# Evaluating Flood-Related Decision-Making and the Role of Information Technologies

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### ABSTRACT

The proposed research consists of an innovative research design and piloting to compare traditional and contemporary approaches to loss-related decisions, concerning flooding risk in particular. By developing and implementing the integration of multiple methods, the proposed research aims to provide detailed and compelling evidence of how disaster-related decisions can be evaluated using an out-of-frame (capacity) and out-of-sample (occurrence) criterion, i.e. instead of taking a more reductive approach to real world problems. Together with other research being conducted around the world, the current initiative will address the contemporary scientific problem of whether traditionally axiomatic or ecological rationality should be used for evaluating disaster-related decisions. Where ecological rationality is found to be more effective, the same research will inform how ecologically rational approaches to flood risk can be improved through promoting particular areas of an information display or interface under particular conditions.

#### Keywords

Risk perception, biases, decision support, research methods

### INTRODUCTION

Many decision-makers facing perilous scenarios need to do so with a shortage of information and varying degrees of time constraints. Most of us have faced relevant scenarios, requiring rapid responses to highly limited information. They include deciding whether to socially distance and/or wear a mask when entering public places during the COVID-19 pandemic, or whether to visit a crowded hospital in order to meet COVID-19 testing requirements. The world has witnessed blatantly erroneous responses to these kinds of scenarios, exhibited in mask-less public gatherings to protest COVID restrictions or even religious ceremonies conducted in closely packed but poorly ventilated venues. Although it is easy to judge the individuals involved, these and other loss-related responses have been highly patterned across populations and certain demographic groups.

Other relevant patterns have been observed in a range of investment decisions researched by Tversky and Kahneman (1992), the selection of romantic partners, discussed by Todd and Gigerenzer (2007), and responses to natural hazards, reviewed by Hudson Doyle et al. (2019). These are a few of many risky scenario types where highly biased decisions, based on certain environmental cues, can have very negative consequences. In a world marked by ongoing pandemic risk, along with the worsening natural hazards, climate change and environmental degradation outlined by Huggins et al. (2018), it is time to extend relatively fundamental theories of erroneous responses to peril.

Relevant perils obviously include near and present hazards such as COVID-19. However, other hazards are just as destructive and are, arguably, even harder to manage. The current research focuses on flood disaster management in particular because flooding disasters are extremely common in many regions of the world. Flooding was the single most common type of natural hazard event from 1995-2015, accounting for 43% of all disasters caused by natural hazards over this period (CRED & UNISDR, 2016). Accelerating climate change and other factors outlined by Adnan and Kreibich (2016) and in the most recent Global Risk Assessment (UNDRR, 2019) means there is little hope that this is going to change. Flooding disasters are also exceedingly hard to manage because the decisions involved need to incorporate many types and sources of information. Much of this information tends to come too late, for the many hundreds of people that are affected by severe flooding every year.

The time and information constraints outlined above combine with cognitive limitations, to mean that decisions in loss-related scenarios typically depend on decision-making shortcuts. Gigerenzer et al. (1999) described these types of shortcuts as *cognitive heuristics*, focused on directly facilitating what a person wants to achieve instead of a more deliberative approach. This means that decision-making heuristics are typically *fast*, compared to responses that take too long to constitute an initial reaction.

The same heuristics tend to be *frugal*, meaning that they depend on a minimal amount of initial information. Frugal information requirements are particularly useful when decision-relevant information is incomplete, or when decision-makers do not have enough time to search for additional cues. Newell et al. (2003) and Bröder and Schiffer (2003) stated that frugality is most relevant in situations when information must be paid for, must be searched for, or when timeframes prevent accessing further information. Kozyreva and Hertwig (2019) reviewed a wide range of relevant research to illustrate how frugality is also common in situations that have no obvious time constraints. Even when a decision-maker decides to search for further information, this initial response is typically selected using cognitive heuristics (Huggins et al., 2018; Jayawardene et al., 2021).

Academic fields such as information science, cognitive psychology, management science, and behavioral economics have a long-running focus on how and why individuals make choices under different conditions. Their findings both diverge and coalesce around a cumulative science of decision-making, where the concepts of preference, utility, and value have been heavily studied alongside themes such as subjective probability, fuzziness, and the relevance of base-rate frequencies. All of these factors, and many others, have been applied to areas as diverse as business management, consumer marketing, and emergency management (Barberis, 2013). These applications have also naturally extended to the design and implementation of information systems for crisis response and management.

A narrative review by Fox et al. (2015) concluded that *prospect theory* and its iterations have become the predominant theory for describing decision-making about risk. This assertion led the current research to focus on contributions to decision-making science, concerning prospect theory in particular. As outlined below, prospect theory provides a broadly fundamental approach for evaluating the rationality of loss-related decisions. The question posed by the current paper is whether we can use evaluations from prospect theory to usefully evaluate the effectiveness of flooding-related decisions.

The current paper is divided into four parts: The current introduction; a summary and critique of basic theoretical assumptions, an innovative set of research methods, and a Conclusion section. Basic theoretical assumptions are outlined with a constructively critical approach to how criteria from prospect theory compare to criteria that may be much more relevant to flooding-related decisions. This is followed by a detailed approach to methods that aspects of prospect theory with alternative decision criteria and with innovative approaches to relevant data leveraging the type of cutting-edge technologies outlined by Liu et al. (2022). The Conclusion section reiterates and expands on the practical and theoretical relevance of the methods proposed.

## BASIC THEORETICAL ASSUMPTIONS

Examples of heuristic-based responses to limited information can be as mundane as using an availability heuristic to choose the subway line that most recently took the decision-maker to work. Other examples can be as perilous as using a satisficing approach to dispatching firefighting crews to the first, minimally viable fire-ground. Although common to the point of being fundamental, these cognitive heuristics are often highly fallible - especially when compared to more deliberate decision-making processes. Over three decades of research into prospect theory has provided a vivid example of how heuristic approaches to financial and other risk are biased towards risk and loss aversion, risk seeking and other distortions (Barberis, 2013). Even when participants were given a well-defined probability, their responses tend to distort that probability, rather than systematically comparing prospective outcomes (Tversky & Kahneman, 1992). Their distorted responses create a set of deviations from axiomatically rational *expected values* (ev) of gains (x) and losses (p) shown by the straight diagonal in Figure 1, where:

$$ev = x \times p$$

Where decision weights, $\pi_i = \pi_{i^+}$ $if\ i \geq 0$ $and$ $\pi_i = \pi_{i^-}$ $if\ i < 0$ , a generalizable description of the values (V) shown in Figure 1 is determined by:

$$V(f) = \sum_{i=-m}^{n} \pi_i v(x_i)$$

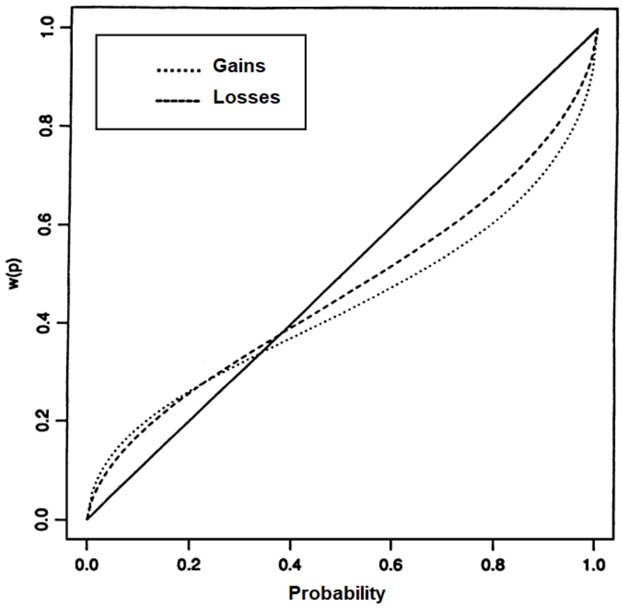


**Figure 1. Deviation from Expected Values Shown on the Diagonal (adapted from Tversky & Kahnemann, 1992)**

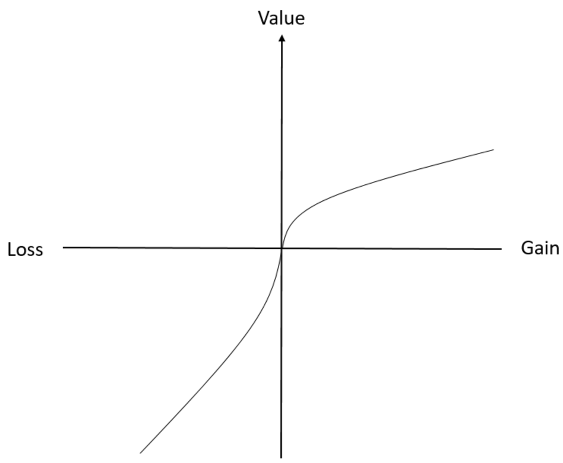


**Figure 2. The Impact of Loss Aversion on the Perceived Value of Prospective Losses (adapted from Kahnemann & Tversky, 1983)**

Along with a range of other descriptive findings reviewed by Chai et al. (2021), many decades of research into iterations of prospect theory has shown that participants tend to be averse to loss at low probabilities. At this level of probability, the value of a potential loss has a much larger impact on decisions, than equivalent gains (Tversky & Kahneman, 1992). The same loss aversion phenomena disrupts the s-shaped curve shown in Figure 2 and can be described as:

$$v0\ (x) < v0\ (-x) \text{ for } x \geq 0$$

Todd and Gigerenzer (2007) have been more optimistic about apparent flaws in heuristic decision-making. They queried whether decision-making heuristics can actually achieve *ecological rationality*, a match between heuristics and the surrounding environment that results in distinctly effective decisions. Examples include choosing the only recognizable option in a relatively novel environment, and searching for a single discriminating cue among information with highly mixed validity. Each of these fast and frugal approaches to decisions can be more effective than a more structured and sequential, algorithmic, approach. The latter example is generally just as accurate as decisions using a multiple regression (Todd & Gigerenzer, 2007).

This *ecological* approach to evaluating heuristic decision processes poses a challenge to the type of *axiomatic* rationality (Gigerenzer, 2019) that is traditionally used to evaluate loss-related decisions under the assumptions of prospect theory and other approaches. Rapidly heuristic decisions have usually been out-performed by steadily calculating and comparing an expected value (total loss or gain x probability) for each option (Barberis, 2013), based on Bayesian logic. This is shown in aspects of cumulative prospect theory, outlined above. However, the expected value of losses in these contexts excludes three other factors affecting cumulative disaster risk: *vulnerability* (V), or conditions increasing susceptibility to hazards; *exposure* (E), or assets situated in a hazard prone area; and reduced by *capacity* (C), i.e. to manage and reduce disaster risks (Huggins et al., 2020). Using these definitions, a more ecologically rational evaluation of disaster risk (DR) becomes:

$$DR = \frac{x\text{-} \times p \times V \times E}{C}$$

Capacity is particularly relevant, because it effectively reduces all other factors determining disaster risk (Huggins et al., 2020). It may also form a heuristic threshold for loss-related decisions, as indicated in pilot research by the current authors, which found that loss-related decisions deviated much more strongly from expected value once the potential loss reached 1,000,000 CNY. These highly tentative results were specific to female participants, partially replicating the several other studies into loss and risk aversion reviewed by Croson and Gneezy (2009). However, the central role played by disaster management capacities mean that these observed responses are not strictly irrational. The thresholds concerned may indicate attention to an amount of loss that participants simply do not have the capacity to face.

These kinds of contextual factors are not Strictly inconsistent with fundamental aspects of cumulative probability theory, shown in Figure 1. This is because responses in Tversky and Kahneman (1992) did not deviate from ev until prospects reached an identifiable threshold (>$200). Rather than treating thresholds as a simple issue of salience, or experimental realism, the innovative methods can focus on this threshold and its relationship with participants' decision context. Beyond the apparent simplicity of *framing effects*, where perceived values are affected by preceding experimental conditions (Tversky & Kahneman, 1986), there are additional, scientific questions to be asked and a growing body of research attempting to answer them.

Zeng (2007) previously found that loss aversion can be exaggerated in a Chinese cultural context. Like the responses of female participants in our own pilot research, this pattern of responses can labelled less-than-rational. However, and further to the relevance of capacities for disaster risk, previously axiomatic criteria for validating risk-related rationality are also limited to what Kozyreva and Hertwig (2019) called a *small-world* approach: characterized by restricted data sets and other, highly artificial, constraints. This means that axiomatic approaches to expected value or utility may result in poor criteria for decisions involving high levels of loss and low probabilities. For example, the historical frequency of catastrophic flooding is still relatively low in many cities that are nonetheless categorized as flood prone. Historical flooding data may provide a poor indicator of present-day conditions and future scenarios being impacted by accelerating climate and land use change. Recent urban development in China's Pearl River Delta provides one example, where the risk of storms, storm surge and riverine flooding has rapidly risen to the highest level faced by any metropolitan area in the world (SwissRE, 2019). Instead of relying on extended sets of semi-relevant longitudinal data, the current research takes an ecological approach to rationality. This assumes following priorities:

1. Formal models of heuristics, as opposed to vague labels.
2. Competitive testing of heuristics, as opposed to null hypothesis tests.
3. Tests of predictive power, such as in out-of-sample prediction, as opposed to data fitting.

(Gigerenzer, 2019, p. 3557).

Methods for addressing each of these priorities are outlined in the following section. They include the way that extant research procedures can be complemented through eye tracking and brain scanning apparatus. The simultaneous use of both apparatuses will help address the methodological difficulties of using brain activity to fully account for the heuristic role of visual attention, outlined by Moore and Zirnsak (2017). The proposed combination of methods, and the scientific questions they address, are important for understanding contemporary decision-making environments, such as worsening flood scenarios. Furthermore, once more ecologically rational, and therefore more effective, heuristic processes are identified, further research will be able to define how information formats and other environmental factors can promote the same processes. In the face of flooding risks worsened by rapid urban development and accelerating climate change, there may be few alternatives to taking these more innovative approaches.

## PROPOSED METHOD

Relevant research can progress from a pilot set of laboratory-based methods, followed by one full set of fully refined methods. The first set will be used to pilot and refine the identification of risk aversion thresholds, as a proxy for loss aversion. Self-reported financial details can also be collected at this stage. The second set of methods generate additional data, collected using eye-tracking and brain scanning apparatus.

**Table 1. Experimental Conditions for Initial Protocol**

| Condition | Pay (*x*) | | Probability (*p*) | | Damage (-*x*) |
|---|---|---|---|---|---|
| 1 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -100,000 RMB |
| 2 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -200,000 RMB |
| 3 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -300,000 RMB |
| 4 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -400,000 RMB |
| 5 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -500,000 RMB |
| 6 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -600,000 RMB |
| 7 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -700,000 RMB |
| 8 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -800,000 RMB |
| 9 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -900,000 RMB |
| 10 | $(p \times -x)^{1.02}$ | to avoid | [base-rate per year] | chance of | -1,000,000 RMB |

### Protocol 1

All data collection needs to be anonymized and assigned to serial numbers, rather than individual identifiers, to promote the ethical need for participant privacy and to encourage accurate responses. All prospective participants will be informed of these conditions, when being asked for informed consent. They can then be randomly allocated to one of several flooding scenarios and either ascending or descending levels of the damage prospects outlined in Figures 3 and 4 below.

The proposed research methods require a set of flooding frequencies, reduced to all but the most recent 5 years of a known sub-sample of historical flood occurrences, in several identifiable locations. The methods also require a single computer terminal operating under tightly controlled, laboratory conditions. The terminal needs to include a single monitor to display a sequence of prospect conditions, displayed using e-Prime software or similar. A single keyboard needs to be provided, allowing participants to select either "f" to accept the prospect displayed, or "g" to reject it. When they select f, the protocol will pause while participants complete a decision log: A brief description of why they selected the prospect in question. This participant interface follows option-based antecedents for testing prospect theory, outlined in Tversky and Kahneman (1992).

Following a very brief introduction to the decision context of flooding and a standard training procedure for using e-Prime, the laboratory procedure will be repeated at various levels of potential losses, i.e. using the conditions shown in Table 1. Among benefits for the transparency of data analysis, this procedure is short enough to avoid participant fatigue. Extended rest periods are not required, because the entire procedure is short enough to conduct in less than 20 minutes. Participants will be guided through the procedure by simply progressing through the conditions using e-Prime software under highly controlled and standardized laboratory conditions. A visual representation of this procedure is shown in Figure 3.

To counter the influence of order effects, or framing effects within prospect theory, participants will be randomly assigned to one order or another. One group of participants will proceed from condition 1 to condition 10, while the other group will proceed from condition 10 to condition 1. To help participants re-focus between conditions, small red crosses will be shown to participants for a standard maximum fixation period of 800 ms, between each prospect condition. The reversed order of conditions is shown in Figure 4.

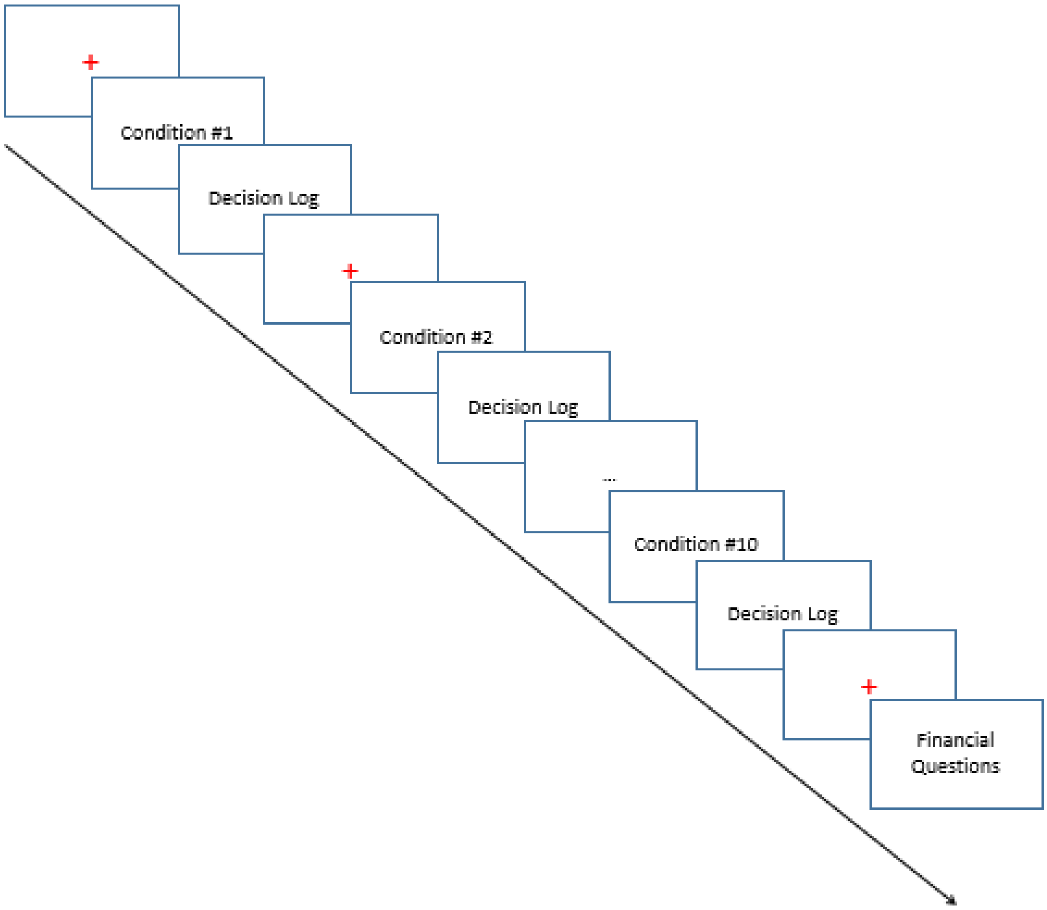


**Figure 3. e-Prime Sequence of Decision-Making Prompts**

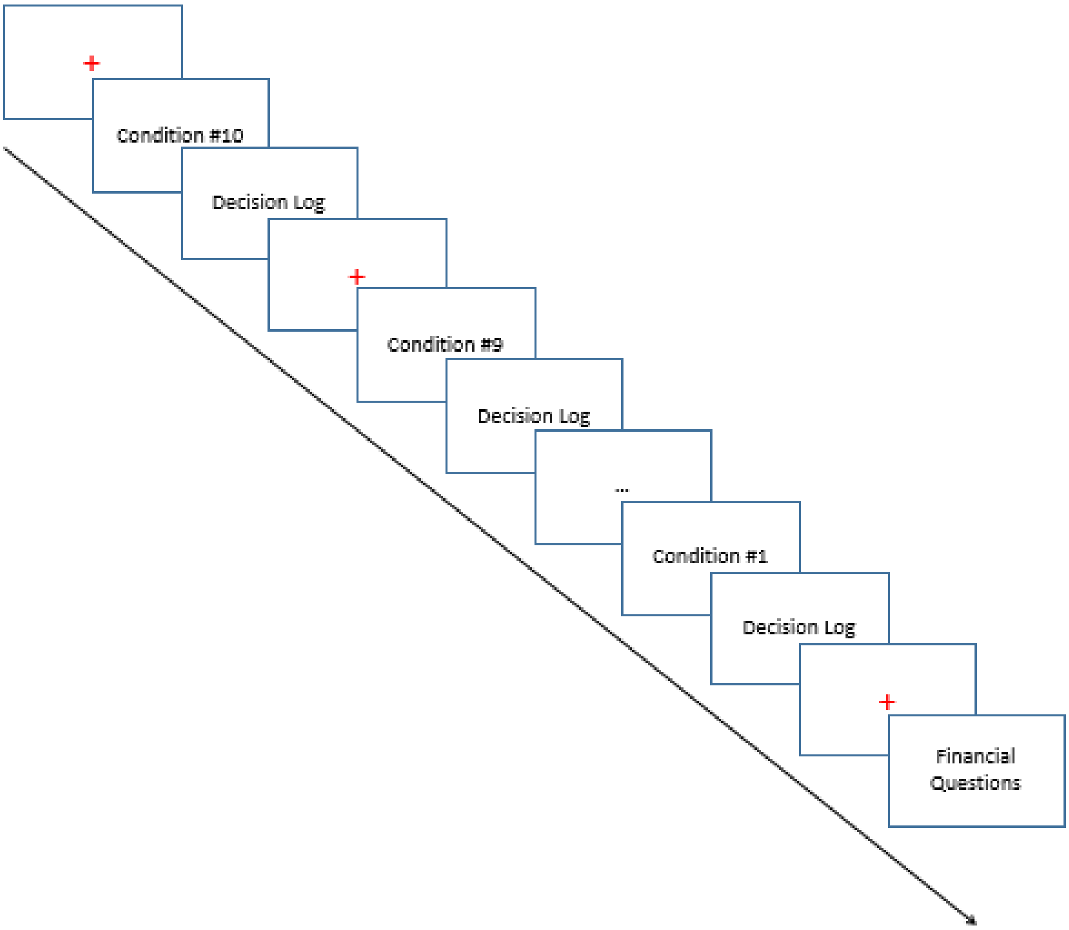


**Figure 4. e-Prime Sequence of Reverse-Order Decision-Making Prompts**

Conditions outlined above will be followed by another brief period of 800 ms. This will be followed by quantitative questions for respectively determining participants' financial net worth (nw) and available capital (ac):

1. Can you please estimate the total value of all financial and non-financial assets that you own?

2. What is the total amount of cash that you would have readily available in a crisis?

*Analysis A:* Threshold levels of loss will be determined by the lowest level of loss (-x) which is more heavily valued than savings from not buying insurance, i.e. where the decision is no longer axiomatically rational:

$$\theta(\text{-}x) = v\,(\text{-}x) > ev\,(\text{-}x)$$

Positive responses indicating a genuine loss (-x) threshold for risk averse responses will be accompanied by positive responses to options at all higher levels of damage. In other words:

$$\theta(\text{-}x) = v_{min}\,(\text{-}x) > ev\,(\text{-}x), \text{ if}$$

$$\left[v\,(\text{-}x)_{i-j} \geq \theta(\text{-}x)\right] \;>\; ev\,(\text{-}x)$$

Responses at the proxy threshold for loss aversion will then be evaluated for ecological rationality using the following criteria:

1. Mean distance between participants' damage thresholds and net worth (nw) that are significantly lower than the equivalent distance for sub-threshold levels of damage.

$$M|\theta(\text{-}x) - nw| < M|x_{max} < \theta(\text{-}x) - nw|$$

2. Mean distance between participants' damage thresholds and available capital (ac) that are significantly lower than the equivalent distance for sub-threshold levels of damage.

$$M|\theta(\text{-}x) - ac| < M|x_{max} < \theta(\text{-}x) - ac|$$

3. Correlation between losses at threshold level and out-of-sample losses (loss occurrence or -xo) that significantly exceeds correlation between losses at immediately sub-threshold level and out-of-sample losses.

$$r\ (\theta(\text{-}x), \text{-}xo) > r\ (x_{max} < \theta(\text{-}x), \text{-}xo)$$

**Protocol 2**

As at the time of writing we planned to recruit an equivalent sample of participants for the next set of laboratory protocols. Participants who have already participated in the initial protocol will be excluded. All materials piloted and adapted during the pilot phase will be used in the fully developed protocol. Additional equipment, including a Tobii eye tracking bar and software, Functional Near-InfraRed Spectography (fNIRS) sensors, a Nirsport2 cap and receiver unit, and two additional laptops will also be prepared for calibration with each participant. Data from the subsequent five years of flooding data samples used in Phase 1 will be used to constitute actual occurrence (-xo).

Before beginning data collection, all participants will be invited to help calibrate Tobii and fNIRS apparatus. Procedures successfully piloted and adjusted from the pilot research will then be replicated, together with the simultaneous collection of eye tracking and brain activity data.

A threshold level of loss will again be determined by the lowest level of loss (-x) which is more heavily valued than savings from not buying insurance, i.e. where the decision is no longer axiomatically rational. Equations (5), (6) and (7) in the Phase 1 protocol outline the criteria for determining this level. We can expect that eye tracking data collected during threshold conditions will reflect a heat map concentrated on the damage amount i.e. rather than any other element of the condition display. An example is shown in Figure 5. This use of eye tracking data will avoid many obstacles for using brain activity to accurately account for visual attention, outlined by Moore & Zirnsak (2017).

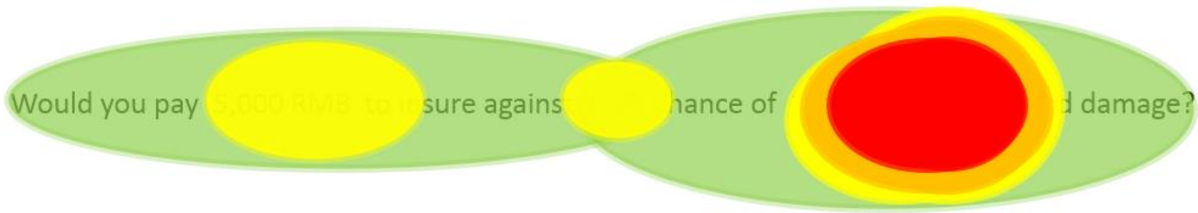


**Figure 5. Synthetic Heat Map Focused on Damage Amount, Indicating Loss Aversion**

Brain activity data can then be used to provide robust indications of mental processes used to process visual data. These mental processes can be observed through patterns of frontal lobe activity that are associated with mental arithmetic (Power et al., 2017). Using a standard sensor array, we expect to observe a reduction in blood flow, or hemodynamic response, within 10 seconds of an axiomatically rational response to particular prospect conditions. As shown in Figure 6, this hemodynamic response would usually indicate mental arithmetic required for estimating expected values. This response is expected to remain significantly more stable for prospect conditions eliciting the loss aversion heuristic. Hemodynamic responses during loss aversion may even increase, when loss aversion elicits a strong emotional response in certain participants.

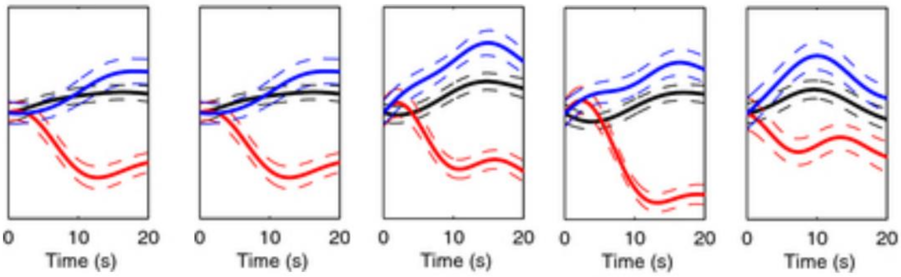


**Figure 6. Typical Hemodynamic Responses to Mental Arithmetic in Red, Music in Blue, and Control Conditions in Black** (adapted from Power et al., 2012, p.7)

## CONCLUSION

Many decades of prior research, including examples outlined in the current paper, have identified how contextual factors affect risk-related decisions. The proposed research builds on these antecedents by studying conditions under which the axiomatic rationality implicit to prospect theory either occurs or does not, i.e. rather than simply noting the way that value and weight curves had to be marginally adapted. This is how the proposed research goes one big step further, by studying a heuristic response that deviates from axiomatic rationality (i.e. through referencing ev) but that may nonetheless lead to highly useful outcomes.

The proposed research will make a novel contribution to fundamental decision-making research, at the intersection of cumulative prospect theory and ecological rationality. The proposed research will also directly inform a very broad range of applied, disaster-related research. As part of a wider program of research into promoting ecologically rational heuristics for effective disaster management, the findings feed into important, real-world applications. These include innovative methods for optimizing public information systems and many other information system interfaces, towards optimizing user responses.

As outlined, the proposed research will help inform efforts to manage a range of natural hazards and potential disasters. However, the research remains most directly applicable to floods. In a world marked by the accelerating, and often interacting, impacts of intensifying rainfall patterns, sea level rise, urban development in coastal areas and flood plains, and both commercial and technological interdependencies that prior generations could barely imagine, the importance of this particular focus cannot be overstated.

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