refining and Agreeing on Judgments Judgments are required to define risk limits and trade-offs. What if the analysis of results could be employed in such a manner as to make comprehensible the sensitivity of the solutions to a given risk limit or to a trade-off? This proves an effective way of verifying the robustness of the results against any imprecisions in judgments (Roy, 2010), refining these parameters, and achieving group agreement upon the baseline levels of the parameters. This agreement process is particularly important for group decision making, given the constructive and malleable nature of preferences (Lichtenstein & Slovic, 2006; Payne et al., 1999; Slovic, 1995) and the role of decision models as learning tools for agreeing upon and consolidating preferences (Roy, 1993).

The sensitivity analysis of the overall evaluation for the vaccination campaign strategies, which was detailed in the eighth chapter, can illustrate this process. The sensitivity analysis graph reproduced in Fig. 11.18, shows the variation of the overall value for each decision alternative if the ranges of the weight allocated to the vaccination campaign cost attribute (w'_4) were to lie between 0% and 100%. The baseline weight for this attribute is 15.0%, with alternative A_3 providing the highest overall value (62.3 points of value as shown in Fig. 11.17). If this weight were to exceed 19.6%, then alternative A_1 would be preferable (as it is cheaper than A_3). This analysis evidences that the solution is relatively sensitive to this attribute weight, so it is indeed critical that the group agree as to whether the baseline attribute weight could in fact reach this 19.6% threshold.

However, a word of caution is required when looking at this last type of analysis. At times, decision makers may feel tempted to "reverse engineer" the model, when they feel somewhat unsatisfied with the solution that the model has provided. In such instances, decision makers may start adjusting the model parameters (weights, probabilities, etc.), until their preferable solution, that is, the solution that has been holistically judged to be the best, is ranked as the highest option by the model. These actions constitute a misuse of decision analysis, and such impulses to manipulate the model should be curbed. Instead, the decision model should be used to foster learning and not be for the retrospective justification of pre-made choices.

The most common reason for the occurrence of this discrepancy between analytical results and holistic assessments stems from the fact that it is cognitively impossible to optimally aggregate all the sources of information that are involved in the decision situation, and so cognitive strategies that simplify this data must be adopted during unstructured decision processes (Payne et al., 1992, 1993). These simplified strategies do not follow a compensatory and decomposed assessment, which considers and adjusts all the components of a decision problem, the process of which is rendered feasible by a decision analysis model. Additionally, a holistic assessment may be driven by some salient factors that are easily recalled (Wänke et al., 1995) or by motivational biases that favor a given alternative (Montibeller & von Winterfeldt, 2015). Hence, the reasoning behind a holistic assessment is necessarily weaker than that of a decomposed assessment (Arkes et al., 2006; Arkes et al., 2009) and an external decision analysis is more comprehensive and logical than a mental comparison of alternatives.

11.3.4 Learning from Implementation Efforts

The implementation of choices proves to be an act that is far from trivial in policy contexts, and consequently, there may arise implementation barriers, the topic of which has been discussed previously in this chapter. Pilot implementations of the chosen options may provide a more realistic appraisal of their benefits, drawbacks, and costs (Banerjee et al., 2019; Newhouse & Normand, 2017), which may support the refinement of the earlier assessment of decision options. Once the full implementation stage commences, initial barriers may arise, taking the form of limited resources for implementation, the inefficient use of allocated resources for planned actions, or political and organizational resistances and so on.

The process of implementing the selected options, and the challenges encountered during the implementation phase may require returning to the planning board and refining the health decision analysis at three decision stages, as illustrated by the learning loops in Fig. 11.19. First, this experience may help in refining the evaluation of decision alternatives and the assessment of impacts from health threats and health security actions. Second, implementation attempts may help decision makers to either identify objectives that had previously been absent, or, to identify disregarded, yet, relevant consequences. Third, issues to execute implementation may require that decision makers create new decision alternatives.

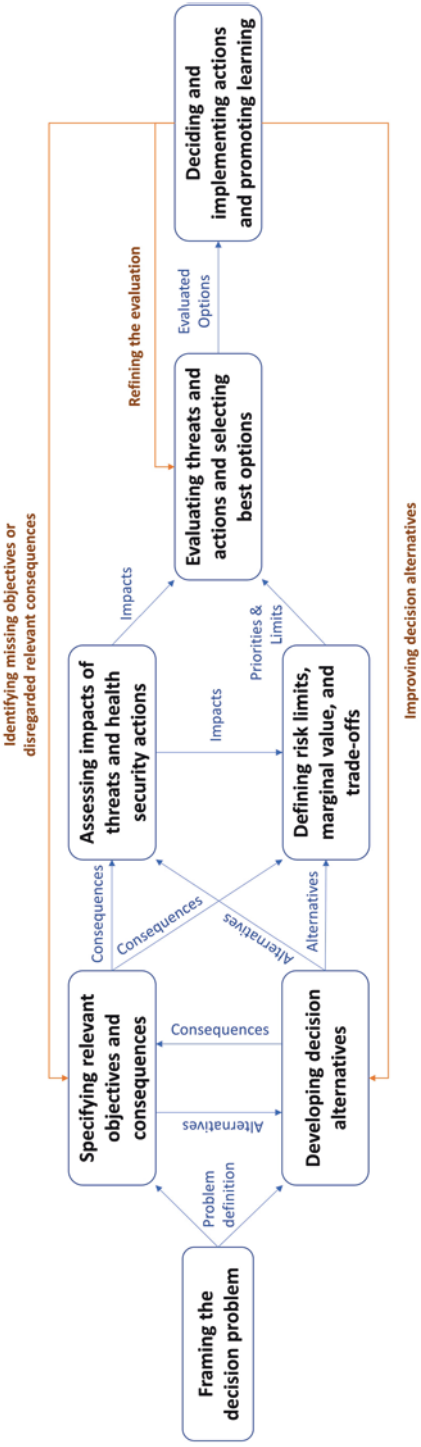

Fig. 11.19 Learning loops from the implementation efforts

Refining the Evaluation of Decision Alternatives Ideally, the earlier phases of the assessment should incorporate plans to undertake implementation barriers as well as the assessment of political feasibility of health security actions. However, in practice, it is rather difficult to develop contingency plans for every possible situation and more difficult still to predict all these possible situations a priori to the implementation. This natural limitation necessitates that the decision process be malleable, in that the decision model should be used recursively to reassess the decision alternatives and, considering this new information, to re-formulate the best course of action in this learning loop.

For instance, let us once again consider the vaccination campaign case and turn toward the results shown in Fig. 11.17. Imagine that the two decision alternatives with the highest overall value, A_1 and A_3, had been selected for an implementation pilot scheme. In each scheme, one vaccination campaign had been implemented in a small region and the results had been assessed on the attributes. For alternative A_1, assume that the actual performances were identical to that of the planned performance and thus the overall performance achieves $V(A_1) = 59.6$ value points. However, the levels of vaccine hesitancy had proved much higher for A_3 than had been predicted, and thus the $v_{1.3}(A_3) = 4.2$ value points on this attribute had not been accrued as predicted (as indicated in the same figure). Hence, after the pilot, the actual value of this alternative would only be: $V(A_3) = 62.3 - 4.2 = 58.1$ value points and, instead, alternative A_1 should be selected.

This example illustrates the importance of using health decision analysis recursively to learn more about the decision problem and to maximize societal value in health security choices. The example also highlights the added benefit of performing well-conducted pilot schemes and trials in policy processes in general, and in health security decisions in particular.

Identifying Missing Objectives and Relevant Consequences Difficulties encountered during the earlier phases of the implementation of the chosen options or knowledge learnt during implementation pilots may indicate that a relevant fundamental objective could have been neglected in the decision analysis, or that a relevant consequence could have been disregarded during the planning process. For instance, it may be that a fundamental objective of a key stakeholder had not been considered in the decision alternative design, and the impact that the selected option has brought about is affecting this group of individuals, causing some to oppose the implementation of the option. Another common issue arises in situations wherein unintended consequences, which had been disregarded or had been somewhat unpredictable at the time at which the option had been conceptualized, are experienced once the actions have started to be implemented.

These early difficulties that decision makers face when implementing health security actions may reveal important sources of information and help to strengthen the health decision analysis. The inclusion of an objective that had been previously absent may identify the impact that the selected option has on a stakeholder, which in turn can provide a more balanced assessment of the societal value of each decision alternative. The inclusion of a disregarded relevant consequence, or a

consequence that had previously been unknown at the time at which the original decision analysis had been developed, may help in rendering the assessment of the decision alternatives more comprehensive in this learning loop.

Improving Decision Alternatives Learning about implementation barriers, revealing hidden objectives, and recognizing that relevant consequences have been disregarded may help in redesigning the chosen health security options and in increasing the societal value of these decision alternatives. These redesigned options may lead to reducing any feeling of resistance of the stakeholders, removing practical constraints, and minimizing organizational impediments. These options may also reduce negative impacts, decrease risks, and increase benefits.

The development of new vaccines provides an excellent example that illustrates the benefits of recursive learning and improvement, making the vaccines typically safer and more effective in the long term. While still less common in practice, here, we suggest that a similar approach for health security actions and policies be adopted, by conducting a systematic assessment of the performances of these actions and policies and a continual improvement in any subsequent decisions. The systematic assessment of options in a health decision analysis can significantly assist the continuous improvement of decision alternatives and health security policies in double-loop learning cycles.

To conclude this section on systematic learning, while throughout this book we have described the decision stages in a rather linear fashion, in practice, decision processes are highly recursive (Mintzberg et al., 1976). The decision stages that we have suggested for enhanced health security should not be perceived as a constraining, rigid structure, which renders decision making an unmalleable process. On the contrary, decision processes should be conducted in such a manner that allows for the inclusion of feedback loops and recursive interactions, and for a focus on continuously learning about the decision situation and developing options with high societal value that significantly enhance health security.

11.4 Undertaking the Complexities in Health Security Decisions

We now return to where the book began, and turn once again toward the several complexities in health security contexts and decision processes, which have been introduced in the First Chapter. Throughout the book we have suggested ways of addressing these challenges, with the use of a rigorous conceptual framework for enhanced health security decisions, by adequately identifying the main decision component, efficiently discussing the possible solutions, and making reasoned choices with high societal value. These suggestions are now summarized in two tables, the first table summarizes how to adequately address the challenges presented by health security decision contexts (Table 11.2) and the second summarizes how to effectively manage the challenges involved in health security processes (Table 11.3).

Table 11.2 Undertaking the complexities in the decision context

Type of complexity	Complexity	How to address the complexity
Varied perspectives	Health security decisions brings about varied perspectives regarding which issues should be considered and which problems should be tackled.	Understand the different perspectives and agree upon a joint problem definition.
Many relevant consequences	Health threats have potentially extensive and severe consequences on human health, economies, and societies. Similarly, health security actions have both benefits and drawbacks.	Represent the multiple relevant consequences in a decision model.
Intangible consequences	Health threats have some relevant intangible consequences, such as distress and fear caused by emerging diseases. Similarly, health security actions may display some intangible benefits and drawbacks.	Represent the relevant intangible consequences in a decision model.
Unclear decision context	Health security situations often have an unclear context, making it difficult to identify what should be included and excluded in the decision making process.	Frame adequately the decision by establishing a clear set of fundamental objectives and a creative set of decision alternatives.
Numerous possible scenarios	There are many possible scenarios in health security decisions, encompassing which health threat may strike, in which area, and affecting a given number of individuals.	Define the possible scenarios based on the evidence available, predictive models, and expert judgment.
Uncertainties concerning impacts	Health threats trigger widespread uncertainties regarding their potential impacts and any health security decision is bounded by uncertainty.	Adequately characterize the key uncertainties in a decision model.
Limited evidence	Public health leaders and health experts often have limited high-quality evidence concerning the relevant consequences related to emerging health threats and concerning the performances of health security actions.	Employ reliable and debiased expert judgment in a decision model.
Dynamics of impacts	Many of the impacts caused by health threats have a dynamic behavior, such as number of cases during an outbreak, which must be considered.	Represent the dynamic impacts in a decision model.
Critical risks	Many health threats pose critical risks to human life and health, such as potential deaths, or severe consequences and long-term sequelae.	Understand the critical risks at stake and represent them in a decision model.
Long term horizons	Health threats often cause long term impacts. Additionally, health security actions can have long term horizons.	Define a planning horizon and establish adequate discounting rates for impacts.

(continued)

Table 11.2 (continued)

Type of complexity	Complexity	How to address the complexity
Limited resources	Health threats must be managed, and health security enhanced, with resources that are necessarily limited.	Identify the health security actions that generate the highest (expected) value-for-money within the budget available.
Difficult to identify good decision alternatives	It is challenging to successfully identify high-value health security actions.	Employ a decision model to evaluate and select decision alternatives that provide high societal value.

Table 11.3 Undertaking the complexities in the decision process

Type of complexity	Complexity	How to address the complexity
Multiple stakeholders	Health security decisions are always related to multiple stakeholders, who have the ability to influence and/or be affected by such issues.	Identify the key stakeholders and plan their level of engagement in the decision process.
Several decision makers	Health security decisions are typically taken by a group of decision makers, the health security team, who may suffer from dysfunctional group dynamics.	Assemble a varied and representative decision making group and adequately manage group dynamics.
Power and political dynamics	Power and politics are present in any health security decision.	Manage adequately power and politics and minimize negative aspects of political behavior.
Difficult trade-offs	Trade-offs are inevitably required to identify priorities among conflicting health security objectives.	Define clear and unbiased trade-offs employing adequate elicitation protocols.
Sensitive risk limits	Risk limits must be adequately defined in health security decisions, as they limit the acceptable impacts and delimit the set of feasible decision alternatives.	Define realistic risk limits for the decision situation.
Varied expertise	Health security decisions, given their multidisciplinary nature, necessarily require different types of expertise.	Identify reliable experts and employ their content-matter to inform the relevant parameters of the decision model.
Expert judgment	Expert judgment may be required in health security decisions in situations wherein reliable predictive models are unavailable, or, where the scientific evidence is incomplete or inadequate.	Debias estimates from experts by employing adequate elicitation protocols and debiasing tools.
Imprecision in estimates	Estimates, which may be imprecise, are typically required in health security decisions, both for current judgments and future estimates.	Conduct a sensitivity analysis on the results of the decision model to assess their robustness against imprecisions in estimates.
Organizational culture	The organizational culture influences how health security decisions are made and therefore may hinder reasoned decision making.	Promote high-quality decision processes and a culture of transparency and accountability in decision making.

(continued)

Table 11.3 (continued)

Type of complexity	Complexity	How to address the complexity
Implementation of health security actions	Barriers may prevent the implementation of health security actions chosen during reasoned decision processes.	Plan the implementation during the decision process and reduce resistance during the implementation phase.
Systematic earning	Organizational learning in health security decisions is challenging but crucial.	Develop a transparent, reasoned and clearly justified health decision analysis. Focus on learning loops during a decision process and across decision processes. Promote a culture of systematic learning.

11.5 Conclusions: Deciding and Implementing Health Security Actions and Promoting Systematic Learning

In this chapter we have described the final decision stage in decision making for enhanced health security, wherein choices are being made and must be successfully implemented. As health security decisions are typically made by a health security team, here, we have focused mainly on group decision making.

We have covered several dysfunctional group dynamics and detrimental group judgment biases. Said dysfunctionalities and judgment biases must be addressed if we wish to minimize group dysfunctional behaviors, maximize the efficiency of teamwork, and maximize decision quality. We have suggested ways of achieving these goals for improved decision processes, a particularly useful tactic is the appointment of an internal or external facilitator to the group. This facilitator may use facilitated decision analysis to, simultaneously, support the group discussions and develop a decision model that helps the group in framing the decision problem, evaluating the decision alternatives, and identifying health security options that maximize societal value.

Once choices have been made by the health security team and the selection of the best options that maximize societal value has been finalized, these options must then be implemented. We have discussed several barriers that can arise when implementing chosen options, from mere inaction to the poor allocation of implementation resources. We have made suggestions as to how such barriers can be minimized, but, for the implementation to prove effective, health security teams should not underestimate the importance of planning and monitoring implementation efforts and activities.

We have also stressed the importance of systematic learning in decision processes by employing a decision model in a recursive fashion to increase the societal value of decision alternatives. A decision model should be considered to be a

powerful *learning tool* and not as an autonomous structure that can somehow provide the "right" choice. This contemporary view on decision models is both a humble and an ambitious take. Humble, as this view recognizes that decisions with conflicting objectives and a high degree of irreducible uncertainty must be always made by humans. And ambitious, as in, this perspective prominently underscores the crucial role of decision models in coping with necessarily limited cognitive capacities of decision makers, in reducing inherent cognitive and motivational biases in judgments, and in managing the high socio-technical complexities of health security decision making.

Reasoned decision making, and high-quality decision processes, provide the platform on which to identify, select and implement effective actions against health threats and on which to identify options with high societal value for enhanced health security. We sincerely hope that the content of this book supports public health leaders and health security teams to further develop stronger health capabilities to improve health preparedness, to design more robust health systems that can improve resilience, and to improve the effectiveness of the responses against emerging health threats.

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