The role of uncertainty in risky intertemporal choices

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1 Introduction

Many of the challenges society faces today stem from the tendency for individuals to prioritise immediate benefits at the expense of longer-term outcomes. This tendency can result in serious financial consequences; for example, when people fail to save enough for the future. According to recent surveys, one-fifth of Australians are unable to raise funds to withstand a major unexpected expense (National Australia Bank, 2017) and over half of Australians do not believe they will save enough for retirement (Members Equity Bank, 2019). In the case of climate change, we observe how these short-sighted preferences can also compound to drive global environmental crises. Despite the growing threat of global warming, people continue to undervalue the urgent need to shift towards pro-environmental behaviour. Addressing these societal issues will require an understanding of how people approach these complex decisions – decisions which involve risk, time delay, and uncertainty. This research proposal will review our current understanding of how people make these risky intertemporal choices and suggest avenues for future research that explore the role uncertainty plays in these decisions.

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2 Literature Review

2.1 Models of Risky Intertemporal Choice

A large body of existing research has explored how risk and time delays can independently influence decision-making (e.g., Berns et al., 2007; Mishra, 2014). Studies investigating risky choices typically present participants with choices between two alternatives that differ in reward size and probability – for example, the choice between a certain win of $3,000 or an 80% chance of winning $4,000 (Kahneman and Tversky, 1979). Studies investigating intertemporal choices employ a similar two-choice paradigm, where the choices instead vary in reward size and time delay in receiving the reward – for example, the choice between receiving $85 today or $100 in 3 months' time (Green et al., 1997).

In both areas of study, it has consistently been shown that people's preferences violate normative economic principles, which describe how a rational decision-maker should behave. A classic example in the risky choice literature is the common ratio effect. To illustrate, consider two sets of choices Kahneman and Tversky (1979) presented to their participants:

1. Would you prefer a certain win of $3,000 or an 80% chance of $4,000?
2. Would you prefer a 25% chance of $3,000 or a 20% chance of $4,000?

According to Expected Utility Theory, a person who prefers the certain win of $3,000 in the first set should also prefer the 25% chance of $3,000 in the second set (Kahneman and Tversky, 1979). Preferences between the two choice sets should remain consistent since the probability of both options has been scaled by the same factor – in this case, divided by four. Instead, Kahneman and Tversky (1979) observed a reversal in preferences: most participants preferred the certain win of $3,000 but the 20% chance of $4,000.

An analogous example in the intertemporal choice literature is the common difference effect, which describes a violation of Discounted Utility Theory. The theory posits that the same temporal discount rate should be applied to all future outcomes (Loewenstein and Prelec, 1992). However, this is not supported by empirical findings. Most people prefer to receive $150 today over $200 in 9 months, yet prefer $200 in 10 years and 9 months over $150 in 10 years (Keren and Roelofsma, 1995). The addition of a common time delay to both options (10 years) should result in equal discounting, and therefore consistent preferences. Instead, the observed reversal of preferences again demonstrates a violation of normative expectations.

These discrepancies between how people should behave and how they actually behave motivated the development of modified models of choice. Expected Utility Theory was replaced with Prospect Theory, which could account for the common ratio effect as well as other 'anomalies of preference' – for example, inconsistent preferences when the same choice is presented using different framing (Kahneman and Tversky, 1979). Likewise, hyperbolic discounting models overtook Discounted Utility Theory as the dominant account of intertemporal choice preferences. These models proposed that outcomes nearer to the present are discounted at a greater rate than outcomes further in the future (Loewenstein and Prelec, 1992). The success of these models in accounting for empirical findings saw them cited and applied widely (e.g., Barberis et al., 2001; Diamond and Köszegi, 2003).

More recently, researchers have shifted their focus towards the development of an integrated model of risky intertemporal choice – a single model capable of capturing preferences between alternatives which vary in both risk and delay. Although some studies suggest that risk and delay are not psychologically equivalent (e.g., Abdellaoui et al., 2013; Chapman and Weber, 2006), there is an accumulating body of evidence favouring the idea that they operate under a common mechanism. For example, Baucells and Heukamp (2010) demonstrated that the common ratio effect described earlier could be reproduced by introducing time delays. While most participants preferred a certain win of €9 over an 80% chance of €12, their preferences reversed both when the probability of the options was divided by ten (common ratio effect) and when a common time delay of three months was added (Baucells and Heukamp, 2010). This result indicates that delay can be translated into uncertainty and complements research suggesting that uncertainty can similarly be translated into delay (e.g., Rachlin et al., 1991). In line with these findings, Luckman et al. (2018) have also shown that models which assume risky and intertemporal choices are underpinned by the same choice mechanism provide a better fit to participant response data than models which assume distinct choice mechanisms.

This growing evidence has spurred the proposal of multiple risky intertemporal choice models in the literature, including: the Hyperbolic Discounting (HD) model (Yi et al., 2006), the Probability and Time Trade-off (PTT) model (Baucells and Heukamp, 2012), the Multiplicative Hyperboloid Discounting (MHD) model (Vanderveldt et al., 2015), and the Risky Intertemporal Choice Heuristic (RITCH) model (Ericson et al., 2015; Luckman et al., in press). Each of these models provides a different description of how people incorporate probability and time delay information into their decision-making. Some fall under the category of utility models; these models assume that people separately evaluate the value of each choice they are presented and then compare between them (Luckman et al., in press). For example, the HD model proposes that people evaluate each choice by first converting the risk into an equivalent time delay, before discounting the choice's value based on the combined time delay (sum of the actual and risk-equivalent time delays). Other models are described as attribute models, which instead assume that people compare between each attribute of the choices available (i.e., outcome value, risk, and time delay) (Luckman et al., in press). For example, the RITCH model proposes that a person's choice is determined by calculating a weighted sum of the absolute and relative differences in the choices' risk and time delays. Despite these differences, all of the models listed above share the same fundamental flaw: they can only describe how decisions are made in an environment without uncertainty – where the decision-maker possesses complete and perfect knowledge of each and every possible choice and outcome.

2.2 Decision Making Under Uncertainty

Consider again the challenge of saving for a future emergency or for retirement. Suppose that an individual has covered their necessary expenses for the month and is left with $500, which can be allocated at their discretion towards spending or saving. For the sake of argument, this decision could be simplified by framing it as a choice between two hypothetical alternatives:

1. Spend all the money. Let us assume that this will earn a certain and immediate 500 "utility points" (representing the benefit gained from making a purchase).
2. Save all the money and build a financial buffer against a possible future emergency. Let us assume that this offers a 10% chance of earning 5,000 utility points in 1 years' time (representing the benefit of being able to cover the emergency).

Under this framing, the risky intertemporal choice models introduced earlier would be capable of offering predictions for how the decisions would be made. However, it should be immediately apparent that this would be an oversimplified and unrealistic representation of the true decisions that individuals are expected to make. Comparing this hypothetical example to the real-life problem highlights two key differences – differences which have motivated the present research and should motivate future extensions of risky intertemporal choice models.

Firstly, there are very few scenarios where the decision-maker has precise knowledge of the probabilities, delays, and outcomes associated with the options they are choosing between. Although there are some instances where decisions can be made from described risks or delays – for example, when a weatherperson forecasts the likelihood of rain – it is far more common that decisions must be made from experience. Unlike the hypothetical example above, people must evaluate the trade-offs between spending and saving without knowing the exact likelihood of a financial emergency or when it might occur. Instead, these may need to be inferred by the decision-maker based on their and others' past experiences.

Past research has shown that people choose differently when making decisions from description (i.e., with full knowledge of the outcomes and risks) and decisions from experience (i.e., when outcomes and risks must be learned via experiential sampling). This difference is known as the 'decision-experience gap' and has been independently observed in risky choices (Barron and Erev, 2003) and intertemporal choices (Dai et al., 2019). In the risky choice domain, the decision-experience gap refers to the tendency for people to overweight small probabilities in decisions from description but underweight them in decisions from experience (Rakow and Newell, 2010). This gap leads to reversals in risk preferences; for example, in situations where one must decide between a certain smaller loss (e.g., lose $3 for sure) and a small risk of a larger loss (e.g., 10% chance of losing $3.20). When such decisions are made from description, people tend to be risk-averse and prefer the certain loss (Hadar and Fox, 2009). In contrast, when such decisions are made from experience, people instead tend to be risk-seeking and opt for the risky choice (Hadar and Fox, 2009). It is unclear how well existing risky intertemporal choice models can account for decisions made from experience, which form most of our daily decisions. This will be necessary to investigate further as these models seek to predict how people do make decisions – unlike their predecessors, the traditional normative models, which instead sought to prescribe how people should rationally make decisions.

The second way in which our hypothetical savings example differs from the real-world decision is the assumption that these choices can be viewed within a vacuum. In the risky intertemporal choice literature, the typical experimental procedure involves observing a participant's preferences across a series of discrete choices, presented in a similar format to our hypothetical example. Each of these choices is independent and has no influence on future choices; for example, whether a participant selects the risky option does not impact the options available in subsequent choice sets. This is a clear departure from the real-world environment, where people are required to consider how their present decisions will constrain their future selves. For instance, a person who spends all their money would have fewer and more limited choices available in subsequent months, compared to if they had saved the money instead.

This interconnectedness between decisions introduces additional sources of uncertainty that are unaccounted for by current risky intertemporal choice models. Consider, for example, the estimated 4.1 million Australians who engage in freelancing work (Australian Industry Group, 2016), which generates them an irregular and inconsistent flow of income. A freelancer cannot solely evaluate the present trade-offs of saving and spending money; they must also consider that their income in the following weeks or months could double or halve. Another type of uncertainty is created by ongoing debate surrounding the required superannuation balance for a comfortable retirement, with some in the industry claiming that over $1 million is needed (Cooper, 2015) while others believe that nearly half the amount would be sufficient (Association of Superannuation Funds of Australia, 2018). With each decision to spend or save, people must continually factor in their overarching goals (e.g., saving for retirement) – a task which becomes increasingly difficult when the goal amount is uncertain.

The role that these different types of uncertainties play in making risky intertemporal choices remains largely unknown. On the one hand, economists often argue that greater uncertainty should motivate people to act more conservatively (e.g., Gourinchas and Parker, 2002); in the household finance context, this might suggest reduced consumption and increased precautionary saving. On the other hand, past psychological research has found that people are more likely to procrastinate and avoid making choices when the complexity of a decision increases (e.g., Chernev et al., 2015). The complexity introduced by greater uncertainty could instead lead people to postpone decisions to set aside money and consequently reduce precautionary savings. In either case, it is again unclear from current risky intertemporal choice models how people handle these multiple types of uncertainty. For future iterations of these existing models to succeed, they will need to find ways to incorporate and integrate these aspects of real-world decision-making.

2.3 Significance and Implications

The present research acknowledges these limitations in the existing risky intertemporal choice literature and seeks to understand how people make these choices in real-world environments, where they are faced with multiple types and degrees of uncertainty. In doing so, the aim is to provide insight into the way in which uncertainty is psychologically represented, and to improve our understanding of its influence over decision-making. A potential avenue for investigation involves observing how people integrate multiple sources of uncertainty. One study found that participants were sensitive to different types of uncertainty (Ballard and Lewandowsky, 2015)); participants were more concerned about climate change when the problem was framed with "time uncertainty" (i.e., knowing global temperatures would rise by 2 degrees sometime between 2054-2083) than when it was framed with "outcome uncertainty" (i.e., knowing global temperatures would rise by between 1.6-2.4 degrees by 2065). However, two subsequent attempts at replicating these findings were unsuccessful (Sleeth-Keppler et al., 2019), suggesting that people may not consider different uncertainties as distinct. Instead, this could indicate that these many uncertainties are pooled in some way before a person makes their decision. Teasing apart these types of psychological mechanisms will inform the development of risky intertemporal choice models, ultimately leading to a deeper understanding of our decision-making processes.

From an applied perspective, this deeper understanding will deliver new insights for practitioners to use in contexts where individuals may be prone to making short-sighted choices at the detriment of their future selves. This has become more important than ever before, with the ongoing COVID-19 crisis introducing an unprecedented level of uncertainty into our everyday lives. For many who now find themselves stood down or unemployed, it also serves as a stark reminder of the importance in having set aside precautionary savings. Behavioural "nudge units", which have grown in popularity around the world, will be looking to these types of research findings to inform the design of products, services, and interventions, as they support our communities in navigating an increasingly uncertain world.

3 Research Plan

3.1 Pilot Experiment

To investigate the role of uncertainty in risky intertemporal choice, we designed a novel financial decision-making task that simulated the challenge of compromising between spending and saving. Although there are existing tasks that have been used in previous savings experiments (e.g., Brown et al., 2009), these tasks are often overly complicated; participants are inundated with pages of instructions and expected to perform complex calculations. With this in mind, we sought to design a task that would compromise between two competing principles. Firstly, it should be simple enough for a participant with complete knowledge to reasonably determine a strategy to reach an optimal or near-optimal outcome. At the same time, it should not be designed such that there is only a singular optimal strategy; rather, the task should allow for the observation of differences in individual preferences. Once we had designed the task, the objective of the pilot experiment was to validate it and test participant comprehension.

Participants and Design

90 first-year psychology students were recruited from the SONA-1 pool and allocated into one of two conditions. In the 'high reward' condition, the task (explained in further detail below) used a points system that incentivised participants to reach the

assigned savings goal. In contrast, in the ‘low reward’ condition, the points system instead incentivised participants to save none of their money. The intention behind these conditions was to examine whether participants would be sensitive to adjustments in the task.

Method

Participants were instructed that they would be completing a financial decision-making game in which they would make decisions related to spending and saving. In the context of the game, participants were asked to imagine that they had opened their first savings account and had set themselves a goal of saving $6,000 after 30 months.

In the first round (month) of the game, participants were provided $500, representing their monthly discretionary income after covering living expenses. They were asked to decide how much of this money to spend. Money that was spent was converted into points according to the system described below. Any money that was saved would remain in their savings account for the next round. In each subsequent round, participants would receive another $500 and would again be asked to allocate their money between spending and saving. This would continue until the participant had completed 30 rounds. Screenshots of the experimental task and instructions can be found in the Appendix.

The objective of the game was to score as many points as possible. To incentivise the maximisation of points, participants were told that those with the highest 20% of scores would be rewarded with $20 in real money. Points could be earned in two ways. To encourage spending, participants earned 5 points per $1 spent throughout the game. To encourage saving, participants were also rewarded for reaching their savings goal ($6,000 in 30 months). Participants in the ‘high reward’ condition earned a bonus 45,000 points for reaching the goal, whereas participants in the ‘low reward’ condition earned a bonus 15,000 points. Based on this points system, participants achieved the maximum points total by saving exactly $6,000 by the end of the game (high reward condition) or saving nothing at all (low reward condition)[1]

Key Results

Contrary to our expectations, we did not observe significant group-level differences between participants in the high and low reward conditions. Although the mean savings at the end of the game was higher for participants in the high reward condition (M = \$6,761.65, SD = \$2,409.70) compared to those in the low reward condition (M = \$5,878.32, SD = \$3,243.49), this difference was not statistically significant, $t(88) = 1.47$, $p = .14$. From a visual inspection of the histogram of final savings (Figure 1), it appears that a small proportion of participants in the low reward condition recognised that it was sub-optimal to save. However, setting aside these participants, savings behaviour appeared identical between the two conditions. This suggests that most participants were insensitive to the difference in points rewards. One possible explanation is that these participants took the instructions at face value (i.e., that they should save for the goal) and did not calculate how this would impact their points total. This could also have occurred because these participants were predisposed towards believing that saving money is typically the right thing to do. Our takeaway from this result is that future adaptations of the task should ensure that the points system is designed to be consistent with the instructions as well as participants' prior beliefs about saving money.

[1] In both conditions, participants earn a total of \$15,000. To score the maximum number of points:

High reward: Save \$6,000 (45,000 bonus points) and spend \$9,000 (45,000 points) = 90,000 total.
Low reward: Save \$0 (0 bonus points) and spend \$15,000 (75,000 points) = 75,000 total.

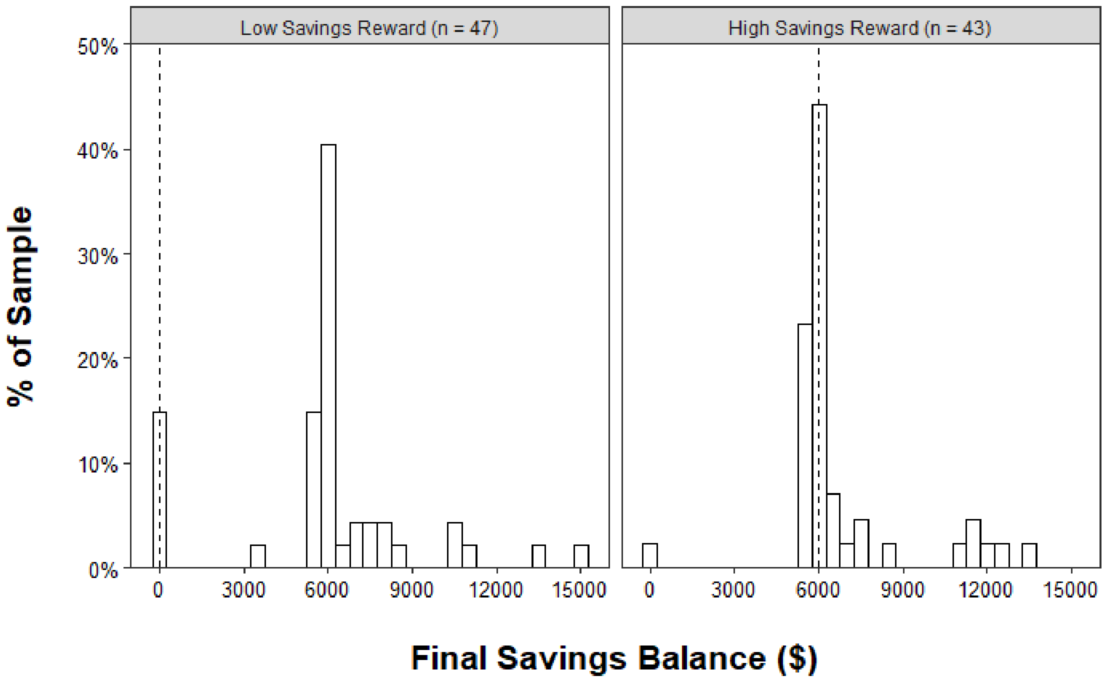


Figure 1: Histogram of participants' savings balance at the end of the 30th round. Dotted line indicates final savings balance that results in maximum points score.

We were also interested in whether we could identify different savings strategies that participants had applied in the task. This analysis was exploratory and was conducted without strong prior hypotheses or expectations. K-means clustering was used to identify five clusters of participants based on their savings behaviour[2]. The features used included: the mean amount saved per block (5 rounds) in the task, the fit of the savings trajectory to a linear model, and the fit to a quadratic model. Table 1 shows the median values per feature within the two largest clusters.

[2]Clustering was conducted on the overall participant sample due to the high similarity in savings behaviour between the high and low reward conditions.

Table 1: Median feature values for clusters 1 and 2

Feature	Cluster 1	Cluster 2
N (% of sample)	47 (52%)	23 (26%)
Mean Savings – Block 1	200.00	497.80
Mean Savings – Block 2	200.00	497.20
Mean Savings – Block 3	200.00	250.00
Mean Savings – Block 4	200.00	10.00
Mean Savings – Block 5	200.00	0.00
Mean Savings – Block 6	196.00	0.00
Linear Model – Slope	200.00	174.74
Linear Model – Intercept	0.00	1766.67
Linear Model – R^2	1.00	0.68
Quadratic Model – Quadratic Slope	0.00	-12.47
Quadratic Model – Linear Slope	205.19	539.80
Quadratic Model – Intercept	0.00	-63.07
Quadratic Model – R^2	1.00	0.96

The clustering analysis indicated that there was heterogeneity in participants' chosen approaches. Figure 2 shows examples of the savings trajectory of participants belonging to the first two clusters. The first cluster accounts for most of the participant sample and appears to capture the strategy of saving consistently to hit the goal by the end of the experiment. In contrast, participants in the second cluster saved aggressively in the early rounds and spent once they had reached the goal. This heterogeneity provides some validation that our task can capture individual differences and is something that we intend to explore further in subsequent experiments.

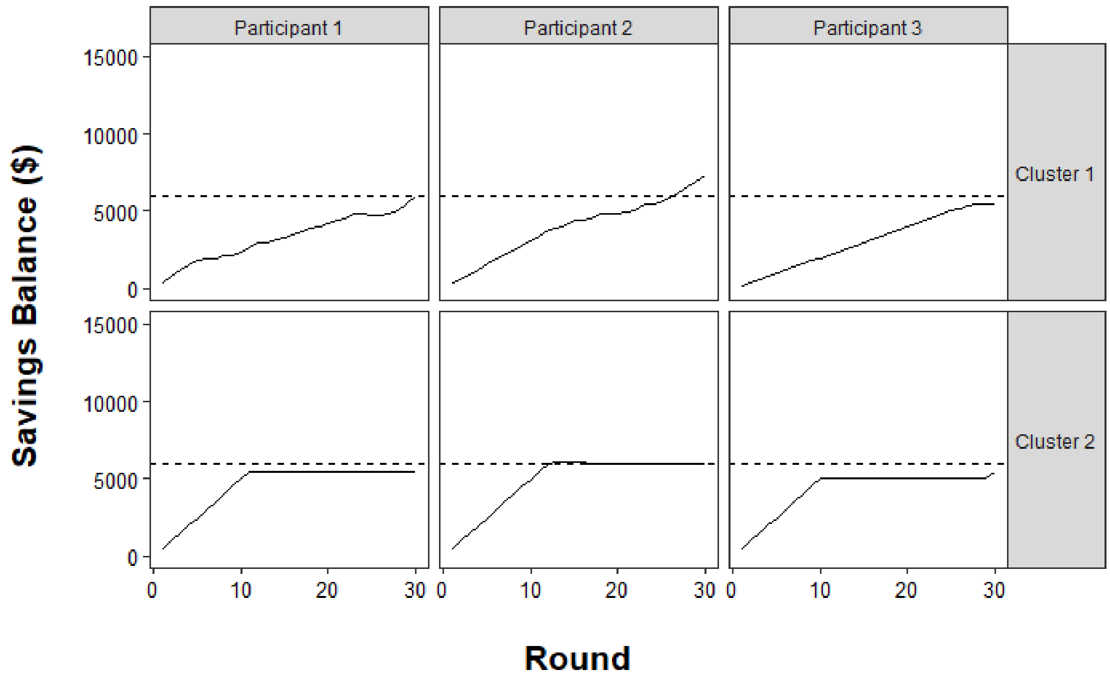


Figure 2: Trajectories of savings balance across the experimental rounds for a sample of participants in Clusters 1 and 2. Dotted line indicates the $6,000 savings goal.

3.2 Experiment 1

In the pilot experiment, participants were privy to full information about the task – such as the number of rounds and the savings goal amount. Their responses in this task provides an indication of how people might make risky intertemporal choices in environments with complete certainty. For the first experiment in my thesis, I will explore how these decisions are influenced once both income and goal uncertainty are introduced.

Design

The experiment will use a 2 (income uncertainty) × 2 (goal uncertainty) between-subjects design summarised in Table 2. In the *income certain* and *goal certain* conditions, participants will know their income and savings goal upfront, as they did in the pilot experiment. In the *income uncertain* conditions, participants' income will vary between a known range. Similarly, in the *goal uncertain* conditions, participants will know a range in which their savings goal will fall between. These ranges represent priors that people would have when estimating their income flow or need for savings.

Table 2: 2×2 Design in Experiment 1

	Income certain	Income uncertain
Goal uncertain	$500 income each month	Income ranges between $250-$750
	$6,000 savings goal	$6,000 savings goal
Goal certain	$500 income each month	Income ranges between $250-$750
	$4,000-$8,000 savings goal	$4,000-$8,000 savings goal

Method

Experiment 1 will closely follow the method outlined for the pilot experiment. Participants will first be presented with instructions and the task information, which will vary depending on which condition they have been allocated to. Participants will then complete 10 practice rounds to familiarise themselves with the task. Following this, their savings balance and points score will be reset, and they will complete the 30 experiment rounds.

Expected Results and Conclusions

The main dependent variable of interest will be participants' savings trajectory across the experiment rounds. We will analyse this using Hierarchical Bayesian Latent Mixture Modelling (HBLMM), an inferential technique that has previously been used to identify different response patterns from latent populations (e.g., Kary et al., 2017). Drawing from our cluster analysis of the pilot experiment data, we expect that the modelling procedure will enable us to classify participants into categories such as:

1. *Consistent Savers:* Participants who aim to reach the goal by saving a consistent amount each round.
2. *Early Savers:* Participants who aim to reach the goal by saving aggressively in early rounds and spending in later rounds.
3. *Non-Savers:* Participants who choose not to aim for the savings goal and instead prioritise earning points by spending their money.

We hypothesise that the analysis will demonstrate that both economic and psychological perspectives of uncertainty hold merit. In line with economic perspectives, we expect that introducing one layer of uncertainty (i.e., either income uncertainty or goal uncertainty) will motivate participants to be more conservative. Thus, a higher proportion of participants in these conditions would be classified as *Early Savers* compared to the condition where both income and goal amount are certain. However, when both layers of uncertainty are introduced, this will greatly increase the complexity of the task. In line with psychological perspectives, we believe that this will overload participants, leading them to focus on aspects in the task that are salient and certain – in particular, the immediate reward from spending. Consequently, we anticipate that there will be a lower proportion of participants who strive to reach the goal (*Consistent Savers* and *Early Savers*) and a higher proportion of *Non-Savers*. Figure 3 shows a potential pattern of results in line with these hypotheses. As we expect that only introducing income uncertainty or goal uncertainty will yield similar effects, we have grouped them as a single layer of uncertainty. We have also included an *Other* category to capture the participants whose saving behaviours cannot be adequately described by the *Consistent Savers*, *Early Savers*, or *Non-Savers* categories.

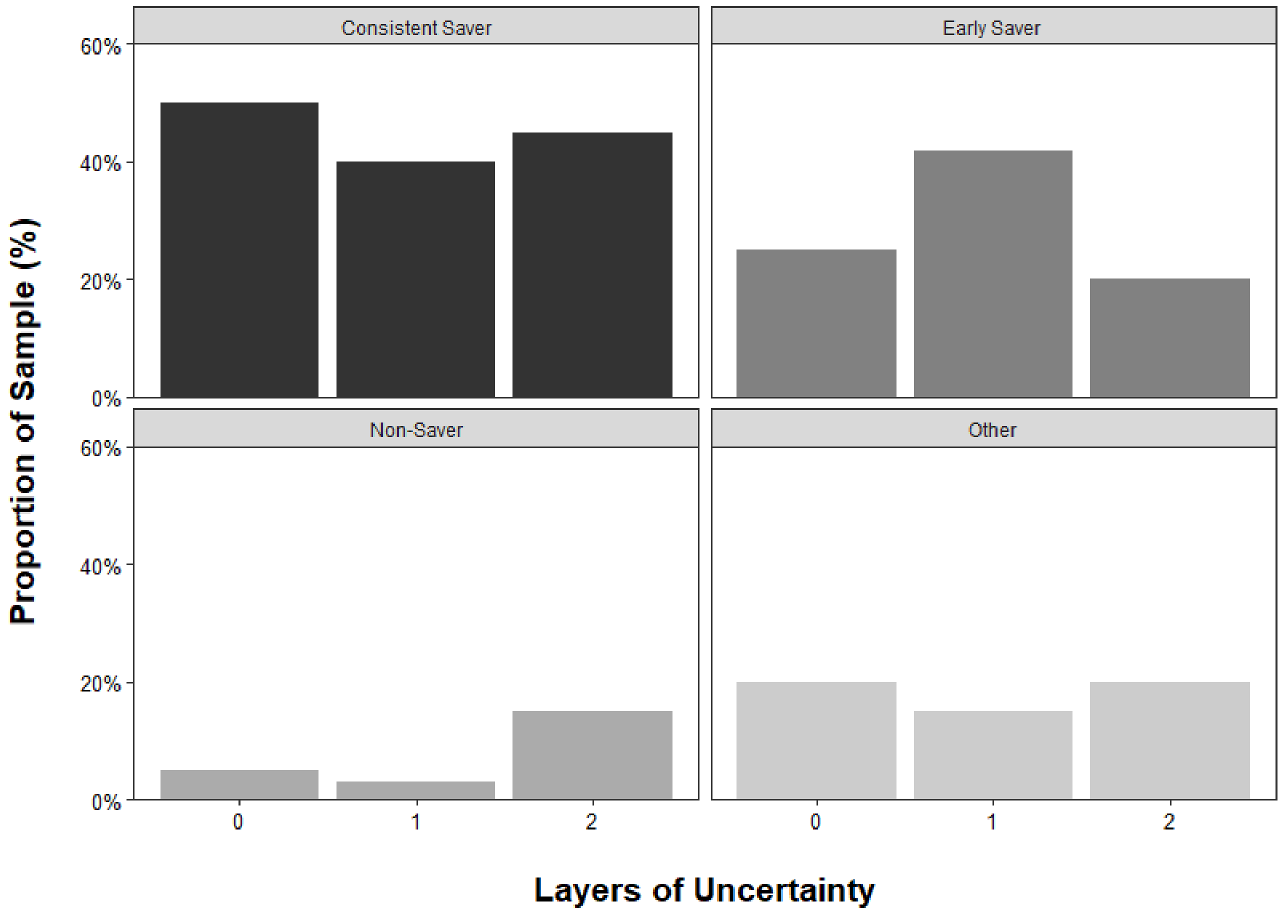


Figure 3: The proportion of participants identified as Consistent Savers, Early Savers, Non-Savers, or Other by layers of uncertainty introduced. Proportion of Early Savers increases with one layer of uncertainty (either income or goal). Proportion of Non-Savers increases when both layers of uncertainty are introduced.

3.3 Future Directions

Additional Types of Uncertainty

Experiment 1 examines the role of income and goal uncertainty in financial decision-making. As alluded to earlier, there are many other common types of uncertainty that people face in making risky intertemporal choices. For example, the first experiment assumes that the savings goal is both necessary and must be reached within a specific timeframe. However, this is not always the case in many real-world scenarios. When people save for retirement, it is unlikely that they know their exact retirement date. Likewise, when people save for financial emergencies, it is unlikely that they know the exact likelihood that one will occur. One future study could examine how *time uncertainty* and *outcome uncertainty* influence decision-making, and whether this influence replicates our findings in Experiment 1.

Varying Levels of Uncertainty

Another avenue for future research is to manipulate the degree to which participants are uncertain about an aspect of the task. In Experiment 1, we will use a single manipulation of uncertainty (e.g., range of possible monthly income). One future study could test the effect of multiple levels of uncertainty. For example, the size of the range could vary between conditions, with larger ranges reflecting greater levels of uncertainty. The greatest level of uncertainty could be achieved by foregoing a range altogether – requiring participants to learn solely via experiential sampling.

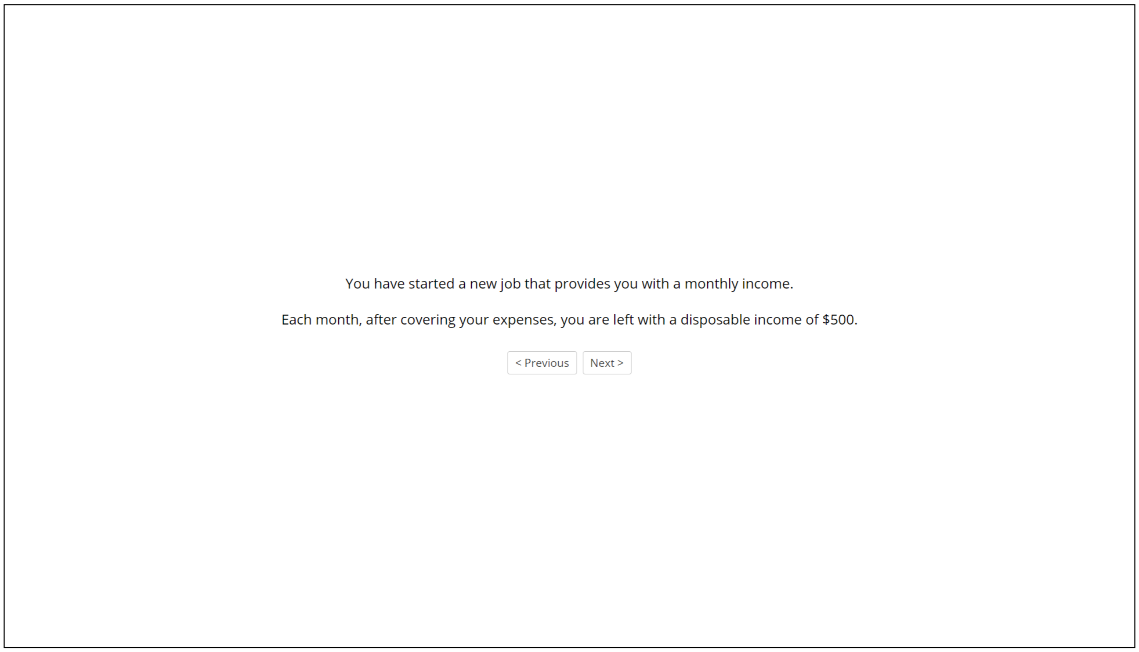
Extending Models of Risky Intertemporal Choice

Finally, we observed earlier that current models of risky intertemporal choice apply in situations with complete certainty, where the risks and time delays are known. The two future research directions outlined above should equip us with a stronger understanding of how our decision-making processes change with the introduction of uncertainty, presenting opportunities to adapt existing models and account for choices made in real-world environments.

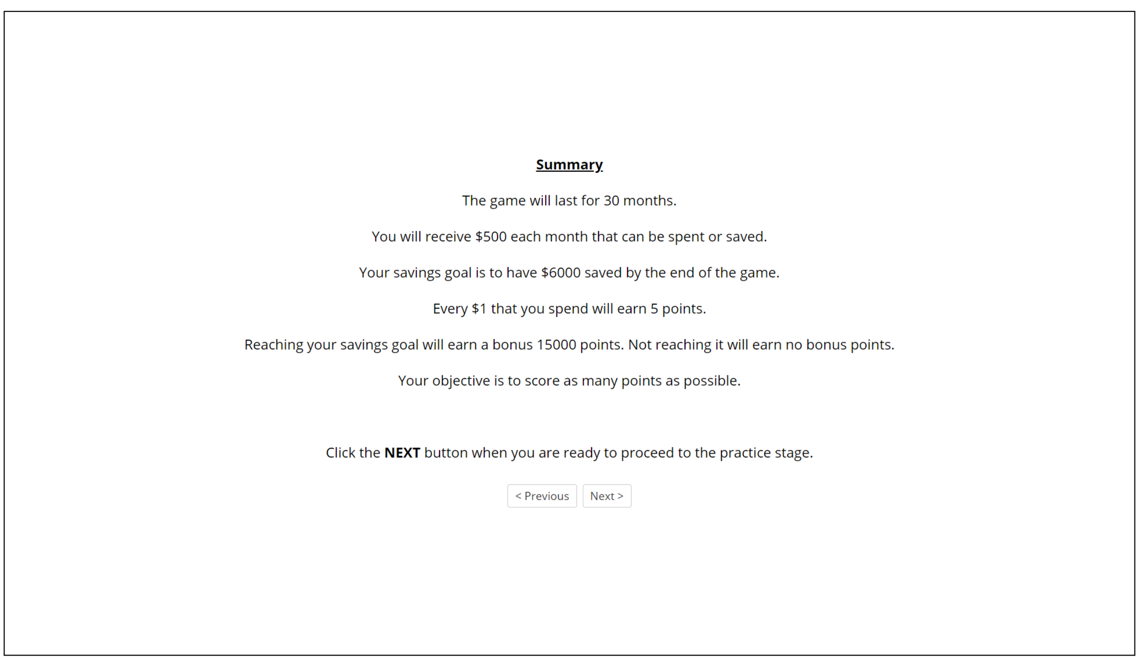
4 Appendix

Screenshots of Financial Decision-Making Task

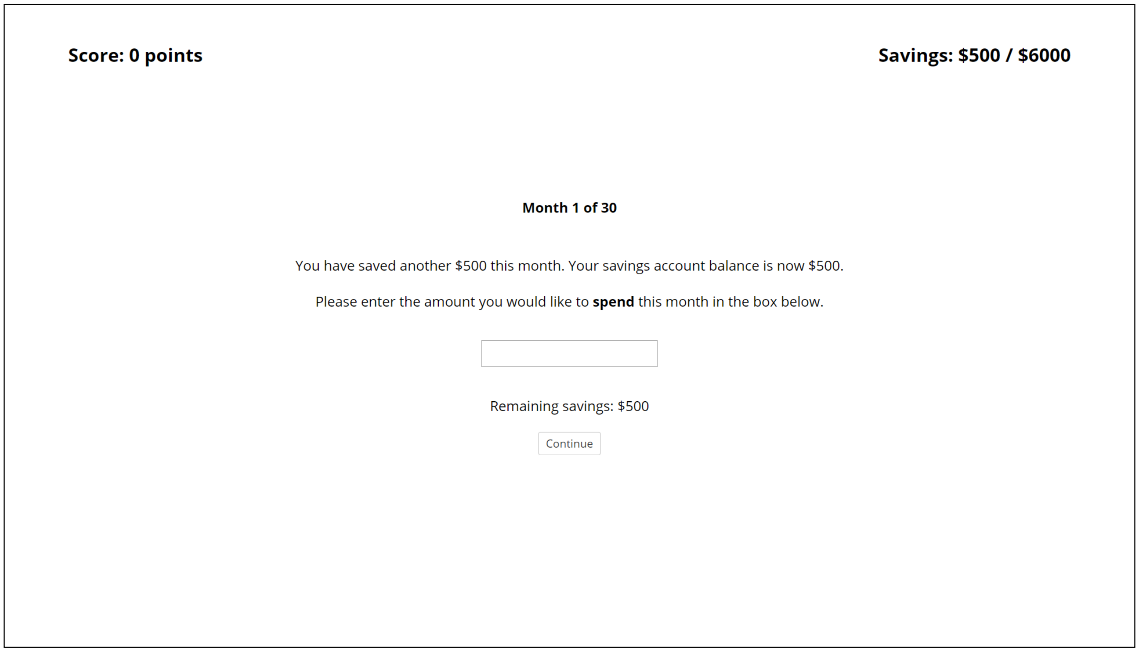
Example of instructions



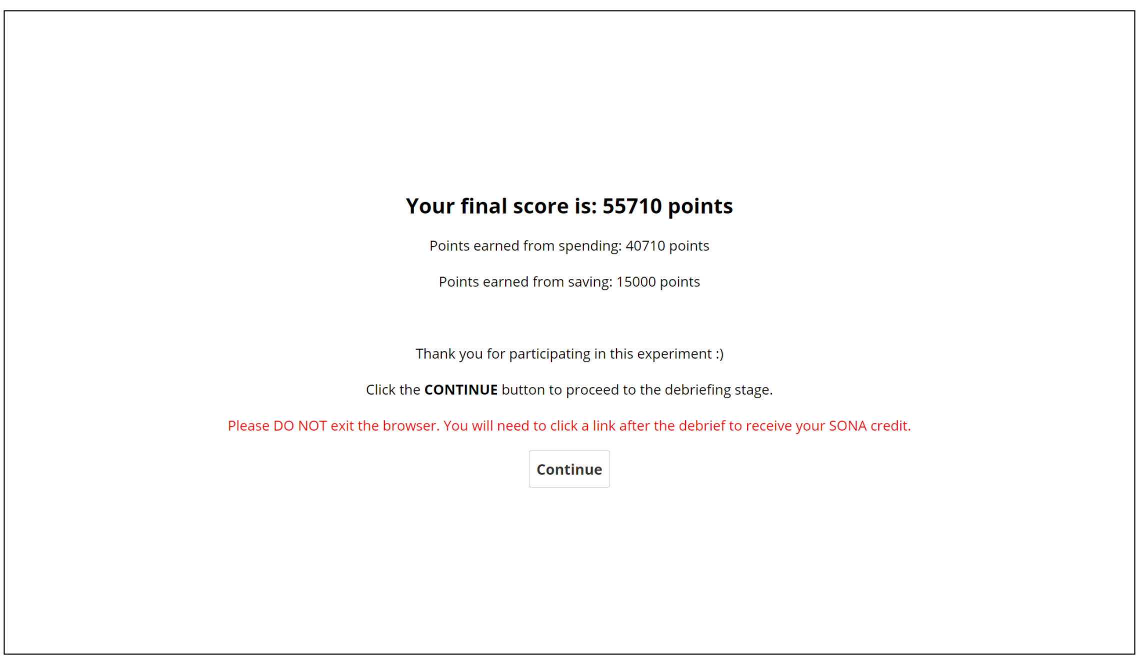
Summary of instructions (presented before start of practice and experiment rounds



Spending and saving decision



Final outcome



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