 DOI: 10.1111/risa.12360

Cognitive and Motivational Biases in Decision and Risk Analysis

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Behavioral decision research has demonstrated that judgments and decisions of ordinary people and experts are subject to numerous biases. Decision and risk analysis were designed to improve judgments and decisions and to overcome many of these biases. However, when eliciting model components and parameters from decisionmakers or experts, analysts often face the very biases they are trying to help overcome. When these inputs are biased they can seriously reduce the quality of the model and resulting analysis. Some of these biases are due to faulty cognitive processes; some are due to motivations for preferred analysis outcomes. This article identifies the cognitive and motivational biases that are relevant for decision and risk analysis because they can distort analysis inputs and are difficult to correct. We also review and provide guidance about the existing debiasing techniques to overcome these biases. In addition, we describe some biases that are less relevant because they can be corrected by using logic or decomposing the elicitation task. We conclude the article with an agenda for future research.

KEY WORDS: Cognitive biases; decision analysis; decision modeling; motivational biases; risk analysis

1. INTRODUCTION

Since Tversky and Kahneman's[(1)] seminal paper, behavioral decision researchers have identified a large number of biases in human judgment and decision making, each showing a deviation from a normative rule of probability or utility theory. Most behavioral research addresses cognitive biases—faulty mental processes that lead judgments and decisions to violate commonly accepted normative principles. Equally important, but much less studied, are motivational biases, which include conscious or subconscious distortions of judgments and decisions because of self-interest, social pressures, or organizational context.

Some decision and risk analysts use the existence of these biases to argue for the use of modeling and analysis tools because these tools can correct human biases and errors in decision making. However, experts and decisionmakers need to provide judgments in risk and decision modeling, thus analysts must worry about biases that may distort the inputs into the very models that are supposed to correct them. For example, when using expert judgments to construct a probability distribution as an input to a risk analysis model, one has to worry about the well-known overconfidence bias. Similarly, when obtaining expert judgments as inputs to estimate possible consequences of decision alternatives, one has to be concerned with the self-interest of experts, who may have a stake in the outcome of the analysis.

In this article, we focus on biases that are relevant for decision and risk analysis because they can significantly distort the results of an analysis and are

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 0272-4332/15/0100-0001$22.00/1

difficult to correct. Examples are the overconfidence bias when eliciting probability distributions from experts in risk analysis, or the equal weighting bias when decisionmakers assign weights to objectives in multicriteria decision analysis. In contrast, there are many biases that are less relevant because they can easily be corrected in the usual tasks of eliciting inputs for decision and risk analysis. Examples are the base rates neglect bias, which can be avoided by eliciting base rates separately from likelihoods, and the nonregressiveness bias, which can be avoided by eliciting means, standard deviations, and correlations instead of conditional estimates.

Despite the relevance of the topic of biases for risk and decision analysis modeling, there are few articles that cover the topic from the perspective of a decision or risk analyst: Meyer and Booker[2] provide an early taxonomy of biases in expert elicitation, which included cognitive and group pressure biases; von Winterfeldt[3] identified several cognitive biases when discussing the implications of behavioral research for decision analysis; Weber and Borcherding[4] examined biases in multiattribute weight assessment; Morton and Fasolo[5] reviewed the implications of biases for multicriteria decision analysis modeling; and Fasolo *et al.*[6] for resource allocation models. Larrick[7] discusses motivational issues related to decision-making performance.

This article includes several novel treatments of the bias literature. First, it includes motivational biases, which have largely been ignored by behavioral decision researchers, even though they are important and pervasive in decision and risk analysis. Second, we view biases from the perspective of an analyst concerned with possible distortions of judgments required for an analysis. Third, we separate biases into those that are difficult to correct versus those that are easy to correct. Fourth, we provide guidance on debiasing techniques, which includes not only the behavioral literature on debiasing but also the growing set of "best practices" in the decision and risk analysis field.

The article has the following structure. The next section defines the concept of bias and spells out some key assumptions and inclusion criteria we used in the article. The subsequent three sections describe the cognitive and motivational biases, as well as debiasing tools, present in each step of uncertainty, value, and choice modeling. The final section concludes the article and suggests a research agenda for biases in risk and decision analysis.

2. BIASES AND DEBIASING

The focus of this article is on biases that can occur when eliciting inputs to a risk or decision analysis from experts or decisionmakers. When these inputs are biased they can seriously reduce the quality of the model and resulting analysis. We show in this article how biases can be reduced or even removed through decomposition of the elicitation task, training, and tools. Larrick[7] adopts a similar "engineering" approach to "fixing" biases in decision and risk analysis. We define more precisely what we mean by cognitive and motivational biases, as well as the concept of debiasing, next.

2.1. Cognitive and Motivational Biases

A cognitive bias is a systematic discrepancy between the "correct" answer in a judgmental task, given by a formal normative rule, and the decisionmaker's or expert's actual answer to such a task.[8] There is a vast literature on cognitive biases and excellent compilations of papers are provided in Kahneman *et al.*[9] and Gilovich *et al.*[10] In this article we are focusing mainly on individual biases, thus assuming that we have a single decisionmaker or expert, but recognizing that some of these biases may be alleviated, or exacerbated, at group level.[11]

We define motivational biases as those in which judgments are influenced by the desirability or undesirability of events, consequences, outcomes, or choices (see also Kunda,[12] von Winterfeldt,[3] and Molden and Higgins[13]). An example of a motivational bias is the deliberate attempt of experts to provide optimistic forecasts for a preferred action or outcome. Another example is the underestimation of the costs of a project to provide more competitive bids. Motivational biases do not always have to be conscious. For example, estimates of the time it takes to complete a software project are often overly optimistic[14] even when there is no outside pressure or value in misrepresenting the actual time. We focus here on outcome motivated biases, as they matter in several modeling steps, but recognize that lack of motivation to provide accurate judgments is also an issue in the elicitation of judgments.[13]

2.2. Biases that are Difficult to Correct

We distinguish between biases in decision and risk analysis that are difficult to correct *versus* biases that are easy to correct. Biases that are difficult to correct tend to be resistant to logic, decomposition, or the use of training and tools. The overconfidence bias,[15,16] anchoring and insufficient adjustment,[1] and the equalizing bias[17] are examples. Logic and decomposition are the most common ways to eliminate biases that are easy to correct. Examples are the conjunction fallacy,[18] which can be corrected by demonstrating the probability logic, and the neglect of base rates,[19,20] which can be fixed by eliciting base rates and conditional probabilities separately. This distinction holds only for cognitive biases—in contrast, all motivational biases in decision and risk analysis are hard to correct.

2.3. Debiasing

Debiasing refers to attempts to eliminate, or at least reduce, cognitive or motivational biases. The narrow literature on debiasing has focused on cognitive biases; early attempts showed the limited efficacy of debiasing tools,[21–23] i.e., to which degree they reduced the bias and brought judgments close to the required normative standard, but more recent article are slightly more optimistic about overcoming biases, particularly with the use of adequate tools.[7,24,25]

The taxonomy suggested by Arkes[24] is useful for considering biases and debiasing techniques. It classifies biases by their psychological origin: *strategy-based* (SB) *errors*, which occur when decisionmakers use a suboptimal cognitive strategy; *association-based* (AB) *errors*, which are a consequence of automatic mental associations; and *psychophysically-based* (PB) *errors*, which result from incorrect mappings between physical stimuli and psychological responses. The use of analytical models is an effective correction of errors related to SB type, so we would expect that when SB type errors occur in decision and risk analysis they can easily be corrected. Correcting AB and PB type errors is more difficult.

In addition to the behavioral literature on biases and debiasing, we also draw on best practices developed in decision and risk analysis. Some of these have been subjected to experimental tests (e.g., Seaver *et al.*[26] and Abbas *et al.*[27] show how the overconfidence bias can be reduced by choice of an appropriate elicitation technique), others have been described in applied research article (e.g., Dillon *et al.*[28] describe attempts to reduce the anchoring and overconfidence biases of engineering cost estimators).

2.4. An Overview of Biases and Debiasing Techniques

Tables I–III provide an overview of biases and debiasing techniques. These tables were created as a result of a review of the bias literature, including previous tables and lists of biases in Refs. 8 and 29–31. The tables cover cognitive biases that are difficult to correct (Table I), motivational biases that are difficult to correct (Table II), and cognitive biases that are easy to correct (Table III). Columns 1 and 2 of Tables I and II describe the biases. Column 3 indicates where they occur in decision and risk analysis (the notation of tasks, UMi, VMi, and CMi, refer to the specific modeling and elicitation tasks in which these biases occur in utility modeling, value modeling, and choice modeling, respectively). Column 4 provides a list of the major debiasing techniques. Table III has a similar structure. Columns 1 and 2 of Table III describe several biases that are easy to correct in decision and risk analysis. Column 3 in the same table indicates how these biases can be corrected.

Tables I and II are self-explanatory. A decision and risk analyst can read them by beginning with a particular bias (columns 1 and 2), looking up (in column 3) how they affect particular tasks, and determining (in column 4) how to reduce the bias in that task. Table III deserves a bit more explanation. The source of the biases and errors in Table III are SB errors, as Arkes[24] calls them. Because they are SB errors, experts and decisionmakers can easily be convinced that they made a mistake and they understand the logic and are willing to use the correct model. The classical example is the conjunction fallacy. Few subjects in experimental studies insist on assigning a higher probability to the conjunction of two events than to each of the separate events.[18] Once they agree that they made an error, it is easy to convince them that the correct model is to us $P(A \cap B) = P(B|A)\ P(A)$ and, if required, elicit the corresponding probabilities from them. Other biases in Table III are corrected by the use of appropriate tools. For example, the sunk cost bias can be eliminated by defining all outcomes in a decision problem as future outcomes, ignoring past costs. Ambiguity aversion can be addressed in decision analysis by developing explicit probability distributions for ambiguous events or variables. This is not to say that decisionmakers will not feel the "tug" of sunk costs or ambiguity aversion, but the tools of decision and risk analysis force them to eliminate these considerations.

Table I. Cognitive Biases in Decision and Risk Analysis that are Difficult to Correct

Bias	Description	Evidence of Bias in Decision and Risk Analysis with Modeling Tasks Affected	Debiasing Techniques
Anchoring (PB errors)	The bias occurs when the estimation of a numerical value is based on an initial value (anchor), which is then insufficiently adjusted to provide the final answer.[1]	*Evidence*: Several areas, such as estimation tasks, pricing decisions, and also in negotiations.[32,33] *Tasks*: UM2, UM3, VM3, CM1, CM3, CM4	• Avoid anchors • Provide multiple and counteranchors • Use different experts who use different anchors
Availability/ease of recall (AB errors)	The bias occurs when the probability of an event that is easily recalled is overstated.[34,35]	*Evidence*: Simple frequency estimates;[34,36] frequency of lethal events;[37] rare events that are anchored on recent examples. *Tasks*: UM1, UM2, VM1, CM1, CM2, CM3	• Conduct probability training • Provide counterexamples • Provide statistics
Certainty effect (PB errors)	People prefer sure things to gambles with similar expected utilities; they discount the utility of sure things dramatically when they are no longer certain.[38,39]	*Evidence*: Probability- versus certainty-equivalent methods produce different results.[40,41] Task: VM3	• Avoid sure things in utility elicitation • Separate value and utility elicitation • Explore relative risk attitude parametrically
Equalizing bias (PB errors)	This bias occurs when decisionmakers allocate similar weights to all objectives[17] or similar probabilities to all events.[42,43]	*Evidence*: Elicitation of probabilities in decision trees[42,43] and elicitation of weights in value trees.[17] *Tasks*: UM2, VM4, CM3	• Rank events or objectives first, then assign ratio weights • Elicit weights or probabilities hierarchically
Gain-loss bias (PB errors)	This bias occurs as alternative descriptions of a choice and its outcomes[44] either as gains or as losses and may lead to different answers[44–46] (see also *status quo* bias below).	*Evidence*: Several areas involving choices of risky options, evaluation of a single option on an attribute, and the way consequences are described to promote a choice.[46,47] *Tasks*: VM2, VM3, VM4, CM3	• Clearly identify the *status quo* (SQ) • For value functions, express values as marginal changes from SQ • For utility functions, elicit utilities for gains and losses separately
Myopic problem representation (AB errors)	This bias occurs when an oversimplified problem representation is adopted[48] based on an incomplete mental model of the decision problem.[49,50]	*Evidence*: focus on a small number of alternatives,[51,52] a small number of objectives,[53,54] or a single future state of the world.[55] See also Payne *et al*.[48] *Tasks*: UM1, VM1, CM1, CM2	• Explicitly encourage to think about more objectives, new alternatives, and other possible states of the future
Omission of important variables (AB errors)	The bias occurs when an important variable is overlooked.[56]	*Evidence*: Definition of objectives;[53,54] identification of decision alternatives;[57,58] and hypothesis generation.[59,60] *Tasks*: UM1, VM1, CM1, CM2	• Prompt for alternatives and objectives • Ask for extreme or unusual scenarios • Use group elicitation techniques
Overconfidence (AB errors)	The bias[15,16] occurs when the decisionmakers provide estimates for a given parameter that are above the actual performance (overestimation) or when the range of variation they provide is too narrow (overprecision).[61]	*Evidence*: Widespread occurrence in quantitative estimates, such as in defense, legal, financial, and engineering decisions.[61,62] Also present in judgments about the completeness of a hypothesis set.[59,63] *Tasks*: UM1, UM2, UM3, CM2, CM3, CM4	• Provide probability training • Start with extreme estimates (low and high), avoid central tendency anchors • Use counterfactuals to challenge extremes • Use fixed value instead of fixed probability elicitations

(*Continued*)

Table I. (Continued)

Bias	Description	Evidence of Bias in Decision and Risk Analysis with Modeling Tasks Affected	Debiasing Techniques
Proxy bias (PB errors)	Proxy attributes receive larger weights than the respective fundamental objectives.[71]	*Evidence*: Elicitation of weights in multiattribute utility and value measurement.[71] *Tasks*: VM2, VM4	• Avoid proxy attributes • Build models relating proxies and fundamental objectives and provide weights for fundamental objectives
Range insensitivity bias (PB errors)	Weights of objectives are not properly adjusted to changes in the range of attributes.[68,72]	*Evidence*: Elicitation of weights in multiattribute utility and value measurement.[68,72] *Task*: VM4	• Make attribute ranges explicit and use swing weighting procedures • Use trade-off or pricing-out procedures • Use multiple elicitation procedures and cross-checks
Scaling (PB errors)	A family of stimulus-response biases[73,74] that comprises: *contraction bias*, *logarithmic response bias*, *range equalizing bias*, *centering bias*, and *equal frequency bias*.	*Evidence*: Assessment of physical and social measurements of various kinds.[73,74] *Tasks*: UM2,VM2, CM4	• Develop scales that match stimuli and responses, being aware of these biases • Choose appropriate scaling techniques for the task at hand
Splitting biases (PB errors)	This bias occurs when the way the objectives are grouped in a value tree affects their weights;[64–66] or the way a fault tree is pruned affects the probabilities placed on the remaining branches.	*Evidence*: Elicitation of weights in multicriteria models.[64,66–69] Elicitation of probabilities in fault trees.[59,70] *Tasks*: VM4, CM3	• Avoid splits with large probability or weight ratios • Use hierarchical estimation of weights or probabilities • Use ratio judgments instead of direct estimation or distribution of points

Note: Type of modeling: VM, value modeling; UM, uncertainty modeling; CM, choice modeling.
Main source of bias: AB, association-based errors; PB, psychophysically-based errors.[24]

In the following sections, we will ignore the biases in Table III and focus instead on those in Tables I and II.

The layout of Tables I and II makes it easy for those who want to study the effects of a specific bias on the decision and risk analysis tasks. However, for a practicing decision and risk analyst, it is more instructive to examine biases and debiasing techniques from the perspective of the task at hand—e.g., eliciting probability distributions from experts when modeling uncertainties or obtaining weights for criteria from decisionmakers when modeling values. The following sections are therefore structured by the decision and risk analysis tasks: modeling uncertainty, value, and choice; and the specific judgmental subtasks. In each subsection, we will first provide an overview of the task and subtasks and then review the applicable biases and debiasing techniques.

3. BIASES IN MODELING UNCERTAINTY

A major purpose of risk analysis is to characterize the uncertainty about the variable of interest (target variable) by defining its probability distribution. This is accomplished by decomposing the target variable into component variables and events, whose distributions are defined and then aggregated (for details, see Morgan and Henrion,[100] Bedford and Cooke,[101] and Lawrence *et al.*[102]). Fig. 1 shows a schematic overview of the judgmental subtasks when modeling uncertainty: the definition of target variable, component variables, and events (UM1); the assessment of probabilities for component variables and conditioning events by experts (UM2); and the aggregation of probabilities from each expert (UM3). Table IV provides an overview of the biases and debiasing techniques relevant for these tasks, which we detail next.

Table II. Motivational Biases in Decision and Risk Analysis

Bias	Description	Evidence of Bias in Decision and Risk Analysis with Modeling Tasks Affected	Debiasing Techniques
Affect influenced (AB errors)	This bias occurs when there is an emotional predisposition for, or against, a specific outcome or option that taints judgments.[75,76]	*Evidence*: Several studies that assess the role of affect causing an inverse perceived relationship between positive and negative consequences related to pandemics and human-caused hazards, etc. (see Siegrist and Sütterlin[77] for details). There is also evidence that affect influences the estimation of probabilities of events.[78] *Tasks*: UM2, VM3, VM4, CM1, CM3, CM4	• Avoid loaded descriptions of consequences in the attributes • Cross-check judgments with alternative elicitation protocols when eliciting value functions, weights, and probabilities • Use multiple experts with alternative points of view
Confirmation (AB errors)	The bias occurs when there is a desire to confirm one's belief, leading to unconscious selectivity in the acquisition and use of evidence.[79]	*Evidence*: Several experimental settings, such as in information gathering, selection tasks, evidence updating, and own-judgment evaluation.[79,80] Also in real-world contexts, such as medical diagnostics, judicial reasoning, and scientific thinking.[79] *Tasks*: UM1, CM2, CM3	• Use multiple experts with different points of view about hypotheses • Challenge probability assessments with counterfactuals • Probe for evidence for alternative hypotheses
Desirability of a positive event or consequence (AB errors)	The bias occurs when the desirability of an outcome leads to an increase in the extent to which it is expected to occur.[81] It is also called "wishful thinking"[82] or "optimism bias."[83]	*Evidence*: Prediction of outcomes in games of chance;[81] impact on estimates of probabilities of future outcomes in expert foresight;[84,85] estimates of costs[28] and duration[14] in projects; as well as some possible effect in sport tournaments.[86] *Tasks*: UM2, UM3, CM3, CM4	• Use multiple experts with alternative points of view • Use scoring rule and place hypothetical bets against the desired event or consequence • Use decomposition and realistic assessment of partial probabilities
Undesirability of a negative event or consequence (AB errors)	This bias occurs when there is a desire to be cautious, prudent, or conservative in estimates that may be related to harmful consequences.[87,88]	*Evidence*: Most evidence related to probabilities of life events;[87,88] but also in long-term estimations of future events in expert foresight[84] and estimates of risks and benefits about risky technologies;[89] some risk assessments that are intentionally biased toward "conservative" estimates in each step (as discussed in the recent report by the Institute of Medicine[90]). *Tasks*: UM2, UM3, CM3, CM4	• Use multiple experts with alternatives points of view • Use scoring rules and place hypothetical bets in favor of the undesired event or consequence • Use decomposition and realistic assessment of partial probabilities to estimate the event probability
Desirability of options/choice (AB errors)	This bias leads to over- or underestimating probabilities, consequences, values, or weights in a direction that favors a desired alternative.[3]	*Evidence*: Only anecdotal evidence, such as the biased estimates of probabilities and impacts in risk assessment by Defra.[91] *Tasks*: UM2, VM3, VM4, CM1, CM3, CM4	• Use analysis with multiple stakeholders providing different value perspectives • Use multiple experts with different opinions • Use incentives and adequate levels of accountability

Note: Type of modeling: VM, value modeling; UM, uncertainty modeling; CM, choice modeling.
Main source of bias: AB, association-based errors; PB, psychophysically-based errors.[24]

Table III. Cognitive Biases in Decision and Risk Analysis that are Easy to Correct

Bias	Description	How to Correct the Bias in Decision and Risk Analysis
Ambiguity aversion/Ellsberg's paradox (SB errors)	People tend to prefer gambles with explicitly stated probabilities over gambles with diffuse or unspecified probabilities.[92]	• Model and quantify ambiguity as probability distribution • Model as parametric uncertainty (e.g., over the bias parameter of a Bernoulii process) or secondary probability distribution
Base rate fallacy/neglect (SB errors)	People tend to ignore base rates when making probability judgments and rely instead on specific individuating information.[19,20]	• Split the task into an assessment of the base rates for the events and the likelihood or likelihood ratio of the data, given the events
Conjunction fallacy (SB errors)	The conjunction (joint occurrence) of two events is judged to be more likely than the constituent event, especially if the probability judgment is based on a reference case that is similar to the conjunction.[18]	• Demonstrate the logic of joint probabilities with Venn diagrams • Assess the probability of the two events separately and then assess conditional probability of one event, given the other event
Conservatism (SB errors)	In some Bayesian estimation tasks, people do not sufficiently revise their probabilities after receiving information about the events under consideration.[93,94]	• Decompose the task into an estimation of prior probabilities (odds) and likelihoods (ratios)
Endowment effect/status quo bias/sunk cost (SB errors)	People ask to get paid more for an item they own than they are willing to pay for it when they do not own it; their disutility for losing is greater than their utility for gaining the same amount;[95] people consider sunk cost when making prospective decisions.[96]	• Show the logic that maximum buying prices and minimum selling prices should converge • Show the logic of symmetry of gains and losses • Do not include sunk cost in analysis
Gambler's fallacy/hot hand (SB errors)	People often think that irrelevant information about the past matters to predict future events, for example, that, when tossing a coin, it is more likely that "heads" comes up after a series of "tails"; for details, see Bar-Eli *et al.*[97]	• Explain of the probability logic and the independence of events
Insensitivity to sample size (SB errors)	According to the laws of probability, extreme averages or proportions are less likely in large samples than in small samples. People tend to ignore sample size and consider extremes equally likely in small and large samples.[98]	• Use statistics to determine the probability of extreme outcomes in samples of varying sizes • Use the sample data and show how and why extreme statistics are logically less likely for larger samples
Nonregressive prediction (SB errors)	When two variables X and Y are imperfectly correlated, the conditional estimate of Y, given a specific value of X, should be regressed toward the mean of Y.[19]	• Use statistics directly • If data are insufficient, decompose the task into an estimate of the standard deviations and the correlation and then calculate the regression line
Subadditivity/superadditivity of probability (SB errors)	When judging individual subevents, the sum of the probabilities is often systematically smaller or larger than the directly estimated probability of the total event. This is true even for mutually exclusive events; for details, see Macchi *et al.*[99]	• Explain the logic of additivity of mutually exclusive events • Also, one can begin by obtaining ratios of the probabilities of subevents and applying the ratios to the probability of the total event

Note: SB, strategy-based errors.[24]

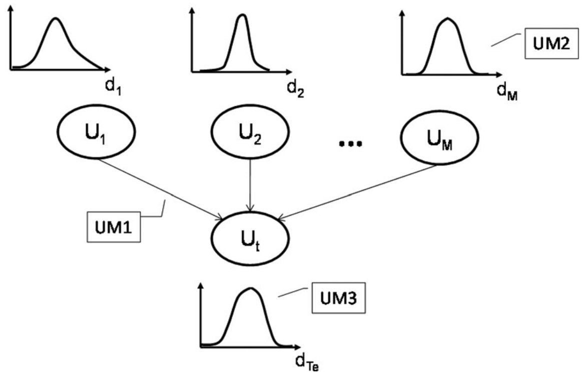

Fig. 1. Steps in modeling uncertainty. UM1 = Definition of target variable, component variables and events; UM2 = Assessment of probabilities for component variables and conditioning events by experts; UM3 = Aggregation of probabilities.

3.1. Definition of Target Variable, Component Variables, and Events (UM1)

The first step in uncertainty modeling is to define an exhaustive set of uncertainties $\boldsymbol{U} = \{U_1, U_2, \ldots, U_M\}$, i.e., the component events or variables (Fig. 1, step UM1), which describe in full the target variable U_t. Research on the generation of component variables or events is rather limited, although there exists some literature on event structuring and hypothesis generation (e.g., Fischhoff *et al.*;[59] see Gettys *et al.*[103] for further references).

Biases

Both naïve subjects and experts generate a relatively small number of hypotheses, when compared with an exhaustive set of hypotheses (for an overview, see Thomas *et al.*[60]). This phenomenon is referred to as an ***omission of important variables bias***.[56] ***Myopic problem representation*** is a related bias that results in an incomplete problem description due to oversimplified mental models.[48–50] The generation of a myopic, often nonexhaustive set of hypotheses is accompanied by the ***overconfidence bias***[15,16] when judging the exhaustiveness of such set.[59,63] Subjects also showed overconfidence when presented with a larger set of hypotheses versus the hypotheses generated by the subjects themselves.[104] Furthermore, the hypotheses generated were the ones with the highest perceived *a priori* probability,[67,105] and the number of hypotheses generated was constrained by working memory capacity and time pressure to generate them. The ***availability bias***[34,35] and the ***confirmation bias***[79] also influence hypothesis generation and definition, leading subjects to generate events and hypotheses that are more easily recalled and to retain those that support their favored hypothesis.[80]

Debiasing

In addition to promoting precise definitions of events and hypotheses,[3] it is common in this step to use group elicitation[106] and counterfactuals to

Table IV. Uncertainty Modeling Subtasks and Associated Biases

Subtask	Biases	Debiasing Suggestions
UM1: Definition of target variable and events	• Availability bias (C) • Confirmation bias (M) • Myopic problem representation bias (C) • Omission bias (C) • Overconfidence bias (C)	Prompting for missing events and variables; group elicitation; stimulation of creativity.
UM2: Assessment of probabilities	• Affect influenced bias (M) • Anchoring bias (C) • Availability bias (C) • Desirability biases (M) • Equalizing bias (C) • Overconfidence bias (C) • Scaling biases (C)	Providing probability training; using multiple experts, counterfactuals, hypothetical gambles, and fixed value techniques.
UM3: Aggregation of probabilities	• Anchoring bias (C) • Desirability biases (M) • Overconfidence bias (C)	Defining balanced expert groups; mixing individual-group elicitations; asking for counterfactuals and hypothetical gambles.

Note: C, Cognitive bias (see Table I for details); M, Motivational bias (see Table II for details).

stimulate creativity and try to reduce the omission and availability biases. The evidence about the quality of group interaction indicates that nominal groups (where members generate ideas in isolation) outperform traditional brainstorming groups, in terms of both heterogeneity and quality of ideas.[107] These benefits of group interaction can be enhanced by asking the experts to write the hypotheses on post-its and glue them on a wall, or by using computer software, which then projects all the hypotheses being generated on a screen.[108] This can be coupled with the presence of a facilitator to ensure group members do not suffer from evaluation apprehension and minimize production blocking.[107] Klayman[80] suggests some ways of debiasing the confirmation bias, such as using experts who know the specific domain of the phenomenon well, making sure there is a concrete context for the elicitation, asking for alternative explanations, and providing feedback on past estimates. MacGregor[109] proposes several useful guidelines on decomposition, such as decomposing when the uncertainty about the target is high, using multiple decomposition approaches to estimate component values, and relying on multiple estimators for each component variable.

3.2. Assessment of Probabilities for Component Variables and Conditioning Events by Experts (UM2)

Once the component events and variables have been defined, a (discrete) probability distribution over events or a (continuous) density function d_j associated with each component variable U_j ($j = 1, 2, \ldots, M$) is elicited from the experts (Fig. 1, UM2). (See details about such elicitation procedures in overviews by Hora[110] and Morgan.[111])

For discrete events, the typical method for eliciting probabilities is by using the split fraction method,[110] which begins with a rank order of the relative likelihoods, followed by ratio assessments, and calculations of probabilities. There are two main methods for eliciting continuous probability distributions, as discussed by Spetzler and Stael von Holstein:[112] asking the expert to provide the probability, given a value of the target variable (fixed value methods) or, inversely, asking for the value of the target variable given a probability (fixed probability methods). In some cases, hypothetical gambles or scoring rules[8] can be used to motivate experts to provide truthful answers.

Biases

There is a strong influence of the ***scaling biases***[73,74] on probability elicitation, for example, the use of a linearly spaced or logarithmic spaced variable is likely to influence the results.[3] Seaver *et al.*[26] and Abbas *et al.*[27] show that the elicitation method (fixed value vs. fixed probability) influences the results, mainly due to the ***anchoring bias***.[1] The same bias also occurs in eliciting probability distributions when the expert uses a small set of data to make the estimates and does not include alternative scenarios.[3,111,112]

The ***overconfidence bias*** is a serious problem in eliciting continuous distributions,[21,113,114] as it prevents decisionmakers to consider extreme cases, beyond the defined endpoints of the target variable, and leads to excessively narrow ranges.[115,116] The ***availability bias*** also plays an important role in probability elicitation, as it leads to overstatement of probabilities for events that are easily remembered.[3,110,111] The ***equalizing bias*** causes probability distributions over discrete events to be too "flat" because subjects appear to begin with an equal probability distribution and make only half-hearted adjustments.[42,43]

Finally, the ***desirability bias*** leads to assigning higher probabilities to events and outcomes that are desirable,[81] or to assigning lower probabilities to those that are undesirable.[88] In the former case, we call it the ***desirability of a positive event bias***, which occurs when the desirability of an outcome leads to an increase in the extent to which it is expected to occur.[81] It is often called "wishful thinking"[82] or "optimism bias."[83] (A real-world example is provided by Dillon *et al.*,[28] who report significant cost underestimation for large projects.) In the latter case, we call it the ***undesirability of a negative event bias***, which occurs when there is a desire to be cautious, prudent, or conservative in estimates that may be related to harmful consequences.[87,88] This bias often occurs in environmental risk analyses, which deliberately use "conservative" models and estimates. In addition, the affect heuristic[75,76] may cause what we denominated as the ***affect influenced bias***, which occurs when the outcomes of an event trigger an emotional reaction that might cause a misestimation of its probability of occurrence[78] and the ***desirability of options bias***,[3] which may lead experts to under-/overestimate probabilities in a direction that favors preferred alternatives.

Debiasing

The elicitation of probabilities is typically preceded by a training session to familiarize experts with the elicitation protocol and warn them about possible biases, particularly about the overconfidence and availability biases.[112,117,118] Fischhoff[21] suggests tools for debiasing overconfidence, but they were shown to have limited efficacy in overcoming the bias. This is not surprising, given that it is an AB error.[24]

Both Seaver *et al.*[26] and Abbas *et al.*[27] show that the fixed value method produces less overconfidence than the commonly used fractile method for eliciting continuous probability distributions. In the fixed value method the experts are given a set of values of the uncertain variable and asked for probabilities of the true value falling above or below; in the fractile method, the experts are given percentiles (e.g., the 75th) and asked for the values of the uncertain variable that represents each percentile (e.g., "What is the value of the uncertain variables, for which the probability of the true value falling below it is 75%?"). In addition, alternative assessment protocols should be employed to elicit a distribution and cross-check judgments.[8,112,119,120] The use of split fractions, ranking, and ratio assessments reduce the equalizing bias.

Risk analysts use decomposition, multiple experts, and the exploration of the extremes of a target variable (including counterfactuals and alternative scenarios) as ways of trying to reduce the overconfidence and availability biases.[3,14] In terms of tackling the anchoring bias, Chapman and Johnson[121] show that prompting assessors to identify features of the target variable different than the anchor, or to consider reasons in conflict with the anchor, are effective in reducing it.

Hypothetical bets and scoring rules[8,119] can reduce motivational biases. For example, after obtaining a median (50–50) estimate of an uncertain variable, an expert should be indifferent between two bets with the same reward on either side of the median. Most experts, however, when asked about such hypothetical bets show a strong preference for one side or the other and it is then easy to convince them to move the median until they are truly indifferent.

3.3. Aggregation of Probabilities (UM3)

There are two types of aggregation of component probability judgments: within-individual expert aggregation is used to calculate the overall event probability d_{Te} for each e-th expert (Fig. 1, UM3); across-experts aggregation is used to combine individual probabilities d_{Te}. The first type is purely computational and involves no additional judgmental task. The second type can be done mathematically or behaviorally, with the latter involving potential biases. (See also the comprehensive reviews on the aggregation of probability distributions by Clemen and Winkler[122] and on the social aspects of group forecasting by Seaver[26] and by Kerr and Tindale.[123])

Biases

There are two main biases in behavioral aggregation: group-***overconfidence***, caused by group polarization;[11] and ***anchoring*** to initial estimates[107] or irrelevant information.[11] Group polarization also may exacerbate individual biases when the group is trying to reach consensus on a judgment, which are then propagated to the group decision-making process,[107,124] including the ***desirability of a positive or a negative event biases***.

Debiasing

These biases may be alleviated by carefully designing the experts' interaction[125] (which may range from several versions of the Delphi method, forced consensus, or free-form discussions) and by using a facilitator to support the group.[126–128] For instance, anchoring across experts may be alleviated by keeping the expert's name anonymous, by managing the order and the way information is presented to the group, and by the type of decision rule that is employed to define the group's estimate.[123] Overconfidence, which tends to be higher in free-form discussions than in more structured formats,[123] may be counteracted by assembling a diverse group of opinions, by guaranteeing procedural justice, and by reducing power imbalances among the group members.

A useful protocol for group elicitation of probabilities and probability distributions was developed in the course of conducting a major expert elicitation exercise in the context of a nuclear power plant risk analysis.[118] In a first round of meetings, experts exchange their views and concerns about a particular risk issue. They then conduct separate individual studies and meet again to discuss their approaches (not their specific probability judgments). In the same meeting their probability distributions are then individually elicited. Subsequently, the results of

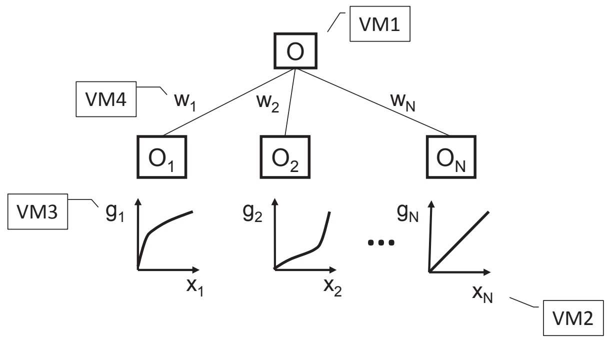

Fig. 2. Steps in modeling value. VM1 = Definition of Objectives; VM2 = Definition of Attributes; VM3 = Elicitation of Partial Values; VM4 = Elicitation of Attribute Weights.

their elicitations are displayed, disagreements are discussed, and, if needed, experts are re-elicited. After re-elicitation, the individual probability distributions are averaged. There is no requirement for consensus. The advantage of this protocol over other procedures that aim at group agreement(126) is that it provides a broad spectrum of opinions and counteracts individual overconfidence by the breadth of opinions across experts. The disadvantage is that the result does not represent a group consensus, which may be required or desirable in some situations.

4. MODELING VALUES[3]

We will limit our discussion in this section to multiattribute utility models.(130,131) These models decompose the assessment of alternatives or options along multiple criteria or attributes, followed by weighting attributes and calculation of an overall value or utility. Typically, experts provide estimates of the performance of the options on the criteria and decisionmakers provide attribute weights and single attribute value or utility functions. Value functions are elicited when there is little or no risk involved in the decision and utility functions are used in case of risk and uncertainty.(132)

There are four judgment steps and one aggregation step involved in developing a multicriteria models (see also Keeney and Raiffa(130) and Keeney(133)). A schematic overview of the subtasks is provided in Fig. 2: the definition of objectives (VM1); the definition of an attribute associated with each objective (VM2); the elicitation of a value function for each attribute (VM3); and the elicitation of attribute weights (VM4). Each step is briefly described below, with a discussion about the most prevalent biases and how to overcome them. Table V summarizes the biases and debiasing techniques for these steps.

[3]An abridged version of this section appeared in the proceedings of the 48th Hawaiian International Conference on Systems Science (HICSS).(129)

4.1. Definition of Objectives (VM1)

The initial task in any multicriteria decision analysis is the specification of which objectives the decisionmakers want to pursue and, therefore, should be used in the evaluation of decision alternatives. These objectives $\boldsymbol{O} = (O_1, O_2, \ldots, O_N)$ are typically organized as a value tree(131) as shown in Fig. 2 (step VM1). They are either directly elicited in interviews with the decisionmakers, or constructed from multiple interviews and general knowledge.(54,134)

Biases

Identifying and structuring objectives rely heavily on decisionmakers' mental models.(135) Research shows that the ***myopic problem representation bias*** tends to generate incomplete problem descriptions, due to oversimplified mental models.(48–50)

Following a value-focused thinking principle(133)—a compelling argument that fundamental objectives, instead of means objectives, should be employed in such assessments (see also Baron(136) and Edvardsson and Hansson(137))—one would expect that defining objectives could be an easy task for decisionmakers. On the contrary, recent evidence(53,54) shows that subjects find it difficult to generate a comprehensive set of objectives. These studies report a strong ***omission bias***,(56) where some important objectives were overlooked by decisionmakers, often due to an ***availability bias***, in which only some salient objectives are available in the memory.(53) This omission bias may lead to poor recommendations,(48) as some important consequences are completely disregarded in the analysis. The simulation performed by Fry *et al.*(138) assessed the impact of omissions of objectives and shows that it tends to increase with the rise of both the number of objectives and the number of missing objectives.

Debiasing

There is limited empirical evidence showing how the omitted variable bias in this context might be avoided, but the general advice is that decisionmakers need external probes. Bond *et al.*(54) found that

Table V. Value Modeling Subtasks and Associated Biases

Subtasks	Biases	Debiasing Suggestions
VM1: Definition of objectives	• Availability bias (C) • Myopic problem representation bias (C) • Omission bias (C)	Providing categories; prompting for more objectives; stimulating creativity.
VM2: Definition of attributes	• Gain-loss bias (C) • Proxy bias (C) • Scaling biases (C)	Using natural scales for attributes; careful selecting attribute endpoints.
VM3: Elicitation of value or utility functions	• Affect influenced bias (M) • Anchoring bias (C) • Certainty effect bias (C) • Desirability of options bias (M) • Gain-loss bias (C)	Separating value and utility modeling; separating assessments of gains and losses; using group procedures.
VM4: Elicitation of attribute weights	• Affect influenced bias (M) • Desirability of options bias (M) • Equalizing bias (C) • Gain-loss bias (C) • Proxy bias (C) • Range insensitivity bias (C) • Splitting bias (C)	Using groups to construct value structure; avoiding the use of direct importance assessments; cross-checking weights with trade-off and pricing-out methods; avoiding the use of proxy attributes.

Note: C, Cognitive bias (see Table I for details); M, Motivational bias (see Table II for details).

the use of generic categories and the challenge to increase the number of objectives generated a more exhaustive set of objectives. Leon[139] discovered that value-focused thinking helped in eliciting not only more objectives, but also objectives that were perceived to have better features as evaluation criteria.

From a prescriptive perspective, Keeney[133] suggests several probes to help decisionmakers in generating objectives, including writing a wish list, thinking about features of good (and bad) alternatives, imagining consequences of actions, considering goals and constraints, and adopting other stakeholders' perspectives, which may help in reducing the myopic problem representation bias. Other tools to identify objectives are the use of causal maps,[140] networks of ideas with a means-end structure,[141,142] or affinity diagrams, where objectives are elicited and clustered.[143]

To obtain a comprehensive set of objectives, practitioners often interview multiple stakeholders.[144] Creating a comprehensive list of objectives from multiple inputs is usually uncontroversial because the decisionmaker(s) can always zero-out selected objectives in the weighting process (see below). Another way of obtaining multiple perspectives is to elicit the objectives in groups, using decision conferencing supported by a facilitator.[126,127]

4.2. Definition of Attributes (VM2)

An attribute X_i measures how well different options achieve the objective O_i (Fig. 2, step VM2). The decision analyst has to make a choice of the most suitable attribute. There is not, as far as we are aware, any descriptive research on the impact of this choice.

Biases

Research on ***scaling biases***,[73,74] a family of biases that occur when stimulus and response scales are mismatched, is relevant to the definition of attributes. This research shows that different ways of presenting and scaling an attribute, as well as the definition of upper and lower limits of the attribute scale, are the main causes of bias. Five biases are encompassed by this family: ***contraction bias*** (underestimating large sizes/differences and overestimating small/size differences); ***logarithmic response bias*** (using step changes in the number of digits used in the response, which fit a log scale); ***range equalizing bias*** (using most of the range of response whatever is the size of the range of the stimuli); ***centering bias*** (producing a symmetric distribution of responses centered on the midpoint of the range of stimuli); and ***equal frequency bias*** (using equally all parts of the response scale).

Studies on attribute framing effects[46,145] are also relevant in the definition of attributes, as they show that the ***gain-loss bias*** may occur when an attribute has a positive or negative connotation (e.g., whether assessing the degree of success, or instead, failure of a decision alternative). Poulton[74] suggests some generic ways of dealing with each magnitude judgment bias, and Levin *et al.*[46] mention in which situations the gain-loss bias is more prevalent.

Proxy attributes are often used in multiattribute utility analysis when fundamental attributes are hard to measure. For example, it is often easier to measure the amounts of pollutants emitted per year by a power plant than to determine the health effects that result from the pollution. Fischer *et al.*[71] have shown that proxy attributes lead to the ***proxy bias***—distortion in weights in multiattribute utility models.

Debiasing

Whenever possible the attribute scales should use natural units (such as dollars to measure profitability), making sure that the range of the scale encompasses the spread of performances of the alternatives. When natural scales are not available, constructed attributes should be used with special attention to steps of the scale and its endpoints.[3] Care should also be taken in considering whether the attribute has a positive or negative frame in assessing performances. From a broader perspective, Keeney[133] emphasizes the importance of the selection of appropriate attributes, and Keeney and Gregory[146] provide excellent guidelines on how to choose and build an appropriate attribute. The analyst must ensure that the attributes are unambiguous for the assessment of consequences, comprehensive in covering the range of consequences, measure as directly as possible a fundamental objective, and are understandable by the decisionmakers.

4.3. Elicitation of Partial Values (VM3)

Once each X_ith attribute is defined, a partial value function v_i or utility function u_i is elicited (indicated as a generalized function g_i in Fig. 2). Value functions express the decisionmaker's strengths of preference for decisions under certainty; and utility functions express both risk attitude and strengths of preference for decisions under uncertainty. There are several elicitation procedures for both value and utility functions,[8,147] with the former requiring judgments about preferences and strengths of preferences among riskless outcomes, and the latter requiring choices among gambles.

Biases

Several studies show that the results of an elicitation of utility functions depend on the design of stimuli and responses.[41,148] In addition to random noise,[149–151] both the ***anchoring bias***,[121] and the ***gain-loss bias***[46] have been identified in this context. Another bias that impacts utility assessment is the ***certainty effect***,[38,39] which suggests that people prefer sure things to gambles with similar expected utilities, and discount the utility of sure things dramatically when they are no longer certainty.[40,41] In addition, the ***desirability of options bias***[3] might distort the utility function in a direction that favors a preferred alternative, and the ***affect influenced bias*** may trigger oversensitivity to some increases in consequences (e.g., the first death in a terrorist attack) over others (e.g., the 100th death).[76]

Examples of the impact of the gain-loss bias are the special role that the *status quo* plays in utility assessment,[152] or the influence of the elicitation procedure employed (certainty equivalent or probability equivalent) on the shape of the function.[40] Another example is the impact that presenting a gamble in terms of gains or losses has on the utility function being elicited.[40] They may be mitigated by Arkes's[24] suggestions on how to reduce PB errors. In terms of anchoring, Chapman and Johnson[121] have shown that value judgments are influenced by irrelevant starting points, but found out that prompting the subjects to consider reasons different than the anchor has alleviated the bias.

Debiasing

Many practitioners adopt simplified forms of elicitation and representation of partial values, given the noise associated with these elicitations and the dependency of the responses on the framing of stimuli.[3] In many ways, value and utility functions are more "constructed" than "elicited."[153] These simplifications include using value functions as proxy for utility functions, as advocated by von Winterfeldt and Edwards;[8] deriving utility functions from value functions;[132] or using standardized shapes for utility functions, such as linear value functions[3] or exponential utility functions.[154] If utility functions are elicited using gambles, the analyst should avoid sure things in the elicitation to reduce the certainty effect.

Often, multicriteria models are created to support group decision making using decision conferences,[126] with the decision analyst as a facilitator.[127] This opens up the issue on how individual value assessments should be combined (see Belton and Pictet[155]) and biases in groups. There is evidence that the degree of shared mental models by group members increases the effectiveness in reaching a decision and satisfaction with the decision-making process;[124] and that aggregation rules that are perceived by the group as procedurally fair can increase satisfaction with and legitimacy of decision making.[123] However, groups are more confident than individuals,[123] sometimes showing overconfidence[11] and, as mentioned previously, they may polarize, thus exacerbating cognitive and motivational biases.

4.4. Elicitation of Attribute Weights (VM4)

The next step in multiattribute utility modeling is the elicitation of weights w_i, $i = 1, \ldots n$, associated with each O_i-th objective or X_i-th attribute (Fig. 2, step VM4). Weights are scaling constants that represent value tradeoffs and aggregate the partial values.[130] $g_i(x_i)$. There are many common mistakes in defining weights,[4,156] and several elicitation protocols for eliciting weights in an appropriate way.[8]

Biases

Research has identified a family of biases affecting the elicitation of weights. According to the ***splitting bias*** objectives that are defined in more detail receive a larger portion of the weights than objectives that are defined in less detail[64–66] (but see some criticisms about the experimental settings of these studies in Pöyhönen and Hämäläinen[157]). With the ***equalizing bias*** decisionmakers tend to allocate similar weights to all objectives.[17,42] The ***gain-loss bias*** may also affect weights, for instance, if tradeoffs are elicited considering relative improvements or degradations of performances.[4]

According to the ***proxy bias*** objectives are overweighted when measured by a proxy attribute instead of by a fundamental attribute.[71] Due to the ***range insensitivity bias***, weights are insensitive to the range of attribute values.[68,72] Because weights are scaling constants that should depend on attribute ranges, this insensitivity can lead to highly distorted weight judgments. In addition, the ***desirability of options bias***[3] may lead to the over-/underweighting of attributes to favor a preferred alternative, and the ***affect influenced bias*** might cause a distortion of weights in favor of attributes that cause positive feelings and against those that provoke negative ones.

Debiasing

Elicitation procedures that ask for direct assessments of importance (e.g., distributing 100 points over attributes) should not be used,[68] but even methods that explicitly make decisionmakers consider the range of attributes, such as swing-weights and the trade-off method, may suffer from range insensitivity bias.[69] In practice, most decision analysts use simple methods, such as swing weights, cross-checked with selected tradeoffs,[3] and they consider the weighting process as an interactive and constructive process rather than one of discovery.[48] To reduce the splitting bias one should avoid excessive detail in some objectives and little detail in others.[158] This can often be achieved by obtaining objectives and attributes from multiple stakeholders, which provide different degrees of detail to different parts for the value tree (e.g., environmentalists provide detail about environmental objectives and engineers provide detail about cost and performance). To reduce the equalizing bias, one can set up the lower and upper anchors of each attribute in a way (as in the case study described by Morton *et al.*[159]) that they indeed allow similar weights for all objectives. Alternatively, one can use ranking and ratio weighting methods, coupled with hierarchical weighting, which generally produce steeper weights.[160] Another way of dealing with the joint effects of the splitting bias and the equalizing bias is the calibration method proposed by Jacobi and Hobbs.[17] Finally, the use of either natural or constructed attributes for fundamental objectives, as recommended by Keeney and Gregory,[146] avoids the proxy bias.

5. MODELING CHOICES

Choices under uncertainty are usually modeled with decision trees.[161,162] Alternatively, the analyst may use influence diagrams,[163] which provide a more compact representation. Fig. 3 schematically shows the subtasks of modeling choices represented by a decision tree: the identification of decision alternatives (CM1); the identification of event nodes and

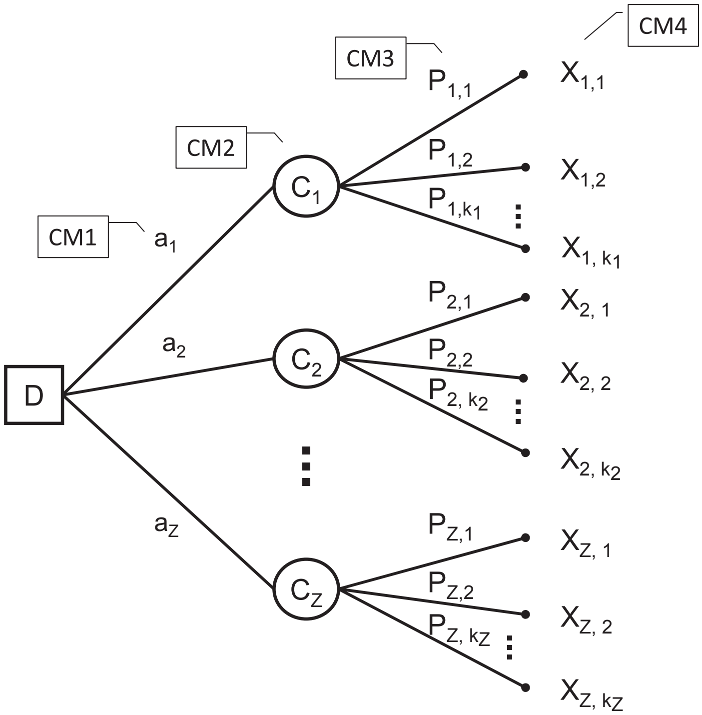

Fig. 3. Steps in modeling choice. CM1 = Identification of Alternatives; CM2 = Identification of Event Nodes and Their Outcomes; CM3 = Assessment of Probabilities of the Event Nodes; CM4 = Estimation of Consequences of Alternatives on Attributes.

their outcomes (CM2); the assessment of probabilities of the event nodes (CM3); and the estimation of consequences of alternatives on attributes (CM4). The steps for modeling choices, and the bias that may occur, are described next and summarized in Table VI.

5.1. Identification of Alternatives (CM1)

The modeling of choices with decision trees typically starts with the identification of a set of decision alternatives $\boldsymbol{A} = \{a_1, a_2, \ldots, a_Z)$ that originate at a decision node D (Fig. 3, step CM1). Identifying potentially good alternatives is crucial in decision making,[133] but individuals and organizations often consider only one alternative,[51,52] defining the problem as a binary choice between this alternative and the *status quo*, or few salient options that are not the best ones that could be designed.[164]

Biases

Several studies suggest that the ***omission bias*** may occur, where important options are not included or generated.[57,58,165] Other biases that play a role in the generation of alternatives are ***anchoring***, when all generated options are anchored on the initial available set,[133] ***myopic problem representation,*** when decisionmakers evoke constraints that prevent them from considering potentially attractive options,[48,55] and ***availability***, when the existence of an easily available alternative prevents the generation of less available ones.[166] In addition, the ***desirability of options bias*** may lead to the exclusion of alternatives that compete with the preferred one, and the ***affect influenced bias*** might cause the inclusion of alternatives that cause positive feelings and the exclusion of those that cause negative ones.

Debiasing

From a prescriptive point of view, Keeney,[133,143,168] Gregory and Keeney,[167] and Keller and Ho[169] suggest an extensive list of strategies to help generating decision alternatives. These can be classified into the following categories:[169] objective-based strategies (e.g., presenting one objective at a time and asking for high-value achieving alternatives, designing options that perform well on high-weighted objectives, etc.), state-based strategies (e.g., presenting possible states one at a time and asking for high-value achieving alternatives in that

Table VI. Choice Modeling Subtasks and Associated Biases

Subtasks	Biases	Debiasing Suggestion
CM1: Identification of alternatives	• Affect influenced bias (M) • Anchoring bias (C) • Availability bias (C) • Desirability of options bias (M) • Myopic problem representation bias (C) • Omission bias (C)	Prompting for alternatives; using objectives to generate alternatives; using group processes; stimulating creativity.
CM2: Identification of events and outcomes	• Availability bias (C) • Confirmation bias (M) • Myopic problem representation bias (C) • Omission bias (C) • Overconfidence bias (C)	Asking for counterfactuals; using multiple experts; adopting group processes; prompting for alternative hypotheses.
CM3: Assessment of probabilities	• Affect influenced bias (M) • Anchoring bias (C) • Availability bias (C) • Confirmation bias (M) • Desirability biases (M) • Equalizing bias (C) • Gain-loss bias (C) • Overconfidence bias (C) • Splitting bias (C)	Avoiding initial anchors; using ratio techniques, not point spreads; using fixed values, not fixed probabilities; asking for counterfactuals and alternative competing hypotheses.
CM4: Estimation of consequences	• Affect influenced bias (M) • Anchoring bias (C) • Desirability biases (M) • Overconfidence bias (C) • Scaling biases (C) • Splitting bias	Using model and data for estimation; avoiding anchors; asking for counterfactuals; using hypothetical gambles.

Note: C, Cognitive bias (see Table I for detains); M, Motivational bias (see Table II for details).

future state, etc.), and alternative-based strategies (e.g., imagining an ideal option and designing alternatives from it, using existing options to generate new ones, etc.). Presenting one objective at a time and asking respondents to generate alternatives that meet this objective generates more alternatives than when no objectives or all objectives together are presented.[57,165] More recently, Butler and Scherer[58] have shown that presenting objectives leads not only to more, but also to better, alternatives. Farquhar and Pratkanis[170] also mention the use of phantom alternatives as a way of stimulating creativity, e.g., the inclusion of an unfeasible "ideal" alternative helping decisionmakers to create new options as described by Phillips.[171]

Tools such as causal maps[141,172] and strategy-generation tables[173] can be used to develop alternatives. In addition, group-based techniques, such as the ones discussed in Section 3.1, either computerized or not, can be employed for the generation of alternatives.

5.2. Identification of Event Nodes and Their Outcomes (CM2)

In a decision tree, a chance node C_r (with $r = 1, 2, \ldots, Z$) represents an uncertainty associated with a discrete set of mutually exclusive and collectively exhaustive events (Fig. 3, step CM2).

Biases

The issues discussed in Section 3.1 also apply to this step. In particular the identification of the event nodes may suffer from the ***myopic problem representation*** and ***omission biases***; the definition of the set of outcomes from each chance node may suffer from ***overconfidence bias*** regarding their exhaustiveness and their range; and such definition may also be affected by both ***availability*** and ***confirmation*** **bias.**

Debiasing

Most debiasing tools discussed in Section 3.1 also apply here. Influence diagrams[163] are powerful tools to support the structuring of decisions under uncertainty. Counterfactuals and the development of long-range scenarios may help to reduce the omission bias and the associated overconfidence that the generated set of events is exhaustive.[174]

5.3. Assessment of Probabilities of the Event Nodes (CM3)

This step requires the assessment of conditional probabilities $P_{r,1}$ (with $1 = 1, 2, \ldots, k_r$) for each of the rth events defined at chance nodes in a decision tree (Fig. 3, step CM3).

Biases

Similar biases described in Section 3.2 occur when there is a discrete set of outcomes. Different elicitation methods[8] may generate ***anchoring*** and ***gain-loss biases***. The ***availability*** and ***desirability of a positive/negative event biases*** also may exert influence on the probabilities' estimates. The ***desirability of options bias*** may lead to over-/underestimation to favor preferred alternatives. The ***overconfidence bias***, as well as the ***confirmation*** and the ***affect influenced biases***, might distort probability estimates.

Additionally, two biases may occur in this step: the ***equalizing bias***[42,43] in which experts assign similar elicited probabilities to all outcomes; and the ***splitting bias***[59,70] in which decisionmakers do not sufficiently adjust their estimates when the decision tree is rearranged and some of its brunches are pruned. Birnbaum[175] shows that when choosing among gambles, splitting events with positive outcomes leads to a preferences for a gamble with the split events; while splitting events with negative outcomes leads to a preference of the gamble without the split events.

Debiasing

Prescriptive guidelines to reduce such biases are similar to the ones mentioned in Section 3.2. Fox and Clemen[42] suggest several strategies to minimize the splitting bias, such as trying to make sure the decisionmaker's attention is focused in a balanced way across the outcome space, or using multiple representations (alternative partitions).

5.4. Estimation of Consequences of Alternatives on Attributes (CM4)

In this step the consequences $X_{r,1}$ (with $1 = 1, 2, \ldots, k_r$) of implementing each rth alternative given the lth event are estimated (Fig. 3, step CM4), using data collection, modeling of systems, and the use of expert judgment.

Biases

When using expert judgment the ***scaling biases*** may occur, as well as ***overconfidence***[3] and ***anchoring***.[121] Another concern is the strong effect that the ***desirability of a positive/negative consequence biases*** may exert on the estimates of consequences that experts provide, with evidence both from lab experiments[81] and real-world interventions.[28] The ***desirability of options bias*** may lead to overestimations of positive consequences and underestimations of negative consequences for preferred alternatives. The ***affect influenced bias*** might cause an overestimation of undesirable consequences that cause negative feelings and of desirable consequences that cause positive feelings.[76]

Debiasing

From a prescriptive point of view, decision analysts should use predictive models and data whenever they provide a sound basis for estimation of consequences.[3] If the consequences are translated to either value or utility, then the same issues discussed in Section 3 apply in this step.

6. CONCLUSIONS AND A RESEARCH AGENDA FOR THE FUTURE

This article provided a review of a comprehensive list of cognitive biases, identified the biases that can significantly affect the judgments in decision and risk analysis, and showed how the use of debiasing techniques can reduce their effect. In the process, we identified a subset of cognitive biases in decision and risk analysts that are difficult to correct as well as several biases that can easily be corrected. We also reviewed several motivational biases, which are equally important to analysts, but are rarely discussed in the literature. We concluded that, unlike cognitive biases, all motivational biases are relevant to decision and risk analysis.

Considering the importance of eliciting judgments (probabilities, values, utilities, weights, etc.) in decision and risk analysis, it is somewhat surprising that relative little attention has been previously paid to the possible distortions of an analysis due to these biases. We thus next suggest a research agenda, which is based on our review of the existing literature on biases and evidence about their effects, as well as on the framework we suggested to classify them.

Further Exploration of Motivational Biases

Motivational biases are very important in decision and risk analysis, ranging from issues related to obvious conflicts of interest to subtle influences of professional association or preferences for outcomes of an analysis. While there exists some literature on motivational biases, it is not directly connected to the judgment tasks involved in decision and risk analysis. Therefore, much more research is needed to better understand the effect of motivational biases in decision and risk analysis and how to reduce these biases.

We take it for granted that the most obvious motivational biases can be dealt with by a deliberate selection of experts and decisionmakers who provide the judgments that are inputs to decision and risk analysis models. To accomplish this, many organizational safeguards are in place, for example, to avoid conflicts of interest or stakes in the outcome of an analysis. We propose that the experimental research instead focus on the less obvious, often subconscious motivational biases—for example, the well-established tendency of engineers and cost estimators to overestimate the performance and underestimate cost and time completion of a project.

Testing Best Practice Methods for Reducing Cognitive Biases

Decision and risk analysts employ many "best practices" in debiasing, but few of those have been tested experimentally. Thus a high-priority item on our research agenda is to identify these best practices, and to test them in controlled experiments. Examples are the use of counterfactuals to reduce anchoring, the fixed value methods to reduce overconfidence, and probing and prompting strategies to reduce omission biases.

Testing Best Practice Methods for Reducing Motivational Biases

This is a virtually unexplored field. Decision and risk analysts use some "tricks" to reduce motivational biases (counterfactuals, hypothetical bets, scoring rules), but with the exception of scoring rules, none of these have been tested. Regarding scoring rules the evidence of their efficacy is mixed, largely because of their well-known "flat maxima"[8] property (they do not penalize experts much for wrong predictions). There is a huge opportunity for experimental researchers to explore current best practices and to test their effectiveness in reducing motivational biases.

Decision and risk analysis were designed to improve judgment and decision making. The fields are closely intertwined with cognitive behavioral research and much can be learned from cognitive psychology to improve the elicitation of the key components of decision and risk analysis models. We hope that with the addition of a research component focused on motivational aspects of judgment and decision making, as well as a stronger research approach to the study of debiasing tools in this context, a rich literature can be created to inform both psychologists and decision and risk analysts with the ultimate purpose to improve decision making.

ACKNOWLEDGMENTS

We would like to thank two anonymous reviewers and the area editor, Michael Siegrist, for helpful comments and suggestions, which have helped us to improve the article. Detlof von Winterfeldt acknowledges support from the U.S. Department of Homeland Security (DHS) through the National Center for Risk and Economic Analysis of Terrorism Events (CREATE) at the University of Southern California (USC) under award number 2010-ST-061-RE0001. However, any opinions, findings, and conclusions or recommendations in this document are those of the authors and do not necessarily reflect views of the U.S. Department of Homeland Security, or the University of Southern California, or CREATE. Gilberto Montibeller would like to thank the LSE Decision Sciences team, in particular Barbara Fasolo and Larry Phillips, for the insightful

discussions about behavioral decision research during the development of this article.

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