Improving Expert Decision Making Processes on High Impact Low Probability Events

Deniz Marti, David Broniatowski
The Department of Engineering Management and Systems Engineering
The George Washington University
Washington, DC, USA

Abstract—Decision-making for system design in the context of high-impact low probability events is challenging because individual cognitive biases tend to neglect extreme probabilities, with potentially catastrophic consequences. In this study, we aim to determine the circumstances under which decision-makers facing such events should rely on categorical, rather than precise, representations of risk. Our novel contribution is to test a strategy suggested by Fuzzy Trace Theory [1], which argues that risk-avoidance associated with categorical risk perception (e.g., “some risk” vs. “no risk”) may actually lead to better outcomes when compared to decisions based on precise (and potentially biased) interval-level representations of risk. We compare the results of computational models in which decision makers use these paradigms to react to high-impact low probability events. Our results elucidate the circumstances under which deviations from classical rationality may lead to better outcomes for design.

Keywords—Decision Making; Fuzzy Trace Theory; Expert Judgment; High Impact Low Probability Events; Cognitive Bias

I. INTRODUCTION

Decision making under deep uncertainty has proven to be a challenge, especially in the case of decisions relating to the design or operation of complex engineered systems. For example, the design of the Fukushima reactor involved significant analysis with respect to risk from tsunamis and yet in retrospect, the associated decisions proved insufficiently protective. According to the “Report of Japanese Government to the IAEA ministerial conference on nuclear safety”, The Fukushima reactors’ height was designed based on analysis from eight tsunamis which occurred in the region in the last century due to earthquakes of magnitude 7.7 to 8.4 Mw on the moment magnitude scale. However, the decision makers were aware of a potentially larger earthquake and corresponding tsunami based on the historical data [2]. Despite this information, the researchers made a decision to rely on their original analysis. The Great East Japan earthquake of magnitude 9.0 Mw hit Japan on March 11, 2011 and a resulting tsunami devastated the region. Considering only the historically observed earthquakes led the decision makers to neglect very small probabilities of major earthquake occurrences, and eventually, to take an unnecessary level of risk in their reactor design decision making.

The central idea of this paper is that leading approaches to decision making under risk may inadvertently expose decision makers to unnecessary levels of risk. In this paper, we draw upon Fuzzy Trace Theory [3], which emphasizes categorical representations of risk, which, if used properly, may lead to protective (i.e., risk avoidant) behavior. Although well-known decision biases [4] lead individual decision makers to deviate from classically rational decision making, a strict adherence to normative decision making paradigms often drives people to “play the odds” exposing them to risks that could otherwise be avoided [1]. Indeed, research has shown that categorical decision making increases with expertise, leading experts and other categorical decision-makers to rely upon protective “some” versus “none” strategies when taking risks [5], and since most decision problems involving engineering systems require expert judgment, incorporating realistic models of experts’ decision making processes is an important area of research. Therefore, we compare the behavior of a simulated agent using traditional Expected Value calculations to an Fuzzy Trace Theory agent in the context of design for earthquake preparedness.

II. LITERATURE REVIEW

Modern techniques for incorporating probability estimates into design decisions assume that more precise analyses of probabilities and outcomes can lead to better decisions and, consequently, better designs. To see why this is the case, a short review of the history of decision theory is in order. Decision theory is a “palimpsest of intellectual disciplines” [6] – an interdisciplinary study that encompasses mathematics, economics, management science, philosophy and psychology [7]. There are three fundamental schools of judgment and decision theory: normative theory, analyzing ideal course of actions; descriptive theory, understanding the actual behavior of decision maker in real world; and finally prescriptive theory, facilitating decision-making processes by engaging the normative analysis with real actions to find the best action [7].

The roots of decision theory may be traced to the early days of the calculus of probability. The mathematical expected value of a gamble is defined as the product of the outcome of an event and its probability (its expected value). Inconsistencies, such as the Bernoullis’ Saint Petersburg
Two alternative programs to combat the disease, which is expected to kill 600 people. Assume that the exact scientific estimates of the consequences of the program are as follows:

1. If Program A is adopted, 200 people will be saved
2. If Program B is adopted, there is a 1/3 probability that 600 people will be saved and a 2/3 probability that no one will be saved.

The text of the gain-framed standard ADP is:

Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the program are as follows:

1. If Program A is adopted, 200 people will be saved
2. If Program B is adopted, there is a 1/3 probability that 600 people will be saved and a 2/3 probability that no one will be saved.

The loss-framed version of the problem uses the same preamble but presents the options as:

3. “If Program C is adopted 400 people will die.
4. If Program D is adopted there is a 1/3 probability that nobody will die, and a 2/3 probability that 600 people will die.”

Options 1 and 3 are typically referred to as the “certain option,” whereas options 2 and 4 are the “gamble option.” The typical result (i.e., the framing effect) is that most people prefer the certain option in the gain frame, but they prefer the risky gamble option in the loss frame. Although the ADP was initially explained with prospect theory [15], subsequent tests supported a fuzzy-trace theory-based interpretation of framing effects [16, 1]. The clearest of these tests include truncation effects (reviewed below) and removal of numerical information in whole or part from choice problems, which increases framing effects, as predicted, due to greater reliance on the simplest (categorical) gist.

In these truncation experiments, the ADP is restated as follows:

1. If Program A is adopted, 200 people will be saved
2. If Program B is adopted, there is a 1/3 probability that 600 people will be saved

The loss-framed version of the problem uses the same preamble but presents the options as:

3. “If Program C is adopted 400 people will die.
4. If Program D is adopted there is a 2/3 probability that 600 people will die.” [1].

When stated in these terms (the “zero-complement truncated ADP”), Reyna and Brainerd found that the framing effect disappeared – subjects were indifferent between the two options in both gain and loss frames. In contrast, when the nonzero-complement was truncated (e.g., “If Program B is adopted, there is a 2/3 probability that nobody will be saved”) subjects showed stronger framing than they did in the standard ADP. These findings violate the predictions of expected utility theory and prospect theory and provide support for Fuzzy Trace Theory’s predictions regarding the categorical processing of probabilities and outcomes, which are described below.

III. THE KEY TENETS OF FUZZY-TRACE THEORY

To a great extent, people are meaning makers. Fuzzy-trace theory incorporates the meaning of a decision stimulus into the decision-making process by recognizing that one’s
representation of a decision problem can drive decision outcomes. This insight is expressed in the following three tenets.

A. Gist and Verbatim Processing

People process multiple levels of mental representations of a decision stimulus. These levels are referred to as gist and verbatim. Whereas gist is the meaning of the stimulus to the individual in its context, verbatim is a detailed symbolic representation of the stimulus. Furthermore, these representation are encoded in parallel (i.e., gist is not derived from verbatim) [17].

B. The Hierarchy of Gist

Humans encode a continuum of gist representations in a hierarchy of precision that is roughly analogous to levels of measurement (e.g., nominal, ordinal, interval, etc.). The most basic, and hence, least precise level, in the hierarchy is a categorical representation of the stimulus (e.g., a contrast between “some” and “none” of a quantity or “possibility” and “impossibility” in the domain of probabilities). Successive levels in the gist hierarchy become more precise, however decision makers prefer to rely on the least precise level of representation that still enables them to make their decisions [1]. According to the theory, a tendency to rely on the simplest meaningful distinction possible leads decision makers to identify risk categories first. However, if the options cannot be distinguished, more precise representations, such as ordinal (more vs. less) or interval (e.g., twice as much) representations will be deployed.

C. Comparison of Valenced Affects

The final tenet of Fuzzy Trace Theory is that decisions between gist categories are made on the basis of valenced affect, or simply binary “good” vs. “bad” distinctions. Thus, once the information is represented as categorical, ordinal, or interval, decisions are made based on whether a given option is positively valenced (e.g., saving some lives or losing no money) or negatively valenced (e.g., saving no lives or losing some money).

IV. CASE STUDY: EARTHQUAKE SCENARIO

Earthquake disasters are considered to be High-Impact Low Probability (HILP) events – i.e., they are rare, but potentially devastating. Thus, we analyze different decision making processes in the context of design for earthquake resilience. Specifically, we use two types of simulated agents for our study, which we call “metric” and “categorical”. Metric agents use classical expected value maximization, whereas categorical agents rely on the hierarchy of gist identified by Fuzzy Trace Theory.

A. Scenario

Imagine that a region is preparing for a major earthquake. Agents are asked to make a decision between two investment options for the design of a system which can withstand earthquakes as follows: an agent can make a smaller investment, which can withstand up to $40 billion in potential loss (as in a major American earthquake in 1994), or a larger investment, which can withstand up to $130 billion in potential loss (as in a major Japanese earthquake in 1995).

The expected losses for these two levels of earthquakes are retrieved from historical earthquake data available on the U.S. Geological Survey (USGS) PAGER-CAT database [18], which contains data regarding earthquake damage occurring from 1905 through 2008. We assume two groups of decision-makers, such that Group 1, making a decision in 1994 (just before the major $130 billion loss Japanese earthquake), only has access to the pre-1995 data, whereas Group 2, making a decision in 2009, has access to the entire historical dataset through 2008.

In order to assess the probabilities of different earthquake levels, we fit a Weibull distribution to the available historical data. The data given to Group 1 (with pre-1995 information), yields a shape parameter of 0.073, and shape parameter of 0.36. Based on the Weibull distribution analysis, the yearly probability of an earthquake that can cause a damage greater than or equal to 130 billion dollars is 2.7x10^-7. In contrast, the data provided to Group 2, (with information through 2008), yields a scale parameter of 0.11, and a shape parameter 0.34. Here, the yearly probability of an earthquake that can cause a damage greater than or equal to 130 billion dollars is 1.71x10^-5 – a difference of over two orders of magnitude.

For the purposes of our analysis, we make the simplistic assumption that the investment required to withstand a given earthquake is proportional to the corresponding expected losses. Specifically, we assume that the constant of proportionality is 0.01% -- one must spend an additional dollar to prevent $10,000 in damage. Hence, preventing a potential loss of $40 billion requires $4 million investment. Similarly, the major earthquake, which caused a $130 billion loss, requires $13 million investment. Finally, we determine the total probability that a city will encounter an earthquake of size s, in t years, as \( \pi_s = 1 - (1-p_s)^t \) where \( p_s \) is the yearly probability that an earthquake of size s will occur, given the total historical data provided.

B. Decision Problem

Inspired by the ADP, we construct an analogous decision scenario in the domain of earthquakes as follows: Imagine that a region is preparing for a major earthquake. A system is already in place to prevent up to $40 billion in losses, at a cost of $4 million. There are two alternative preparedness investment programs that are expected to prevent potential damage caused by the two types of earthquake level:
Program A- investment for a larger earthquake with expected loss of $130 billion, which will cost an additional $9 million and Program B- no additional investment beyond the $4 million investment already made.

For simplicity, we assume that earthquakes larger than $40 billion will cause $130 billion in damage. Thus, Program A is analogous to the certain option of the ADP, whereas Program B is analogous to the risky gamble because there is a chance of a large loss of at least $130 billion, but also some chance of no loss.

C. Analysis

We begin by comparing the performance of metric agents across groups. As per our formulation, a metric agent in group 1 (pre-1995) would be indifferent between the two options given an expected lifetime of 256 years (for longer lifetimes, they would prefer the certain options, whereas for shorter lifetimes, they would prefer the risky gamble). Thus, this agent would play the odds for any system that is designed to last under seven generations. Specifically, the agent’s estimate of the probability of at least one earthquake with greater than $130 billion in losses within 256 years is $9.33x10^{-5}$. In contrast, a metric agent in group 2 (through 2008) would be indifferent given an expected lifetime of 4 years (the probability of a $130 billion earthquake within 4 years is 0.0043), well within their expected lifetime. This means that, with ten additional years of earthquake data, one’s estimate of expected lifetime changes by a factor of 64 (see Table 1). This example illustrates that a few years’ worth of additional data may lead to different decision outcomes, even though both decisions makers use the same strategy. In other words, the metric agent’s decision is extremely sensitive to the data available.

Table I Summary of Expected Values of Probabilistic Options

<table>
<thead>
<tr>
<th>t=4 years</th>
<th>Probability</th>
<th>EV[A] ($ in Million)</th>
<th>EV[B] ($ in Million)</th>
<th>Decision Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metric agent 1</td>
<td>3.98x10^-6</td>
<td>9</td>
<td>1.41x10^-1</td>
<td>B</td>
</tr>
<tr>
<td>Metric agent 2</td>
<td>8.55x10^-5</td>
<td>9</td>
<td>9</td>
<td>Indifferent</td>
</tr>
</tbody>
</table>

Next, we compare metric decision making agents to categorical agents. According to Fuzzy Trace Theory, experts prefer to rely on gist representations. Thus, we may think of categorical agents as “experts”. Here, probabilities and outcomes are mapped to “some” and “none” as discussed above.

Given our formulation as a loss-framed problem, Fuzzy Trace Theory predicts (consistent with Prospect Theory) that our agents will be risk-taking (see Table 2). Specifically, given a choice between A: some loss for sure; and B: maybe some loss and maybe no loss, our agents would prefer option B since losing some is worse than losing none. This seems to suggest that metric agents will outperform categorical agents. Since categorical agents are more representative of real human behavior, this motivates an analysis of how we can improve decision-making. Fuzzy Trace Theory suggests truncation as a viable option (see Table 3). Specifically, by truncating the zero complement, we can expect that the categorical agent will behave in the same way as a metric agent. When the problem is stated in this manner, the gist representation becomes ‘lose some’ versus ‘lose some’. Since both options have the same gist, the categorical decision maker is indifferent and reverts to a more precise ordinal representation: ‘lose less with more chance’ vs. ‘lose more with less chance’. This encoding also is indifferent, leading the decision-maker to revert to an interval expected value representation, which gives the same decision outcome as the metric agent.

Fuzzy Trace Theory suggests a way that we can improve on the metric agent. Prior research has shown that communications that focus decision-makers on outcomes, exclusive of probabilities, can lead to protective action. For example, Reyna & Mills showed that gist statements such as “If only one person” reduce peoples’ intentions to engage in risky sexual behaviors [19]. A similar strategy can be used here to incentivize risk avoidant behavior in our categorical agents. Specifically, we note that the cost of $9 million is negligible when compared to the potential loss of $130 billion. Furthermore, our analysis above indicates that the likelihood of an earthquake within a decision-maker’s lifetime can be interpreted to suggest that such an earthquake will eventually happen. In this case, the gist of the decision boils down to:

A) Lose essentially nothing within the city’s lifetime
B) Lose $130 billion within the city’s lifetime

Table 4 shows that a categorical agent would always choose option A given this representation. Given the propensity for our probability estimates to be incorrect, this protective action could well save many resources (as well as lives).

Table II Loss Framed Decision Problem and The Decision Outcomes of Categorical Agents

<table>
<thead>
<tr>
<th>t=4, Designing an earthquake plan that resists up to 4 years</th>
<th>Agent Group</th>
<th>Decision Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Option A: Spend 9 Million</td>
<td>Group 1</td>
<td>B</td>
</tr>
<tr>
<td>Option B: Lose $130 billion with the chance of 1.08x10^-6, or lose nothing</td>
<td>Group 2</td>
<td>B</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>t=256, Designing an earthquake plan that resists up to 256 years</th>
<th>Agent Group</th>
<th>Decision Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Option A: Spend 9 Million</td>
<td>Group 1</td>
<td>B</td>
</tr>
<tr>
<td>Option B: Lose $130 billion with the chance of 1.14x10^-5, or lose nothing</td>
<td>Group 2</td>
<td>B</td>
</tr>
</tbody>
</table>

### Table 2

<table>
<thead>
<tr>
<th>Type</th>
<th>Loss Framed Problem</th>
<th>Agent Group</th>
<th>Decision Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>t=4, Designing an earthquake plan that resists up to 4 years</td>
<td>Option A: Spend 9 Million</td>
<td>Group 1</td>
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</tr>
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<td></td>
</tr>
</tbody>
</table>
Overall, the analysis above showed how presenting the problem to the experts with various frames could lead experts to encode the information with different gist representations. Since experts are more likely to rely on gist [20], with changing the frame of the decision problem, we could expect experts’ risk preferences differ across problems depending on how the problems are provided to them. However, novices’ decision outcomes do not differ across the problems, since they tend to rely on the exact numbers when they make decisions. Making decisions based on the probability estimates do not guarantee better decision making since probability estimates can be biased or inaccurate.

V. DISCUSSION

Our analysis shows that metric decision makers can outperform categorical decision makers in the context of a loss-framed problem. However, the same cognitive resources that lead to risky decision-making can be coopted to incentivize protective decision-making. This may be especially important when our confidence in the estimates of HILP events is low.

VI. CONCLUSION

Making decisions with uncertainty has become increasingly important for designing engineered systems. There has been a long tradition of research on mental representation that elucidates how preferences differ from standard normative approaches. These normative approaches can outperform risk-takers who may be subject to cognitive biases; however, even normative decision-makers play the odds, thus exposing themselves to risks that are difficult to estimate precisely and may be orders of magnitude higher than expected. Ultimately, the same features of human cognition that lead to biased decision-making could be used to incentivize protective action, thereby protecting decision-makers against outsize risks when data are sparse, unreliable, or unbounded in their variance.

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REFERENCES


