

# Reasoned Decision Making Without Math?

## Adaptability and Robustness in Response to Surprise

Michael Smithson  
Department of Psychology  
Australian National University  
Canberra, Australia  
Michael.Smithson@anu.edu.au

Yakov Ben-Haim  
Yitzhak Moda'i Chair in  
Technology and Economics  
Technion—Israel Institute of Technology  
Haifa 32000 Israel  
yakov@technion.ac.il

## Contents

<b>1 Introduction</b>	<b>2</b>
<b>2 Ignorance and Surprise</b>	<b>2</b>
<b>3 Decisions Without Math: Epidemiology and Public Health</b>	<b>3</b>
<b>4 Optimizing, Satisficing and Robustness: SARS Example</b>	<b>4</b>
<b>5 Adaptability and Robustness: The Human Dimension</b>	<b>6</b>
5.1 Achieving Inter-Personal Adaptability . . . . .	7
5.2 Achieving Intra-Personal Adaptability . . . . .	8
<b>6 Conclusion: Deliberative Decision Making and the SARS Outbreak</b>	<b>8</b>
<b>7 References</b>	<b>11</b>

**Abstract:** Many real-world planning and decision problems are far too uncertain, too variable, and too complicated to support realistic mathematical models. Nonetheless, we explain the usefulness, in these situations, of qualitative insights from mathematical decision theory. We demonstrate the integration of info-gap robustness in decision problems in which surprise and ignorance are predominant and where personal and collective psychological factors are critical. We present practical guidelines for employing adaptable choice-strategies as a proxy for robustness against uncertainty. These guidelines include being prepared for more surprises than we intuitively expect, retaining sufficiently many options to avoid premature closure and conflicts among preferences, and prioritizing outcomes that are steerable, whose consequences are observable, and that do not entail sunk costs, resource depletion, or high transition costs. We illustrate these concepts and guidelines with the example of the medical management of the 2003 SARS outbreak in Vietnam.

**Keywords:** adaptability, robustness, uncertainty, ignorance, surprise, info-gap

# 1 Introduction

There are well-understood formal frameworks for decision making under risk, i.e., when we know all of the possible outcomes of our acts, and we know the probabilities of those outcomes conditional on our acts, and we know the quality or utility of each outcome. Under these conditions we can maximize a measure of quality (such as expected utility) and thereby optimize our choice of acts. An often unstated assumption here is that we know all of these things precisely, i.e., without error.

In the presence of error, maximization and optimization of outcomes may no longer be reliable. Nevertheless, frameworks such as info-gap theory, fuzzy logic and imprecise probability provide principled, mathematically-grounded methods for decision making when we have only vague estimates of probabilities and utilities.

However, what if we don't know probabilities or utilities or even all possible acts and outcomes? What constitutes reasoned decision-making when mathematics cannot be applied? What are "robust" or "adaptable" decisions? How to apply qualitative insights from mathematical decision theory, to situations without mathematical models?

We make the following claims about reasoned decisions without math.

1. In an open world, rich in undiscovered contingencies, we are ignorant of important aspects of the future. Under ignorance, prepare to be surprised (section 2). In section 3 we briefly describe severe uncertainties facing decision makers in epidemiology and public health.
2. Under severe uncertainty, optimizing the quality of the outcome is infeasible and unwise. Satisfying outcome requirements is better than attempting to optimize the outcome-quality (section 4).
3. Adaptable choices allow innovation or improvisation as new information and understanding emerges. Adaptable or reversible choices are more robust than "locked-in" choices (provided the decision maker avoids indecision). More options are better than fewer, unless we become indecisive. Adaptability is a proxy for robustness against surprise and ignorance (section 5).

These ideas are evaluated in section 6 by discussing the 2003 SARS outbreak in Vietnam.

## 2 Ignorance and Surprise

We should consider surprises to be far more likely than our intuition tells us that they are. Experimental research demonstrates that human judges chronically under-estimate the likelihood of novel events. Even experts err in their domains of expertise.

The Catch-All Underestimation Bias (CAUB),<sup>(1)</sup> stipulates that if event categories are combined under a single super-set then the probability that people assign to the super-set typically is less than the sum of the probabilities assigned to the component categories (see also Tversky and Koehler<sup>(2)</sup>). For example, someone asked to estimate the probability that they will be delayed tomorrow will usually assign a lower number than the sum of the numbers they

would assign to the probabilities of being late to rise, delayed by traffic, distracted at lunch, etc. The super-set skips the details and thus ignores unanticipated and surprising events.

In addition to the CAUB, human judges are susceptible to “partition dependence”. On grounds of insufficient reason, a probability of  $1/K$  is assigned to  $K$  mutually exclusive possible events when nothing is known about the likelihood of those events. Fox and Rottenstreich<sup>(3)</sup> demonstrated experimentally that subjective probability judgments are biased towards this prior probability distribution even given contrary evidence. Probability judgments are partition dependent in the sense that they are influenced by the value of  $K$  that people believe is applicable. The value of  $K$  is influenced by the agent’s perceptions of possible events and ignores surprising or unanticipated categories.

Various methods can make an agent’s intuitive probability of surprise larger and more realistic. First, exploit people’s suggestibility regarding partitions, and explicitly include a “novel outcome” category. Second, detailed descriptions of unknowns will tend to increase the intuitive partitioning of novel events, thereby increasing the intuitive probability of surprise. Third, and conversely, less detailed descriptions of previously observed outcomes will tend to coarsen the partitioning of known events, thereby biasing people towards a lower total probability of encountering familiar events.

### **3 Decisions Without Math: Epidemiology and Public Health**

Mathematical models can be quite useful in determining public health policy for prevention or control of epidemic disease. For instance, linear differential equations can predict the course of tuberculosis (TB) in a population.<sup>(4)</sup> Such models can be used to determine the fraction of new cases that must be detected, and of these, the fraction that must be successfully treated, in order to achieve specified long-term reduction of the disease in the population.

The value of mathematical models of epidemiological processes is limited by uncertainties. For instance, the population dynamics of TB is altered in conflicting and uncertain ways by the presence of HIV/AIDS. On the one hand, HIV/AIDS enhances the spread of TB by making individuals more vulnerable to infection. On the other hand, HIV/AIDS is a major cause of death and can thereby reduce the spread of TB. These conflicting tendencies make it challenging (though not impossible) to use quantitative epidemiological models of TB to formulate public health policy in the presence of HIV/AIDS. For instance, if prevention of HIV/AIDS is enhanced, existing TB models do not always provide clear indication of whether intervention against TB can be reduced or must be enhanced, and by how much. Nonetheless, the main features of the disease are understood, and existing TB models can be usefully employed by robustifying them against uncertainties resulting from HIV/AIDS.<sup>(5)</sup>

The situation with a new disease is quite different. Consider, for instance, the 2003 SARS outbreak in Vietnam, as described by Plant.<sup>(6)</sup> The infectious organism was unidentified and public health officials did not know the clinical course (“would everyone die?”), the mechanism of spread, the timing of recovery and infectiousness, and other elements that are crucial for

disease management. As Plant writes: “Despite these unknowns, we had to make decisions—who to admit to hospital, how to manage their clinical course and what to advise their relatives or the health staff looking after them.” Mathematical models, as well as much requisite scientific knowledge, are unavailable when these decisions must be made.

## 4 Optimizing, Satisficing and Robustness: SARS Example

We will consider an example motivated by the discussion of SARS in section 3. A new and evidently highly contagious disease has caused a sharp rise of illness and a number of deaths in an economically and politically important city. The course of the disease, mechanisms of transmission, and severity are all very poorly known. A team of medical experts is tasked with containing the disease while not unduly disrupting daily life in the city and beyond. They must choose among several distinct actions. In simplified form, the team may need to choose between (1) complete travel prohibition to and from the city, (2) ten-day quarantine of all individuals before exiting the city, (3) ten-day quarantine of individuals exposed to symptomatic individuals before exiting the city, and (4) free entrance and exit. We will ignore the many other decisions that must be made.

Three sources of uncertainties can be identified. First, the degree of similarity to known diseases is highly uncertain. In the present case, the infecting organism has not been identified and its medical characteristics are hardly known. Second, the degree of disruption resulting from each of the 4 available actions is uncertain and depends on whose travel is restricted, and for how long, and on the extent to which electronic communications can replace travel for maintaining economic and political activity. Third, the relative importance of, and interdependence between, control of the disease and disruption of daily life, are both difficult to assess.

Using judgment based on experience, the team is able to make rough predictions of epidemiological, economic and political impacts of each of the 4 interventions. However, it is clear to the team that these predictions could be substantially wrong: either better or worse than subsequent real outcomes.

This realization—that predictions are highly unreliable—leads the team to its **first methodological conclusion**: *Prioritizing the interventions based on their predicted outcomes is highly unreliable*. As an example, suppose that complete travel prohibition is predicted to have a better overall outcome than, say, quarantine of exposed individuals. Because the predictions are highly uncertain it might well be that quarantine is more propitious than expected, and that complete closure more pernicious than predicted. The quality of the actual future outcomes may in fact be ranked in the reverse order from the predictions. Due to the severe uncertainties that accompany the available understanding, we can have little confidence that the putative ranking is accurate. Consequently, complete closure cannot be reliably preferred over quarantine.

How should the team rank the action-alternatives, if not with predictions based on the best

available knowledge? The answer to this question depends on the **second methodological conclusion**: *the quality of outcome that can be guaranteed gets worse as the level of uncertainty rises*. We explain this as follows.

Let  $A_i$  denote one of the available actions that the medical team could choose. Our best understanding predicts an outcome of implementing this action, which we will refer to as the putative prediction for action  $A_i$ . Suppose we err at most just a little: our information and understanding are at most just a little bit uncertain. What is the worst outcome that could happen with  $A_i$ ? If the worst were to happen (assuming we err just a little) the outcome would be a little bit worse than the putative prediction.

Now suppose we err a bit more (we face slightly larger epistemic uncertainty). The worst outcome with  $A_i$  is poorer than before. As we consider greater level of error, the worst that could result from action  $A_i$  gets worse. The worst that could happen (or equivalently, the best that can be guaranteed) gets worse as the horizon of uncertainty increases. This is the trade off between guaranteed outcome and uncertainty.

We must now introduce the idea of robustness to uncertainty, and this hinges on the idea of acceptable outcomes. Our discussion of robustness is framed in the context of info-gap decision theory.<sup>(8)</sup>

The medical team is charged with containing the disease and with not disrupting daily life. In a world with perfect information and understanding the disease would be eradicated with minimal adverse impact. The team is too realistic to demand any such wonderful outcome. However, they (or other authorities) are able to make judgments of the lowest degree of disease containment and the greatest social disruption that are acceptable. There may be different combinations of containment and disruption that are acceptable, and these judgments themselves may be uncertain.

**The robustness to uncertainty** of an intervention,  $A_i$ , is the greatest level of uncertainty at which an acceptable outcome is guaranteed. If an action is putatively unacceptable, then it has no robustness to uncertainty because an acceptable outcome cannot be guaranteed at any level of uncertainty.

Let us suppose that available action  $A_i$  is putatively acceptable. As we have explained, the worst that could occur as a result of action  $A_i$  gets progressively worse as the level of uncertainty increases. The worst possible outcome with  $A_i$  crosses the threshold from acceptable to unacceptable at some level of uncertainty. This level is the robustness to uncertainty of action  $A_i$ .

Combining the trade off between guaranteed outcome and level of uncertainty, with the ideas of robustness and acceptable outcome, leads us to the **third methodological conclusion**: *available actions should be prioritized according to their robustness against uncertainty for achieving acceptable outcomes*. The medical team should prefer action  $A_i$  over  $A_j$  if  $A_i$  is more robust than  $A_j$  for achieving an acceptable outcome. The most robust action will lead to an acceptable outcome over the widest range of deviation of future reality from current understanding. This methodological conclusion asserts that the medical team should choose

the action that will satisfy the outcome requirements as robustly as possible. This is called *robust satisficing*. What is optimized is robustness against surprise, rather than optimizing the substantive outcome. Robustness is an attribute of an action but it is not an outcome of substantive importance like disease eradication or economic and political functionality.

The most robust action may, or may not, be the putatively optimal action. The action that is predicted to be best may, or may not, be the most robust for achieving an acceptable outcome. Prioritizing the actions based on their robustness for satisfying the outcome requirements, may not agree with prioritizing based on predicted outcomes. Optimizing substantive outcomes based on the best available knowledge, and robustly satisfying outcome requirements, are conceptually different decision strategies that may lead to different decisions, as we now illustrate.

There are two situations in which robust satisficing and outcome optimizing are operationally the same. If the putatively best action is also the least uncertain, then its trade off between quality and uncertainty is least severe. It will then be more robust than any other available action at any level of required outcome. In this case, the robust satisficing and outcome optimizing strategies will agree on the decision, though for different reasons.

Robust satisficing and outcome optimizing also lead to the same decision if the required outcome is extremely demanding. In this case, only the putatively optimal action has any robustness at all for satisfying the outcome requirement. Once again the robust satisficer and the putative optimizer agree on the decision, though for different reasons.

Outcome optimizing and robust satisficing lead to different decisions if the putative optimum is more uncertain than an alternative and if the outcome requirement is not too demanding. In this case, due to the trade off between guaranteed outcome and uncertainty, the putative optimum could be the less robust alternative. This is common when the putative optimum exploits an innovative technology which, because it's new, is less well understood than more familiar alternatives.<sup>(9)</sup>

The robust satisficing decision strategy is advantageous when facing severe uncertainty. In the next section we ask: how can one make the judgments needed for implementing this strategy, without mathematical analysis?

## 5 Adaptability and Robustness: The Human Dimension

We defined robustness-to-uncertainty, of an intervention, as the greatest level of uncertainty at which an acceptable outcome is guaranteed. Under extreme uncertainty it may be impossible to quantify robustness or levels of uncertainty, and it may also be impossible to ascertain when an acceptable outcome is guaranteed. Nevertheless, a decision maker's ability to adapt—to revise, reverse or correct earlier actions—is a plausible proxy for robustness against surprise and ignorance. Adaptability enables the decision maker to persist in the pursuit of specified goals despite ignorance and in response to surprise and the discovery of error.

Our argument in this section is that the feasibility of deliberative—rather than computa-

tional—implementation of robust satisficing hinges on the successful facilitation of adaptability. Adaptability must be achieved in response to both personal and inter-personal uncertainties.

## 5.1 Achieving Inter-Personal Adaptability

Important decisions often are made in social contexts. Likewise, decision makers have psychological natures that must be accounted for in enhancing adaptability.

Decision-related consequences arising from other people typically pertain to issues of accountability, exploitation, and, of course, negative or positive responses to decisions. Tetlock<sup>(10)</sup> discusses three adaptive imperatives. First, decision makers must cope with accountability demands from others in their networks or groups. These settings stipulate who must answer to whom, for what, and by what rules. Second, the decision maker must be able to exert social influence, to impose accountability demands on others who might otherwise exploit the decision maker (and others) without contributing their fair share or respecting other important social norms. Third, the decision maker must retain a moral compass, i.e., to be able to believe that the prevailing accountability norms and social influence measures are not immoral but instead legitimated by an authority that transcends accidents or whims of dominant persons or groups.

Accountability, social influence, and legitimation usually are achieved and enforced by means of policies, laws, contracts, and related practices that contribute to what may be called “assurance”. Unfortunately for decision makers who wish to keep options open in the pursuit of robustness, assurance eliminates options in the name of predictability and control. Elimination of options is the essence of bureaucratic regulation, and is one way of reducing uncertainty. However, by impeding adaptability, bureaucratic regulation loses robustness against either surprises from the physical world or resistance from those people being regulated.

Decision makers can avoid restrictive regulations and accountability demands by subverting them via secrecy, avoiding accountability by evading the imposition of measurable outcomes or specified goals (e.g. Moore<sup>(11)</sup> on politicians’ decisional practices), and disguising illicit practices as legitimate. This coping style also is seen at the group or organizational level, as described in Goffman’s work on organizational “back-stage” operations<sup>(12)</sup> and March and Olsen’s garbage-can model of group decision making.<sup>(13)</sup> Goffman documented the necessity of informal operations and arrangements in order for members to perform their organizational roles. In the garbage can model, organizational decision making not only often is subterranean but also post-hoc, in the sense that the problem for which a choice is supposed to be a “solution” will be defined only after the choice has been made. Moral qualms about secrecy and disinformation aside, neither of these practices are robust against the potential reactions of other stakeholders.

An alternative way of keeping options open while dealing with social requirements is to build relationships and networks based on trust instead of assurance. Trust-based relationships obviate accountability to some extent because trust precludes intense surveillance of an entrusted party by the trusting party. Likewise, mutual trust entrains mutual social influence via interdependence, thereby eliminating the need for social control practices that insure

against exploitation. Some risk theorists, e.g. Kasperson,<sup>(14)</sup> claim that when uncertainties loom large, trust is important for decision making and getting things done.

## 5.2 Achieving Intra-Personal Adaptability

We now consider the psychology of the decision maker. Decision-related surprises arising from the decision maker often involve changes in the decision maker’s beliefs, preferences, or criteria for decision making. Decision makers can enhance their own robustness against these uncertainties by keeping options open. Two issues are central: avoiding incompatible preferences and decisional criteria, and avoiding indecision. The first is an example of the benefits of multiple alternatives and the second is an example of the risks therein.

Increasing the number of alternatives can resolve incompatible preferences and decisional criteria by providing intermediate options.<sup>(15,16)</sup>

However, the presence of multiple alternatives may increase the likelihood of indecisiveness. Indecision is a potential threat to adaptability and robustness. Nonetheless, the risk of indecision is enhanced only by particular kinds of choice sets and decisional conditions.

There are two kinds of indecision: Decision aversion and decision obsession.<sup>(17)</sup> Decision aversion (DA) is a disposition to avoid undertaking decisions altogether, and may be driven by decisional costs or difficulty, anticipated emotions such as regrets, and anticipatory emotions such as dread or depression. Decision obsession (DO) is a tendency to ruminate excessively about a decision, thereby impeding it. DO includes “paralysis by analysis” and may be driven by accountability requirements, need for self-justification, or perceived magnitude or importance of consequences. Thus, DO usually results in decisions being delayed or revisited many times, whereas DA results in failures to initiate the decision making process at all. There is extensive literature on the factors that can increase DA or DO.<sup>(18,19,20)</sup>

## 6 Conclusion: Deliberative Decision Making and the SARS Outbreak

We will conclude by engaging in a dialog between the main points of the paper and a case-study. Plant’s description<sup>(6)</sup> of her team’s experiences during the SARS outbreak in Vietnam is sufficiently detailed that we can examine it for instances of our recommendations or, on the other hand, decisional tactics or strategies that we did not cover.

In section 2 we link ignorance with surprise and recommend ways for decision makers to prepare themselves for surprises. The greatest challenge of severe uncertainty is that its identity is unknown. In the SARS example this is illustrated by the medical team not knowing all of the decisions that they will have to make. For instance “If a woman has SARS, should her husband be allowed to serve food in his restaurant?”<sup>(6,p.48)</sup> The SARS case demonstrates the importance of characterizing the uncertain quantities while combating the tendency to under-estimate the likelihood of surprises.

In section 4 we highlighted three methodological points regarding decision making. Our first

conclusion was that predicted outcomes are highly unreliable, with the implication that these predictions, per se, should not be used to select an action. Second, we explained the trade off between the level of uncertainty and the quality of an outcome that can be guaranteed. Finally, combining the first two points, we concluded that alternatives should be prioritized according to their robustness against uncertainty in achieving acceptable outcomes. In short, we advocated robust satisficing rather than optimizing the outcome. Plant refers to an idea somewhat related to the idea of satisficing when she describes her responses to questions from the public as being “as good as I could manage in a changing state of understanding about the outbreak”<sup>(6,p.52)</sup>.

Plant does not refer to robustness per se, but mentions on several occasions that her team based many early decisions on assuming that SARS was a virus and treated it as similar to other viruses.<sup>(6,p.49)</sup> The use of analogs between new unknown phenomena and previous experience is commonplace, especially for decision making in complex dynamic environments,<sup>(21)</sup> but its robustness to uncertainty is debatable. The high uncertainty of analogical reasoning motivates the strategy of learning and adapting, as the SARS team did very explicitly. The SARS team had to gather more information (including surprises) to resolve the issue of when to “think outside the box” or to continue reasoning analogically from past experience. Plant also indicates an adaptive approach to resolving uncertainties, saying that questions about why the outbreak occurred and possible health system failures had to await the identification of the virus, inventing a test for it and determining its modes of transmission.

Recommendations for adaptable decision alternatives are:

1. Leave desirable options open rather than prematurely closing them off.
2. Retain sufficiently many alternatives to avoid conflicts between outcome preferences and for choosing between alternatives.
3. Prioritize reversible or steerable options over irrevocable ones.
4. Prioritize options that do not require sunk costs, resource depletion, or high transition costs.
5. Where possible, ensure that decision outcomes are observable. Monitor and learn from outcomes.

Plant’s account directly refers to item 5. and implicitly to 1. and 3. Although the team began by acting on assumptions about SARS, they quickly moved to testing those assumptions: “Even before we had blood tests, we were planning studies to determine how many people were infected with the virus but had no symptoms, and how many people the average sick person infected, to name just two areas of interest”<sup>(6,p.49)</sup> Thus, a major proportion of the team’s resources and time were devoted to obtaining new information. Implicit is the recognition that treatment decisions and policies had to be malleable as new information came in, and that other options might need to be kept open. The team also was aware that new information might not immediately resolve uncertainties and could even generate new ones: “Even as information accumulates, we may still not know how to interpret that information. Does the [newly obtained] fact that SARS virus can no longer be detected in respiratory secretions mean

that the person is no longer infectious? Does the [new] fact that SARS virus can be detected in faeces mean that the person is infectious?”<sup>(6,p.49)</sup>

Other examples of how additional information could add to uncertainty are found in post-epidemic accounts such as Johnston and Conly.<sup>(7)</sup> They noted that while the majority of data indicated contagion by droplet and contact, at least two clusters of cases suggested the possibility of airborne spread. They also observed that hospital and health-care worker experiences and risks outside of Vietnam often diverged substantially from the Vietnam experience, thereby casting doubt on some of the initial conclusions about how to manage risks to health-care workers.

Section 5 also emphasizes the importance of uncertainties stemming from psychological and social sources. Plant discusses this issue at length, noting that “Perhaps the most challenging part of uncertainty is in dealing with the human side of uncertainty and its resultant anxiety.”<sup>(6,p.49)</sup> Anxiety arising from unknowns is a key concern for her, because in her view it is chiefly responsible for the variety of dysfunctional or irrelevant ways of coping with the outbreak that she describes.<sup>(6,pp.49–51)</sup> A few of the coping styles in her list correspond to our descriptions of decision aversion and decision obsession, both of which are types of indecision. We recognize that anxiety is likely to be a major concern for decision makers under extreme uncertainty and pressure. However, our discussion of indecision focused on factors contributing to the difficulty of selecting among alternatives, and a full discussion of ways of dealing with anxiety is beyond our scope. Nevertheless, our recommendations of ways to decrease selection difficulty would decrease anxiety as a byproduct.

The material in section 5 on inter-personal adaptability emphasized the benefits of building trust-based relationships where possible, preventing reactance by avoiding unnecessary regulations or restrictions, and seeking input from stakeholders with diverse viewpoints. In addition to managing the SARS team, Plant’s role as team leader included liaising with the Ministry of Health, consulate staff at several embassies, international agencies, and the Vietnamese press. She refers to the importance of trust in establishing effective links with key stakeholders, i.e., leaders, spokespeople and media. A key point here is the rapidity with which these links needed to be made in order to head off the potential impact of rumors or misinformation. An absence of trust would have made that impossible.

Plant makes a pertinent observation about the desirability of diverse inputs:

Ten years ago the call would have been for epidemiologists, clinicians and perhaps laboratory people. Now a typical team will consist of two epidemiologists, one social mobiliser (to deal with issues around the response such as working with communication via local leaders, radio stations etc.) and two medical anthropologists. This change reflects our current knowledge in dealing with an outbreak, namely that it is important to recognise the framework within which the affected population operates . . . A person such as a medical anthropologist would, of course, provide a different view of the outbreak and the issues that were uncertain (and their management) from mine”.<sup>(6,p.46)</sup>

This last sentence is interesting for its observation that different stakeholders may not only know different things, but also may have different views about the unknowns. Under extreme uncertainty, diverse inputs about the nature of the unknowns may be one of the most important correctives to a decision maker’s initial appraisal of a problem and its prospects.

Decisions under uncertainty arise in every domain of human activity, and mathematical analysis is often applicable. There are, however, important situations in which information and understanding are insufficient to realistically and responsibly support mathematical analysis. Nonetheless, qualitative insights from quantitative decision theory are still relevant. Difficult judgments remain to be made, and a “language barrier” between the mathematical analysts and the decision makers in qualitative domains must be crossed. Resolving these difficulties is as important as the decisions themselves. Furthermore, the nature of the uncertainties and methods for dealing with them are changed by the absence of mathematics. Uncertainty about the physical world becomes in large measure a human uncertainty that must be managed through inter- and intra-personal adaptability.

## 7 References

1. Fischhoff, B., P. Slovic, and S. Lichtenstein. 1978. Fault trees: Sensitivity of estimated failure probabilities to problem representation. *Journal of Experimental Psychology: Human Perception Performance*, 4: 330–344.
2. Tversky, A. and D. Koehler. 1994, Support theory: A nonextensional representation of subjective probability. *Psychological Review*, 101: 547–567.
3. Fox, C. R. and Y. Rottenstreich. 2003. Partition priming in judgment under uncertainty. *Psychological Science*, 13: 195–200.
4. Murray CJL and JA Salomon, 1998, Modeling the impact of global tuberculosis control strategies. *Proc Natl Acad Sci USA*, 95: 13881–13886.
5. Ben-Haim, Yakov, Nicola M. Zetola and Clifford Dacso, 2012, Info-Gap Management of Public Health Policy for TB with HIV-Prevalence, *BMC Public Health*, 12: 1091.
6. Plant, Aileen J., 2008, When action can’t wait: Investigating infectious disease outbreaks, in Bammer and Smithson, 2008, op. cit., pp45–54.
7. Johnston, L.N. and J.M.Conly, 2004, Severe acute respiratory syndrome: What have we learned two years later? *The Canadian Journal of Infectious Diseases and Medical Microbiology*, 15: 309–312.
8. Ben-Haim, Yakov, 2006, *Info-Gap Decision Theory: Decisions Under Severe Uncertainty*, 2nd edition, Academic Press, London.
9. Ben-Haim, Yakov, Craig D. Osteen and L. Joe Moffitt, 2013, Policy Dilemma of Innovation: An Info-Gap Approach, *Ecological Economics*, 85: 130–138.
10. Tetlock, P.E. 2002, Social functionalist frameworks for judgment and choice: Intuitive politicians, theologians, and prosecutors. *Psychological Review*, 109: 451–471.

11. Moore, M. 2008, Political practice: Uncertainty, ethics and outcomes. In Bammer, G. and Smithson, M. (Eds.) *Uncertainty and Risk: Multidisciplinary Perspectives*. London: Earthscan, pp.171–182.
12. Goffman, E. 1969, *Strategic interaction*. University of Pennsylvania Press, Philadelphia.
13. March, J. G. and Olsen, J. P. 1979, *Ambiguity and Choice in Organizations*, 2nd Ed. Universitetsforlaget, Bergen.
14. Kasperson, R.E. 2008, Coping with deep uncertainty: Challenges for environmental assessment and decision making. In Bammer, G. and Smithson, M. (Eds.) *Uncertainty and Risk: Multidisciplinary Perspectives*. London: Earthscan, pp.337–348.
15. Connolly, T. 1987, Decision theory, reasonable doubt, and the utility of erroneous acquittals. *Law and Human Behavior*, 11: 101–112.
16. Smithson, M. 2006. Scale construction from a decisional viewpoint. *Minds and Machines*, 16: 339–64.
17. Anderson, C.J. 2003, The psychology of doing nothing: Forms of decision avoidance result from reason and emotion. *Psychological Bulletin*, 129: 139–167.
18. Dhar, R. 1997a, Consumer preference for a no-choice option. *Journal of Consumer Research*, 24: 215–231.
19. Dhar, R. 1997b, Context and task effects on choice deferral. *Marketing Letters*, 8: 119–130.
20. Dhar, R. and Nowlis, S. M. 1999, The effect of time pressure on consumer choice deferral. *Journal of Consumer Research*, 25: 369–384.
21. Zsombok, C.E. and Klein, G. 1997, *Naturalistic Decision Making*, Lawrence Erlbaum Associates, Mahwah, NJ.
22. Bammer, Gabriele and Michael Smithson, (Eds.), 2008, *Uncertainty and Risk: Multidisciplinary Perspectives*, Earthscan, London.