The interplay between memory and value-based risky choice

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Abstract

Most of the decisions we make in our everyday lives are based on our past experiences with similar situations. This ranges from trivial decisions, such as deciding which snack to buy while grocery shopping, to more complex decisions, like how to best invest your money or where to go on holiday. In this thesis, I present findings from a series of empirical studies examining how people integrate information into memory and utilize it in subsequent choices. Specifically, the experimental studies presented in this thesis examined how people encode and treat task-relevant and task-irrelevant information, allocate attention to available choice options, and assess the temporal dynamics of risky choice. Across all experimental studies, I also examine how formation integration changes with learning. Together, the work presented in this thesis provides theoretical advances to our understanding of how memory and decision-making interact and shape each other.

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Introduction

"*If, before every action, we were to begin by weighing up the consequences, thinking about them in earnest, first the immediate consequences, then the probable, then the possible, then the imaginable ones, we should never move beyond the point where our first thought brought us to a halt.*" – **Jose Saramago** (Blindness)

Memory is a critical part of the human experience, allowing us to draw on past experiences to inform our current choices. An individual may draw on directly experienced scenarios or abstract concepts and general knowledge to inform their choices. For example, vivid episodic memory of a previous accident (e.g., a car crash) may increase the probability an individual wears a seatbelt. The same individual may also rely on semantic memories related to their financial situation (e.g., the importance of saving money), which leads them to invest in stocks. Given this clear relationship between memory and decision-making, it is no surprise it has, in recent years, become the focus of extensive research investigating how memories guide choices. This growing literature has shown interactions in learning and memory systems that can be used to make predictions about decision-making (Bornstein & Norman, 2017; Gershman & Daw, 2017; Rouhani et al., 2018; Rouhani & Niv, 2021; Shohamy & Daw, 2015; Wimmer et al., 2014; Wimmer & Shohamy, 2012). Extending to value-based decision-making, these are used to guide future choices (Barron et al., 2013; Shohamy & Daw, 2015), where better-memorized items are more likely to be chosen (Gluth et al., 2015; Weilbächer et al., 2021). The critical interaction between memory systems and decision-making is further highlighted by individuals with amnesia having impaired decision-making abilities (Bakkour et al., 2019).

Rewards have been found to greatly impact how information is remembered; information associated with higher reward magnitudes becomes more memorable during subsequent memory testing (Adcock et al., 2006; Castel et al., 2002; Madan & Spetch, 2012, 2012; Murayama & Kitagami, 2014; Wimmer & Shohamy, 2012; Wittmann et al., 2011). A growing body of evidence demonstrates the important role reward plays in shaping our memories through incidental and intentional encoding (for review, see Simonsen & Madan, 2021). The memory-enhancing effects of rewards are widely thought to, at least partially, be due to reward-related activation of the dopaminergic midbrain facilitating memory

formation in the hippocampus (Adcock et al., 2006; Shohamy & Adcock, 2010; Wolosin et al., 2012). This activation of the dopaminergic midbrain is linked to reward prediction errors (i.e., rapid reinforcement signals tracking the difference between actual and expected rewards) which further shapes how memory for rewarding experiences is encoded with larger prediction errors leading to better memorability of reward predictive stimuli (Rouhani et al., 2018; Schultz et al., 1997). Together, this illustrates the interrelationship between rewards and memory, whereby rewarding experiences enhance memory, causing these experiences to be more easily retrievable for future choices.

Because rewarding (or more rewarding) experiences are much more memorable than their unrewarding (or less rewarding) counterparts, our decisions can become biased. This leads to dynamic changes in how we make decisions in a given choice environment as we gain more experience with said environment. As a result, these dynamic changes and biases lead to deviations predicted by normative (Von Neumann & Morgenstern, 1953) and descriptive theories (Kahneman & Tversky, 1979) of decision-making. For example, since experiences are not judged by their average or sum but by the peak or end of the experience (known as the peak-end rule; Fredrickson & Kahneman, 1993), these experiences can bias future choices by making individuals endure prolonged uncomfortability if the end is less painful (Redelmeier et al., 2003). In parallel, extreme outcomes are more memorable (Hoffart et al., 2022; Ludvig et al., 2014; Madan et al., 2014, 2017), resulting in overrepresentations in memory, causing such events to be overweighted. It has been argued that the overweighting of extreme outcomes reflects the rational allocation of limited cognitive resources (Lieder et al., 2018).

The evidence accumulation framework has been proposed to explain how temporal dynamics on decision-making and has become widely used to describe how prior experiences are used to inform decision-making. Briefly, the evidence accumulation framework (e.g., see Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & McKoon, 2008) posits people integrate noisy information into their decision process until a decision threshold is reached. A decision is made once sufficient evidence has been gathered and the threshold is reached. Several theories of memory and decision-making utilize this framework to explain how people sample experiences from memories, where each sample constitutes evidence favoring an option. Theories using this framework include Instance-Based Learning Theory (IBLT; Gonzalez & Dutt, 2011), Decision-by-Sampling (DbS; Stewart et al., 2006), and Query

Theory (Johnson et al., 2007). Although these theories rely on the evidence accumulation framework, they make different assumptions about how people draw from memory to inform choice. For example, when choosing between two restaurants, IBLT predicts that the aggregated experienced utility of all retrieved instances is directly compared, thus, the restaurant with the highest aggregated experienced utility will be chosen. Conversely, DbS predicts that a random sample of information is drawn from memory, with the attributes being directly compared. In sum, it is widely believed that memory-based decision-making relies on an evidence accumulation process where noisy information drawn from memory is sequentially sampled and compared until a decision boundary is reached.

In **Chapter 1**, a comprehensive literature review explored how information is integrated under uncertainty. Two types of decisions were used to explore information integration under uncertainty (memory-based and perceptual decisions) to provide a clearer distinction in how information integration and utilization differ between these two types of decisions. Different accumulation-to-threshold models are also discussed and outlined to characterize their similarities and differences and how they enable novel insight into how people integrate information.

In **Chapter 2**, optimality is discussed in the context of optimal stopping theory. Here, optimal stopping in decision-making is broadly discussed, followed by outlining several key optimal stopping problems, some of which have been used for psychological and economic research. To help demonstrate the utility and generalizability of optimal stopping policies, one optimal stopping problem – the *Secretary Problem* – was simulated using different set sizes. Simulations revealed that with larger set sizes, the optimal policy stabilizes. Lastly, the usefulness of applying optimal stopping policies is discussed, drawing parallels to real-world scenarios where applying such policies has utility.

In **Chapter 3**, the interaction between reward processing and memory formation in risky choice was assessed. To do this, in a series of pre-registered experiments conducted in an online sample, a risky choice task was used where participants repeatedly chose between two options and had to learn the underlying reward structures. Participants saw trial unique images interleaved between choosing and receiving reward feedback. Importantly, the task was designed such that reward anticipation should decline with increased experience. Participants' memory was found to be overall poor, and recognition memory for task-irrelevant stimuli was found to be mixed between experiments. Furthermore, replicating

previous results of curiosity-enhancing effects on incidental encoding failed in an online sample. Thus, although behavioral results may indicate incidental encoding of task-irrelevant stimuli is down-regulated to prioritize incremental learning, these results should be interpreted cautiously.

In **Chapter 4**, visual attention in risky choice was assessed using eye-tracking methods to understand how attention informs people's choices and reflects memory biases. Using a similar risky associative-learning task as in **Chapter 3**, participants had to learn the underlying reward structures with the aim of earning as many points as possible. People allocated more attention to the chosen option and became increasingly risk-averse for losses and low-value rewards than gains and high-value rewards with learning replicating prior work. In addition, participants allocated more attention to probabilistic options on gains and high-value reward trials and more attention to the deterministic option on loss and low-value reward trials. Following a decision, participants were shown all possible reward outcomes but did not exhibit an attentional bias towards the best or worst outcome locations following a risky choice. Participants' pupil dilations were larger when looking at probabilistic compared to deterministic options and when receiving the worst possible outcome following a risky choice but only for the high/low-value condition.

In **Chapter 5**, the cognitive mechanisms associated with risky choice were assessed using computational modeling. Drift-diffusion modeling was used to model two pre-existing datasets (Madan et al., 2017, 2021) to better understand the cognitive mechanisms associated with risky choice in different decision contexts. Results showed that increased familiarity with the choice environment results in lower response caution and that there are similarities in evidence accumulation (drift rate) depending on the decision context. Furthermore, as participants gained increased experience with their choice environments, the magnitude of the drift rate changed differentially based on the decision context. These novel results show how people move in parameter space with increased learning.

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Chapter 1

The accumulation and integration of information under uncertainty

Abstract

Life is inherently uncertain, with some choices being riskier and more uncertain than others. For any decision to be made, we must accumulate information and integrate it into our decision process. However, how we accumulate and integrate information may differ depending on the situation. Here, we provide a comprehensive overview of the literature on how people integrate information during a wide variety of choices. Firstly, we review the literature on perceptual and memory-dependent decision-making to provide an overview of our current understanding of evidence accumulation. We further discuss mechanistic differences between the two types of choice. Lastly, we provide an overview of the utility of using evidence accumulation models to better understand how people make decisions and provide a brief overview of findings from research using these models.

Keywords: decision-making, evidence accumulation, memory, perceptual choice, description-experience gap

1. Introduction

We make countless decisions daily ranging in difficulty, complexity, and relative importance. Depending on these factors, some decisions will ultimately require more information to be acquired and evaluated before committing to one decision over others. The acquisition and integration of information into the decision process over time are paramount to any decision we make and is more commonly referred to as 'evidence accumulation'. Converging evidence suggests that decisions are made by sequentially sampling and integrating noisy information for all possible decisions until sufficient evidence in favor of one decision over the alternatives has been acquired (Logan et al., 2014; Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & McKoon, 2008; Usher & McClelland, 2001). The amount

of favorable evidence needed to be accumulated before committing to a decision lies on a continuum; easy and trivia decisions require less, while more difficult and complex decisions require more favorable evidence (Ratcliff & McKoon, 2008). For example, more favorable evidence is needed when deciding which stocks to invest in to maximize profit than when deciding which snack to buy.

1.1 Distinguishing between sampling from perception and sampling from memory

Decision-making as a dynamic process, with preferences evolving with time, has become central in explaining choice behavior in various psychological domains. The sequential sampling framework, as outlined above, assumes that only when sufficient information has been accumulated a decision is made. Importantly, the noisy information being sampled differs depending on the type of decision being made. Perceptual decisions depend on a continuous stream of perceptual information, while value-based decisions depend on sampling memories of past experiences (Shadlen & Shohamy, 2016). The latter case being well captured by various theoretical accounts of memory and decision-making (e.g., Decision-by-Sampling [Stewart et al., 2006]; Query Theory [Johnson et al., 2007]; Instance-Based Learning [Gonzalez & Dutt, 2011]).

Since these two types of decisions depend on vastly different types of evidence being accumulated (i.e., integration of sensory evidence versus encoding-retrieval mechanisms of reward predictions), the way information is acquired and utilized in decision-making depends on distinctly different mechanisms. Perceptual and, more generally, sensory decisions depend on integrating a continuous stream of information rather than retrieving instances of past experiences that were incrementally acquired over time. Conversely, evidence accumulation for memory-guided decisions can be separated into two distinct categories. Firstly, for each choice, memories are sequentially sampled from all available memories at that time. Secondly, with each new experience, more evidence becomes readily available in memory, reinforcing or diminishing currently held preferences and heuristics (Sutton & Barto, 2018), thus creating a new sample of memories to draw from for subsequent decisions. That is, value-based and preferential choices depend on incrementally gathering evidence by encoding choice-outcome associations and the ability to retrieve these associations accurately. While accumulation-to-threshold mechanisms may conceptually be similar, how the evidence is acquired fundamentally differs (i.e., integration

of continuous stream of information versus past experiences). Similarly, both types of evidence accumulation may become biased by internal states, with these biases fundamentally differing based on how information is acquired and integrated into the decision process. For instance, sampling from perception may be affected by motivational biases (i.e., seeing what one wants to see; e.g., Gesiarz et al., 2019), while sampling from memory is more likely to be affected by encoding and retrieval biases (e.g., see Madan et al., 2021). Indeed, some research has suggested these two types of evidence accumulation, albeit unequivocally intertwined, rely on different cognitive mechanisms (Dutilh & Rieskamp, 2016; Vanunu et al., 2020; Zeigenfuse et al., 2014).

Here, we review findings from perceptual and memory-dependent decision-making to provide an overview of our current understanding of evidence accumulation. The review focuses on the acquisition and integration of information into the decision process for each of the two sub-fields. Moreover, mechanistic differences between these two types of decision-making will also be discussed to illuminate how the evidence accumulation processes differ. The utility of the drift-diffusion model (DDM) in research and what can be inferred about underlying behavioral mechanisms by applying the model is also highlighted. In addition, we also review the contributions of the DDM in other areas of psychology.

2. Sampling from perception

The first step in any decision is to integrate sensory information about our immediate choice environment. Most typically, this occurs via the integration of visual information – a process in which evidence is integrated through a continuous stream of perceptual information. For instance, when determining whether crossing the street is safe, checking for oncoming traffic and integrating the available perceptual information into the decision-making process (i.e., to cross or not to cross) is imperative. Although memories may play a role (e.g., knowledge of traffic on the street), they are not the primary determinant for such choices; these choices are critically dependent on the ability to accurately accumulate and integrate available perceptual information. For instance, detecting an approaching car can be explained by continuously monitoring and integrating time-varying visual looming (Markkula et al., 2021). The evidence may become biased during the accumulating and integrating process, leading to weighted evidence being integrated into the decision process. This is particularly apparent in cases where *priors* are available, where less

evidence has to be accumulated for choices aligning with these *priors* (Gesiarz et al., 2019). These motivational influences are associated with increased arousal, where higher arousal increases the likelihood of making motivational-consistent decisions rather than utilizing objective available information (Leong et al., 2021). Perceptual information is also given more weight when awareness of the utility of the accumulating information becomes explicit – leading to attentional switches (Shenhav et al., 2018). However, this weighted information does not lead to faster decisions, highlighting that the same amount of evidence is required before choosing, irrespective of weighting. When information is acquired early in the evidence accumulation process, choices become accurate decisions (Winkel et al., 2014), potentially due to less interference from metacognitive error monitoring mechanisms and decreased probability of biasing factors influencing the accumulation process.

2.1 Confidence as metacognitive error monitoring

Every decision is accompanied by a certain amount of confidence, such that choices are mainly made when accompanied by high confidence levels. People make remarkably accurate metacognitive judgments about the accuracy of their choices to the extent where confidence monotonically increases with choice accuracy despite the uncertainty associated with perceptual tasks (Desender et al., 2021; Hebart et al., 2016; Murphy et al., 2015). Indeed, confidence is lower on trials where erroneous responses are made (Desender et al., 2021), with these erroneous responses being detected faster than when making the initial erroneous choice (Murphy et al., 2015). Confidence may leak when making multiple judgments such that initial choices accompanied by high confidence predict high confidence for the second choice, independent of reaction times and accuracy (Rahnev et al., 2015). In addition, uncertainty-weighted trial history is incorporated into current perceptual judgments where confidence becomes serial dependent, leading to inflated or deflated confidence on subsequent trials, affecting the attractiveness of subsequent judgments (Braun et al., 2018; Samaha et al., 2019; Urai et al., 2017) an effect which grows steadily with elapsed time (Urai et al., 2019). Making accurate metacognitive judgments depends on sensory reliability and the ability to discriminate between the directionality of the information and a reference point (Bang & Fleming, 2018). Despite this, decisions are typically executed before all available information is accumulated, with additional post-

decisional evidence accumulation informing confidence judgments (Balsdon et al., 2020). Although these factors may influence confidence on a given trial (or subsequent trials, in cases of trial history spill-over), confidence is also affected by evidence volatility (i.e., variance in momentary evidence). Paradoxically, increased volatility leads to faster decisions accompanied by higher levels of confidence, which likely reflects an increased acceleration of accumulated evidence towards a decision threshold (Zylberberg et al., 2016), something which may be guided by pre-existing motivations (Gesiarz et al., 2019) or trial history (e.g., Samaha et al., 2019).

2.2 Post-decisional error monitoring

Perceptual information rarely disappears the moment one commits to or initializes a choice. For example, uncertainty may arise between the initiation of the choice and its execution, leading to decreased confidence in the initial decision, potentially resulting in a change of mind. In an influential study, Resulaj et al. (2009) had participants make judgments about whether most on-screen dots were moving left or right. Participants indicated their responses by moving a lever to the corresponding corners of a response contraption. Critically, the dots remained on screen, allowing for continued evidence accumulation after initiating the initial response until the lever reached either of the corners. The study illustrated that participants continued accumulating post-decisional evidence and utilized the additional information to rectify erroneous decisions, highlighting continuous metacognitive awareness of ongoing decisions. Such post-decisional monitoring has been proposed as a mechanism for biases in confidence judgments (Navajas et al., 2016; van den Berg et al., 2016). Indeed, changes of mind are accompanied by last-minute switches in confidence from low to high confidence (van den Berg et al., 2016). These findings of post-decisional monitoring are indicative of bottom-up processing during the accumulation period, both pre- and post-decision, when post-decisional evidence is available. In contrast, when post-decisional evidence is unavailable, post-decisional monitoring occurs through top-down uncertainty monitoring (Atiya et al., 2020) and internal sampling of earlier experienced evidence (Desender et al., 2021). These two factors inform whether a change of mind is warranted in the absence of explicit post-decisional evidence. Despite post-decisional evidence justifying a change of mind, it may have increased costs to do so, and we may, therefore, deliberately decide against correcting erroneous decisions.

Correcting erroneous decisions is contingent on the amount of physical effort that needs to be exerted, with the willingness to correct erroneous decisions decreasing as physical effort increases (Burk et al., 2014; Moher & Song, 2014), suggesting a cost-benefit analysis occurs in parallel with the post-decisional monitoring period.

2.3. Evidence accumulation of implied motion

Perceptual evidence accumulation is not restricted to real perceptual motion (as is the case for random dot kinematograms), as motion may also be implied by static images presented in quick succession. Perceptual judgments of implied motion are studied using Glass patterns (Glass, 1969) which are geometric shapes formed by arranging multiple static dot pairs. These are typically used to investigate how local perceptual signals transform into a global percept of form. Rapidly presenting a series of static Glass patterns results in the apparent movement of the static dots (i.e., dynamic Glass patterns). Detection thresholds of perceptual information differ between static Glass patterns, dynamic Glass patterns, and real motion; the threshold of determining perceptual patterns has consistently been found to be lower for dynamic Glass patterns compared to static Glass patterns but higher for real motion (Burr & Ross, 2006; Day & Palomares, 2014; Joshi et al., 2021; Nankoo et al., 2012, 2015; Or et al., 2007). Thus, while evidence accumulation occurs through a continuous stream of perceptual information regardless of the perceptual information being integrated, the underlying mechanisms differ where form detection of dynamic compared to purely static perceptual information is easier but harder than real motion.

Form detection of dynamic Glass patterns depends on interactions between form and motion, where specific patterns lead to enhanced form detection compared to others (Day & Palomares, 2014; Nankoo et al., 2012; Pavan et al., 2019). This, by extension, leads to more accurate judgments as more coherent information enters the evidence accumulation process. Although detection thresholds for implied motion (i.e., dynamic Glass patterns) decrease linearly with higher temporal frequencies (Day & Palomares, 2014), the number of unique frames showed also plays a crucial role where an increased number of unique frames lowers detection thresholds (Nankoo et al., 2015). As such, the discriminability of dynamic perceptual information may be driven by a temporal summation mechanism that depends on the number of unique frames and temporal frequencies available during the

evidence accumulation process. Like real motion, this temporal summation mechanism can occur without visual awareness (Chung & Khuu, 2014) and without allocating substantial attentional resources (Pavan et al., 2019). Counterintuitively, diverting attention away from dynamic Glass patterns increases form after-effects. An effect that is size-dependent where small Glass patterns are negatively affected by attentional distraction, leading to less or no form after-effects (Pavan et al., 2019). Taken together, these findings suggest temporal summation of motion patterns is similar for dynamically updating perceptual information and real motion, but with additional input from global form systems.

3. Sampling from memory

How information is acquired is critical to how decisions are made, where decisions based on described information significantly differ from those based on past experiences. In an experimental setting, participants are typically explicitly informed about possible outcomes and probability distributions associated with options when studying decisions-from-description. Importantly, choices are hypothetical, i.e., they never resolve, resulting in an inability to learn the outcomes of one's decisions. Findings based on described prospects show people are risk-averse for gains but risk-seeking for losses and make decisions as if small probabilities are overweighted (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981), findings which successfully replicate "in the wild" (e.g., Camerer, 1998; Ruggeri et al., 2020). However, introducing feedback and enabling participants to learn from their decisions reverse these otherwise robust findings. People instead become risk-seeking for gains and risk-averse for losses and make decisions as though small probabilities are underweighted (Y.-J. Chen & Corter, 2014; Jessup et al., 2008). The discrepancy between these two decision formats – where learning is impossible in one format but possible in the other – has become known as the description-experience gap (see Hertwig & Erev, 2009, for a comprehensive review).

This clear discrepancy in choice behavior between the two decision formats is partly due to the differences in evidence accumulation. Potential outcomes and probability distributions are known in decisions-from-description, whereas decisions-from-experience depend on incrementally learning outcomes and probability distributions through experience. In the latter case, decisions ought to improve as knowledge about outcomes and their underlying probability distributions becomes known. Paradoxically, personal

experiences with choice outcomes negatively impact the ability to utilize accompanying described information when making decisions (Lejarraga, 2010; Newell & Rakow, 2007; Yechiam et al., 2005). Three decision paradigms are used when studying memory-dependent evidence accumulation: sampling, partial or full feedback. Critically, the three paradigms differ in how evidence is accumulated and the amount of evidence available (e.g., see Fig. 1), thereby differentially affecting the evidence accumulation process.

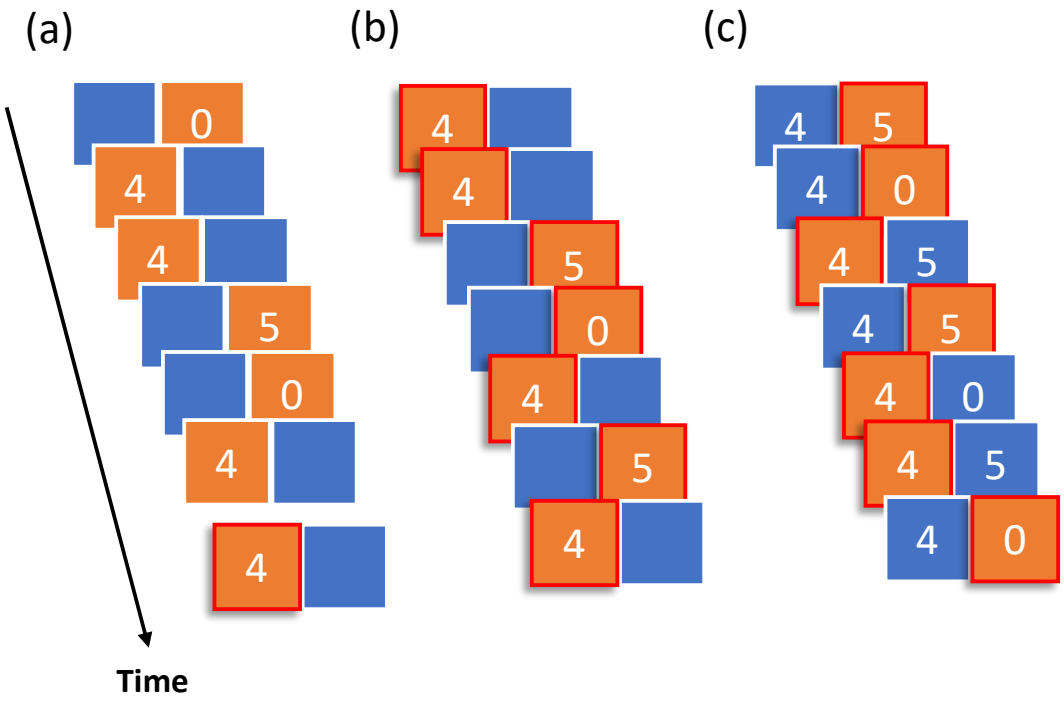


Figure 1. Different memory-dependent decision-making paradigms. (a) The sampling paradigm consists of a sampling stage where participants explore the payoff distributions at no cost. After the sampling stage, participants make a consequential choice, which results in the actual outcome. (b) In the partial-feedback paradigm, every choice is final, and feedback is only provided for the chosen option. Feedback is only provided for the chosen option. (c) The full-feedback paradigm is identical to the partial-feedback paradigm, except feedback is also provided for the foregone option. Choices of a hypothetical agent are illustrated by the orange squares, where red borders represent final, consequential, choices.

3.1 Sampling

The sampling paradigm requires participants to sample information about underlying probability distributions by repeatedly choosing between alternatives (Hertwig et al., 2004). In some cases, sampling may continue until participants feel confident to make a final, consequential decision (e.g., Hertwig et al., 2004; Hertwig & Pleskac, 2010), while in other

instances, participants are given a limited number of samples to use before making their consequential decision (Camilleri & Newell, 2011b; Hadar & Fox, 2009; Ungemach et al., 2009). As outcomes and probability distributions are unknown, participants need to keep track of the possible outcomes associated with each option and the degree to which options are probabilistic. Thus, participants accumulate evidence with every draw and utilize this information when making their consequential decision.

3.1.1 Sampling error

Critical to the evidence accumulation process, and by extension, choice behavior, is the number of samples participants decide to draw. Drawing only a limited sample limits the possibility of experiencing all possible outcomes and negatively impacts one's representation of the objective probability distribution (Hertwig & Pleskac, 2010). When given the opportunity to freely sample, people draw frugally, leading to sampling errors (Hau et al., 2010; Hertwig et al., 2004), resulting in sub-optimal decisions. Indeed, as the number of samples increases, the probability of choosing the highest expected value option increases (Hertwig & Pleskac, 2010). Two explanations for frugal sampling have been suggested: It may either be due to opportunity costs (Hau et al., 2008) or choice simplification, where fewer samples make options more distinct, thereby making choice easier, because it amplifies differences between associated earnings and payoff distributions (Hertwig & Pleskac, 2008, 2010).

It is possible that people treat low-probability outcomes as if they are underweighted solely due to sampling error. Several studies have aimed to eliminate sampling error to directly assess this possibility, but this has yielded mixed results. Some studies show by eliminating sampling error, resulting in increased experience with low probability outcomes, these low probability outcomes are no longer underweighted in decisions (Camilleri & Newell, 2009, 2011a; Fox & Hadar, 2006; Hadar & Fox, 2009; Rakow et al., 2008). Conversely, others show that supposed underweighting of low probability outcomes cannot entirely be attributed to sampling error, as underweighting only diminishes when sampling error is eliminated (Barron & Ursino, 2013; Hau et al., 2008, 2010; Ungemach et al., 2009). For example, Ungemach et al. (2009) used a paradigm where some participants sampled an equal number of outcomes from each option where outcome frequencies matched the underlying probability distribution. They observed small probabilities were still

underweighted across participants, even for those where sampling error had been eliminated. Despite these mixed results, a recent meta-analysis revealed that even when sampling error is eliminated, small probability outcomes are still treated as if they are underweighted (Wulff et al., 2018). These findings may be due to individual differences in learning styles (i.e., Bayesian versus frequentist), where evaluations of probability distribution change with increased sample size for Bayesian learnings but not for frequentist learners (Hoffart et al., 2022).

3.1.2 Order effects

Sampling error cannot entirely be attributed to the influence that leads to underweighting of low-probability outcomes. Given the structure of the sampling paradigm (i.e., drawing samples before making a consequential decision), experienced outcomes may not be equally represented when retrieving said experienced outcomes. *Order effects* – both recency and primacy effects – are well known to influence judgments and decisions (González Vallejo et al., 2014; Hogarth & Einhorn, 1992; Rey et al., 2020), providing a potential explanatory candidate as to why low probability outcomes may be underweighted in memory-dependent decisions.

However, like sampling error, research findings are mixed when implicating order effects as a contributing factor to the underweighting of low-probability outcomes. One set of studies robustly showed that more recent experienced outcomes (i.e., a recency effect) influence (under)weighting of rare probability outcomes (Hertwig et al., 2004; Rakow et al., 2008; Rakow & Rahim, 2010). Conversely, another set of studies shows no significant recency effect (Abdellaoui et al., 2011; Hau et al., 2008; Ungemach et al., 2009). Besides finding a recency effect, Rakow and Rahim (2010) also found that primacy effects may be a contributing factor. However, across three experiments, order effects were found to vary. Wulff et al. (2018) suggest that order effects may only occur when the agent is given autonomy of the sampling process (i.e., how many samples to draw and when to stop) and not when participants are forced to draw a specific number of samples. Indeed, this is corroborated by Rakow et al. (2008), showing participants only elicited recency effects during free sampling but not when sampling was yoked. Of particular interest is a recent study by Plonsky et al. (2015) illustrating a wavy recency effect in the sampling paradigm, suggesting people recall and apply the most recent sequence of outcomes experienced out

of all previously experienced sequences. Because very few sequences include low-probability outcomes, these outcomes are treated as though they were underweighted in the decision process.

3.2 Partial feedback

In contrast to sampling, every choice made in the partial-feedback paradigm is consequential. Participants typically make binary choices and receive feedback for whichever option they choose, enabling associative learning. Initially, participants are promoted to engage in exploratory choice behavior to learn these stimuli-outcome associations. Once learning has been successfully established through repeated exposure, choice behavior shifts towards exploitative. Although the incremental evidence accumulation process occurs differently in sampling compared to the partial-feedback paradigm, similar choice behavior has been observed (Camilleri & Newell, 2011b; Hertwig & Erev, 2009). A classical partial-feedback task is the Iowa Gambling Task (IGT; Bechara et al., 1994); in the IGT, participants choose between cards from four decks with the goal of earning as much money as possible. Through experience, participants incrementally accumulate evidence, allowing for the distinguishing between which decks are more advantageous. Recent research using the partial-feedback paradigm has illustrated various factors influencing this incremental evidence accumulation process.

3.2.1 Episodic memory

Unlike sampling, the partial-feedback paradigm relies particularly on episodic memory to form stimulus-outcome associations. This reliance on episodic memory in the evidence accumulation process shows participants become more risk-seeking for gains and risk-averse for losses with increased experience when making risky choices (Ludvig & Spetch, 2011; Ludvig et al., 2014, 2018; Madan et al., 2014, 2017). Indeed, enhancing episodic memories increases risk-seeking in the gain domain, while downplaying episodic memories increases risk aversion in the loss domain (St-Amand et al., 2018). Similarly, when faced with a choice similar to one made in the past, being reminded of what one previously did increases the likelihood of making the same choice again (Bornstein et al., 2017). This effect extends to encoding contexts where making choices in familiar contexts increases the likelihood of choosing the option previously experienced in the same context (Bornstein &

Norman, 2017; Duncan et al., 2019; Duncan & Shohamy, 2016). However, the encoding context may be more critical than the retrieval context. Madan et al. (2021) made participants make sets of risky decisions in two different contexts (depicted by distinct backgrounds), where one set of choices was made in one context and another set in the other context. The authors found that choices depend on the local encoding context rather than the overall global encoding context, despite shared overlap in reward values for two decision sets between the two choice contexts. Moreover, swapping the context between decision sets did not affect choice behavior. This is likely due to the critical preference formation during encoding, where the encoding context may be more critical than the retrieval context, such that risk preferences are dependent on outcomes experienced during encoding.

3.2.3 Extreme outcomes

The extremity of possible outcomes has been found to be particularly important in the evidence accumulation process as they bias memory. Extreme outcomes are overweighted in both the gain and loss domains and have been dubbed the *extreme-outcome rule* (Hoffart et al., 2022; Konstantinidis et al., 2018; Ludvig et al., 2014, 2014; Madan et al., 2014, 2017). The *extreme-outcome rule* posits that extremities are more saliently experienced and, therefore, ascribed greater importance in the accumulation process, making people more sensitive to the extreme evidence (Madan et al., 2014), with outcomes closer to these extremities being more vivid (Ludvig et al., 2018). This has been cooperated further by findings showing extreme outcomes are better recalled (St-Amand et al., 2018). Although this may suggest that overweighting occurs due to oversampling of the extreme outcomes during retrieval, other alternatives have been suggested. One account has suggested increased saliency for outcomes with greater deviations from the center of the distribution (Tsetsos et al., 2012; but see Konstantinidis et al., 2018), while a different account suggests biased memory for extreme outcomes is a rational strategy of allocating limited cognitive resources (Lieder et al., 2018).

3.3 Full feedback

When making a choice, an agent always learns about the outcome of their choice, even if it is not learned instantaneously (e.g., waiting a few days before learning whether

one bought a winning lottery ticket or not). However, some decision, albeit very rare, provides the agent with the privilege of obtaining complete feedback following a choice (i.e., knowing the outcome of the chosen and the foregone outcome). Like the partial-feedback procedure, full feedback also utilizes associative learning but where feedback is provided for all available options (Fig. 1c). Thus, the information acquisition process differs significantly in that additional information is provided with the full feedback procedure, which promotes exploitative behavior *ab initio* rather than initial exploratory behavior.

An influential and widely used task in psychology to assess risk preferences, utilizing the full feedback format, is the balloon analogue risk task (BART; Lejuez et al., 2002). In the task, participants are supposed to pump up a balloon where, with each pump, the chances of the balloon popping increase. Here, full feedback is conveyed by the state of the balloon when a participant decides to make a pump. Using this task, researchers have shown that increased experience with the underlying probability distributions changes risk-seeking (i.e., increased risk-seeking when learning the probability of failure is low). This behavior appears to be driven by functional impulsivity (i.e., making quick decisions when it is optimal and beneficial), where high levels of functional impulsivity result in higher risk-seeking behavior when the probability of failure is low (Vigil-Colet, 2007). Failures in the task lead to increased physiological response while also inhibiting risk-seeking in subsequent trials (Wright & Rakow, 2017). Recently, FitzGibbon et al. (2021) used a modified version of the BART where participants could receive information about the balloon's limit on any given trial where they decided to 'bank' their earnings. The authors showed that – beyond eliciting experienced regret when receiving information about foregone outcomes – people consistently engage in counterfactual curiosity (i.e., obtaining information that does not benefit future decisions).

In a similar vein to the BART, two-alternative forced-choice tasks are used when wanting to assess decision-making when participants acquire information about foregone outcomes. Utilizing two-alternative forced-choice tasks allows for systematically assessing how low-probability outcomes affect exploration-exploitation behavior under full feedback. Consistent with findings from research using BART, providing people with information about foregone outcomes leads to increased risk-seeking (Avrahami et al., 2017; Plonsky & Teodorescu, 2019; Yechiam & Busemeyer, 2006). By virtue of the task, these findings also suggest that rare outcomes are treated as though they are increasingly more

underweighted compared to the partial feedback paradigm. Crucially, increased risk-seeking is only observed when foregone outcomes are better on a previous trial; if the foregone outcome is worse than the chosen option risk, risk-seeking is decreased (Plonsky & Teodorescu, 2019). Moreover, increased switch rates are also observed when better outcomes are missed (Avrahami et al., 2017), but these switch rates are context-dependent where feedback for better foregone outcomes only affect switch rates in favorable choice environments (i.e., where probabilities of obtaining a superior outcome are high; Rakow et al., 2015). This illustrates that information acquisition for foregone outcomes increases risk-seeking and exploitative behavior only when it is favorable. However, the underlying mechanisms responsible for such behavior have yet to be determined.

4. Computational models of evidence accumulation

Applying computational models to explain mechanisms of decision-making has become an increasingly larger part of decision research. Relatedly, sequential sampling models of decision-making have become widely used to understand the underlying mechanism of evidence accumulation. Within the literature, two types of sequential sampling models are typically used: diffusion and race models. Although both types of models aim to describe the cognitive processes involved in simple decision-making, they make different assumptions about the decision process. Here, we outline these two types of sequential sampling models, followed by a direct comparison between the drift-diffusion model (DDM; Ratcliff, 1978) and the linear ballistic accumulator (LBA; Logan et al., 2014) race model. Following this comparison, we illustrate the utility of using the DDM in explaining choice behavior beyond value-based decision-making.

4.1 Diffusion models of evidence accumulation

As most sequential sampling model, diffusion models assumes that choices are made based on a constant integration of noise information over time from a given starting point until a response boundary is reached (see Figure 2a). The accumulation process starts from the starting point (denoted by *z*), where *noisy* information is integrated until either of the two boundaries are reached (denoted by A and 0). Once either of the boundaries is reached, a subsequent decision is made, corresponding to the respective decision boundary that was reached. The rate of accumulation (known as drift rate and denoted by *v*) is dependent on

the quality of the accumulated information (e.g., stimulus difficulty). Diffusion models further assume that time is needed for encoding and executive response processes (non-decision time, denoted by T_{er}), which is not part of the accumulation process itself. These parameters are assumed to have between-trial variability, with the drift rate being drawn from a normal distribution (with a given standard deviation), while the starting point and non-decision times are drawn from uniform distributions. The drift rate has additional within-trial stochasticity in the form of Gaussian noise. Importantly, only a single diffusion process is assumed such that evidence for one choice counts against evidence for another rather than a racing process (i.e., independent accumulators).

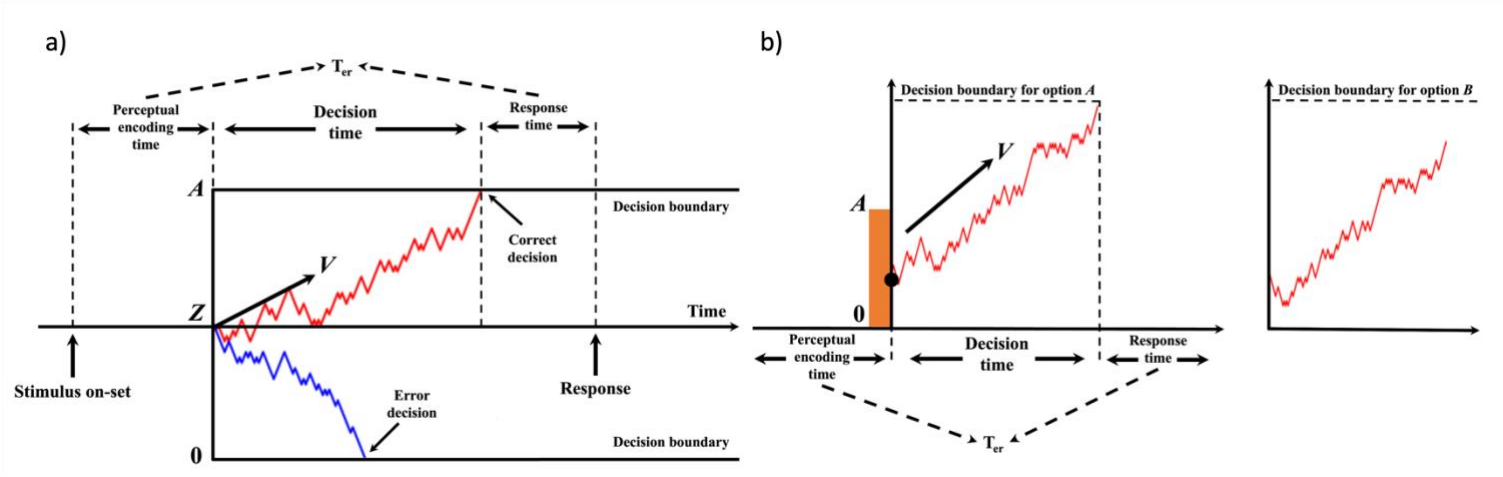


Figure 2. Schematic of two evidence accumulation models. Panel a) is a schematic of the drift-diffusion model; Panel b) is a schematic of a Race Decision Model (race model with Wiener diffusion process, e.g., see (Tillman et al., 2020).

The earliest and most prominent diffusion model used is the drift-diffusion model (DDM; Ratcliff, 1978), which, since the original model, has seen numerous extensions (e.g., to allow for starting point biases; Ratcliff et al., 2016; Ratcliff & McKoon, 2008, 2015). Other variations of the diffusion model have also played a prominent role in theories of decision-making, such as in the case of Decision Field Theory (Busemeyer & Townsend, 1993; Roe et al., 2001), using an Ornstein-Uhlenbeck diffusion process (i.e., applying decay to drift) rather than a Weiner process. Moreover, a recent and influential extension to the DDM incorporates fixation data into the model, assuming that attention moderates the drift rate by increasing the relative weighting of evidence associated with attended stimuli (Krajbich et al., 2010, 2012). Thus, this attentional drift-diffusion model predicts that attentional shifts

lead to systematic choice biases. Model parameters of these diffusion models provide psychologically meaningful interpretations. They provide an assessment of processing efficiency (i.e., ability in a task; drift rate), assessment of the decision criterion before making decisions (i.e., conservative/liberal; boundary separation), potential biases towards options (i.e., starting-point bias), and assessment of peripheral processes (i.e., non-decision time). By extension, these models further allow for assessing how individuals set criteria that prioritize either speed or accuracy during decision-making.

4.2 Race models of decision making

Race models of evidence accumulations make similar assumptions to diffusion models but with one critical difference. Although some race models may assume varying starting points (e.g., Usher & McClelland, 2001), denoted by the range between *0* and *A*) or non-decision time (T_{er}; e.g., Brown & Heathcote, 2008), they all assume independent non-competing accumulators (Logan et al., 2014; Logan & Cowan, 1984). That is, each independent accumulator represents favorable evidence for a particular outcome, and a decision is made based on which accumulator first reaches the decision threshold. Notable race models include the *linear ballistic accumulator* (*LBA*; Brown & Heathcote, 2008), the *leaky competing accumulator* (*LCA*; Usher & McClelland, 2001), and the *general race model* (Logan et al., 2014), with the latter two being hybrid accumulator/diffusion models.

The *LBA* (Brown & Heathcote, 2008) assumes no within-trial variability as the accumulation process of each accumulator is assumed to be ballistic (i.e., noise-free linear evidence accumulation). The *LBA* has between-trial variability in starting point bias and drift rate (drawn from uniform and normal distributions, respectively) but no additional noise. The *LCA* (Usher & McClelland, 2001) makes similar predictions but assumes evidence that one accumulator can inhibit other accumulators, resulting in accumulation rates slowing or becoming negative. The *LCA* further assumes evidence accumulation to be "leaky," such that information may be lost during the integration process. Unlike the LBA and LCA, the *general race* (Logan et al., 2014) is not a general model but rather used to address behavior in the stop-signal task. This model describes a race between response accumulators, including the stop response, and assumes accumulators to be stochastically and contextually independent. That is, response time distributions for stop and go processes are independent, where the go process is unaffected by the presence of a stop signal.

Importantly, the *general race model* does not commit to any particular stochastic accumulator model.

4.3 Comparing the DDM and LBA

As described above, the type of model used to describe the evidence accumulation process in decision-making relies on different assumptions about model parameters. As such, fitting data to either model type may bring different interpretations and conclusions about evidence accumulation and decision-making more broadly. One study compared DDM fits to simulated data from the DDM, LBA, and LCA (van Ravenzwaaij & Oberauer, 2009). The authors found that the DDM and LCA showed a one-to-one correspondence between model parameters, but no such correspondence was found between the DDM and LBA. Indeed, other studies have found incompatibility between the DDM and LBA models, but not to the same extent as initially illustrated. When comparing fits to behavioral, rather than simulated, data, model parameters show a one-to-one correspondence except for the boundary separation parameter (Donkin et al., 2011; Goldfarb et al., 2014; Heathcote & Hayes, 2012). Thus, the main conclusions drawn from either model regarding drift rate and starting point bias appear to be robust and consistent, but interpretations related to response caution (i.e., boundary separation parameter) appear to be less so. Therefore, should either model suggest a selective influence of response caution, it may be prudent to use the alternative model to verify findings before interpretations and conclusions are made about behavior.

The following section highlights findings from studies utilizing the DDM to make inferences about behavior-related cognitive processes. We focus only on studies using the DDM for two main reasons: 1) it is the model with the most widespread use in the literature, and 2) under specific parameterizations, the *LCA* is equivalent to the standard DDM (Bogacz et al., 2006). Moreover, Bogacz et al. (2006) has shown that the standard DDM implements a statistically optimal algorithm to optimize speed-accuracy trade-offs. Additionally, unlike the DDM, race models are better suited for multi-attribute and multi-alternative decision-making, as each possible option is represented by an independent accumulator. Because much of psychological research is conducted in a vacuum – e.g., by using two-alternative forced choice tasks – the DDM is a better descriptive model for most studies within psychology.

4.4 The DDM and aging

Utilizing the DDM to understand age-related changes in memory has illustrated that such changes are not due to reduced access to evidence from memory, as information processing appears to be consistent with age (e.g., Ratcliff et al., 2004; Ratcliff et al., 2007). Rather, older adults have increased response caution (due to wider decision boundaries), where the accumulated information is integrated into the decision process and executed slower, as highlighted by longer non-decision times. (Ratcliff et al., 2004, 2010; Spaniol et al., 2006). However, lower drift rates have been found for associative recognition in older compared to younger adults (Ratcliff & McKoon, 2015), illustrating worse memory strength for associative memory than simple item memory. Age-related differences in drift rate are also observed for episodic but not semantic memory (Spaniol et al., 2006) which may suggest that the quality of stored episodic memories is worse for older than younger adults. Spaniol et al. (2006) also illustrated anchoring effects on the response option presented first in instructions (old/new and living/non-living) where participants' starting point was biased towards 'old' because it appeared first in the instructions (and 'living' in semantic memory), an effect which is greater for older adults.

4.5 Using the DDM in social cognition

Often, our decisions are made in the presence of others, where their opinions or decisions can influence our judgments of the information acquired. The influential study by Asch (1951) illustrated that even the simplest of judgments can become distorted when in the presence of others, highlighting the extensive influence others have on our judgments and decisions. In recent years, the DDM has been applied to the social-psychological domain to elucidate the underlying cognitive mechanisms when interacting with others and how such interactions shape our decisions. Applying the DDM to a similar task as that initially used by Asch (1951) reveals important aspects of how the choices of others may lead to conformity. Rather than inducing judgment biases, social information (i.e., prior knowledge of majority responses before making one's own judgment) induces perceptual biases highlighted by changes in drift rate but not starting point bias parameters of the DDM (Germar et al., 2014, 2016). That is, the stimulus is perceived as more advantageous, leading to faster accumulation of favorable evidence for said stimulus. Despite increased processing efficiency caused by the weighted social information on the drift-rate parameter, increased

amounts of information are required to be accumulated before making a decision under social influences, reflected by greater boundary separations (Germar et al., 2016). However, when adhering to social norms, decreased drift rate and changes in starting point bias when deciding against a majority are observed (Toelch et al., 2018). Starting point bias is modulated such that it increases when social norms are congruent but decreases when incongruent with social information. This potentially suggests that social information elicits an unbiased starting point, which is then modulated by social norms. Moreover, information is processed more efficiently and takes less time to encode when responding to judgments about one's own race (reflected by drift rate and non-decision time, respectively; van Ravenzwaaij et al., 2011).

Studies using the DDM to study reciprocity have shown increased pro-sociality amongst other pro-social individuals due to differences in starting point bias. Pro-social actions require less favorable evidence when others are also pro-social, and similarly, selfish actions require less evidence when others are selfish (F. Chen & Krajbich, 2018; Hutcherson et al., 2015; Yu et al., 2021) where faster collapse rates of response boundaries lead to increased pro-social behavior (Hutcherson et al., 2015). Starting point bias is further amplified by time pressure, where pro-socially predisposed individuals are increasingly more likely to be pro-social under time pressure (F. Chen & Krajbich, 2018). Similarly, when choosing for others, the likeness between their preferences and one's own preferences affects processing efficiency. People with similar (*dietary*) preferences to oneself increase while individuals with dissimilar preferences decrease processing efficiency (Harris et al., 2018). Moreover, response caution increases when people have dissimilar preferences as themselves. Processing efficiency extends to sensory information judgments (where correct judgments lead to monetary rewards), where processing efficiency is higher when making judgments for oneself than others (Bottemanne & Dreher, 2019). Together, this further illustrates better information processing for oneself and individuals with similar preferences as oneself with greater response caution for dissimilar individuals.

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Chapter 2:

Knowing When to Stop: Optimal stopping in sequential decision-making

Abstract

People often make risky or uncertain decisions that are at odds with an objectively correct choice. Instead of relying on potential optimal policies, people often rely on their experiences and biases, and it is believed they set an internal decision criterion. Here, we review and describe several optimal stopping problems – some of which have had widespread use in psychology. We further outline their respective optimal policies and draw comparisons between these problems. Simulations of the standard *Secretary Problem* highlight the generalizability of its optimal policy across several different set sizes and show that with larger set sizes, the optimal policy stabilizes. A brief discussion of the usefulness of optimal stopping policies in everyday life is also outlined. Using sequential decision tasks with optimal policies may provide a better understanding of how people make decisions, deviate from optimality, and help inform how to make people more accurately engage in optimality.

Keywords: Optimal stopping, decision-making, mathematical psychology, rationality, optimality

Introduction

Every decision is inherently uncertain and carries risk – be it a little or a lot – meaning it can often be difficult to make an optimal decision in a given situation. Indeed, the difficulty associated with making optimal decisions has been observed extensively in both animals (Herrnstein, 1961, 1997) and humans (Hacking, 1980; Kahneman & Tversky, 1984; Loewenstein & Thaler, 1989). For example, the relative position of an item within a choice set can inflate or deflate the value of other items in the choice set (Simonson & Tversky, 1992), highlighting arbitrary anchoring effects in simple choice. To minimize the inherent uncertainty and risk associated with our decisions, we gather information until we feel confident enough to commit to a decision (e.g., Balsdon et al., 2020; Desender et al., 2021), where a decision is made when a given level of confidence is reached. This level of confidence also serves the purpose of optimizing our decisions to minimize costs and maximize rewards. One account of how this evidence-gathering process manifests is the sequential sampling framework, which posits that noisy information is sequentially sampled

until a decision criterion is reached where a choice is ultimately made (Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & McKoon, 2008).

Although the sequential sampling framework offers an explanatory account of how information is acquired over time, how the decision criterion is arbitrarily determined is less known. Technically, the agent would benefit most from sampling until certainty and risk are eliminated, something that is ecologically invalid due to cognitive biases and cognitively computationally infeasible. Instead, people appear to utilize heuristics that guide the decision to make a choice (i.e., a naturally occurring stopping rule; Costa & Averbeck, 2015). One theoretical account of termination in choice is that an internal termination threshold is set. A choice is made when the termination threshold is reached, leading to either a true-negative response or a false-negative error (Wolfe, 2021). The termination threshold is set adaptively, where with each correct response, the termination threshold is lowered, resulting in subsequent faster terminations (and vice versa). Akin to Signal Detection Theory (Tanner Jr. & Swets, 1954), judgments are based on an internal criterion that shifts with the amount of prevalence of information. Low prevalence of information leads to internal criterion shifts becoming more conservative, while greater prevalence of information leads to internal criterion shifts becoming more liberal (Chun & Wolfe, 1996; Wolfe, 2021; Wolfe & Van Wert, 2010). However, slowing down does not correct the prevalence effect, as agents are more likely to make incorrect judgments when prevalence is low versus high (Wolfe & Van Wert, 2010)

However, not all choices are made equal; some are based solely on preferences, while others are more inherently risky or uncertain than others. Similarly, some choices have higher probabilities of being correct or result in reward maximization if a particular decision strategy is applied. Optimal stopping is one such academic endeavor that concerns itself with how a particular action or set of actions leads to the maximization of expected rewards and the minimization of expected costs. Optimal stopping has been applied in various other disciplines, such as mathematics, statistics, and economics, to uncover the objectively best solution to a given problem. The utility of optimal stopping in real-world scenarios, beyond simple arbitrary statistical problems, can be highlighted in games such as Blackjack. In this paper, we first describe select optimal stopping problems – some of which have previously been utilized to understand choice behavior – highlight their corresponding optimal policies, and contrast these problems. Following this, we will highlight the generalizability of the

optimal policy for the *Secretary Problem*. Lastly, we discuss the utility of optimal stopping policies in the real world.

Optimal stopping problems

In psychology, several tasks – where an optimal policy is available – have been used to study various aspects of judgment and decision-making. These tasks have, for example, been used to assess when and why people violate or comply with the optimal policies associated with optimal stopping problems (e.g., see Lloyd et al., 2022; van de Wouw et al., 2021). Below are four optimal stopping problems that vary in their respective optimal policy.

Secretary Problem

The *Secretary Problem* is likely the most well-known optimal stopping problem and is also known by numerous names such as the marriage problem, game of Googol, and the best choice problem. In the *Secretary Problem*, the agent is faced with *n* number of applications with the aim of finding the most suitable candidate for a hypothetical position. To do this, the agent must go through each application sequentially and stop when they believe they have found the most suitable candidate. Candidates may only be sampled once such that an agent is not allowed to return to and choose any previous candidates. Once an agent believes they have found the most suitable candidate, they can hire them, and the game is over.

Applying optimal stopping theory to the *Secretary Problem* illustrates that the likelihood of correctly choosing the most suitable candidate is 1/3 chance. Specifically, the optimal stopping point is derived by using the following equation (Ferguson, 1989):

$$\frac{n}{e} \qquad \text{Eq. 1}$$

where *n* is the total number of candidates available, and *e* is Euler's constant. The result of applying the equation is rounded to the nearest integer and reflects the number of candidates needed to be sampled before committing. As such, the agent should make *n* samples and commit to the next candidate with a larger score than any of the previous sampled numbers. Although optimal stopping theory provides a useful framework for when to stop sampling candidates, the math-based system is not always correct. If one candidate has a sufficiently large score, the agent will likely choose the candidate, causing sampling to

end despite what optimal stopping theory might suggest. Other variations of the *Secretary Problem* include, for example, choosing the second-best candidate (Vanderbei, 2012), offer refusal (i.e., an associated probability that the chosen candidate may reject the offer), or allowing the agent to make multiple choices (Gilbert & Mosteller, 1966). Crucially, using different variations to the problem changes the optimal policy, e.g., having to use backward induction if agents are allowed to make multiple choices (Costa & Averbeck, 2015; Gilbert & Mosteller, 1966; van de Wouw et al., 2021).

Devil's Task

The *Devil's task* was initially created to assess risk preferences (Slovic, 1966) and has, since its creation, been widely used in psychology (e.g., Dahne et al., 2013; Liu et al., 2022; Studer et al., 2013). The task is a binary sequential decision task where agents are faced with either opening a box or stopping the game on every trial, where the number of boxes within a game can vary. The boxes are opened sequentially, and the agent can stop at any given point in the game. All but one of the boxes contains rewards that are earned when opened – the box not containing a reward instead contains a devil. If the agent opens the box containing the devil, the agent loses all accumulated rewards, and the game starts over. The optimal strategy is denoted as follows (Büchel et al., 2011; Slovic, 1966):

$$V_i = \big(1 - p(i)\big) \times i \qquad \text{Eq. 2}$$

where $p(i)$ is the probability of revealing the Devil in the i^{th} box. Assume a sequence of 10 boxes with unbiased probabilities of finding the Devil in any box i (i.e., 10%); the optimal stopping strategy is to choose half the total number of boxes, as the expected value decreases for the sixth box. Note, however, that if the underlying probability structure is biased (e.g., a 5% chance of finding the Devil in the first box but a 10% chance of finding it in the second box), the stopping point shifts based on this biased probability structure. Thus, the optimal stopping rule relies on the agent having an (potentially imperfect) understanding of the underlying probability distribution in order to apply it successfully.

Burglar Problem

A burglar has the opportunity of carrying out a sequence of robberies. With each robbery, the burglar earns rewards, but for each robbery, there is a chance for the burglar to get caught. The loot increases with each successful robbery, but all accumulated gains are

lost if caught. Crucial to this problem is that the likelihood of successfully getting away with each robbery is known. Thus, the only difference between the *Devil's Task* and the *Burglar Problem* is that the probability of losing on any i^{th} trial is known. Utilizing optimal stopping theory, the number of robberies that should be carried out is derived from the following equation (Haggstrom, 1967):

$$V_i = \max\{i, p\sum_j p_j V(i+j)\} \quad \text{Eq. 3.1}$$

The burglar should stop in state i if $i \geq p(\sum_j p_j(i+j)$, where the optimal stopping condition is $i \geq p(i+\mu)$ as $\mu = \sum_j j p_j$ denotes the expected utility from a successful robbery. Together this gives:

$$i \geq \frac{p\mu}{1-p} \quad \text{Eq. 3.2}$$

Thus, the robber should stop whenever the current state is greater than or equal to the probability of succeeding.

A simpler version of the formulations above can be demonstrated by:

$$N \cong \frac{P(x)}{P(y)} \quad \text{Eq. 3.3}$$

where *x* is the probability of succeeding with the robbery and *y* is the probability of getting caught. For example, if a skilled burglar has a 90% chance of successfully robbing a house (and, therefore, a 10% chance of getting caught), the optimal stopping point is $\frac{P(90)}{P(10)} \approx 9$ robberies.

Game of Pigs

The *Game of Pigs* (also known as *Pass the Pigs*) is, unlike the other problems, a competitive game involving two rather than one agent. On any given round, one agent rolls two d6 die, where the agent earns the number of eyes in points of each roll. If the die lands on '1', all accumulated points are lost, and the turn is passed onto the other agent. An agent can decide to stop rolling the die, and all accumulated points are added to the agent's score. The game finishes once one of the agents reaches a predetermined score (e.g., 100 points). In the commercial version of the game, commonly known as *Pass the Pig*, the game is played by throwing two custom asymmetrical dice in the form of two pigs. How the pigs land

determines how many points are earned or whether the turn is lost and passed to the second agent.

Maximizing the odds of winning, an agent can apply a pseudo-optimal strategy, which takes its form as a *score heuristic*. This strategy is given by solving the following equation (Neller & Presser, 2004):

$$\frac{5}{6}(\mu + n) > n \qquad \text{Eq. 4.1}$$

where $\frac{5}{6}$ is the probability of rolling anything other than a 1, and μ reflects the average number of points (4) that can be earned on any roll. n represents the current score. Solving the equation reveals that an agent should continue to roll for as long as $n < 20$. Thus, an agent should continue to roll for as long as $n < 20$, where when $n \geq 20$, the associated risk of rolling again grows increasingly larger as how much can be lost is cumulative.

An optimal strategy can be applied to the game to improve the odds of winning, which has to be applied on each dice toss. Applying a value iteration algorithm that iteratively estimates the value of any given action in all possible states to maximize future rewards (Neller & Presser, 2004). The estimated value at any given state ($V(s)$) is given by:

$$\max_a \sum_{s'} P^a_{ss'} [R^a_{ss'} + \gamma V(s')] \qquad \text{Eq. 4.2}$$

where s and s' are the current known and future states, respectively, and a is an action. $P^a_{ss'}$ is the probability transitioning from state s to s' when taking action a, and $R^a_{ss'}$ is the expected immediate reward for each such transition.

This optimal strategy may inform an agent how to play at any given game stage (e.g., see Figures 3 & 4 of Neller & Presser, 2004). However, applying the strategy is cognitively computationally infeasible due to the number of probabilities that need to be calculated on any throw and the limited cognitive resources available in the human brain.

Contrasting optimal stopping problems

Across the aforementioned problems, there are some shared commonalities (see Table 1), yet the subtle difference between problems means no optimal policy is shared among them. Such differences between problems may ultimately subject a naïve agent to different cognitive biases. For example, in the Secretary Problem, the agent is instructed to find the most suitable/superior candidate (i.e., a described problem), while the other problems are

experiential in nature. This may subsequently promote differential decision-making (assuming the agent is oblivious to the optimal strategy for any given problem *i*), akin to that illustrated by the description-experience gap (Hertwig & Erev, 2009; Hertwig & Wulff, 2022; Ludvig & Spetch, 2011). In a similar vein, when the problem is descriptive, a static rather than an iterative choice rule can be applied because relevant probabilities are known and immutable with any given choice *n*. Another key difference between the problems is whether they employ a static or iterative choice rule; where a static, unlike iterative, choice rule does not have to be re-evaluated after each choice *n*. In case of the *Burglar Problem* and *Game of Pigs*, the optimal policy has to be revised after each choice, but utilizing the simplified – or pseudo-optimal policies – results in a static choice rule (i.e., predetermined *n* choices have to be made). For example, in the *Game of Pigs,* using the pseudo-optimal policy means the agent should simply continue to roll the dice until they reach 20 points rather than iteratively assess if each state is optimal.

A stark difference between the optimal policies across problems is their inherent complexity. The problems with more complex optimal policies (i.e., *Game of Pigs* and the *Burglar Problem*) also have a simplified version that is pseudo-optimal but more easily implemented in practice. The change from optimal to pseudo-optimal policies manifests itself by straying away from value iterative policies to more static heuristics. This highlights the problem with overly complex optimal policies and illustrates the need for simplified versions – or static heuristics – which provide approximations of the optimal policy. Specifically, due to limited cognitive resources, value iterative policies (e.g., like in *Game of Pigs*) can become infeasible to implement in practice.

Table 1

Characteristics of optimal stopping problems

Optimal stopping problems	Described or experiential	Memory component	Known likelihoods	Static or iterative choice rule	Probabilistic outcomes	Has simplified policy?
Secretary Problem	Described	Yes*	No	Static	No	No
Devil's Task	Experiential	No	No	Static	Yes	No
Burglar Problem	Experiential	No	Yes	Both	Yes	Yes
Game of Pigs	Experiential	No	Conditional**	Both	Yes	Yes

Note. The table highlights differences between optimal stopping problem-based select problem characteristics.

* Assuming participants do not have full trial history (traditional version does not have trial history).

** Assuming a fair die, the likelihood is known, but if pig figurines are used, the likelihood is unknown.

Simulating the Secretary Problem

The utility of optimal stopping rules is given by their generalizability across *n* options. If a given rule is only optimal under certain conditions, the rule's utility is minimized in cases where *n* size is small, given that the optimality of choice changes based on conditional restraints. The optimal stopping rule in the Secretary Problem is a perfect example of a generalizable heuristic. Simulating the Secretary Problem using the previously outlined optimal stopping rule across various set sizes highlights its generalizability. Simulating the problem using 100 exponentially spaced set sizes (10 to 100,000) illustrates that at least 37% of all chosen candidates across all set sizes is the best possible candidate (see Table 2). As the set sizes grow larger, the percentage of the chosen candidates in the top 1% increases (up to 64%). Five billion simulations were conducted for set sizes smaller than 1.070, whereas 1 billion simulations were conducted for larger than 1.070.

Table 2

Results of applying the optimal stopping rule to the Secretary Problem across 10 different set sizes

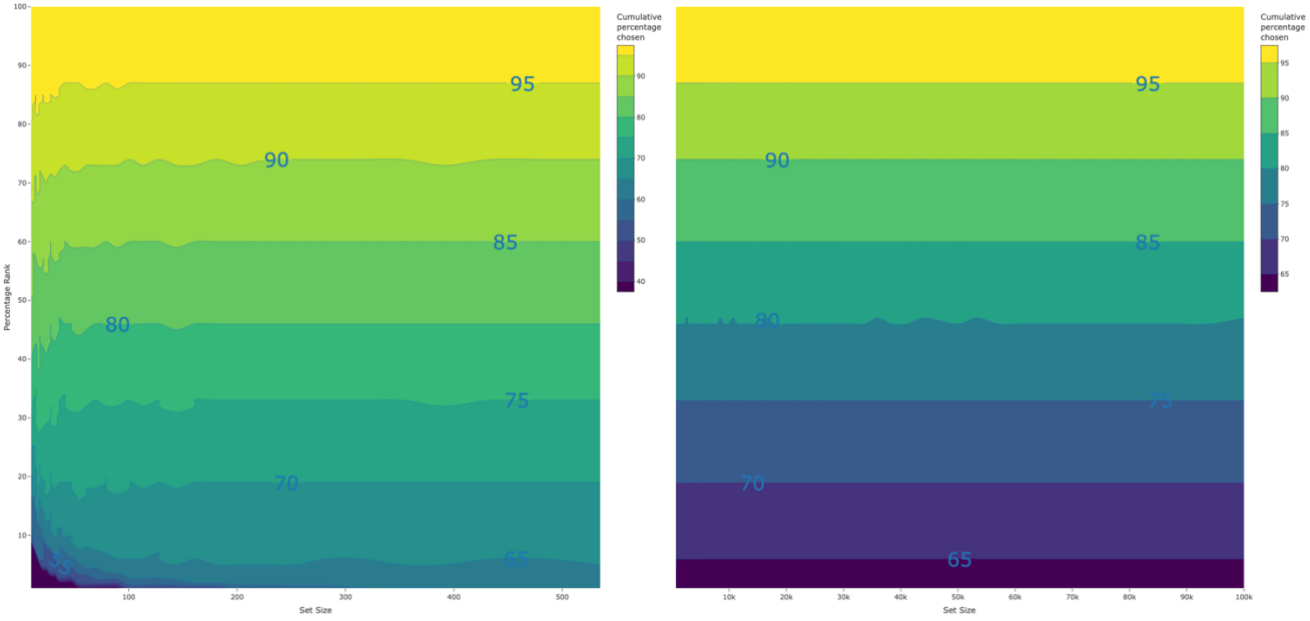
Rank	Set sizes									
	10	21	36	101	161	1.070	4.091	15.473	46.881	100.000
Best Item Chosen	40%	38%	38%	37%	37%	37%	37%	37%	37%	37%
1%	40%	38%	38%	51%	51%	64%	64%	64%	64%	64%
5%	40%	55%	53%	64%	65%	65%	65%	65%	65%	65%
10%	40%	63%	64%	67%	67%	67%	67%	67%	67%	67%
20%	60%	72%	71%	71%	71%	71%	71%	71%	71%	71%
25%	71%	74%	72%	73%	73%	72%	72%	72%	72%	72%
50%	83%	83%	81%	82%	82%	82%	82%	82%	82%	82%
75%	93%	92%	91%	91%	91%	91%	91%	91%	91%	91%
100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Last Item Chosen	33%	4%	3%	2%	1%	0%	0%	0%	0%	0%

Note. The table shows the cumulative percentage of chosen candidates and their respective ranks. As the set sizes grow larger, the last candidate to be chosen rapidly becomes 0%.

In addition, as set sizes grow larger, the optimal policy becomes more stable across time despite fewer simulations where a candidate in the top 5% becomes more likely to be chosen (Figure 1). The increased stability is particularly evident as the curve plateaus as the set sizes grow larger.

Figure 1.

Cumulative percentage rank of chosen candidates in Secretary Problem simulations.



Note. Contour plot of the cumulative percentage chosen for a given candidate and their percentage rank amongst all other candidates across 100 exponentially spaced set sizes. The left panel illustrates set sizes ranging from 10-535, whereas the right panel illustrates set sizes ranging from 535-100.000.

Optimal stopping in the real world

Thus far, the utility of optimal stopping rules has been illustrated in arbitrary mathematical problems. Here, the utility of optimal stopping rules will be highlighted in the context of Blackjack and power analysis (e.g., Baker et al., 2021). Additionally, the importance of available samples will be illuminated by showing that optimal choices differ as a function of available evidence (i.e., suboptimal choice when samples are limited).

Blackjack

The goal of Blackjack is to get a total score of 21 or as close to 21 as possible without going over for both the player and dealer. If the total sum of all cards held by the player is

below the total sum of the dealer, the player loses. Although at first glance, Blackjack may appear to be a game of chance only – beyond the strategy of counting cards[1] – the game has an optimal strategy to minimize house advantage and increase the probability that the player wins (Baldwin et al., 1956). The optimal strategy – also known as the basic strategy – is based on the player's hand at any given stage and the hand of the dealer and is given by (Baldwin et al., 1956):

$$v(x,y) = \max(\mu(x,y), \sum_{c=1}^{y} P(c) \times v(x+c,y)) \quad \text{Eq. 5}$$

where *x*, *y* is the player's total hand and the dealer's hand, respectively, and *v*(*x*, *y*) is the maximum expected utility given these. $\mu(x,y)$ represents the expected utility of standing given the hand of the player and dealer. *P*(c) represents the probability of getting any card *c*. This strategy also extends to cases where multiple decks are used, as *P*(c) is the only thing that changes, though house advantage increases with additional decks.

Because all possible outcomes are known prior to playing (i.e., all possible combinations of player and dealer hands), this strategy can be used to create a table with the optimal strategy prior to playing the game. Leveraging this information will give the player the best possible odds of minimizing losses when playing Blackjack.

Power analyses

The use of optimal stopping is also relevant in the world of science, particularly when determining the appropriate sample size for a given study. Conducting power analyses has become a widespread tool among scientists to approximate the appropriate sample size given a particular design. This is, indeed, useful as low statistical powered studies provide unreliable results and exaggerate effect sizes (Button et al., 2013; Elliott et al., 2020). Power analysis can be further optimized by accounting for measurement reliability. The number of participants needed for a given experiment decreases as a function of effect size and measurement reliability (Zuo et al., 2019). One way to increase measurement reliability – beyond ensuring its validity – can be to increase the number of trials in the experiment. Representing statistical power as a joint function of sample size and the number of trials

[1] A strategy rarely useful, as the deck is typically reshuffled after each game, especially in casinos. In a similar vein, house rules may differ, potentially not allowing surrendering or doubling down, or apply restrictions for splits (e.g., cards must be of same rank).

used in an experiment enable situations where statistical power is not compromised when using fewer participants if participants complete a larger number of trials (Baker et al., 2021). As such, assessing and ensuring measurement reliability is pertinent to optimize participant sampling and minimize research costs. This relationship between statistical power and measurement reliability highlights the utility of creating optimal and pseudo-optimal policies as they can help minimize costs associated with and ensure the quality of research, something which extends beyond academia.

Limited samples

In more generalizable real-world optimal stopping, the available samples can often be scarce. When samples are limited or come at a cost, optimal choices differ as a function of the available evidence. For example, when introducing a sampling cost, the optimal choice strategy in the *Secretary Problem* change (Lorenzen, 1981). In more generalizable situations, when samples are limited, people's representations of objective probability distributions become distorted (Hertwig & Pleskac, 2010). This problem is further perpetuated by the fact that people typically sample frugally, leading to sampling errors (Hau et al., 2010; Hertwig et al., 2004), resulting in sub-optimal decisions. A problem that is minimized or completely mitigated as the number of available samples increases (Hertwig & Pleskac, 2010), illustrating the importance of large samples to make accurate and optimal choices. Of course, generously sampling to make optimal decisions may not be as simple despite the inherent desirability of making well-informed and optimal choices. Specifically, once sampling costs enter the equation, which makes a typical simple optimal stopping policy more complex (e.g., Lorenzen, 1981), potentially to the point where approximations become less labor-intensive and cheaper.

Concluding remarks

For any given decision, optimality is most desirable as it maximizes the probability of rewards and minimizes the probability of undesirable states (e.g., increased costs). While optimal policies can effortlessly be applied in certain situations, we highlight that, at times, it is cognitively infeasible for individuals to apply the most optimal policy and instead must rely on more simplified heuristics (e.g., in the *Game of Pigs*). In contrast, cognitively feasible and

simple policies have the utility of being generalizable to larger problems without compromising the expected value of a given choice.

Despite the many interesting findings found by using sequential choice tasks with an optimal policy, there is still plenty left to be discovered; the translation between choice behavior between two-alternative forced-choice tasks and sequential choice tasks and their relation to optimality/rationality is yet to be determined. Relatedly, while experimentation using the *Devils' task* has shown that striatal activity is associated with missed opportunities and predicts future choices (Büchel et al., 2011), one might be curious whether these findings persist if participants are aware of and utilize the optimal policy. That is, do neural substrates differ when knowing one behaves optimally despite losing or experiencing missed opportunities? We believe that utilizing sequential choice paradigms with optimal policies of varying difficulty will allow researchers to investigate how people deviate from optimality and why this may be the case.

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Chapter 3

Exploring reward anticipatory on incidental encoding during learning in risky choice

Abstract

Rewards and reward anticipation play a crucial role in shaping behavior, and prior research consistently demonstrates their positive impact on the incidental encoding of task-irrelevant stimuli. These memory-enhancing effects are attributed to increased activation of the dopaminergic midbrain during reward anticipation, facilitating subsequent memory formation in the hippocampus. However, the influence of learning processes on reward anticipation and incidental encoding remains unclear. In a series of pre-registered experiments, we investigated the effects of reward anticipation on incidental encoding of task-irrelevant stimuli in a risky associative learning task where participants had to learn about the underlying reward structures. We successfully replicated previous findings showing changes in risk-seeking behavior and memory-related biases. However, the results for recognition memory for task-irrelevant stimuli were mixed, with Experiment 2 showing no significant effects. In contrast, Experiment 3 found that high-value rewards significantly influenced recognition memory when making risky choices, while choosing the fixed-outcome option significantly affected recognition memory compared to choosing the risky option. Two attempts to replicate the curiosity-enhancing effects on incidental encoding were unsuccessful in an online sample. Together, these results potentially suggest that the prioritization of incremental learning may down-regulate incidental encoding of task-irrelevant stimuli. However, given the mixed results and potential confounds, such as divided attention, this line of research warrants further investigations using in-lab samples. Moreover, such experiments would further help elucidate the complex relationship between stimuli memorability, experienced-based memories, and decision-making.

Keywords: risky choice, decisions from experience, reward anticipation, episodic memory

Introduction

Memory is a fundamental cognitive process critical for guiding behavior and shaping decision-making processes (Madan et al., 2021; Murty et al., 2016; Shohamy & Daw, 2015; Wimmer & Shohamy, 2012). Converging findings have shown superior memory for rewarding and punishing stimuli (e.g., Murayama & Kitagami, 2014; Shigemune et al., 2014) and high- compared to low-value reward-associated stimuli (Adcock et al., 2006; Bowen et al., 2020; Castel et al., 2002), with a few exceptions (Wittmann et al., 2005, 2011). Furthermore, reward values differentially affect memory consolidation, with higher rewards associated with better memory retention (Shohamy & Adcock, 2010; Wittmann et al., 2005, 2011). These memory-enhancing effects are believed to arise from reward anticipation leading to enhanced encoding via increased reward-related activation of the dopaminergic midbrain, facilitating subsequent memory formation in the hippocampus (Shohamy & Adcock, 2010; Wolosin et al., 2012). Crucially, the influence of reward anticipation affects not only memory for reward-predictive stimuli but also incidental encoding of unrelated stimuli (Fandakova & Gruber, 2021; Mather & Schoeke, 2011), where items with low-reward anticipation are impaired (Gruber et al., 2014). These reward anticipation effects extend beyond monetary rewards as curiosity for knowledge shows the same effects on incidental encoding (e.g., Fandakova & Gruber, 2021; Gruber et al., 2014).

However, most research assessing reward anticipation (monetary, motivational, or curiosity) neglects the potential influence of learning processes on reward anticipation (for discussion, see Simonsen & Madan, 2021). Related work has shown the importance of reward prediction errors (Schultz et al., 1997) when learning about rewards, and how they play a significant role in incidental encoding, where large prediction errors result in better remembrance of stimuli (Rouhani et al., 2018). Moreover, the relative placement between stimulus and reward further affects incidental encoding. Specifically, when an item is temporally farther from the reward, memory is enhanced, but only when obtaining a reward is uncertain (Stanek et al., 2019). Interestingly, episodic memory of the incidentally encoded unrelated stimuli has been found to decrease reward prediction errors and interfere with reward learning in a probabilistic bandit task (Wimmer et al., 2014). As such, it is likely that as people, over time, adaptably learn and acquire knowledge about reward structures in their choice environment (e.g., Daw et al., 2011; Gershman & Daw, 2017), they adjust their

reward anticipatory responses accordingly. Consequently, the magnitude of anticipatory responses may diminish as learning progresses, potentially impacting the encoding of task-irrelevant stimuli.

Unsurprisingly, as people gain increased experience with the choice environment, they gradually improve their choices (e.g., Madan et al., 2012; Madan & Spetch, 2012), but they also become biased in their choices. Priming past choices or making choices in a familiar environment increases the likelihood of making the same choice again (Bornstein et al., 2017; Bornstein & Norman, 2017; Duncan et al., 2019; Duncan & Shohamy, 2016). Moreover, in risky choice environments, people shift their risk preferences, becoming moderately more risk-seeking for gains but more risk-averse for losses with increased experience (e.g., Ludvig et al., 2018; Madan et al., 2014, 2017) postulated to be due to memory biases and allocation of limited cognitive resources (Lieder et al., 2018). Due to memory biases, these changes in risk preferences with increased learning likely cause participants to adjust their reward anticipatory responses, leading to differential effects of reward anticipation and reward prediction errors on encoding.

In a series of pre-registered studies, we aimed to better understand the interaction between reward processing and memory formation in risky choices. To do so, we employed a risky value-based associative learning task in which participants chose between a probabilistic and deterministic option and had to learn about the underlying reward structures. This allowed us to investigate whether reward cues associated with differential values of rewards (high vs. low) affected memory for task-irrelevant stimuli during learning, where reward anticipation should, theoretically, decline with increased experience. Specifically, we hypothesized participants' memory for task-irrelevant stimuli would be negatively affected with experience such that participants would exhibit a primacy effect (i.e., worse memory for task-irrelevant stimuli as the experiment progressed). Moreover, we expected participants to have better memory for items associated with high- compared low-value rewards replicating past research (e.g., Adcock et al., 2006; Bowen et al., 2020; Castel et al., 2002), and when choosing the probabilistic risky option (i.e., increased reward anticipation due to uncertainty). Lastly, we hypothesized memory for task-irrelevant stimuli would be enhanced when participants received the worst possible outcome following a risky decision through reward prediction error mechanisms (e.g., Rouhani et al., 2018; Rouhani & Niv, 2021).

Experiments 1-3

Methods

We first conducted a direct replication study to ensure the risky choice task could replicate past findings in an online sample (Experiment 1). Following the results of Experiment 1, we conducted two pre-registered studies to address the main research question: whether reward anticipation would dissipate with increased learning of underlying reward structures. Data and experimental tasks for all experiments are available on the Open Science Framework (OSF; https://osf.io/kxh3a/).

Participants

In Experiment 1, 112 participants were recruited to participate in the study (59 female and 12 undisclosed; M_{age} = 27.08 years, *SD* = 6.72). In Experiment 2, 101 were recruited (59 female and 10 undisclosed; M_{age} = 26.74 years, *SD* = 4.96). In Experiment 3, 202 participants were recruited (82 female and 5 undisclosed; M_{age} = 26.93 years, *SD* = 4.71). Participants across all three experiments were recruited from Prolific.

In all three experiments, participants were paid £5 for participating. In Experiments 1 and 2, participants were paid a £1 bonus for every 384 points after the first 12,600 points earned, up to a maximum of £5. Conversely, in Experiment 3, participants were paid a £1 bonus for every 256 points after the first 8,640 points earned. Experiment 1 was approved by the University of Alberta's ethics board, and Experiments 2 and 3 were approved by the University of Nottingham's ethics board.

Procedure

Across all three experiments, participants chose between two doors selected from four possible doors on most trials. Doors led to either a fixed low-value gain (25), a fixed high-value gain (65), a risky low-value gain (15 or 35), or a risky high-value gain (55 or 75). Probabilities for either of the outcomes for risky doors were 50%. Participants learned about probability distributions and outcomes by choosing the doors. After selecting a door, the door disappeared, and feedback of the number of points earned appeared along with a cartoon graphic of a pot of gold for 1.1 s. After receiving reward feedback, a black circle

appeared in the middle of the screen, which had to be clicked to start the next trial and was used to re-center the cursor. The next trial was initiated 1 s. after clicking the black circle. The total amount of accumulated points was displayed continuously on the screen.

Participants were shown trial-unique images in Experiments 2 and 3 before receiving their reward. In Experiment 2, the images were shown for 1 s. while in Experiment 3, the images were shown for 2 s. In Experiment 3, participants were also asked to make an animacy judgment (animal or object) about the images. If a judgment were not made within the first 2 s., the trial-unique image would disappear, and the trial would continue once a judgment had been made.

The number of blocks differed between experiments: Experiments 1 and 2 consisted of 5 blocks, whereas Experiment 3 consisted of 4 blocks[2]. Each experimental block consisted of 48 trials and included three trial types. There were 24 *decision trials* requiring participants to choose between two doors: one *fixed* and one *risky*. These doors were always matched in expected value (i.e., choosing between low-value *fixed* and *risky* doors). There were 16 *catch trials* requiring a choice between a high-value and a low-value door (i.e., different expected values), and were used as an attentional check to ensure participants learned reward contingencies and were choosing to maximize their overall point total. Lastly, there were 8 *single-door trials* where participants were shown only one door and had to choose it. These trials ensured all possible reward contingencies were experienced, even if doors initially resulted in undesirable outcomes, thereby limiting hot-stove effects. Trial order in all blocks was randomized, and each door appeared equally often on either side of the screen.

[2] The discrepancy in the number of blocks used between experiments was based on a pilot study for Experiment 3 showing that 4 blocks was sufficient to induce changes in risk-seeking behavior.

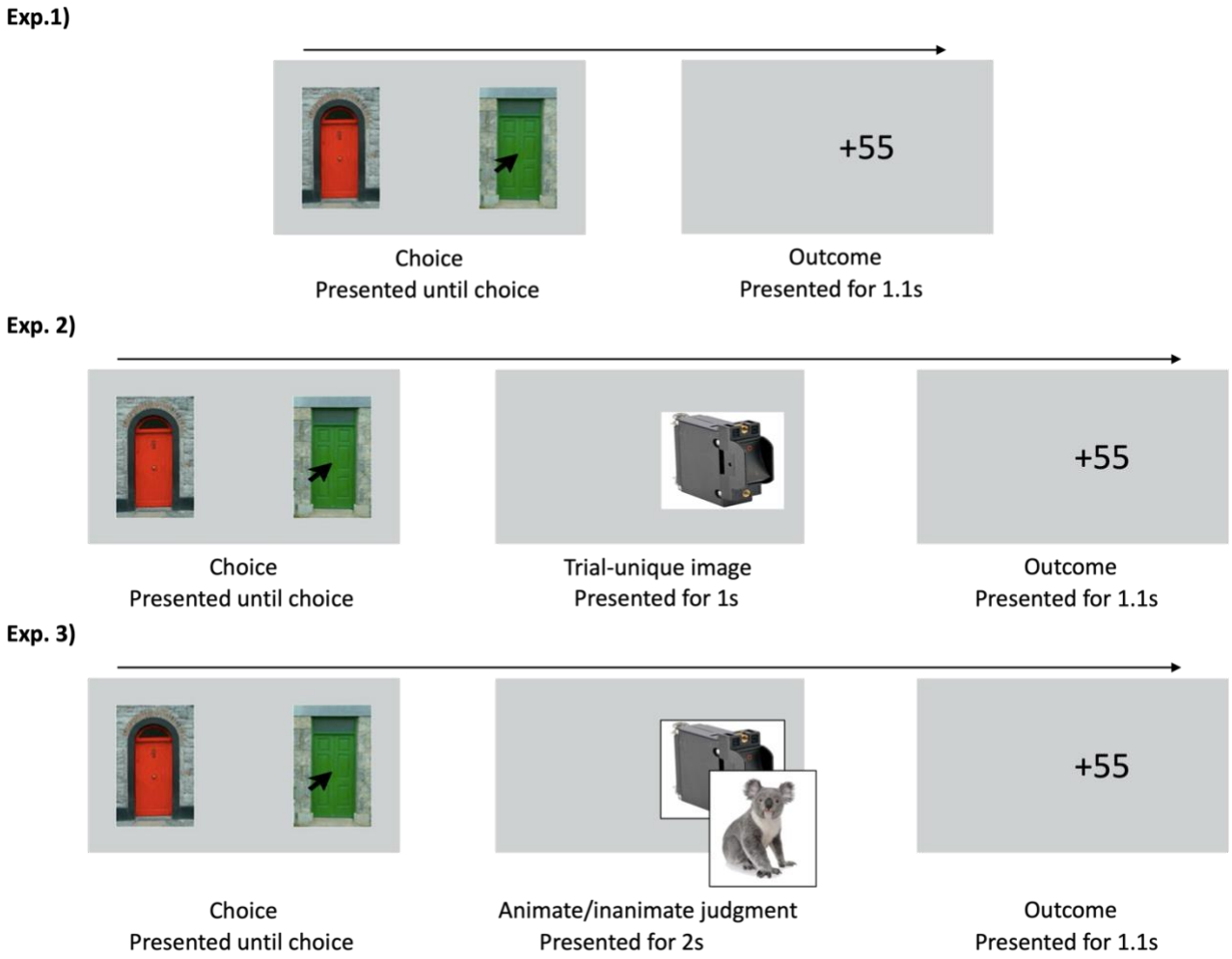


Fig. 1. Example of hypothetical trials for Experiments 1-3. In Exp. 1, participants chose between choice options and received a reward based on their choice. In Exp. 2, participants completed the same task but saw a trial-unique image for 1s. before receiving a reward. In Exp. 3, participants completed the same task as in Exp. 2, but the image was shown for 2s. and they had to make an animacy judgment before the trial continued.

In Experiments 2 and 3, participants were given a surprise recognition test after the decision task. Experiment 2 used the Mnemonic Similarity Task (MST; Stark et al., 2013, 2019), whereas Experiment 3 used a standard old/new recognition test. In the MST, participants are shown an image belonging to one of three categories: old, new, or similar (Fig. 2). Old images had previously been seen in the decision task, similar images were highly similar to previously seen old images, and new images were completely new and did not resemble old images. In Experiment 2, participants saw 120 images from each category. Old images were drawn equally from each of the 5 blocks (i.e., 24 images from each block), with an equal number of images associated with each possible outcome (i.e., the fixed outcomes and best/worst for the risky options) for both conditions (i.e., high/low). A random image

was chosen if an insufficient number of images associated with the outcome values from a given block was unavailable (e.g., because participants did not choose a given option enough in a block). In Experiment 3, participants saw 192 old images and 96 new images. The stimuli used in Experiment 3 were derived from several image databases (Brodeur et al., 2014; Hovhannisyan et al., 2021; Konkle & Caramazza, 2013; Moreno-Martínez & Montoro, 2012). In addition to images from these databases, additional high-quality images were retrieved from the internet. All the images used for the experiments are available on OSF, with the experiment files and experimental data.

In Experiment 1, following the completion of the decision task, participants' memory for each door-outcome association was tested. These memory-related tests were presented to participants following the recognition task in Experiments 2-3. First, participants were presented with the four doors in random order and asked to report the first outcome that came to mind for each of the doors. Second, participants were again shown each door in random order, along with all possible outcomes experienced in the experiment. Participants were asked to judge the frequency in percentage with which each outcome had occurred. All possible outcomes were displayed simultaneously for each door, and participants typed a number between 0 and 100.



Fig. 2. Example of the stimuli used in Experiment 2. The old images were seen during the choice task. During the surprise recognition memory test, participants saw these 'old' images, highly similar images, and completely new images.

Data analysis

Performance lower than 60% on catch trials was used as an exclusion criterion following established protocol (Ludvig et al., 2014; Ludvig & Spetch, 2011; Madan et al., 2014). In Experiments 1 and 2, catch trial performance was calculated across the entire

experiment, whereas for Experiment 3, catch trial performance was calculated across the two last blocks only. In addition, participants were excluded if they had a d-prime score lower than 0.1 on the recognition memory tests in Experiments 2 and 3. Participants were further excluded from Experiment 3 if they made more than 10% incorrect animacy judgments in the decision task. Participants' animacy judgments were reversed if they had made more than 90% incorrect judgments, as this showed a systematic misunderstanding of the key mappings (15 participants had their responses reversed). Following exclusion, a total of 100, 58, and 86 participants were eligible for analysis for Experiments 1-3, respectively. The total number of excluded participants for each exclusion criterion is shown in Table 1. Responses faster than 200ms on recognition memory trials were removed when calculating participants' overall recognition memory performance.

Risk preference was calculated as the probability of choosing the risky door. Changes in risk preference over time were assessed using a Value x Block ANOVA (2 x 5 in Experiments 1 and 2; 2 x 4 in Experiment 3), and differences in risk preference were compared across the last two blocks using a t-test. Only the last two blocks were selected as participants would have had sufficient opportunity to learn the underlying reward structures.

In Experiment 2, two types of recognition memory were calculated for all participants: corrected recognition scores and the lure discrimination index (LDI; Stark et al., 2013, 2019). Corrected recognition scores were calculated as the hit rate subtracted from the false alarm rate. The LDI was calculated as the correct proportion of 'similar' responses to similar items – 'similar' responses to new items. A 2 (Memory Type) x 5 (Block) x 2 (Choice) x 2 (Value) ANOVA was performed to assess the effect of experience with reward contingencies on the two memory types as a function of the choice made (fixed/risky) and value (high/low). To assess the effects of reward outcomes when making risky choices (best/worst) and value (high/low) on memory, a 2 (Memory Type) x 2 (Outcome) x 2 (Value) ANOVA was conducted. A separate set of ANOVAs were also conducted using proportion correct for old and similar images to ensure consistency in analyses across Experiment 2 and 3 since Experiment 3 used an unequal number of images during the recognition test.

Similar statistical analyses were applied in Experiment 3 to assess the same effects but did not include different memory formats. Moreover, as Experiment 3 used an unequal number of images during the recognition test, we used proportion correct as a proxy for recognition memory. We also included animacy in the ANOVAs as previous research

indicated better memory for animate than inanimate stimuli (e.g., Nairne et al., 2013, 2017). Thus, in Experiment 3, a 5 (Block) x 2 (Choice) x 2 (Value) x 2 (Animacy) ANOVA was used to assess the effect of experience with the reward contingencies on memory as a function of the choice made (fixed/risky) and value (high/low). A 2 (Outcome) x 2 (Value) x 2 (Animacy) ANOVA was used to test the effects of reward outcomes when making risky choices (best/worst) and value (high/low) on memory.

In all experiments, the first outcome reported test was assessed using two χ^2 tests – one for each risky option. For the frequency judgment test, two paired t-tests were used. In the frequency judgment analysis, participants were excluded from a given option if the summed response for that option fell below 75% or rose above 150%. The relationship between risky choice and memory was assessed using partial correlations controlling for experienced outcomes.

Given the *a priori* hypotheses, all tests were one-tailed. Greenhouse-Geisser correction for non-sphericity was applied where appropriate, and all tests were repeated-measures.

Table 1

Exclusions across Experiments

Note. Some participants met multiple criteria for exclusion, so the final row "total" value does not reflect the total number of participants listed within the column but instead represents the total number of participants excluded.

Reason for Exclusion	Experiment 1	Experiment 2	Experiment 3
Sample size	114	101	200
Technical issues: e.g., crashes	0	0	9 (4.5%)
Catch trials: performance lower than 60%	14 (12.28%)	12 (11.88%)	98 (49%)
d-prime: scores lower than 0.1	NA	35 (34.65%)	4 (2%)
Animacy judgments: More than 10% incorrect judgments	NA	NA	14 (7%)
Total	14 (12.28%)	43 (42.57%)	114 (56.99%)

Results

Dual-processing

To ensure the high exclusion rate in Experiments 2 and 3 was not due to dual processing interfering with reward contingency learning, a correlational analysis was conducted between participant catch trial rates and d-prime scores. Neither experiment indicated dual processing affecting performance for participants eligible for data analysis [Exp. 2: $r(56) = -0.14$, $p = .279$; Exp. 3: $r(84) = -.08$, $p = .457$]. In Experiment 3, there was, however, a significant correlation between catch trial rates and d-prime scores in the excluded sample [$r(102) = -.19$, $p < .05$]. Importantly, this significant correlation was not found when removing one excluded participant [$r(101) = -.12$, $p = .213$] who reported 'new' to all images during the recognition memory test. No significant correlation between catch trial rates and d-prime scores was observed in Experiment 2 [$r(43) = -0.154$, $p = .324$]. Thus, we cannot assume that dual processing caused interference in the task.

Risk preferences

In Experiments 1 and 2, participants' risk preferences significantly changed across the five blocks as a function of reward value [Exp. 1: main effect of Block: $F(2.9, 284.3) = 2.05$, $p = .108$, $\eta_p^2 = .021$; main effect of Value: $F(1, 97) = 41.98$, $p < .001$, $\eta_p^2 = .302$; Block × Value interaction: $F(3.4, 332.8) = 2.94$, $p < .027$, $\eta_p^2 = 0.29$; Exp. 2: $F(2.259, 128.778) = 3.545$, $p < .02$, $\eta^2_p = .059$; main effect of Value: $F(1, 57) = 13.472$, $p < .01$, $\eta^2_p = .191$; Block × Value interaction: $F(2.818, 160.639) = 5.691$, $p < .003$, $\eta^2_p = .091$]. However, no statistically significant change in risk preference across blocks as a function of Value was observed for Experiment 3 [main effect of Block: $F(2.273, 193.237) = 1.139$, $p = .327$ $\eta^2_p = .013$; Main effect of Value: $F(1, 85) = 11.394$, $p < .001$, $\eta^2_p = .118$; Block × Value interaction: $F(2.726, 231.674) = 2.035$, $p = .116$, $\eta^2_p = .023$].

Across the last two blocks, participants were 21.39 ± 1.8% (*M* ± 95% C.I.), 21.12 ± 2.23% (*M* ± 95% C.I.), 14.85 ± 2.12% (*M* ± 95% C.I.) more risk seeking for the high- than low-value option for Experiments 1-3, respectively. In all experiments, this difference in risk-seeking across the two last blocks was statistically significant [Exp. 1: $t(97) = 6.67$, $p < .001$, Cohen's $d = 0.67$; Exp. 2: $t(57) = 4.461$, $p < .001$, Cohen's $d = 0.586$; Exp. 3: $t(85) = 3.254$, $p < .001$, $d = 0.351$]. Figure 3 shows the proportion of risky choices made for the three experiments.

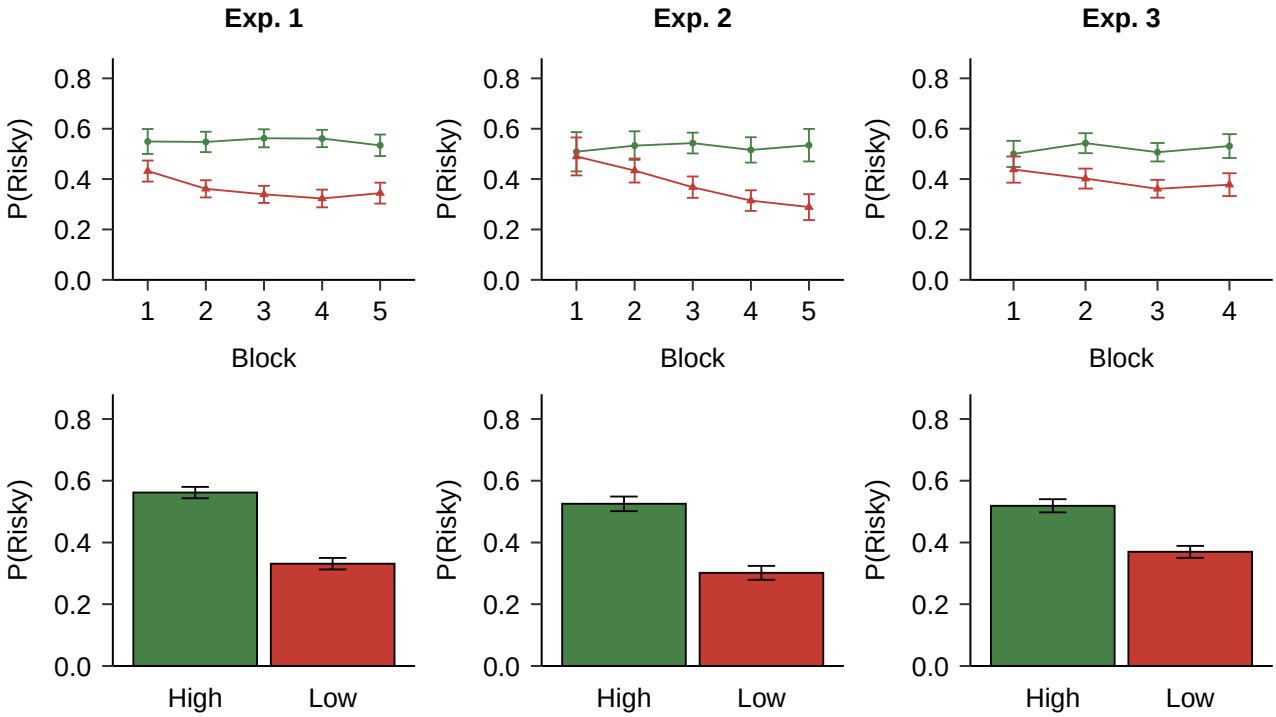


Fig. 3. Proportion of risky choices made for each condition (high/low) across all three experiments. (A-C) shows the proportion of risky choices as a function of block for Exps. 1-3, respectively, and (D-F) shows the proportion of risky choices averaged across the last two blocks for Exps. 1-3, respectively. Error bars represent 95% confidence intervals, corrected for a within-subject design (Morey, 2008).

Memory biases influencing risk-preference

Consistent with prior findings (e.g., Ludvig et al., 2014; Madan et al., 2014, 2021), people were found to overweight extreme outcomes (Fig. 4). When asked to report the first outcome that came to mind when individually seeing all the options, participants reported the best outcome (75) significantly more than the worst outcome (55) for the high-value condition in Experiment 1 [$\chi^2(1, N = 62) = 5.2$, $p < .022$], but not in Experiments 2 or 3 [Exp. 2: $\chi^2(1, N = 44) = 1.445$, $p = .228$; Exp. 3: $\chi^2(1, N = 47) = 0.532$, $p = .466$]. However, in all three experiments, participants reported the worst possible outcome (15) significantly more than the best outcome (25) for the low-value condition [Exp. 1: $\chi^2(1, N = 67) = 25.1$, $p < .001$; Exp. 2: $\chi^2(1, N = 41) = 12.902$, $p < .001$; Exp. 3: $\chi^2(1, N = 46) = 17.043$, $p < .001$].

For the high-value condition, participants reporting the best outcome (75) were significantly more risk-seeking [Exp. 1: $t(60) = 2.94$, $p < .001$, $d = 0.78$; Exp. 2: $t(42) = 5.393$, $p < .001$, $d = 1.654$; Exp. 3: $t(45) = 3.487$, $p < .001$, $d = 1.023$], even when correcting for

outcomes experienced [Exp. 1: $r(62) = .374$, $p < .001$; Exp. 2: $r(44) = .52$, $p < .001$; Exp. 3: $r(47) = .407$, $p < .002$]. Similarly, for the low-value condition, participants reporting the best outcome (35) were significantly more risk-seeking [Exp. 1: $t(65) = 2.88$, $p < .003$, $d = 0.89$; Exp. 2: $t(39) = 3.417$, $p < .001$, $d = 1.289$; Exp. 3: $t(44) = 4.066$, $p < .001$, $d = 1.511$], even when correcting for outcomes experienced [Exp. 1: $r(57) = .274$, $p < .013$; Exp. 2: $r(41) = .44$, $p < .002$; Exp. 3: $r(46) = .476$, $p < .001$].

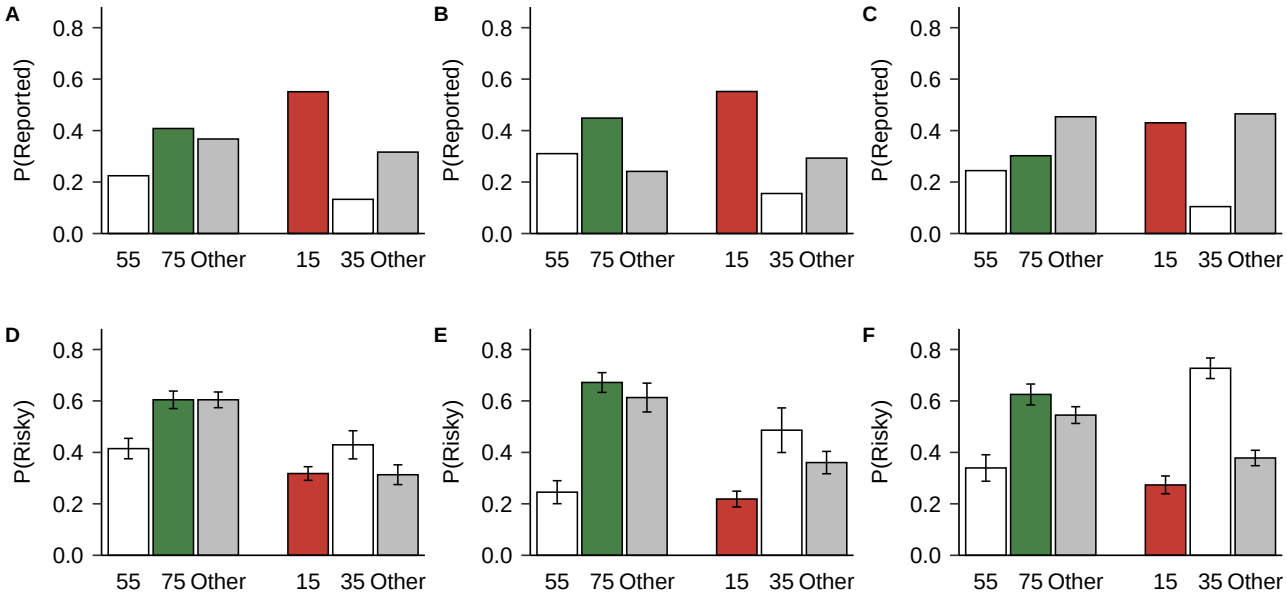


Fig. 4. Results of the first outcome reported memory test. (A-C) shows the proportion of participants who reported each outcome as the first that came to mind for Experiments 1-3, respectively. (D-F) shows the proportion of risky choices as a function of which outcome first came to mind for Experiments 1-3, respectively. Error bars represent 95% confidence intervals, corrected for a within-subject design.

Frequency judgments showed a similar pattern (Fig. 5): participants judged the worst outcome as having occurred significantly more frequent than the best outcome for the low-value condition [Exp. 1: $t(73) = 5.37$, $p < .001$, $d = 0.62$; Exp. 2: $t(51) = 5.14$, $p < .001$, $d = 0.71$; Exp. 3: $t(72) = 4.733$, $p < .001$, $d = 0.554$]. However, no reliable differences in frequency judgments were observed for the outcomes in the high-value condition [Exp. 1: $t(75) = 0.39$, $p = .653$, $d = 0.05$; Exp. 2: $t(52) = .34$, $p = .65$, $d = 0.05$; Exp. 3: $t(71) = 0.043$, $p = .517$, $d = 0.005$].

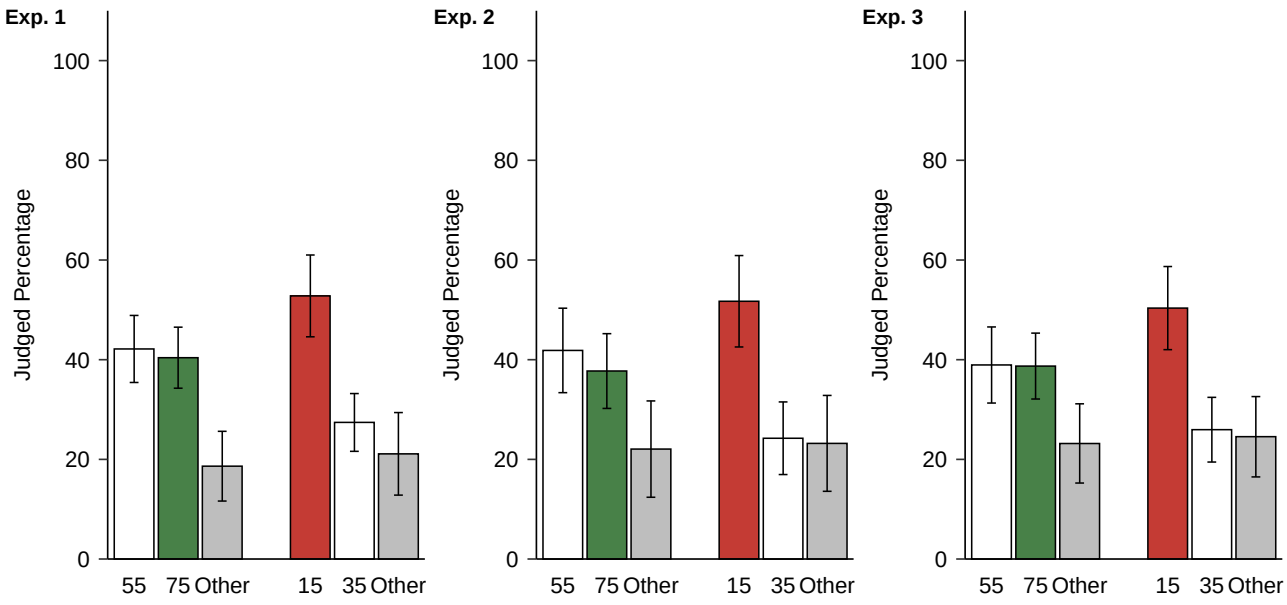


Fig. 5. Graph showing participants' judgments of the frequency of each outcome associated with a risky choice for each of the three experiments. Error bars represent 95% confidence intervals, corrected for a within-subject design.

For the low-value condition, risk-seeking decreased with judged frequencies of the worst outcome [15; Exp. 1: $r(74) = -.269$, $p < .01$; Exp. 2: $r(52) = -.35$, $p < .005$; Exp. 3: $r(72) = -.477$, $p < .001$], even after correcting for experienced outcomes [Exp. 1: $r(74) = -.215$, $p < .034$; Exp. 2: $r(52) = -.25$, $p < .036$; Exp. 3: $r(72) = -.339$, $p < .002$]. Risk-seeking was unaffected by judged frequencies for the high-value condition in Experiment 1 [$r(76) = .146$, $p = .104$], even when correcting for experienced outcomes [$r(76) = .186$, $p = .055$]. In Experiment 2, risk-seeking increased with judged frequencies of the best outcome [$r(52) = .27$, $p < .026$] for the high-value condition, but only before correcting for experienced outcomes [$r(52) = .22$, $p = .061$]. However, in Experiment 3, risk-seeking increased with judged frequencies of the best outcome [$r(72) = .329$, $p < .002$] for the high-value condition, even when correcting for experienced outcomes [$r(72) = .223$, $p < .031$].

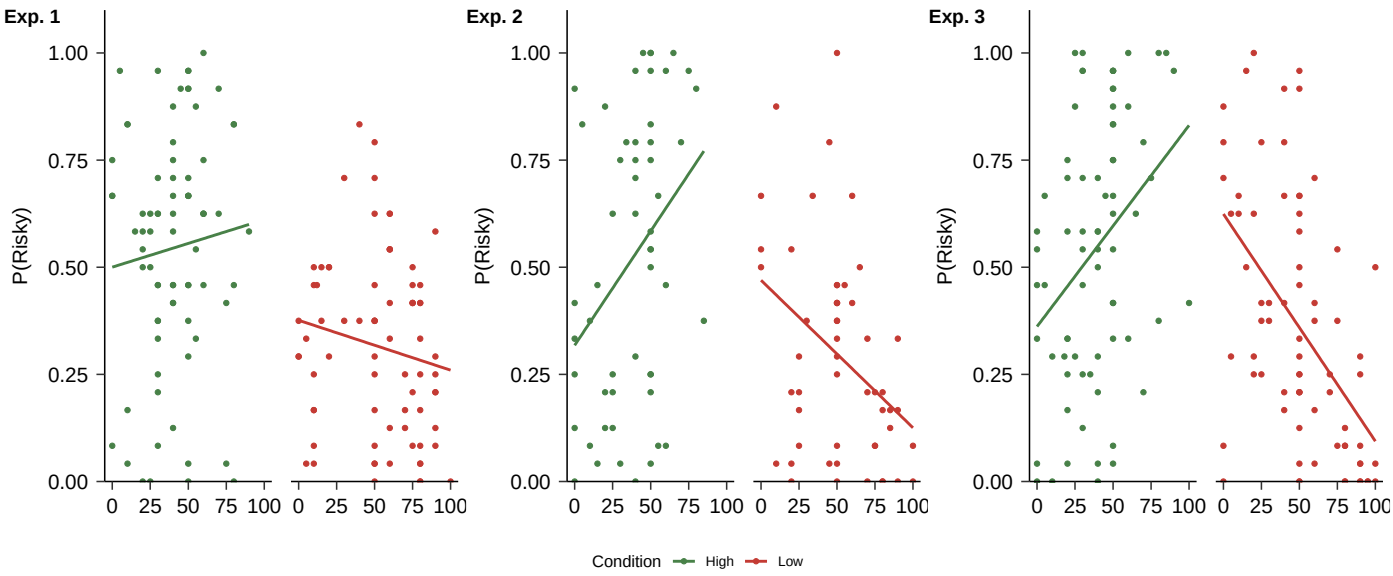


Fig. 6. Proportion of risky choices made based on the judged frequency of occurrence for the best outcome (75) for the high-value condition and the worst outcome for the low-value condition (15) for each of the three experiments.

Recognition memory tests

Recognition memory was overall poor and participants had recognition memory scores lower than chance for old stimuli both Experiments (see Fig. 7). In Experiment 2, recognition memory performance was found to significantly differ based on memory type (corrected recognition vs. LDI), with performance decreasing over time for both memory types [main effect of Memory Type: $F(1, 57) = 144.909$, $p < .001$, $\eta^2_p = .718$; main effect of Block: $F(3.841, 218.953) = 31.977$, $p < .001$, $\eta^2_p = 0.359$; Memory Type × Block interaction: $F(3.510, 200.061) = 6.337$, $p < .001$, $\eta^2_p = .100$]. Overall recognition memory performance was significantly better for REC than LDI, $t(57) = 12.038$, $p_{bonf} < .001$, $d = 1.017$. However, memory performance was unaffected by Value (high/low) and Choice (fixed/risky) for both memory types [main effect of Value: $F(1, 57) = 0.048$, $p < .828$, $\eta^2_p = 8.366e\text{-}4$; main effect of Choice: $F(1, 57) = 0.006$, $p < .936$, $\eta^2_p = 1.138e\text{-}4$; no interactions reached statistical significance].

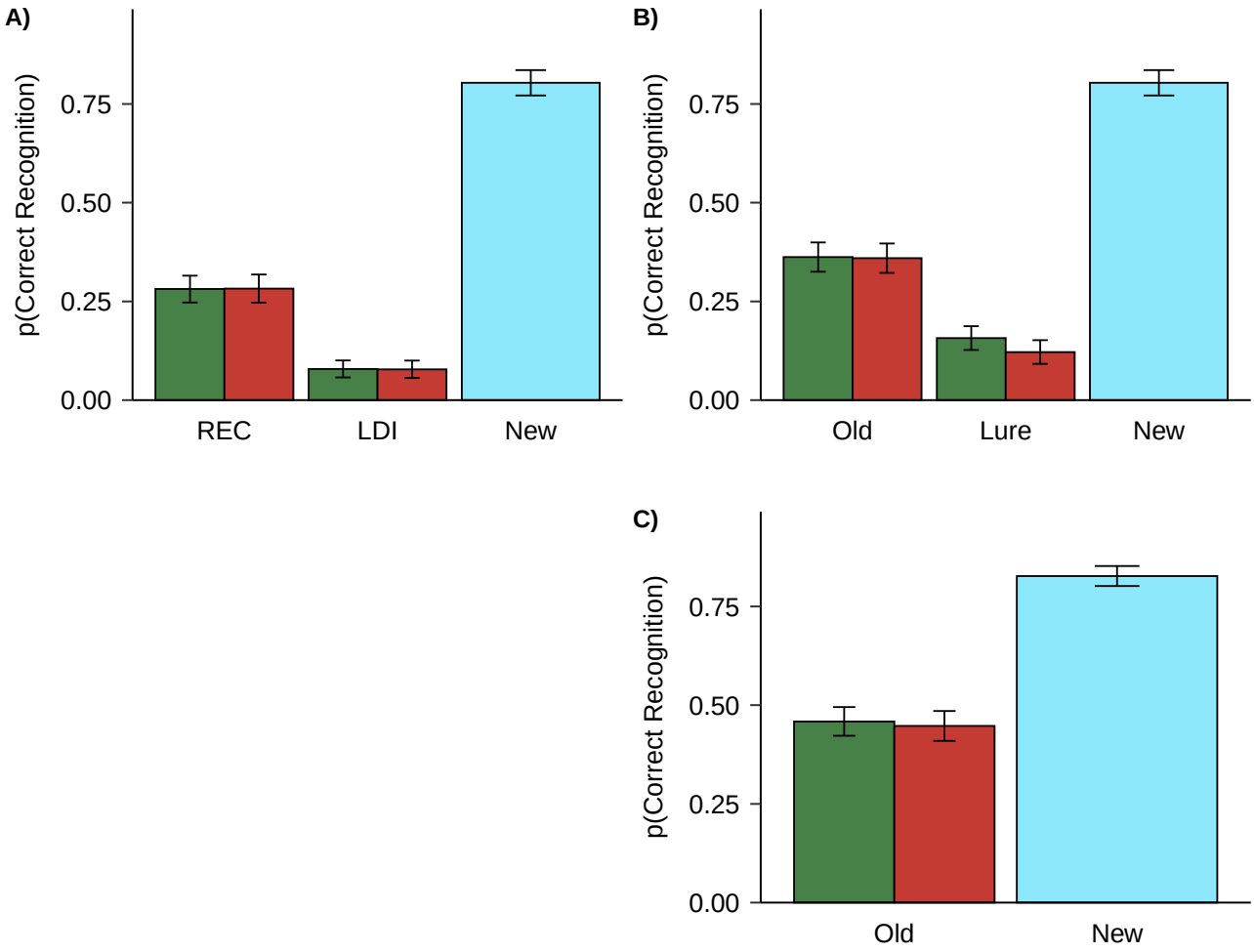


Fig. 7. Overall recognition memory performance for Experiments 2-3. A) shows the corrected recognition memory for REC (old) and LDI (highly similar) and the proportion of correct recognition memory for new stimuli, and B) shows the proportion of correct recognition for all types of stimuli used (i.e., old, highly similar, and new images) for Experiment 2. C) shows the overall for old and new images in Experiment 3. Green bars represent stimuli associated with high-value rewards, and red bars represent stimuli associated with low-value rewards. Error bars represent 95% confidence intervals.

The same results were obtained when using proportion correct for old and similar images. Specifically, recognition memory performance decreased over time for both types of memory [main effect of Memory Type: $F(1, 57) = 125.663$, $p < .001$, $\eta^2_p = .688$; main effect of Block: $F(3.882, 221.277) = 32.721$, $p < .001$, $\eta^2_p = .365$; Memory Type × Block interaction: $F(3.422, 195.035) = 5.320$, $p < .001$, $\eta^2_p = .085$]. Overall proportion correct was significantly higher for old than similar images, $t(57) = 11.210$, $p_{bonf} < .001$, $d = 1.024$. Proportion correct was also unaffected by Value (high/low) and Choice (fixed/risky) for both memory types

[main effect of Value: $F(1, 57) = 3.964$, $p = .051$, $\eta^2_p = .065$; main effect of Choice: $F(1, 57) = 0.437$, $p = .511$, $\eta^2_p = .008$; no interactions reached statistical significance].

For Experiment 3, recognition memory performance decreased across blocks [main effect of Block: $F(2.259, 192.029) = 112.509$, $p < .001$, $\eta_p^2 = .570$], and was influenced by whether a participant made a fixed or risky choice on a given trial [main effect of Choice: $F(1, 85) = 7.471$, $p < .01$, $\eta^2 = .081$], with better memory for images associated when making a fixed choice [$t(85) = 2.733$, $p_{bonf} < .01$, $d = 0.083$]. However, memory was unaffected by Value (high/low) and Animacy (animal/object) [main effect of Value: $F(1, 85) = 2.176$, $p = .144$, $\eta^2 = .025$; main effect of Animacy: $F(1, 85) = 1.376$, $p = .244$, $\eta^2 = .016$]. No interactions reached statistical significance.

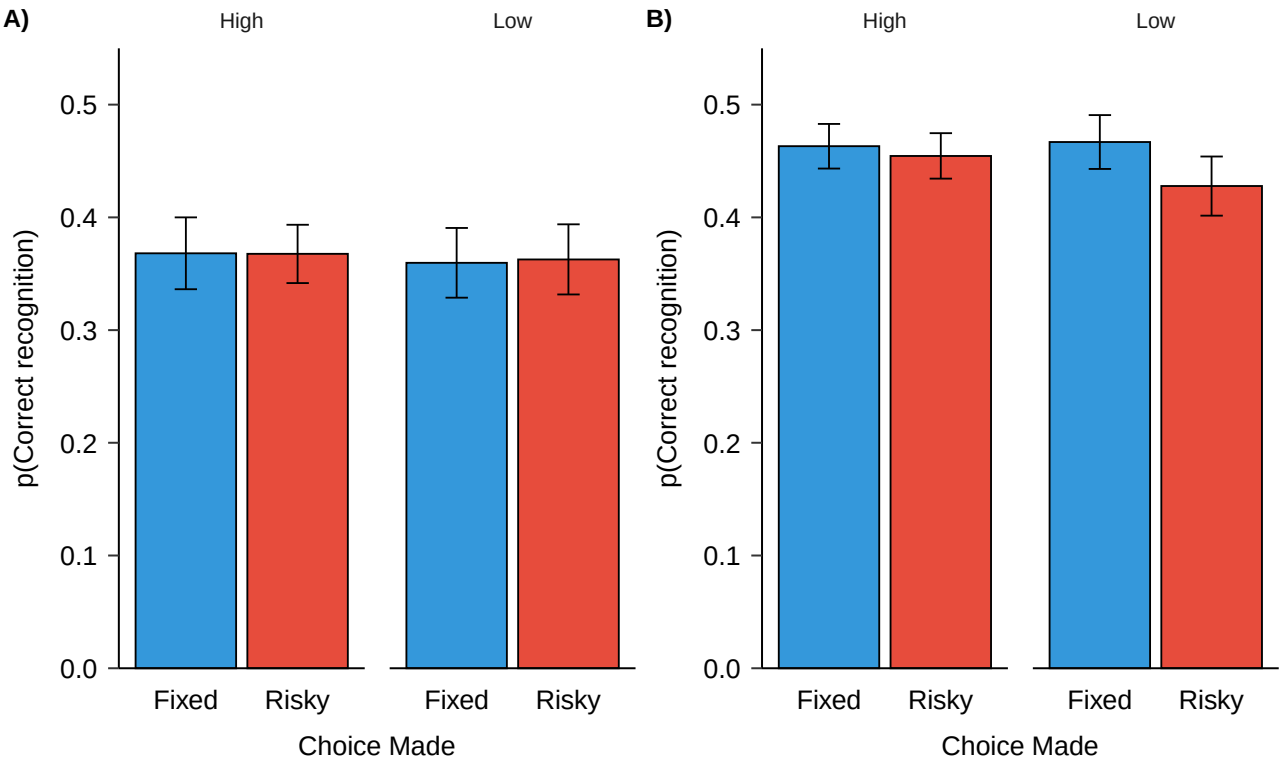


Fig. 8. Overall memory performance as a function of the choice made (fixed or risky) and the decision context (high- or low-value). A) shows the proportion of correct recognition memory for Experiment 2. B) shows the proportion of correct recognition memory for Experiment 3. Error bars represent 95% confidence intervals.

To assess the effects of reward outcomes when making risky choices and value on memory across the entire experiment a 2 (Memory Type) x 2 (Outcome) x 2 (Value) ANOVA was conducted for both experiments.

In Experiment 2, participants' memory performance for both types of memory measure was unaffected by the Outcome (best/worst) and Value (high/low) when making a risky choice [main effect of Outcome: $F(1, 57) = 0.069$, $p = .793$, $\eta^2_p = 0.001$; main effect of Value: $F(1, 57) = 1.660$, $p = .203$, $\eta^2_p = .028$; no interactions reached statistical significance]. The same results were obtained when using proportion correct [main effect of Outcome: $F(1, 57) = 0.049$, $p = .825$, $\eta^2_p = 8.633e\text{-}4$; main effect of Value: $F(1, 57) = 0.034$, $p = .854$, $\eta^2_p = 5.999e\text{-}4$; no interactions reached statistical significance].

In contrast, in Experiment 3, participants' memory for the unrelated stimuli was influenced by Value (high/low) when making risky choices [main effect of Value: $F(1, 85) = 5.247$, $p < .03$, $\eta_p^2 = .058$] with better memory for stimuli associated with high- compared to low-value rewards [$t(85) = 2.291$, $p_{bonf} < .03$, $d = 0.070$. However, memory was unaffected by Outcome (best/worst) and Animacy (animal/object) [main effect of Outcome: $F(1, 85) = 0.198$, $p = .657$, $\eta_p^2 = .002$; main effect of Animacy: $F(1, 85) = 0.416$, $p < .521$, $\eta_p^2 = .002$]. No interaction reached statistical significance.

Experiments 4-5

Although we were able to replicate risk preference and memory bias results from past research (Ludvig & Spetch, 2011; Madan et al., 2014), we were unable to find support for our primary hypotheses. To rule out that the stimuli used in Experiment 3 were not a confound, we conducted an additional incidental encoding study and found participants had good recognition memory for the stimuli (see supplemental Exp. S1 for further details).

To further assess the validity of our results (i.e., can we observe reward anticipation in an online sample), we more directly test reward anticipatory effects on incidental encoding by using methodological designs used to show that curiosity enhances incidental encoding (Fandakova & Gruber, 2021; Gruber et al., 2014). Moreover, it has been established that there is a clear link between states of curiosity and the reward system (Gruber & Ranganath, 2019; Kang et al., 2009; Rueterbories et al., 2023). In Experiment 4, we attempted to replicate the curiosity-enhancing effects on incidental encoding by conducting a conceptual replication of Gruber et al. (2014) using images of objects and animals to assess if the memory-enhancing effects of curiosity generalize to circumstances where the incidentally encoded stimuli are not directly linked to the trivia question itself. In Experiment 5, we used

a design more closely resembling that of Gruber et al. (2014) using stimuli of people where the procedure clearly connects the incidental stimuli to the trivia question (unlike Experiment 4) by asking if participants believe the person knows the answer to the question, leading to increased processing of the stimuli.

Methods

Participants

In Experiment 4, 55 participants were recruited (14 female; M_{age} = 26.35 years, *SD* = 4.56), and 50 participants were recruited in Experiment 5 (21 female; M_{age} = 27.96 years, *SD* = 4.49). All participants were recruited from Prolific and were paid £9 for their participation. Both experiments were approved by the University of Nottingham's ethics board.

Incidental encoding task

Both experiments used protocols similar to Gruber et al. (2014). In both experiments, participants first saw a random trivia question before being shown a random, unrelated image. In Experiment 4, participants were asked to make an animacy judgment, and if participants did not respond within the allocated time, the image disappeared, and the experiment waited for participants to make a judgment before continuing. However, in Experiment 5, participants were shown images of faces and asked to make a self-paced 'knowledge' judgment about whether they believed the person would know the answer to the trivia question. Following the incidental image, participants were shown the answer to the trivia question and, lastly, were asked to rate the level of interest they felt when they saw the trivia answer (post-answer curiosity) on a 10-point Likert scale. See Fig. 9 for visual illustrations and timings. Participants completed 112 trials, and all were shown the same 112 trivia questions based on an independent rating study (see supplement Exp. S2). The images used for incidental encoding in Experiment 4 were the same as those used in Experiment 3, while those used in Experiment 5 were selected from a face database (Minear & Park, 2004).

Recognition task

Following the incidental encoding task, participants were immediately asked to complete an old/new recognition task with confidence ratings. Participants were asked to

indicate whether they were confident or unconfident an image was old or new. Participants were shown the 112 old images interleaved in the encoding task and 56 new images.

Cued recall task

Following the recognition task, participants completed a cued recall task. Each trivia question was randomly displayed on screen, and participants were asked to report the associated answer. The trivia questions stayed on-screen until participants submitted their answers.

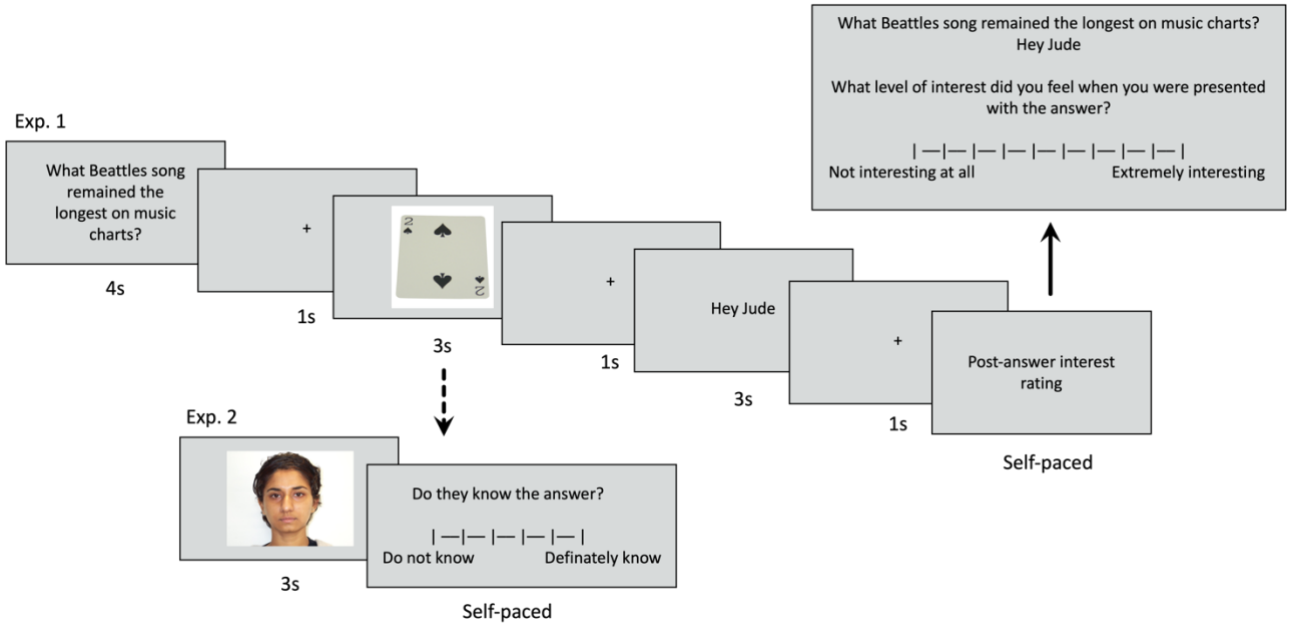


Fig. 9. General experimental procedure for Experiments. 4-5. The only difference between Experiments 4 and 5 was the stimuli used (Exp. 4: animals and objects; Exp. 5 faces) and how participants responded to the stimuli. In Exp. 4, participants made animacy judgments, whereas in Exp. 5, they were asked if they believed the person they saw knew the answer to the trivia question.

Data analysis

Participants were excluded from data analysis if they had a d-prime score lower than 0.1 to ensure their recognition sensitivity was greater than chance (d-prime of 0). In Experiment 4, participants were additionally excluded if they had more than 10% incorrect animacy judgments. Four participants were excluded from Experiment 4, and four participants were excluded from Experiment 5. To ensure that the curiosity ratings obtained from the independent rating study (pre-answer curiosity; Exp. S2) were related to the

curiosity ratings from Experiments 4 and 5, a correlation between the pre-answer and post-answer curiosity ratings was performed. A regression analysis was used to assess the relationship between curiosity and recognition memory for stimuli associated with each trivia question. Lastly, a correlation between recall accuracy for each trivia question and post-answer curiosity was conducted to assess whether curiosity influenced the ability to recall the answers to the trivia questions. Reported answers that were similar or close to matching the correct answer (e.g., reporting 'grape' rather than 'grapes') were considered as correct answers. The same statistical tests were run for both experiments.

Result

Curiosity correlation

The pre-answer curiosity ratings (Exp. S2) were highly similar to the post-answer curiosity ratings from both experiments. Both experiments showed significant positive correlations between the post- and pre-answer curiosity ratings for the trivia questions (Exp. 4: r(110) = 0.732, $p < .001$; Exp. 5: r(110) = 0.659, $p < .001$).

Recognition memory

Recognition was overall better for 'New' stimuli compared to 'Old' stimuli in Experiment 4 (M_{new} = .79, SD_{new} = 0.42; M_{old} = .68, SD_{old} = 0.47) and Experiment 5 (M_{new} = .74, SD_{new} = 0.44; M_{old} = .55, SD_{old} = 0.50). In both cases, memory for the 'Old' stimuli was better than chance [Exp. 4: $t(50) = 11.461$, $p < .001$; Exp. 5: $t(44) = 2.5035$, $p < .009$]. However, neither levels of pre-answer curiosity [Exp. 4_{pre}: $\beta = -0.0068$, $t(110) = -0.530$, $p = 0.597$; Exp. 5_{pre}: $\beta = 0.0115$, $t(110) = 0.737$, $p = 0.462$] or post-answer curiosity [Exp. 4_{post}: $\beta = 0.0026$, $t(110) = 0.296$, $p = 0.768$; Exp. 5_{post}: $\beta = 0.0072$, $t(110) = 0.657$, $p = 0.513$] predicted recognition memory performance.

Cued recall

Although curiosity levels did not predict recognition memory performance, curiosity significantly correlated with the ability to retrieve trivia answers during cued recall. A significant positive correlation was found in both Experiment 4 [r(110) = .398, $p < .001$] and Experiment 5 [r(110) = .397, $p < .001$].

Discussion

In a series of pre-registered experiments, we aimed to assess reward anticipation effects on incidental encoding using an associative learning paradigm where reward anticipation should gradually decrease with increased experience. We were able to replicate past findings showing differential changes in risk preferences across learning depending on reward value (e.g., Ludvig & Spetch, 2011; Madan et al., 2021) and replicate memory biases in risky choice with participants exhibiting the extreme-outcome rule (Ludvig et al., 2014, 2018; Madan et al., 2014). However, contrary to our hypotheses, we could not find evidence for reward anticipatory effects affecting incidental encoding of task-irrelevant stimuli. Specifically, we found no general influence of reward value on recognition memory performance in Experiments 2 or 3. We observed an effect of participants' choices (fixed vs. risky) on recognition memory performance in Experiment 3 but not in Experiment 2. Contrary to our hypothesis, participants elicited better recognition memory rates for fixed outcomes than risky choices in Experiment 3. As hypothesized, when making risky choices, recognition memory performance was higher for high- compared to low-value associated stimuli. This inconsistency in results between Experiments 2 and 3 may have been two-fold: firstly, Experiment 2 had a significantly greater number of stimuli and, secondly, including highly similar items in Experiment 2 may have increased the difficulty and, by extension interfered with the ability to determine if an item had indeed previously been seen. To ensure we could capture reward anticipation effects on incidental encoding in an online sample, we conducted two conceptual replications (Gruber et al., 2014) assessing curiosity and incidental encoding. Although we were unable to replicate the effects of curiosity on recognition memory, we could replicate the effect of curiosity on the ability to retrieve trivia answers during cued recall.

Although we did not observe any results supporting our hypotheses for Experiment 2, we did observe statistically significant results contradicting one of our hypotheses in Experiment 3. Namely, we expected participants to elicit better recognition memory for items associated with risky choices due to uncertainty and reward prediction errors (Rouhani et al., 2018; Rouhani & Niv, 2021; Schultz et al., 1997; Wimmer et al., 2014), but instead, we observed better recognition memory for fixed-outcome choices. One possibility is that our paradigm was unable to elicit sufficient reward prediction errors to influence memory consolidation of task-irrelevant stimuli. Past research showing the effect of reward

prediction errors on incidental encoding typically uses probabilistic learning tasks where the probability of pay-off varies on each trial (e.g., Duncan et al., 2019; Duncan & Shohamy, 2016; Wimmer et al., 2014), thus likely resulting in greater reward prediction errors. However, other research has shown that reward uncertainty may not enhance episodic memory but rather that it depends on the reward magnitude (Mason et al., 2017, 2019). This may partly explain why better memory for fixed-outcome choices was observed in Experiment 3 since the reward magnitude was constant and always better than the risky options 50% of the time. When making risky choices, however, we did observe the enhancing effects of high-value rewards on memory, replicating previous work (e.g., Adcock et al., 2006; Wittmann et al., 2005).

Recent evidence has shown a trade-off between incremental learning and recruitment of episodic memory when making decisions. Increased volatility in the choice environment leads to increased use of incremental learning rates (Behrens et al., 2007; Piray & Daw, 2020; Yu & Dayan, 2005), but when volatility is low, episodic memory is more likely to guide decisions (Nicholas et al., 2022). Moreover, memory retrieval processes involved in decision-making appear to be distinctly different from the general retrieval processes that make stimuli memorable (Li et al., 2022). That is, participants' encoding and retrieval processes may have been more focused on incremental learning and, therefore, down-regulating the incidental encoding of task-irrelevant stimuli. Indeed, value-based decision-making appears to be driven by idiosyncratic and experienced-based memories to construct subjective values, whereas general stimuli memorability appears to be a global feature aiding the prioritization of perceptual information (Li et al., 2022). This would further support the notion that due to prioritization in our value-based risky choice task, incidental encoding was down-regulated, particularly when choosing the risky option. This also helps explain why we observe enhanced memory for stimuli associated with fixed-outcome choices (in Experiment 3) since the construction and refining of subjective values and incremental learning would be minimal for this set of choices.

However, these explanations do not extend to Experiments 4 and 5, where we attempted to replicate previous robust findings of curiosity-enhancing incidental encoding (Fandakova & Gruber, 2021; Galli et al., 2018; Gruber et al., 2014; Stare et al., 2018). We specifically attempted to replicate these results due to their past replicability but also given the clear link between states of curiosity and the reward system (Gruber & Ranganath, 2019;

Kang et al., 2009; Rueterbories et al., 2023), allowing for consistency across experiments. However, in neither experiment were we able to replicate the effects of curiosity on incidental encoding of task-irrelevant stimuli. Critically, it has previously been shown that the effects of curiosity do not necessarily enhance incidental encoding (Swirsky et al., 2021), which has been attributed to small effect sizes and sample sizes of past studies. In addition, small methodological differences between the present experiments and past studies may also have contributed to the unsuccessful replications. Together, this highlights the increased need for and relevance of replication studies and the usefulness of testing the extent to which findings will replicate when making subtle methodological changes.

A likely explanation for the results in Experiments 2-5 and the inability to replicate previously well-established results (e.g., Gruber et al., 2014) is using an online sample where certain aspects (e.g., attention) are less controllable than in-person lab experiments. Indeed, recent memory studies have also shown worse memory performance in online experiments compared to in-lab testing (James et al., 2020; Mason et al., 2022; Palombo et al., 2021; Yeh & Koen, 2023). Moreover, intrinsic motivation and divided attention may have resulted in poorer memory performance than would otherwise be observed from in-lab testing. Since it is impossible to rule out any effects of intrinsic motivation and divided attention on performance with the current experimental design, further studies will be conducted. Conducting in-lab replication studies with students – whose intrinsic motivation may likely be higher than the current sample – will help minimize motivation and attention as potential confounds and enable a closer assessment of how stimuli memorability and experience-based memories in decision-making may interact. Additionally, these experiments will enable a more direct comparison between two distinct samples and see how much online experiments deviate from in-lab testing.

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Supplemental

Exp. S1: Image-only study

As the results of Experiments 2-3 contradicted our *a priori* hypotheses, we wanted to ensure that the stimuli were not the main cause of our null results. That is, if the stimuli itself was not memorable that could explain, at least partially, why we observe null results. To assess if this was the case, we conducted an experiment asking participants to classify stimuli (animacy judgments) without informing them of a subsequent memory test.

Participants

For Experiment S1, 50 participants were recruited (12 female and 1 undisclosed; M_{age} = 26.84 years, *SD* = 3.98). All participants were recruited from Prolific and were paid £3. The experiment took approximately 20 minutes to complete and was approved by the University of Nottingham's ethics board.

Methods

Participants were instructed that they would see a series of images and had to classify whether the images were animals or objects. On every trial, participants saw a random image and had to indicate if it was an animal or an object. The image was shown for 2s, and during this time, participants could make an animacy judgment. Only after the 2s would the trial continue if participants had also made an animacy judgment. If participants did not make an animacy judgment within the 2s, the image disappeared, and the program waited

until the participants made an animacy judgment before continuing to the next trial. After the animacy judgment, participants saw a blank screen for 1.1s before seeing a new image. All images were the same as those used in Experiment 3, and participants completed 192 trials before getting a surprise recognition test. During the surprise old/new recognition test, participants were shown all 192 old images and 96 new images.

Data analysis

Participants were excluded from data analysis if they had d-prime scores lower than 0.1 and if they had more than 10% incorrect animacy judgments. A total of 7 (3 for d-prime; 1 for animacy judgments; 3 for technical issues) participants were excluded from data analysis. A one-sample t-test assessed recognition memory performance for old images against chance.

Results

Participants were significantly better than chance at recognizing 'old' images as being 'old', $t(42) = 6.975$, $p < .001$, $d = 1.064$, (Fig S1). This suggests the results of Experiment 3 is not because of the stimuli used. We furthermore believe these results suggest the findings of Experiment 2 are not because of the stimuli used, as that stimulus has been used successfully in previous research.

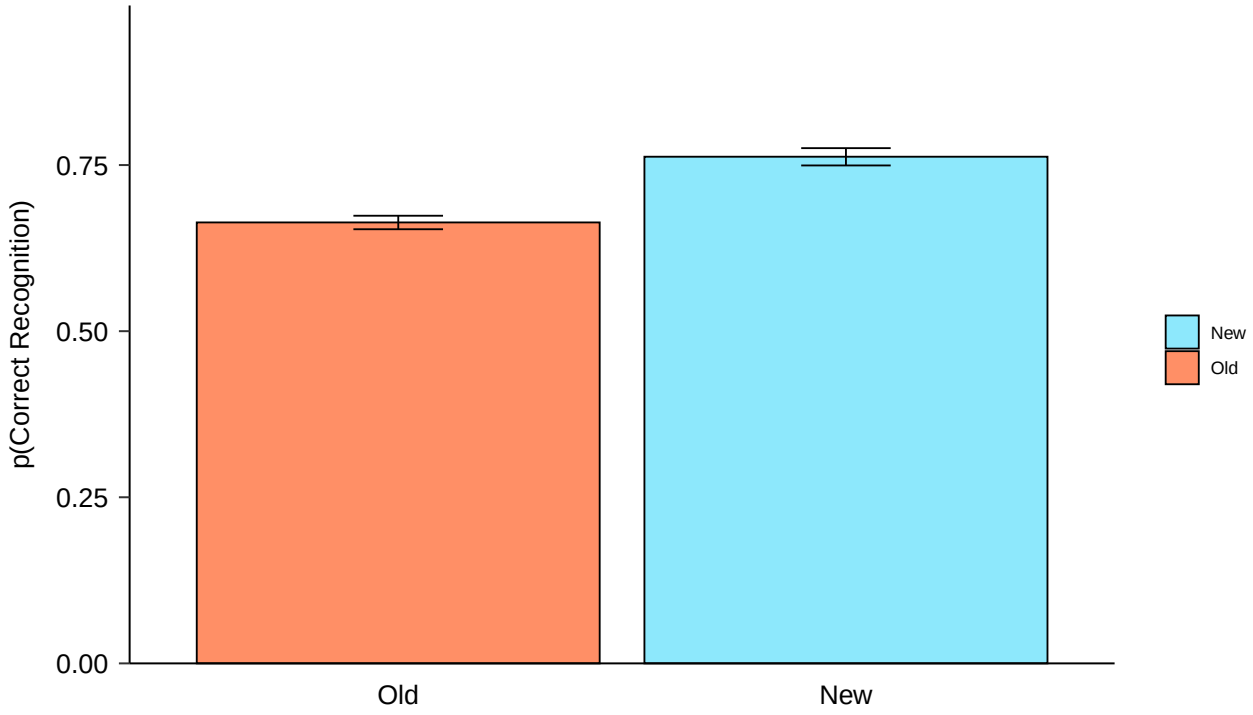


Fig. S1. Overall recognition memory performance for 'old' and 'new' images. Error bars represent 95% confidence intervals.

Exp. S2: Trivia rating study

Before conducting Experiments 4-5, we first wanted to ensure the normed curiosity ratings by Fastrich et al. (2018) were replicable in an online sample. Secondly, we wanted to minimize the time spent on the experimental tasks to minimize fatigue and attrition effects. As such, we decided to conduct a trivia rating study using the materials by Fastrich et al. (2018) and, subsequently, used a subset of the trivia questions for Experiments 4 and 5.

Participants

For Experiment S2, 50 participants (12 female and 5 undisclosed; M_{age} = 26.55 years, *SD* = 4.57) were recruited from Prolific. The experiment took approximately 45 minutes to complete, and participants were paid £5. The study was approved by the University of Nottingham's ethics board.

Methods

Participants were instructed they would be shown a trivia answer and had to rate their curiosity in knowing the answer. The trivia answer remained on-screen until participants made a curiosity rating. Ratings were made on a 9-point Likert scale with '1' being labeled 'Not interesting at all' and '9' being labeled 'Extremely interesting'. After participants rated their curiosity, a fixation cross appeared for 1s before they saw the corresponding answer for 2s. Participants completed 4 blocks of 49 trials and 1 block of 48 trials for a total of 244 trials. After each block, participants were allowed to take a short break. All 244 trivia questions were taken from Fastrich et al. (2018).

Design

Three participants were excluded from data analysis because they had unnaturally fast reaction times (< 300ms) for several curiosity ratings. Item-wise correlations were conducted to assess how well the collected curiosity ratings compared to the normed curiosity ratings from Fastrich et al. (2018). In addition, to ensure the trivia ratings were reflective of the collected sample, a correlation was performed to assess the within-sample reliability.

Results

Item-wise correlations showed a significant positive correlation between the collected and normed curiosity ratings [$r(242) = .253$, $p < .001$]. In addition, the curiosity ratings had good within-sample reliability [$r(242) = .802$, $p < .001$]. Based on these results, we selected 112 trivia questions representing a range of curiosity ratings. In cases where trivia questions had the same means, the trivia question with the smallest standard deviation was selected.

Reference

Fastrich, G. M., Kerr, T., Castel, A. D., & Murayama, K. (2018). The role of interest in memory for trivia questions: An investigation with a large-scale database. *Motivation Science*, *4*(3), 227–250. https://doi.org/10.1037/mot0000087

Chapter 4:

Visual attention and pupil dilation in risky decisions from experience

Abstract

A large body of work has shown that attention plays a critical role in shaping decision-making processes. In the current study, we used eye-tracking to assess how people allocate attention during risky choice and how it might inform their choices. Participants completed a risky associative learning task and had to learn the underlying reward structures through experience. Replicating past work, participants allocated more attention to the option they chose and became increasingly risk-averse for losses and low-value rewards than gains and high-value rewards. Interestingly, we find evidence to suggest that choice options for low-value rewards may have been perceived differently from losses despite similar risk-seeking behavior. Following a choice, participants were shown all possible reward outcomes to assess whether the extremes would attract more attention; however, we found no evidence to support this notion. Lastly, we show that pupil dilation may be a better indicator of risk-aversive behavior than fixation data by reflecting value beliefs and reward uncertainty. In sum, the present study provides insight into the complexities of how attention and physiological arousal interact with decision processes in risky choice.

Keywords: Visual attention, pupil dilation, risky choice, decisions from experience, eye tracking, behavioral economics

Introduction

Visual attention plays a significant role in how we navigate the world and shapes our decision-making processes. As people navigate visually complex environments (e.g., in a supermarket), they are bombarded with a myriad of stimuli. Consequently, they must selectively allocate their attention to only the most relevant stimuli. The allocation of

attention shapes decision-making processes where different visual biases can Influence choice and cognitive representations of options (Orquin et al., 2018). The duration of time spent fixating on an option increases the probability of choosing said option independent of the option's value (Armel et al., 2008; Krajbich et al., 2010, 2012; Shimojo et al., 2003; Stewart et al., 2006; Thomas et al., 2019), and, similarly, the final fixation as a choice is made is significantly biased towards the chosen option (Fiedler & Glöckner, 2012; Krajbich et al., 2010; Krajbich & Rangel, 2011; Shimojo et al., 2003). Indeed, the saliency of any given option also leads to systematic changes in saccadic biases, influencing choice processes even further (Liao & Anderson, 2020). These biases in visual attention play a pivotal role in how people evaluate options, process information, and ultimately make choices; creating different visual representations of the same information can divert visual attention, leading to different choice outcomes. For example, when choosing between medical treatments, a patient may focus on survival rates in one visual representation but mortality rates in another (cf. Witt, 2020), leading to different preferences.

Visual attention also plays a substantial role in shaping risky choice, influencing the cognitive representations of available options. In risky choice, saliency for positive and negative values reflect habitual gaze behavior where, once learning has been established, gaze and fixations are increasingly drawn to stimuli associated with positive reward values over losses (Hwang et al., 2022; Liao & Anderson, 2020), highlighting habitual gaze preferences for reward predictive stimuli. The rank value of an option further increases gaze dwell durations with higher rank values resulting in longer dwell times (Stojić et al., 2020; Vanunu et al., 2021) and gaze durations for extreme ranks predicting risky choice (Vanunu et al., 2021). Visual attention is not solely guided by value but also the uncertainty associated with an option; larger uncertainty attracts more relative fixations, and – like unsigned reward prediction errors – absolute fixations decrease across learning (Stojić et al., 2020). This gaze-weighted attentional effects on choice also extend to multi-alternative risky choice (Molter et al., 2022), highlighting the value of decoy options captures attention and interferes with optimal decision-making (Gluth et al., 2018). Computationally, people employing model-based learning are less influenced by relative dwell times, whereas those employing model-free learning are influenced more by relative dwell times (Konovalov & Krajbich, 2016), highlighting model-based learners likely know what they will choose before the options appear whereas model-free learners employ on-the-spot value computations ignoring

underlying reward structures. Additionally, increased gaze dwell times reflect greater drift-rate, whereas larger pupil dilation reflects greater decision boundaries in evidence accumulation models (Cavanagh et al., 2014).

Not only does pupil dilation affect cognitive computational mechanisms involved in risky choice, it also directly predicts future choices (Kozunova et al., 2021). Pupil dilation tracks value beliefs and reflects the arousal associated with the expected reward of an option (Fiedler & Glöckner, 2012; Van Slooten et al., 2018). Increased pupil dilation before making a choice reflects the value of an option and is associated with the riskiness of said choice (Cherkasova et al., 2018), whereas it reflects uncertainty about the value after making a choice (Van Slooten et al., 2018). Crucially, larger pupil dilation only reflects decision uncertainty pre-feedback, whereas it reflects reward prediction errors post-feedback (Urai et al., 2017; Van Slooten et al., 2018). Pupil dilation also reflects learning rates, where greater average pupil dilation during learning directly results in higher average learning rates (Nassar et al., 2012).

In decision-making – and by extension, risky choice – two ideas have been proposed as to how choice outcomes are broadly perceived and evaluated. One is the optimism bias (Korn et al., 2014; Sharot, 2011; Sharot et al., 2007), which causes people to overweight (underweight) the probability of positive (negative) events occurring. Indeed, positive stimuli receive visual attention as predicted by the optimism bias (Kress et al., 2018). Conversely, the loss attention hypothesis (Yechiam & Hochman, 2013a, 2013b, 2014) posits that people allocate more overall attention towards losses in a given decision set, likely extending to the worst possible option in a given dataset. These two hypotheses about attention in decision-making make contradictory predictions for the underlying mechanisms associated with visual attention, choice, and search behavior. Specifically, the optimism bias would predict that people direct their (visual) attention toward positive outcomes associated with risky choices while neglecting or minimizing attention towards negative outcomes in a decision set, whereas the loss attention hypothesis would predict the opposite (i.e., heightened sensitivity and allocation of visual attention towards the worst possible outcomes and losses).

In a pre-registered study using a mixed factorial design, we assessed visual fixations and pupil dilation in a risky choice task where participants had to learn about the underlying reward structures by choosing between two options (deterministic versus probabilistic) with

the same expected value. Similar to previous research (Stojić et al., 2020), we assessed whether participants elicited differential gaze durations with increased learning such that they would have longer fixations on the deterministic option in the decision set containing low-value rewards and losses but not for high-value rewards or gains. While awaiting feedback, we predicted participants would fixate on a location associated with an expected reward for the chosen option. Moreover, we directly tested the competing predictions made by the optimism bias and the loss attention hypothesis: we assessed whether, when choosing the probabilistic option on a given trial, participants would either 1) fixate more on the location associated with the best possible outcome for any given option in all decision frames or 2) fixate more on the best possible location for high-value rewards and gains but fixate more on the location associated with the worst possible outcome for low-value rewards and losses. We further predicted that as the delay between making a choice and receiving a reward grew larger, participants would be increasingly more likely to shift their gaze towards another location (e.g., directing their gaze from the best to the worst possible outcome) when choosing the probabilistic option. Furthermore, we predicted participants would have larger average pupil dilation on loss and low-value trials and larger average pupil dilations when fixating on the probabilistic compared to the deterministic option reflecting reward uncertainty (Van Slooten et al., 2018). Lastly, average pupil dilations were predicted to be larger when receiving the worst possible outcome when choosing the probabilistic option, reflecting reward prediction errors (Urai et al., 2019; Van Slooten et al., 2018).

Method

All raw data and Python eye-tracking data processing files for this study can be found on the Open Science Framework website (https://osf.io/kc6ba/).

Participants

A power analysis indicated a sample size of 88 participants for a combined between-subjects and within-subjects design was required (alpha of .05, 95% power, and effect size Cohen's d of 0.39). A total of 79 participants were recruited, but data from 15 participants were excluded because the eye-tracker was unable to track participants' eyes (4), failed attentional checks (10), or technical issues (1). Participants' behavioral data was still included in the behavioral analyses even when the eye-tracker could not track their eyes. Thus, a total

sample size of 69 (46 female and 2 other, M_{age} = 21.16 years, *SD* = 3.06) was used for the behavioral analyses, and a total sample size of 65 was used for fixation and pupillometry analyses (42 female and 2 other, M_{age} = 21.27 years, *SD* = 3.12). One participant did not state their age or gender. Participants were either paid £5 or received course credit for participating. Due to practical considerations, recruitment was stopped early before reaching the sample size suggested by the power analysis. The study was approved by the University of Nottingham's ethics board.

Apparatus

Participants were seated in front of a 25-in monitor with a resolution of 1920 x 1080 (an aspect ratio of 16:9). They used a chinrest approximately 50 cm. from the screen. An EyeLink-1000 eye-tracker (SR Research) with a monocular sampling rate of 500 Hz was used. The calibration and validation sequences consisted of 9-points displayed in a 3x3 grid. If the validation sequence failed, drift corrections were applied and repeated. In cases where the validation sequence failed multiple times, the participant completed the experiment without the eye tracker. The experiment was created using PsychoPy version 2022.2.4 (Peirce et al., 2019) and executed all relevant eye-tracking commands. The default algorithm provided by SR Research was used to detect fixations. To ensure the luminance of the choice stimuli did not confound our measure of pupil dilation, the choice stimuli were luminance-corrected (i.e., all choice stimuli had the same luminance) in CIELAB color space. A delta for the luminance parameter (*L*) was calculated by subtracting the luminance of a reference (blue-colored door choice stimulus) from the luminance of the other choice stimuli and applying the difference to said stimuli.

Procedure

Choice task

After participants gave informed consent, they were pseudo-randomly assigned a condition (gain/loss or high/low value) and were given written instructions about the task. Two decision frames were used as saliency effects may cause low-value rewards to be perceived differently from losses. Specifically, the degree of saliency corresponds to the absolute value of the predicted outcome (Bromberg-Martin et al., 2010; Kahnt et al., 2014),

with the extremes being more salient. Furthermore, a reward-driven saccadic bias has been observed toward high-value rewards over low-value rewards (Liao & Anderson, 2020). Thus, using two reward frames allows for disentangling saliency effects that may affect fixations and pupil dilation.

The experiment consisted of three trial types: single-option trials, catch trials, and decision trials. On single-option trials, participants only had one option to choose from and had to select it for the experiment to progress. These trials ensured that participants experienced all possible outcomes associated with an option and minimized potential hot-stove effects. Participants completed 8 single-option trials as a practice block to familiarize them with the experiments' structure before the experimental trials began. Catch trials were used as attentional checks where participants were given the choice between two options of different expected value and had to choose the option with the highest expected value. On decision trials, participants chose between two options from a total of four distinct options. In the gain/loss condition, choice options led to either a fixed loss (-20), a fixed gain (20), a risky loss (-10 or -30), or a risky gain (10 or 30). Similarly, choice options in the high/low-value condition led to either a fixed low-value gain (20), a fixed high-value gain (60), a risky low-value gain (10 or 30), or a risky high-value gain (50 or 70). Probabilities for either of the risky outcomes in both conditions were 50%, and participants learned about probability distributions and outcomes by selecting between the choice options. The experiment consisted of 5 blocks, each with 48 trials; each block had 8 single-option trials, 16 catch trials, and 24 decision trials.

After selecting an option, the option disappeared, and a black dot appeared in the middle of the screen that had to be clicked to continue. After clicking the black dot, participants saw an octagon-shaped array of all possible outcomes associated with their respective conditions. After a random 800-1200ms interstimulus interval, in increments of 25ms., one of the outcomes was highlighted, signaling the reward earned based on their choice. The reward outcomes were placed on top of circles where the combined colors of the circle and reward outcome averaged to have the same luminance as the background using the same approach as for the choice stimuli. The earned reward remained highlighted for 1100ms.; after it had disappeared, a black dot appeared in the middle of the screen, which had to be clicked to proceed to the next trial. The black dots were used to re-center

participants' gazes in between the different stages of the trials, minimizing potential fixation biases. See Fig. 1 for an example of an experimental trial.

Reward outcome locations were pseudo-randomized across participants; the placements rotated counterclockwise equal to the participant ID. The total amount of accumulated points was displayed continuously on the screen, and participants were incentivized to earn as many points as possible to rank the highest on a leaderboard. Participants were allowed to take a short rest after each block, but prior to starting the experiment, they had been informed to remain seated and move as little as possible.

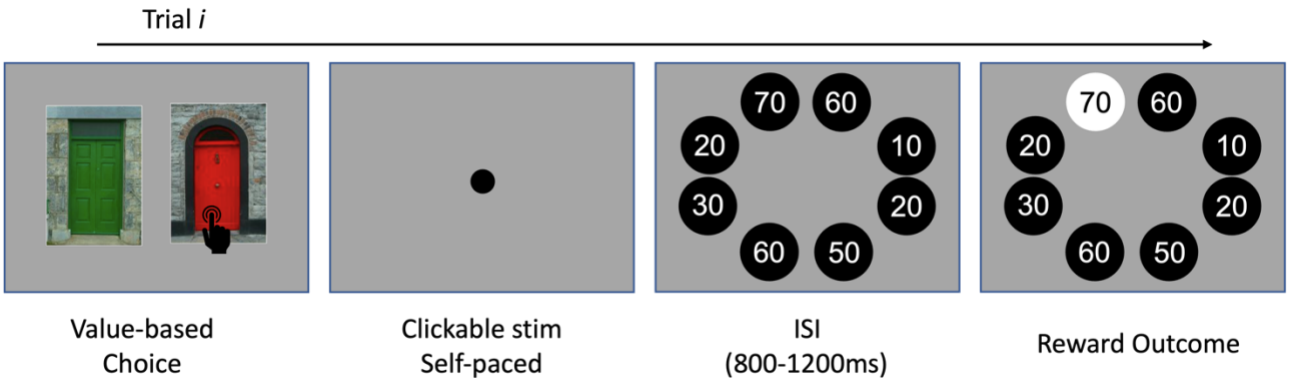


Fig. 1. Example of an experimental trial. After choosing an option, participants had to click a circle in the middle of the screen, which was used to re-center participants' gaze. Participants were shown all possible reward outcomes at distinct locations held constant within-subject. Following the interstimulus interval, one of the outcomes was highlighted, indicating the reward earned on that trial based on the chosen option. Choice stimuli and reward values were luminance corrected.

Memory tests

After completing the choice task, participants were given two memory tests related to the outcomes experienced. In the first memory test, participants were presented with the four doors in random order and asked to report the first outcome that came to mind when seeing each of the doors. In the second memory test, participants were asked to judge the frequency in percentage with which each outcome had occurred. All possible outcomes were displayed simultaneously for each door, and participants typed a number between 0 and 100.

Data analysis

Data exclusion

Following a previous well-established protocol (Ludvig et al., 2018; Ludvig & Spetch, 2011; Madan et al., 2021), participants with catch-trial rates lower than 60% across the two last blocks of the experiment were excluded from data analysis. To re-iterate, 10 participants were excluded from data analysis for not paying sufficient attention during the choice task.

Eye-tracking pre-processing

The raw fixation and pupillometry data were extracted from the Hierarchical Data Format (HDF5) files generated by PsychoPy using a Python script. Areas of interest (AOIs) were defined as the stimuli rectangles in the choice stages and the circles surrounding the rewards in the ISI and feedback stages. In addition, the AOIs in the ISI and feedback stages were increased from a radius of 108 pixels to 156 pixels (44.44% increase from their original size) to better capture looks in the direction of the reward outcomes, as participants may have relied on peripheral vision. The AOIs radii did not overlap. Fixations outside of the pre-defined AOIs were counted as empty gazes. All fixations were aggregated at the trial level for each participant. Following the procedure of Weilbächer et al. (2021), a gaze proportion for each option *i* was computed as follows:

$$\frac{0.5 \times nonfixation\ time + total\ fixation\ time_i}{response\ time}$$

This correction was applied to avoid any over-weighting of small differences on trials with poor recording quality. Trials where no fixation was made to any option, were removed to minimize impacting the results (240 trials were removed from the choice data). A gaze bias was then calculated by subtracting the gaze proportion for each option *i*, resulting in a single continuous measurement for each of the three stages individually. For the choice stage, the gaze bias was calculated based on the difference in gaze proportion between the probabilistic and deterministic options on decision trials. In the ISI and feedback stages, the gaze bias was calculated based on the difference in gaze proportion between the best and worst possible outcomes for a given choice when participants chose the probabilistic option.

Assessing gaze influence on choice

To assess if visual attention had an influence on choice as shown by previous research (e.g., Krajbich & Rangel, 2011; Weilbächer et al., 2021), a one-tailed paired-samples t-test comparing the average fixation duration for the chosen versus unchosen options. A linear mixed effects model of the relationship between gaze bias, condition, block, and choice context (gain or loss trials; high- or low-value trials) was conducted to assess whether visual attention changed across learning. Condition, block, and choice context were entered into the model as fixed effects, whereas the intercepts for the participants were entered as random effects. If the gaze bias is positive, participants fixate more on the deterministic option, whereas if it is negative, participants fixate more on the probabilistic option. The total model equation was:

$$gaze\ bias \sim condition + block + choice\ context + (1|Participant) + \varepsilon$$

Assessing gaze bias when awaiting feedback

The same approach used for assessing gaze influence on choice was used for assessing gaze bias in visual attention when awaiting feedback. The model allowed for evaluating the contradictory predictions made by the optimism bias and the loss attention hypothesis. That is, whether participants would elicit a visual fixation bias towards the reward locations associated with the best or worst possible outcomes following a risky choice. In addition, a separate linear mixed effects model was fitted, adding the interstimulus intervals as an additional fixed effects to enable testing whether participants were more likely to redirect their gaze towards a different location as the delay between choice and reward grew larger. If the gaze bias is positive, participants fixate more on the best possible outcome, whereas if it is negative, they fixate more on the worst possible outcome.

Assessing pupil dilation in risky choice

One-tailed paired-sample t-tests were used to assess the average pupil dilation associated with each choice context (i.e., gains vs. losses and high- vs. low-value rewards). To test whether average pupil dilation was larger when fixating on the probabilistic compared to deterministic a 2 (Condition) x 2 (Option: probabilistic/deterministic) x 2 (Value) mixed-model ANOVA was used. In addition, a 2 (Condition) x 2 (Outcome: Best/Worst) x 2 (Value)

mixed-model ANOVA was used to assess if average pupil dilation was larger when receiving the worst outcome when choosing the probabilistic options.

Assessing changes in risky choice with increased experience

Risk preference was calculated as the proportion of times participants chose the probabilistic option. Changes in risk preference as a function of learning were assessed using a 2 (Value) x 5 (Block) x 2 (Condition) ANOVA, and differences in risk preference were compared across the last two blocks using t-tests for each of the conditions. Only the last two blocks were used to assess differences in risk preference to ensure participants had sufficient opportunity to learn the underlying reward structures.

Assessing memory biases in risky choice

The first outcome reported data was assessed by using χ^2 tests. Frequency judgments were assessed by using paired sample t-tests. Participants were excluded from the frequency judgment analysis if their summed responses were below 75% or above 150%. The relationship between risky choice and memory responses was assessed using partial correlations controlling for experienced outcomes.

All statistical analyses were applied on choice trial data only. Greenhouse-Geisser correction for non-sphericity was applied where appropriate, and all tests were repeated-measures. R^2 was used to denote effect sizes for all mixed linear effects models.

Results

Risk seeking differentially change with experience

Participants' risk preference significantly changed across the five blocks as a function of reward value for both conditions [main effect of Block: $F(2.449, 163.446) = 5.660$, $p < .01$, $\eta_p^2 = 0.078$; main effect of Value: $F(1, 67) = 22.869$, $p < .001$, $\eta_p^2 = 0.254$; main effect of Condition: $F(1, 67) = 0.999$, $p = .321$, $\eta_p^2 = 0.015$; Block × Value interaction: $F(3.524, 236.117) = 3.135$, $p < .05$, $\eta_p^2 = 0.045$; Block × Value × Condition interaction: $F(3.524, 236.117)$ $p < .05$, $\eta_p^2 = 0.037$]. Across the last two blocks, participants were 21.55 ± 6% (*M* ± 95% C.I.) more risk-seeking for gains than losses and 14.83 ± 6.2% (*M* ± 95% C.I.) more risk seeking for high-

than low-value rewards across the last two blocks. These differences in risk-seeking across the two last blocks were statistically significant for the gain/loss condition [$t(34) = 3.370$, $p < .01$, Cohen's $d = 0.570$] and the high-/low-value condition [$t(33) = 3.699$, $p < .001$, $d = 0.634$].

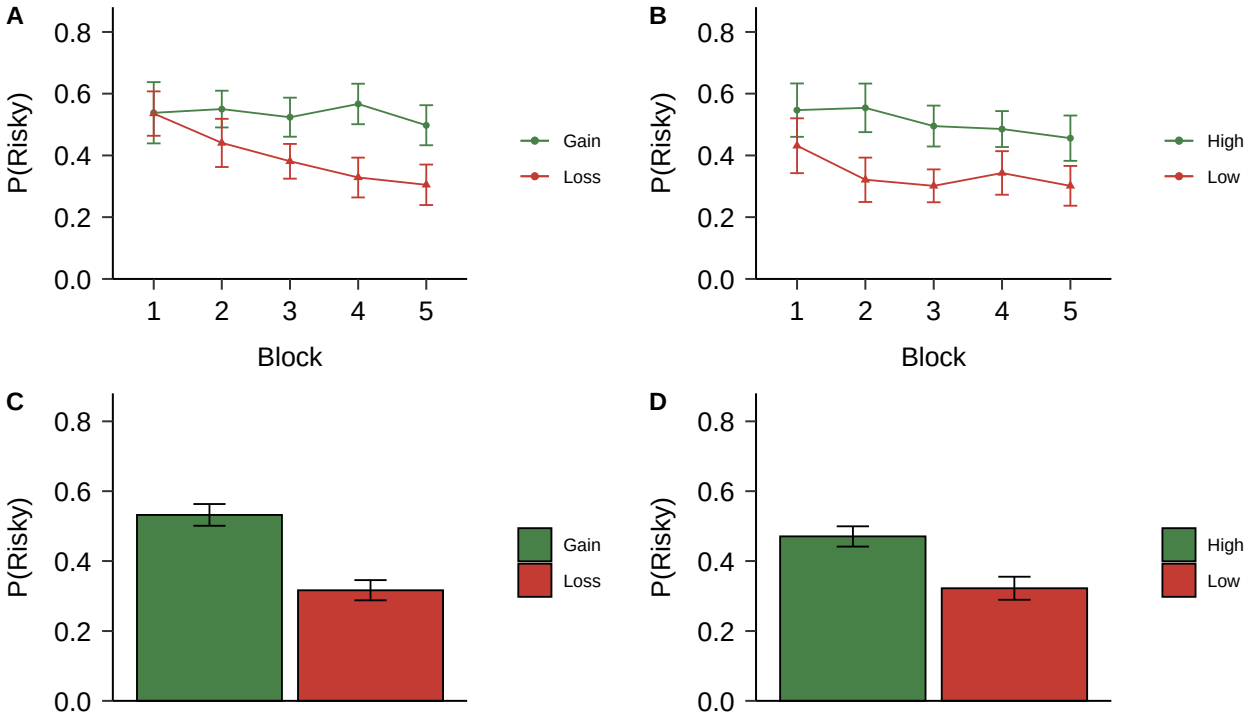


Fig. 2. Proportion of risk-seeking made for both conditions. (A-B) shows the proportion of risk-seeking across all five blocks for the gain/loss and high-/low-value conditions, respectively. (C-D) shows the proportion of risk-seeking averaged across the last two blocks for the gain/loss and high-/low-value conditions, respectively. Error bars represent 95% confidence intervals, corrected for a within-subject design (Morey, 2008).

People fixate more on the chosen option but allocate attention to different options depending on choice context

Consistent with previous research (Fiedler & Glöckner, 2012; Krajbich et al., 2010), participants fixated more on the chosen compared to the unchosen option for gains [$t(33) = 21.859$, $p < .001$, $d = 3.749$], losses [$t(33) = 17.125$, $p < .001$, $d = 2.937$], high-value [$t(30) = 18.935$, $p < .001$, $d = 3.401$] and low-value rewards [$t(30) = 16.777$, $p < .001$, $d = 3.013$]. Results from the linear mixed effects model revealed that participants' gaze bias was influenced by the fixed effects [$t(199.946) = -3.159$, $p < .01$, $R^2 = .26$], suggesting significant differences between some or all of the predictors. Post-hoc contrasts revealed that overall,

participants had a significantly lower gaze bias in the gain and high-value compared to the loss and low-value contexts [$t(580) = -5.185$, $p < .001$]. This illustrates, across the entire experiment, participants allocated, on average, more visual attention to the probabilistic options for gains and high-value rewards, but more visual attention to the deterministic options for losses and low-value rewards. When comparing the individual conditions to zero (i.e., no gaze bias), results were partially consistent with our hypothesis: participants allocated significantly more attention towards the deterministic over the probabilistic option for low-value rewards [$t(30) = 3.287$, $p < .001$, $d = 0.590$], but not for losses [$t(33) = 0.842$, $p = .203$, $d = 0.144$]. Participants were found not to elicit this gaze bias in the high-value [$t(30) = -1.366$, $p = .182$, $d = 0.245$] or gain [$t(33) = -1.240$, $p = .224$, $d = 0.213$] conditions. Moreover, participants' gaze bias increased across blocks (see Table 1), but the difference in gaze bias was only statistically significant when comparing the first and last blocks [$t(580) = 3.051$, $p < .01$], regardless of choice context and condition. There were no differences in gaze bias across conditions [$t(62.99) = 0.839$, $p = .40$]. Together, these findings suggest that the influence of attention on risk preference depends on the decision context, an effect which, across contexts, gradually changes with increased experience.

Table 1

Post-hoc contrasts of Block fixed effect

Contrast	Estimate	SE	T-statistic	p-value
Block 1 vs. 5	0.036	0.0118	3.05	0.002**
Block 2 vs. 5	0.026	0.0118	2.19	0.028
Block 3 vs. 5	0.022	0.0118	1.88	0.613
Block 4 vs. 5	0.013	0.0118	1.09	0.276

Note. Table shows estimates and test statistics based on post-hoc contrast for Block levels. Across conditions, gaze bias increased across blocks with different magnitudes, as indicated by all positive estimates. With increased experience, the magnitude change decreases, illustrating smaller (positive) changes in gaze bias as participants obtain more experience with the underlying reward structures. SE is the standard error.

** $p < .01$.

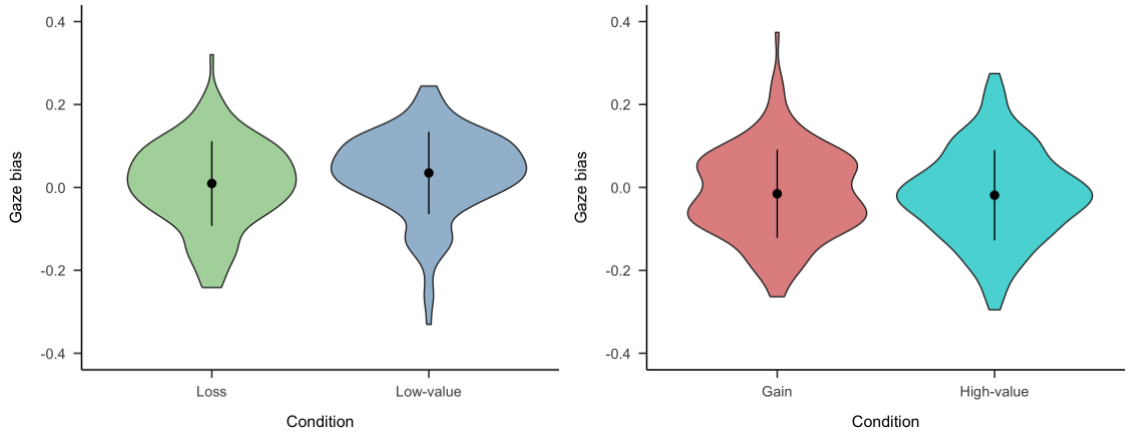


Fig. 3. Gaze bias for each condition (loss, low-value, gain, and high-value). The gaze bias indicates the difference in visual attention allocated to the options associated with a given condition (risky option – fixed option). The black dots represent mean gaze bias, and error bars 95% confidence intervals.

Reward Values Do Not Attract Visual Attention Following a Risky Choice

Contrary to our hypotheses, linear mixed-effects models showed that participants did not have an attentional bias for reward locations following a risky choice [$t(142.950) = -1.772$, $p = .08$, $R^2 = .33$]. Moreover, the interstimulus interval duration did not affect participants' visual attention [$t(901.244) = -0.693$, $p = .49$, $R^2 = .16$].

Choice context and reward value influence pupil dilation

We predicted that the choice context would affect pupil dilation, reflecting increased arousal. Two paired-sample t-tests, one for each choice context, were conducted and showed participants had larger pupil dilations when choosing between gains compared to losses [$t(33) = 2.024$, $p < .05$, $d = 0.347$] but not when choosing between high- compared to low-value rewards [$t(30) = 1.662$, $p = .053$, $d = 0.299$]. In addition, a 2 (Condition) x 2 (Option: probabilistic/deterministic) x 2 (Value) mixed-model ANOVA was conducted to further assess whether pupil dilation was larger when fixating on the probabilistic option compared to the deterministic option. Participants' pupil dilation significantly changed based on the option they looked at as a function of reward value [main effect of Option: $F(1, 62) = 7.427$, $p < .01$, $\eta_p^2 = 0.107$; Value [$F(1, 62) = 4.593$, $p < .05$, $\eta_p^2 = 0.069$; Option × Value interaction: $F(1, 62) = 7.639$, $p < .01$, $\eta_p^2 = 0.110$], but did not differ based on condition [main effect of Condition [$F(1, 62) = 1.317$, $p = .256$, $\eta_p^2 = 0.021$; no other interaction reached statistical significance].

Consistent with our hypotheses, post-hoc t-tests indicated that participants had significantly larger pupil dilation when fixating on probabilistic over the deterministic options [$t(62) = 2.727$, $p_{bonf} < .05$, $d = 0.058$]. Participants also had significantly larger pupil dilation on gain and high-value trials compared to loss and low-value trials [$t(62) = 2.143$, $p_{bonf} < .05$, $d = 0.047$]. Lastly, the interaction analysis revealed participants had significantly larger pupil dilation when fixating on the deterministic option on gain and high-value trials compared to loss and low-value trials [$t(62) = 3.268$, $p_{bonf} < .01$, $d = 0.085$], when fixating on the probabilistic option for gain and high-value trials compared to the deterministic option for loss and low-value trials [$t(62) = 3.428$, $p_{bonf} < .01$, $d = 0.105$], and when fixating on the probabilistic option compared to deterministic option on loss and low-value trials [$t(62) = 3.790$, $p_{bonf} < .01$, $d = 0.096$]. Together, these results indicate that an arousal response occurs when looking at options resulting in higher rewards in a given decision context and when looking at options that are inherently uncertain.

Reward outcome affects pupil dilation

Next, we wanted to assess whether pupil dilation was larger when receiving the worst possible outcome following a risky choice. A mixed effects ANOVA revealed participants' pupil dilation was associated with the outcome (i.e., best or worst) following a risky choice [main effect of Outcome: $F(1, 60) = 10.442$, $p < .01$, $\eta_p^2 = 0.148$; main effect of Condition ($F(1, 60) = 1.052$, $p = .309$, $\eta_p^2 = 0.017$)] which interacted with condition [Outcome × Condition interaction: $F(1, 60) = 8.888$, $p < .01$, $\eta_p^2 = 0.129$]. However, pupil dilation was not influenced by reward value [main effect of Value: $F(1, 60) = 0.212$, $p = .647$, $\eta_p^2 = 0.004$]. No other interaction was statistically significant (all $p > .07$). Post-hoc t-tests revealed significantly larger average pupil dilations for the best compared to the worst possible outcome in the high/low-value condition [$t(31) = 4.393$, $p_{bonf} < .001$, $d = 0.105$], but no significant differences in the gain/loss condition [$t(31) = 0.177$, $p_{bonf} = 1$, $d = 0.004$). These findings suggest a larger physiological arousal response is elicited when receiving the best possible outcome after making a risky choice than when receiving the worst possible outcome, but only when making choices for high- and low-value rewards, but not for gains and losses.

Overweighting of extreme outcomes

Inconsistent with previous results (e.g., Ludvig et al., 2018; Madan et al., 2017), we find that participants only overweighted extreme outcomes for gains and high-value rewards but not for losses or low-value rewards (Fig. 4). Specifically, when asked to report the first outcome that came to mind when individually seeing all the options, participants reported the best outcome significantly more than the worst outcome for gains [30 vs. 10; $\chi^2(1, N = 29) = 5.828$, $p < .05$] and high-value rewards [70 vs. 50; $\chi^2(1, N = 31) = 7.258$, $p < .01$], but did not report the worst outcomes for losses [-30 vs. -10; $\chi^2(1, N = 28) = 1.286$, $p = .257$] or low-value rewards [30 vs. 10; $\chi^2(1, N = 30) = 0$, $p = 1$]. Participants reporting the best outcome were significantly more risk-seeking for gains [$t(26) = 4.318$, $p < .001$, $d = 1.885$], even when correcting for outcomes experienced [$r(28) = 0.581$, $p < .001$]. Similarly, participants reporting the best outcome for losses were also significantly more risk seeking [$t(26) = 2.229$, $p < .05$, $d = 0.863$], but only before correcting for outcomes experienced [$r(28) = 0.345$, $p = .08$]. Conversely, participants reporting the best outcome for high-value rewards were not significantly more risk seeking [$t(29) = 0.616$, $p = .271$, $d = 0.253$], even when correcting for outcomes experienced [$r(31) = 0.020$, $p = 0.542$]. Participants who reported the best outcome for low-value rewards were significantly more risk-seeking [$t(28) = 2.694$, $p < .01$, $d = 0.984$], even when correcting for outcomes experienced [$r(30) = 0.415$, $p < .05$].

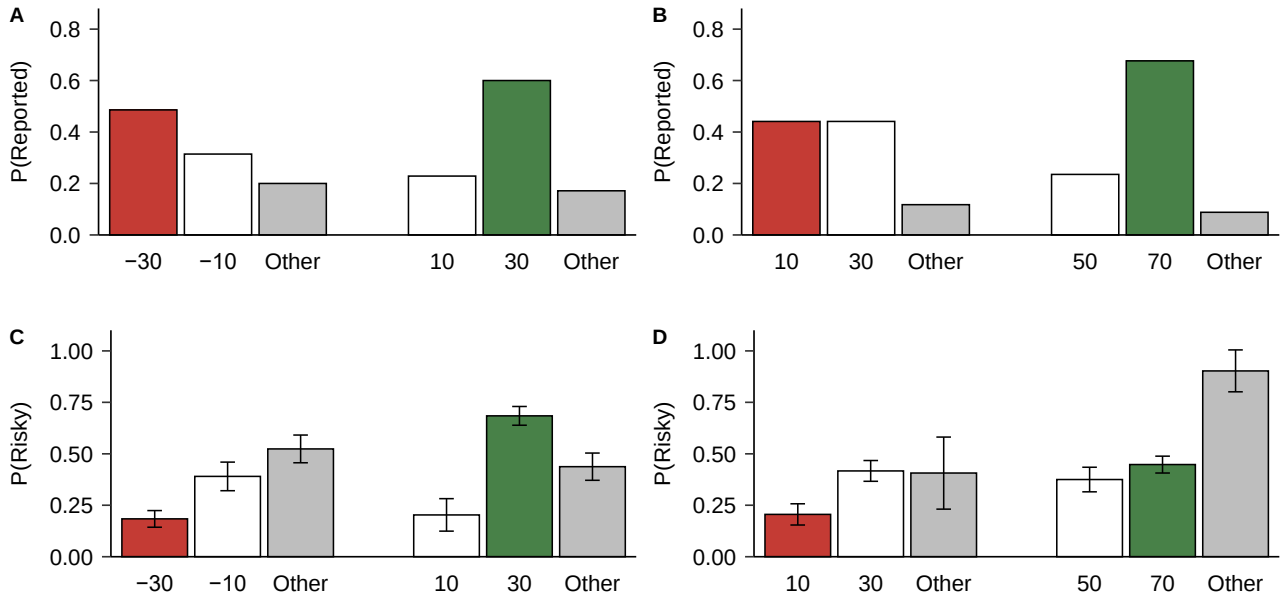


Fig. 4. First outcome reported. (A-B) shows the proportion of participants reporting each outcome as the first outcome that came to mind for the gain/loss and high-/low-value conditions, respectively. (C-D) shows the

risk-seeking propensities as a function of which outcome first came to mind for the gain/loss and high-/low-value conditions, respectively. Error bars represent 95% confidence intervals, corrected for a within-subject design.

Overweighting outcome frequencies and their influence on risk-seeking depend on the condition

When asked to judge the frequency of outcomes, participants judged the worst outcome as having occurred significantly more frequently than the best outcome for the loss [$t(32) = 2.606$, $p < .01$, $d = 0.454$] and low-value [$t(31) = 2.255$, $p < .05$, $d = 0.399$] conditions. However, no reliable differences in frequency judgments were observed for the outcomes in the gain [$t(33) = 0.537$, $p = .297$, $d = 0.092$] or high-value [$t(31) = 0.776$, $p = .222$, $d = 0.137$] conditions. Moreover, risk-seeing decreased with judged frequency of the worst outcome for losses [$r(33) = -.390$, $p < .05$], but only before correcting for experienced outcomes [$r(33) = -.292$, $p = .052$;]. Risk-seeking also decreased with judged frequency of the worst outcome for low-value rewards [$r(32) = -.370$, $p < .05$], even after correcting for experienced outcomes [$r(32) = -.306$, $p < .05$]. Risk-seeking increased with judged frequencies of the best outcome for gains [$r(33) = .376$, $p < .05$] but not for high-value rewards [$r(32) = -.073$, $p = .654$]. After correcting for experienced outcomes, risk-seeking was not influenced by judged frequencies of the best outcome for either gains or high-value rewards [gain: $r(33) = .153$, $p = .202$; high-value: $r(32) = -.086$, $p = .678$].

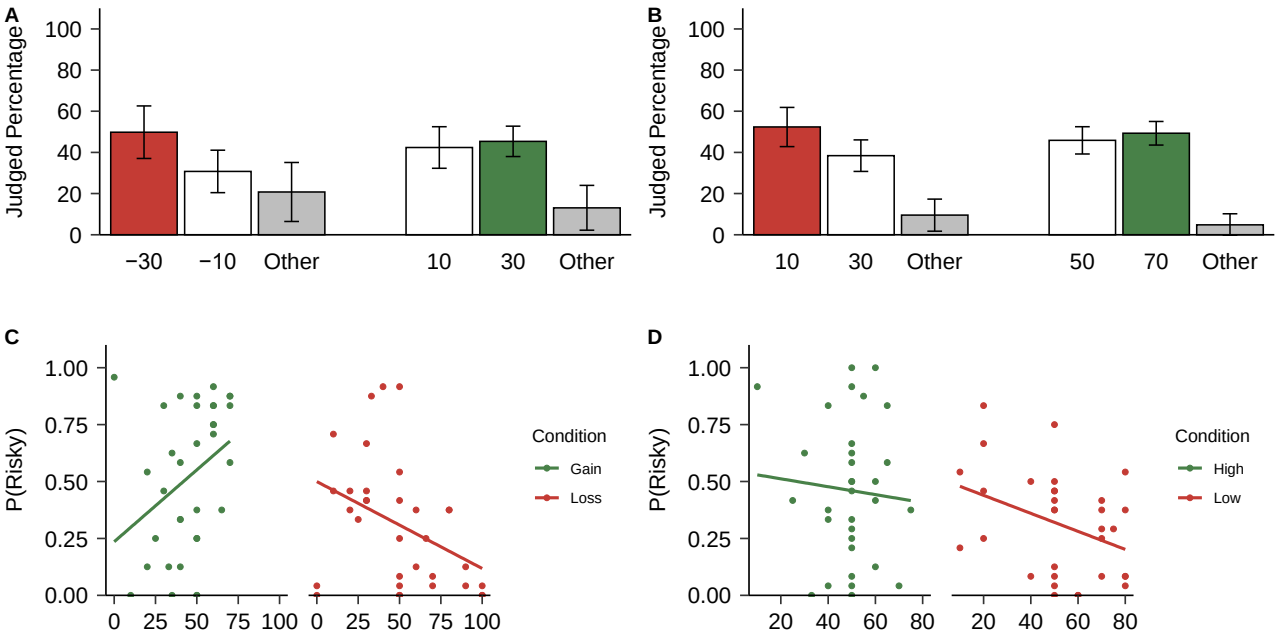


Fig 5. Results from frequency judgment memory test. (A-B) shows participants' judged frequencies for each outcome associated with a risky choice for the gain/loss and high-/low-value conditions, respectively. (C-D) shows risk-seeking propensities as a function of the judged frequency of occurrence for the best outcome for the gain (30) and high-value (70) conditions and the worst outcome for the loss (-30) and low-value conditions (10). Error bars represent 95% confidence intervals, corrected for a within-subject design.

Discussion

A growing body of literature has implicated attention as playing a pivotal role in decision-making processes (Fiedler & Glöckner, 2012; Krajbich et al., 2010, 2012; Liao & Anderson, 2020; Orquin et al., 2018; Stojić et al., 2020; Weilbächer et al., 2021), and it has been suggested eye-tracking can provide a window into associated cognitive mechanisms (Spering, 2022). This study examined the role of visual attention and pupil dilation in memory-based preferential risky choice, aiming to gain a deeper understanding of the cognitive mechanisms associated with memory biases and changes in risk preference with learning. Consistent with previous work, people fixate more on the option they choose (e.g., Fiedler & Glöckner, 2012; Shimojo et al., 2003). Although we found that participants allocated more attention to probabilistic options for gains and high-value rewards compared to losses and low-value rewards across conditions, people only significantly allocated more attention to the deterministic over the probabilistic option for low-value rewards, with no reliable differences for losses, gains, or high-value rewards. Participants were also found to have larger average pupil dilation for gains compared to losses and high- compared to low-value rewards and when fixating on the deterministic (probabilistic) over the probabilistic (deterministic) option for gains and high-value rewards (losses and low-value rewards). Participants were found to have larger average pupil dilation when fixating on the probabilistic option over the deterministic option for losses and low-value rewards, but not for gains or high-value rewards. Moreover, larger pupil dilation was observed when participants fixated on the probabilistic and deterministic options for gains and high-value rewards than when fixating on the deterministic option for losses and low-value rewards. No difference in pupil dilation was observed between gain and high-value options and the loss and low-value probabilistic options. Lastly, we find that participants had larger pupil dilation when receiving the worst compared to the best possible outcome following a risky choice.

Crucially, however, this was only the case for the high/low-value condition and not the gain/loss condition.

Framing and loss aversion can explain the discrepancy between gaze bias observed for low-value rewards (i.e., allocating more attention to the deterministic option) and the absence of attentional favoritism for losses. Although behaviorally, participants engaged in a similar risk aversion for losses and low-value rewards, the options may still have been perceived differently where low-value rewards appear less impactful to participants' overall goal (i.e., earning as many points as possible) than their loss counterpart. As a result, certainty could be prioritized for low-value rewards (leading to a deterministic option gaze bias), whereas since the deterministic option still implies a loss, equal amounts of attention are attributed to either option when comparing losses. The higher salience and emotional impact associated with losses over gains (Tversky & Kahneman, 1992) may further have overshadowed attentional mechanisms when choosing between two options, resulting in the observed differences in attentional allocation between low-value rewards and losses.

The current study further attempted to directly assess the optimism bias (Sharot, 2011) and the loss attention hypothesis (Yechiam & Hochman, 2013a) in visual attention when awaiting reward feedback following a risky choice. Briefly, the optimism bias would posit more attention allocated to the best possible outcome, whereas the loss attention hypothesis would posit more attention allocated to negative outcomes and losses. We find that our results contradict both of these competing hypotheses. The lack of attentional over-allocation towards either the best or worst outcomes challenges the notion that people consistently overemphasize favorable events while, at the same time, questioning the universality of the loss attention hypothesis. It is important to note that this interpretation is rooted solely in overt attention and extends not necessarily to covert attention and internal mental representations. In fact, the results from the first outcome reported memory test may indicate selective covert visual attention. Participants may have elicited more covert attention towards the best possible outcome for gains and high-value rewards when choosing the probabilistic option – thereby causing these values to become overweighted in memory – but not discriminated between possible outcomes for losses and low-value rewards. However, this interpretation should be approached with some care as the inability to replicate overweighting of extreme outcomes in the first outcome reported memory test

– an otherwise robust effect (e.g., Ludvig et al., 2018; Madan et al., 2014, 2017) – may be due to insufficient power.

We only partially find evidence of pupil dilation reflecting option value (Fiedler & Glöckner, 2012; Van Slooten et al., 2018), as participants only had larger pupil dilation when choosing between gains compared to losses but not when choosing between high- compared to low-value rewards. This discrepancy may, as previously outlined, be indicative of the higher visual and emotional saliency (Tversky & Kahneman, 1992). Relatedly, participants also had larger pupil dilation when fixating on the probabilistic option for losses and low-value rewards (but not gains or high-value rewards), which likely reflects internal representations of the riskiness associated with these options (Cherkasova et al., 2018). That is, the loss and the low-value reward probabilistic option were perceived as inherently riskier than their counterparts, consistent with the risk-seeking behavior elicited by participants. Participants' increased perceived riskiness for the loss and low-value reward probabilistic option makes them increasingly risk-averse with experience. In contrast, the probabilistic option is not perceived as significantly riskier for gains and high-value rewards, leading to risk-neutral choice behavior. Post-feedback positive reward prediction errors (e.g., Urai et al., 2019) were also observed as participants had larger pupil dilations when experiencing the best compared to the worst possible outcomes, but only for the high/low-value condition.

The current results underscore the complexity of attention in preferential risky choice and the importance of incorporating context effects into models of attention and decision-making. Deviations from predictions of the optimism bias and the loss attention highlight the multifaceted nature of cognitive processes associated with (visual) attention. Although participants displayed a gaze bias towards the chosen options, attention allocation varied across choice contexts. In fact, in the present study, visual attention appears largely independent of actual choice behavior as participants elicited a significant gaze bias toward the deterministic option but only for low-value rewards, despite participants equally becoming increasingly risk-averse for low-value rewards and losses. Instead, pupil dilation appears to be a better determinant of loss-aversive behavior in these contexts, as the probabilistic options appear riskier for losses and low-value rewards (Cherkasova et al., 2018) than their positive counterparts. Further understanding of how choice contexts shape preferential (risky) choices is crucial for a more comprehensive account of human decision-making. Assessing the temporal dynamics of preferential choices in different choice contexts

by using models such as the attentional drift-diffusion model (Krajbich et al., 2010) or the gaze-weighted linear accumulator model (Thomas et al., 2019; Weilbächer et al., 2021) may further help explain these findings by computationally highlighting how attention in different choice contexts shape decision-making.

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Chapter 5:

Modeling the temporal dynamics of context-based decision biases in risky choice

Abstract

The context in which we make decisions is critical in shaping how we choose between available options. This is also the case for risky decisions, but the underlying mechanisms remain elusive. We use computational modeling to assess the temporal dynamics associated with risky choice biases in different decision contexts. Two existing datasets were used in which participants made repeated decisions in various decision contexts. Utilizing hierarchical drift diffusion modeling, we find that increased experience with the choice environments decreases the amount of information needed to commit to a decision. Furthermore, we show the magnitude of evidence accumulation favoring an option differently depending on the choice context. We provide novel insight into how people move in parameter space by modeling how parameters change over time as people learn.

Keywords: risky choice, computational modeling, drift-diffusion model, description-experience gap, decisions-from-experience

Introduction

Making risky choices is a fundamental aspect of human behavior. Whether it is trading stocks, taking the car to work, or deciding when to purchase a house, people must constantly navigate a complex, uncertain considering potential gains and losses associated with their choices. People's risk-seeking propensities in such uncertain environments are influenced by a plethora of factors, such as subjective perceptions of risk and uncertainty, subjective preferences, various unconscious choice and memory biases, and the interplay between description and direct experience of outcomes (Camilleri & Newell, 2013; Kahneman & Tversky, 1979; Simonson & Tversky, 1992; Thaler & Johnson, 1990; Weber & Johnson, 2006; Weiss-Cohen et al., 2016, 2021). Moreover, the decision context itself (i.e.,

choices based on description or experience) significantly influences how people make risky choices (Hertwig & Erev, 2009; Kahneman & Tversky, 1979; Ludvig & Spetch, 2011), even when the underlying reward structures remains constant across contexts (Madan et al., 2017). Specifically, people tend to exhibit greater risk-seeking behavior for relative gains than losses when making decisions based on experience, whereas the opposite pattern emerges when decisions are based on description (Hertwig & Erev, 2009). This discrepancy in risk propensities between decision contexts – known as the description-experience gap – suggests the involvement of distinct cognitive mechanisms in risky decision-making due to memory biases (Madan et al., 2017), findings that can be captured by a reinforcement learning cumulative prospect theory model (Haines et al., 2023). In the past decade, a significant amount of research has been conducted on the description-experience gap (for reviews see, e.g., Garcia et al., 2021; Hertwig & Erev, 2009; Hertwig & Wulff, 2022) to better understand how and why the gap arises, as it poses major challenges to current theories of decision-making under uncertainty and neuroeconomics (Garcia et al., 2021).

Because of the difference in available information between described end experiential prospects, one suggested explanation of the description-experience gap is context-dependence (e.g., Madan et al., 2017, 2021). The cognitive mechanisms involved in the two decision contexts differ as the outcome distribution of the risky option is used to contextually evaluate the safe option for experiential prospects but not described prospects (Glöckner et al., 2016). Consequently, subjective representations of the outcomes and probabilities systematically vary depending on the decision context (Kellen et al., 2016). Interestingly, even in decisions solely based on experience, context-dependent effects emerge, leading people to evaluate options based on the local encoding context rather than the global encoding context (Madan et al., 2021). Notably, these contextual influences on decision-making extend beyond risky choice alone. For instance, making decisions within a familiar context biases choice, making people more susceptible to being influenced by memories of past events (Bornstein & Norman, 2017; Duncan et al., 2019; Duncan & Shohamy, 2016). In this regard, priming people with prior choices increases the probability of repeating decisions previously resulting in a gain, while discouraging people from repeating decisions previously resulting in a loss (Bornstein et al., 2017). Even in cases where statistical learning does not need to be established, context-dependent effects still influence people's decisions. Introducing additional available options can influence which option is

chosen and even reverse consumer preferences (Huber et al., 1982; Simonson & Tversky, 1992; Spektor et al., 2019). Similarly, when people choose consumer items, they are swayed by their surroundings, such as playing German (French) music increasing the purchases of German (French) wine (North et al., 1997). Together, these findings highlight the importance of understanding contextual choice effects for psychological and economic theories of risky choice and for a better understanding of consumer behavior.

While behavioral analyses offer valuable, insightful descriptions of risky choice and the contextual effects surrounding (risky) decision-making processes, they may not necessarily provide sufficient explanations of the underlying mechanisms. Thus, computational models have been employed to gain a deeper understanding of decision-making by capturing the underlying cognitive processes (e.g., see Gershman & Daw, 2017). Research using reinforcement learning (RL) models has revealed wins and losses may be represented as separate states during learning (Palminteri et al., 2015; Redish et al., 2007), and that people rely on a combination of model-based and model-free RL in multistep decisions involving risk (Daw et al., 2011). The drift-diffusion (DDM) model has, in particular, been proven useful in explaining the temporal characteristics of decision-making and has even been integrated into RL models (Fontanesi et al., 2019; Pedersen et al., 2017; Peters & D'Esposito, 2020). For instance, the DDM has shown greater response caution when making value-based compared to memory-based decisions (Kraemer & Gluth, 2023). Furthermore, asymmetries are observed in evidence accumulation during risky choice, with decreased evidence accumulation for gambles compared to safe alternatives but increased evidence accumulation as the gambles become increasingly more attractive (e.g., increased probability of winning gamble; Dutilh & Rieskamp, 2016; Zeigenfuse et al., 2014). People also exhibit *a priori* preferences for ambiguous gambles (Dutilh & Rieskamp, 2016) and, when highly loss averse, have slower evidence accumulation rates, but only for gains (Clay et al., 2017).

However, how cognitive mechanisms and computational parameters may evolve with learning in risky choice and how they compare between decision contexts remain elusive. We engage in an interdisciplinary approach drawing from cognitive psychology, behavioral economics, and computational modeling to investigate the cognitive mechanisms influencing risky decision-making depending on the decision context. Firstly, we investigate potential computational differences between description- and experience-based risky

preferential choices using a within-subjects design (Madan et al., 2017) to better characterize the cognitive mechanisms involved in the description-experience gap. Extending this, we further attempt to describe the computational differences when modeling the emergence of context-based choices in decisions-from-experience (Madan et al., 2021, Exp. 1). Lastly, we leverage methodological designs that enable an assessment of how changes in cognitive processes and representations of risk and reward shape computational parameters to better characterize the temporal dynamics of evidence accumulation in risky choice (e.g., for review on related topic see Harris & Hutcherson, 2022).

Methods

Data and modeling scripts for this study are available on the Open Science Framework (https://osf.io/vktge/).

Participants

For *Experiments 1* and *2*, a total of 384 participants were recruited from the University of Alberta. All methods were approved by the University of Alberta's ethics board. Participants received course credit and a cash bonus for participating. In *Experiment 1* (Madan et al., 2017), data from 256 participants (146 female; M_{age} = 19.3, *SD* ± 2.6) were recruited, and 128 participants (99 female, M_{age} = 19.4, *SD* ± 1.9) were recruited in *Experiment 2* (Madan et al., 2021, Exp. 1). Participants were excluded from data analysis and computational modeling if performance on attentional checks (i.e., choosing the objectively higher expected value option on certain trials) was lower than 60%. A total of 21 participants were excluded from *Experiment 1,* and 9 participants were excluded from *Experiment 2*.

Experimental protocols

Experiment 1: Madan et al. (2017)

In *Experiment 1*, participants completed a within-subjects decision-making task where participants made decisions from experience and decisions from description. Overall, participants completed five blocks (two decisions from description blocks and three decisions from experience blocks) where experience and description blocks occurred consecutively. All participants started by completing an experience block followed by a description block. In both decision types, participants mainly chose between a deterministic

and a probabilistic equiprobable option that resulted either in a gain or a loss. The same outcomes for either reward condition were used across decision types (fixed gain of 20, risky gain of 0 or 40, fixed loss of -20, risky loss of 0 or -40). Participants completed 32 of these self-paced decision trials in each block. For a more in-depth description of the methods and procedure, see Madan et al. (2017).

Experiment 2: Madan et al. (2021)

In *Experiment 2*, participants made choices in a decisions-from-experience task consisting of 2 different contexts: Gain/Loss and High/Low-value contexts. Similar to *Experiment 1*, on most trials, participants chose between a deterministic and a probabilistic equiprobable option. In the Gain/Loss context, the fixed options led to either a fixed gain (+20) or a fixed loss (-20), and the risky options led to either a risky gain (+10 or +30) or a risky loss (-10 or -30). In the High/Low-value context, the fixed options led to either a fixed high-value gain (+60) or a fixed low-value gain (+20), and the risky options led to either a high-value risky gain (+50 or +70) or a low-value risky gain (+10 or +30). Participants completed 32 of these self-paced decision trials in each block. For a more in-depth description of the methods and procedure, see Madan et al. (2021, Exp. 1).

DDM modeling

Because the DDM is sensitive to outliers and best characterized for fast decisions (Ratcliff & McKoon, 2008), we excluded trials with reaction times slower than 10s in *Experiment 1* and 5s in *Experiment 2*. A different reaction time threshold was used between the two studies because of their methodological differences. That is, since *Experiment 1* included described prospects – which naturally takes longer to process – a less conservative threshold was used for both the described and experienced modes in *Experiment 1*. As such, we removed 446 (1.09%) trials from *Experiment 1* and 362 (1.47%) trials in *Experiment 2*. For consistency, behavioral and DDM analyses were performed on this trimmed data. To further ensure that outliers did not affect the DDM estimates, our model assumed 5% of trials were distributed from a uniform distribution as recommended as best practice by the HDDM developers (Wiecki et al., 2013). In *Experiment 1*, mean drift rate, decision threshold, and starting point bias for each reward type were modeled (e.g., gains and loss in description or gain and loss in experience). Conversely, in *Experiment 2,* only the mean drift rate and

decision thresholds for each reward type were modeled. For *Experiment 1*, this means that 2 blocks were modeled for the description models, and 3 blocks were modeled for the experience models. Conversely, in *Experiment 2*, 5 blocks were modeled for all decision contexts. In both experiments, the mean parameters were calculated by using the first block as the regression intercept and comparing it to the regression coefficient of all subsequent blocks.

The HDDM uses the Markov Chain Monte Carlo sampling method to generate posterior distributions for estimated parameters. We obtained 25,000 samples of each posterior distribution to ensure smooth parameter estimates and assessed chain convergence using the Gelman-Rubin $\hat{R}$ statistic (where a value < 1.1 for each parameter assumes convergence; Gelman et al., 2004). Multiple models were conducted to find the best-fitting model where different parameters were allowed to vary by the number of blocks within each condition reward context. Reported model parameters are from the best-fitting model. Model selection was based on the Deviance Information Criterion (DIC), which assesses the goodness of model fit while penalizing for model complexity (see Tables S1-S4 in Supplemental Methods for model fits). Posterior Predictive Checks (PPC) were conducted to assess whether there were systematic discrepancies between real and simulated replicated data under the fitted model. Details on PPC are discussed further in the Supplementary Methods.

Crucially, the standard DDM was unable to capture the behavioral data for the decisions-from-experience, as highlighted by failed posterior predictive checks. However, using a DDM with collapsing bounds was able to capture the behavioral data. A collapsing bounds model has previously been found to be optimal and lead to greater predictive reward across an entire decision sequence (Drugowitsch et al., 2012; Tajima et al., 2016). Thus, for decisions-from-experience, we report parameter estimates from a collapsing bounds model.

Results

Experiment 1:

To assess the information integration process in risky choice, the DDM uses participant choices and reaction time distributions to characterize the evidence

accumulation process across different blocks relative to when learning first occurs. This enables us to break down the decision-making process into meaningful psychological parameters (Ratcliff & McKoon, 2008): drift rate (v), decision threshold (a), and starting point bias (z). The drift rate is the strength of evidence favoring either making a risky or safe choice. The decision threshold is the amount of evidence needed to be integrated before deciding. The greater the threshold, the more evidence is needed before making a choice, thus reflecting response caution. Lastly, the starting point bias is the extent to which people are more biased toward making a risky or safe choice before accumulating evidence. Central to our aim, the evidence strength reflects psychological processes associated with how the valuation of risky choice preferences in each decision context is dynamically integrated. Thus, the DDM enables us to rigorously assess the underlying cognitive mechanisms underpinning risky decision-making. We used the Hierarchical Drift-Diffusion Model python package (HDDM; Fengler et al., 2021; Wiecki et al., 2013) to perform hierarchical Bayesian estimations of the drift rate (v), threshold (a), and starting-point bias (z) parameters. Parameters were estimated at the group level. Decisions to make a risky choice were mapped to the upper boundary, and decisions to make a safe choice were mapped to the lower boundary of the DDM. Separate parameters were fit for each decision context, where all parameters were allowed to vary for each block.

The HDDM provides Bayesian parameter estimations of the DDM, meaning traditional frequentist hypothesis testing cannot be applied to the parameter estimates. Instead, Bayesian hypothesis testing involves comparing the proportion of values in a posterior distribution falling above or below a certain value or the mean of another posterior distribution. Thus, Bayesian hypothesis testing is conceptually akin to performing a frequentist t-test (Kruschke, 2013). We define significance as 95% of posterior values falling above or below (depending on the analysis) a specified value and report posterior values as 1-*p* to more closely resemble p-values from frequentists significance testing to avoid confusion.

Differential risk seeking based on decision format

Behaviorally, participants showed the reflection effect for described prospects (i.e., risk seeking for losses but risk averse for gains) and the reverse reflection effect for experienced prospects (i.e., risk seeking for gains but risk averse for losses). A 2 (decision

context; description/experience) × 2 (value; gain/loss) ANOVA revealed an interaction between decision context and value [$F(1, 254) = 12.037$, $p < .001$, $\eta_p^2 = 0.045$], but no main effects [decision context: $F(1, 254) = 0.003$, $p = .958$, $\eta_p^2 < .001$; value: $F(1, 254) = 3.030$, $p = .083$, $\eta_p^2 = 0.012$]. For described prospects, participants were significantly more risk-seeking for losses than gains [$t(254) = 3.166$, $p < .001$, $d = 0.198$] and, for experienced prospects, significantly more risk-seeking for gains than losses [$t(254) = 2.520$, $p < .001$, $d = 0.158$] across the two last blocks. For more comprehensive behavioral analyses (e.g., memory biases), see Madan et al. (2017).

Changes in drift rate with learning

Based on these behavioral results, we predicted that drift rate (v) would increase in magnitude across blocks for the deterministic option for experienced losses but increase in magnitude for the probabilistic option for experienced gains. As more memories become more readily available to sample from, it impacts the rate of accumulation differentially because the extreme outcomes experienced would be overweighted in memory (Ludvig et al., 2018; Madan et al., 2014, 2021). This leads to more favorable evidence being accumulated for the deterministic option for losses and probabilistic option for gains because instances of the worst possible losses and best possible gains will be overrepresented in the memory sampling pool. However, we did not predict significant differences in drift rate across blocks for described prospects. The reasoning being that, although described gains and losses elicit different risk-seeking propensities, the description format would require more deliberation and, therefore, not shift the evidence accumulation process significantly. The magnitude of the drift rate reflects the strength of favorable evidence accumulated for an option (i.e., a larger magnitude reflects faster evidence accumulation). The sign reflects whether evidence favors the probabilistic (positive) or deterministic option (negative). Partially consistent with this prediction (Fig. 1), the drift rate magnitude increased in favor of the deterministic option for losses and gains across blocks when making decisions-from-experience, but no significant changes when making decisions-from-description. Average drift rate did not differ between decision contexts (all posterior *P*s > .05).

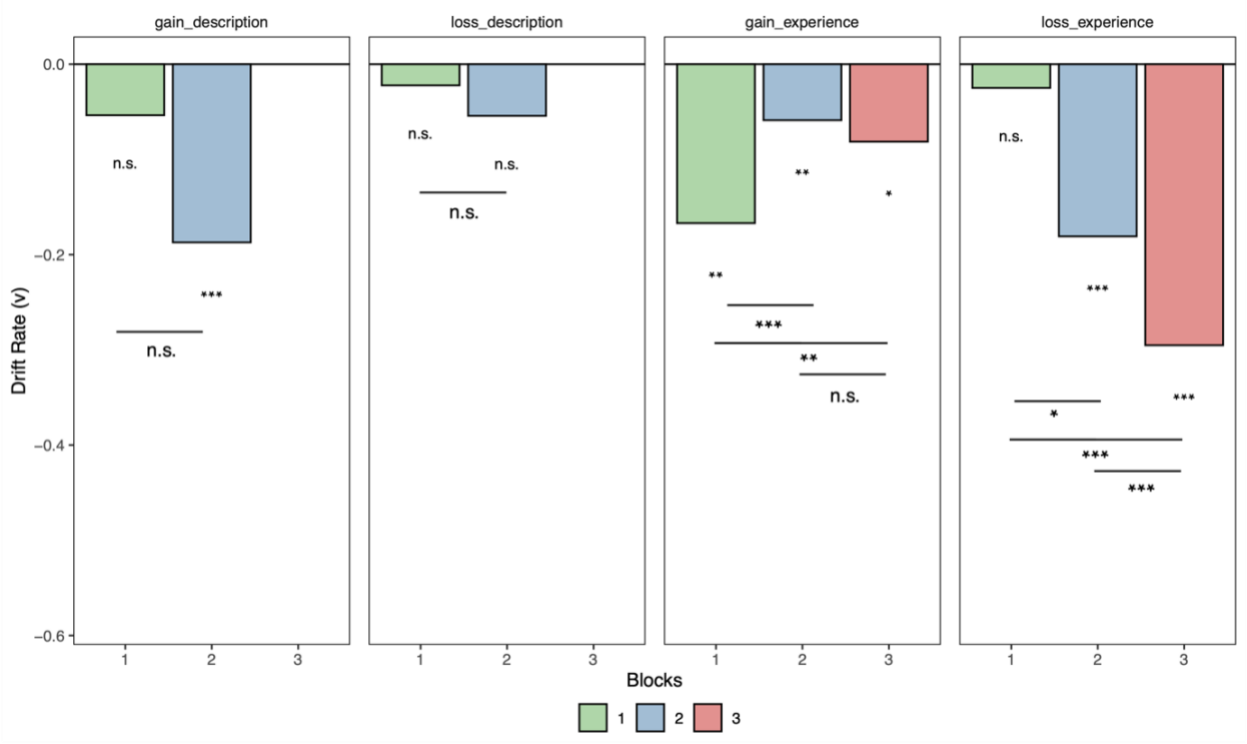


Fig 1. Mean drift rate parameter estimates for each block in each decision context. Significance asterisks represent differences from 0 (i.e., no difference in drift rate), and significance bars represent pairwise comparisons. Single asterisks (*) denote posterior $p < .05$, double asterisks (**) denote posterior $p < .01$, and triple (***) denote posterior $p < .001$.

Changes in decision threshold with learning

We predicted that participants would require less evidence to make a decision (i.e., a decreasing decision threshold) following increased experience with the gambles in the different decision contexts. Consistent with this prediction (Fig. 2), the average decision threshold (a) decreased as a function of learning for all contexts (all posterior Ps < .001).

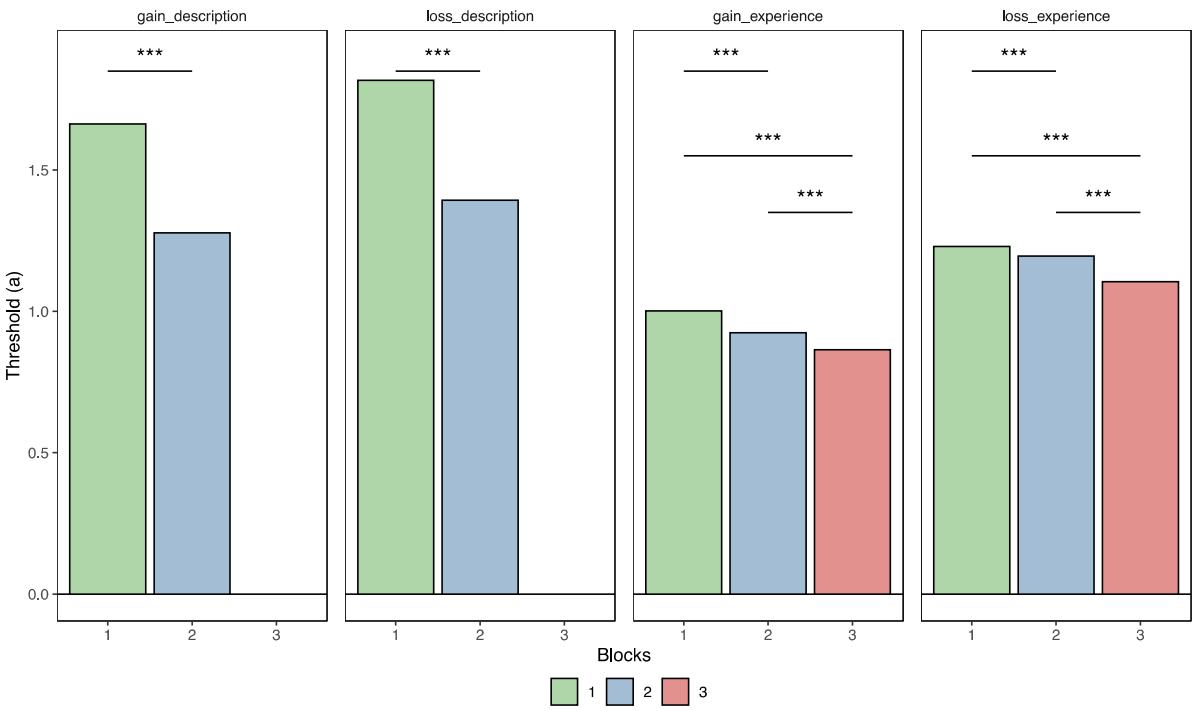


Fig 2. Mean decision threshold parameter estimates for each block in each decision context. The average decision threshold decreased significantly in all decision contexts as participants gain more experience with the gambles (posterior $p < .001$).

Average decision threshold was also found to differ as a function of decision contexts. Experienced gains had a significantly lower average threshold than experienced losses (posterior $p < .001$), described gains (posterior $p < .001$), and described losses (posterior $p < .001$). Experienced losses had a lower decision threshold than described gains (posterior $p < .001$) and described losses (posterior $p < .001$), and described gains had a lower decision threshold than described losses (posterior $p < .001$). Together, this illustrates lower response caution for experienced prospects compared to described prospects and lower response caution for gains compared to losses.

Differences in starting point bias

Lastly, we assessed whether participants elicited a starting point bias (z) and how it might change across blocks. We had no *a priori* predictions for this set of analyses. If the average starting point bias parameter is 0.5, it indicates that participants were unbiased toward either of the decision boundaries. Conversely, z parameter values greater than 0.5 indicates an initial bias – or preference – for the probabilistic option, whereas values less

than 0.5 indicates an initial bias towards the deterministic option. Participants starting point bias changed across blocks; a bias was only exhibited in the first block towards the deterministic option for gains in the described (average z = 0.43; posterior p < .001) and experienced (average z = 0.47, posterior p < .01) contexts. For experienced losses, participants exhibited a bias towards the probabilistic option in the first block (average z = 0.529, posterior p < .05), no bias in the second block (average z = 0.496; posterior p = .059), but exhibited a bias towards the deterministic option in the third block (average z = 0.494; posterior p < .05). Participants did not exhibit a bias for described losses in either block (all posterior Ps > .05).

Participants were more biased towards the deterministic option for experienced gains compared to experienced losses (posterior p < .001) and compared to described losses (posterior p < .01). Conversely, participants were more biased towards the deterministic option for described gains compared to experienced gains (posterior p < .05), compared to described losses (posterior p < .001), and compared to experienced losses (posterior p < .001). There was no difference in bias between described and experienced losses (posterior p = .13). This illustrates participants started closer to the deterministic option for gains compared to losses and for described prospects compared to experienced prospects (but not when comparing losses).

Experiment 2:

Experiment 1 illustrated clear differences in computational parameters between described and experienced prospects. In addition, it revealed a clear link between risk-seeking propensities, the decision context, and how parameter estimates change with learning, particularly in the experience-based decision contexts. To further elucidate and validate these results, we decided to focus on modeling context-based choice biases in experienced-based risky choice where learning is a central element. To this end, we used another pre-existing dataset from Madan et al. (2021, Exp. 1). We only report results from Exp. 1 of Madan et al. (2021) because all modeling attempts of Exp. 2 were unsuccessful, highlighted by failed PPCs. Indeed, reducing the dataset of Exp. 1 to the same number of trials as Exp. 2 (from 48 to 24) revealed the same problem, clearly illustrating that the reduced number of trials cannot be modeled using a drift-diffusion process. This likely reflects slower learning that cannot be captured by the models. The only difference in the

modeling process between *Experiment 1* and *Experiment* 2 was the number of parameters that were allowed to freely vary. The best-fitting model for *Experiment 2* included only the drift rate and decision threshold parameters. As such, we again fit these parameters for each decision context, allowing drift rate and decision threshold to vary for each block. A single bias parameter was estimated for each decision context.

Local encoding context determines risky choice

Similar to *Experiment 1*, participants were more risk-seeking for gains compared to losses [$t(124) = 3.041$, $p < .001$, $d = 0.272$] and, similarly, were more risk-seeking for high- compared to low-value rewards [$t(124) = 4.931$, $p < .001$, $d = 0.441$]. Together, these behavioral results illustrate that the local encoding context determines the risk-seeking propensities rather than the global encoding context. For more comprehensive behavioral analyses, see Madan et al. (2021).

Changes in drift rate with learning

Given the results from *Experiment 1* and the behavioral results outlined above, we predicted that drift rate (v) magnitude would increase in favor of the deterministic option across blocks for the loss and low-value contexts but not for the gain or high-value reward contexts. Consistent with this prediction (Fig. 3), drift rate magnitude increased in favor of the deterministic option for the loss and low-value contexts across blocks, but no significant change in the high-value context was observed. Although drift rate magnitude did increase in favor of the deterministic option in the gain context, it was only significantly different from 0 in the last block, and the change in drift rate between blocks was not significant. Furthermore, average drift rate was found to differ significantly between decision contexts. The average drift rate was significantly lower for the loss context compared to the gain (posterior $p < .05$) and high-value contexts (posterior $p < .001$). The low-value context also had a significantly lower drift rate compared to the gain (posterior $p < .01$) and high-value (posterior $p < .001$) contexts. No differences were observed between the loss and low-value contexts (posterior $p = .80$) or the gain and high-value contexts (posterior $p = .06$). Together, this illustrates similar evidence accumulation processes based on the local encoding context (i.e., lower average drift rate for the worst compared to the best decision set in a decision context). Moreover, evidence accumulation appears comparable across the global context,

where evidence for the deterministic option is accumulated faster for the worst decision sets (i.e., losses and low-value rewards) but not for the best decision.

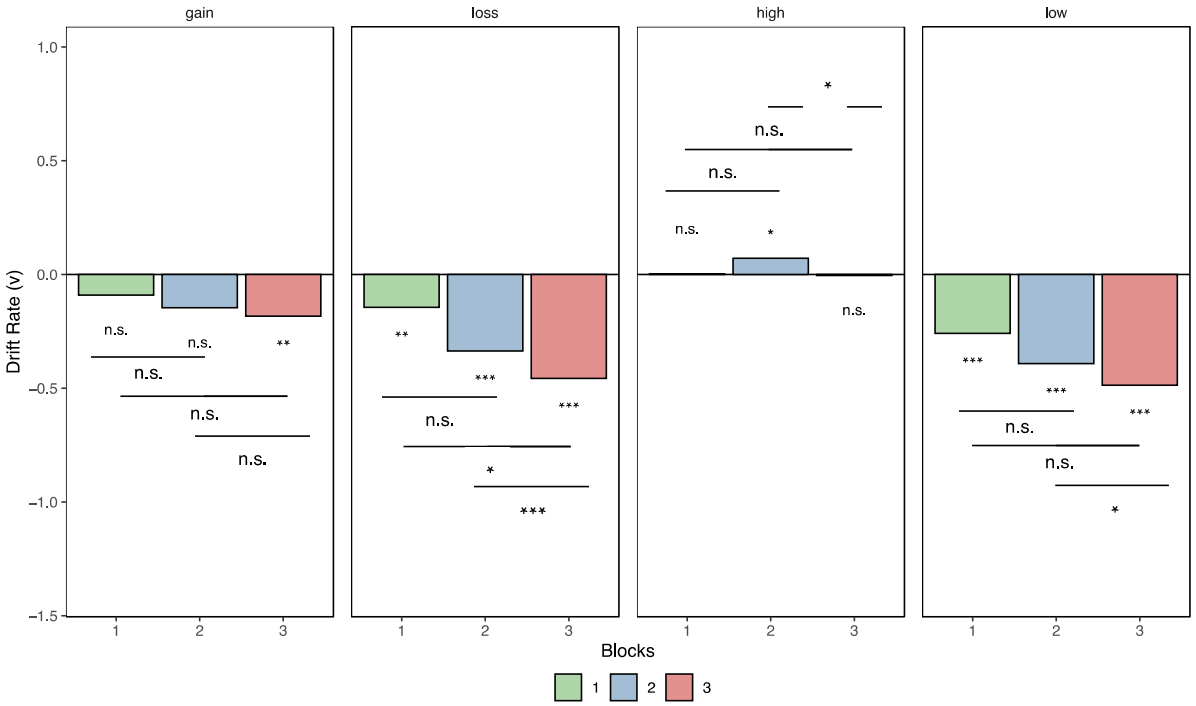


Fig 3. Mean drift rate parameter estimates for each block in each decision context. Drift rate decreases significantly with increased experience in the loss and low-value contexts showing increased evidence accumulation favoring the deterministic option. For the gain and high-value contexts, evidence accumulation is closer to neutral.

Changes in decision threshold with experience

Similar to *Experiment 1*, we predicted that participants would require less evidence to make a decision with increased experience. We also predicted that participants would have a higher average decision threshold for the gain compared to loss context and the high-value compared to low-value context. Consistent with our prediction (Fig. 4), the average decision threshold (*a*) significantly decreased as a function of learning for all of the contexts (all posterior *P*s < .001).

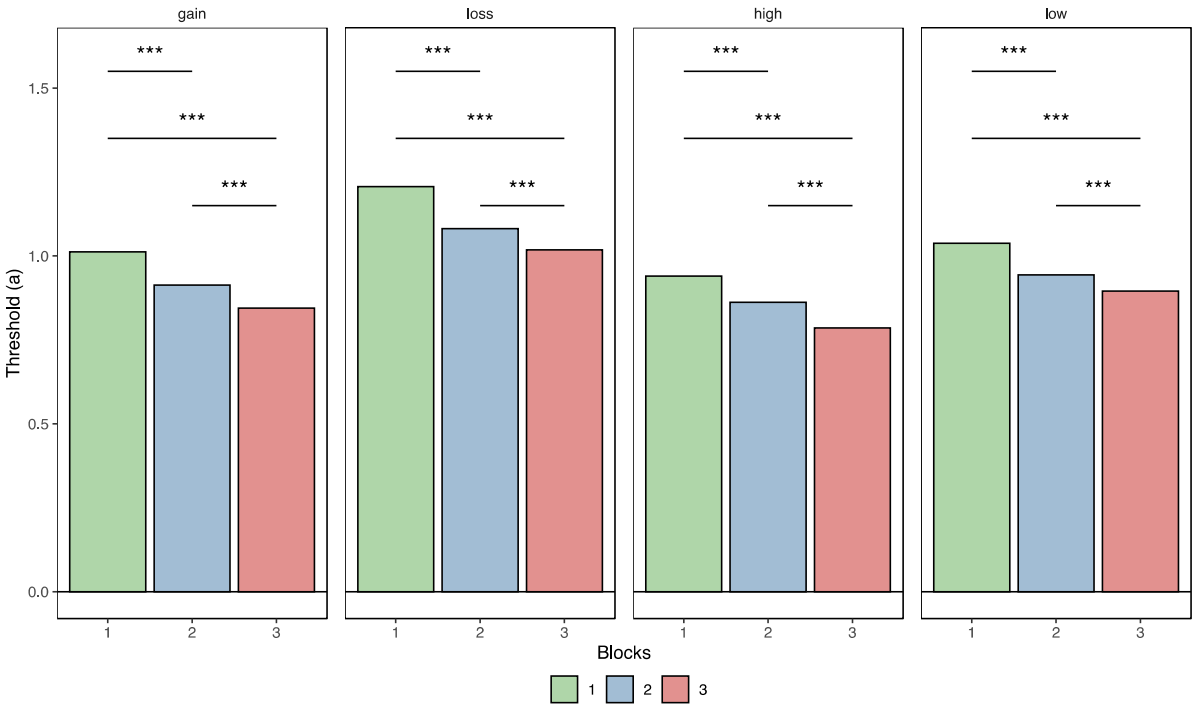


Fig 4. Mean decision threshold parameter estimates for each block in each decision context. The average decision threshold decreased significantly in all decision contexts with increased learning (all posterior *P*s < .001).

Consistent with our second prediction, the average decision threshold was lower for the gain compared to the loss context (posterior $p < .001$) and lower for the high-value compared to low-value context (posterior $p < .001$). In addition, the average threshold was lower for the high-value context compared to gain (posterior $p < .01$) and loss (posterior $p < .001$) contexts. The threshold was also lower for the low-value compared to loss context (posterior $p < .001$). There was no significant difference in threshold between the gain and low-value context (posterior $p = .08$). These results illustrate lower response caution for losses (low-value rewards) compared to gains (high-value rewards).

Differences in starting point bias

Since the best-fitting model did not include bias (z) as a freely varying parameter, we made no *a prior* predictions. A starting point bias was found for the loss context showing a bias towards the probabilistic option (average $z = 0.53$, posterior $p < .01$). Participants did not exhibit a starting point bias in any of the other contexts (all posterior *P*s > .13). Average

starting point bias was found to be significantly larger for the loss compared to high-value condition (posterior $p < .05$). Average starting point bias did not vary as a function for any of the other decision contexts (all posterior *P*s > .14).

Discussion

The context in which a decision is made strongly influences how we choose between options (Huber et al., 1982; Simonson & Tversky, 1992; Spektor et al., 2019). Understanding the cognitive and computational mechanisms associated with how different decision contexts influence decision-making is crucial to understand how people become biased and rely on heuristics. Here, we assessed the temporal dynamics associated with decision-making in different decision contexts and how these computational parameters change over time with increased learning. We show that computational parameters change as a function of learning in both experiments. In both experiments, less evidence was needed to commit to a decision with increased experience, as illustrated by lower average decision thresholds across blocks. Similarly, the magnitude in evidence accumulation increased with learning for the deterministic option for described gains and experienced losses in *Experiment 1* and increased with learning for the deterministic option for experienced losses and low-value rewards in *Experiment 2*. Evidence accumulation for experienced gains in *Experiment 1* was also found to favor the deterministic option, but this was not the case in *Experiment 2*. We suspect this difference has to do with the differences in experimental paradigms where half of the decision contexts were description in *Experiment 1*, but all of the decision contexts were experienced-based in *Experiment 2*.

Consistent with previous work, we show that the computational mechanisms differ based on the decision formats. In *Experiment 1*, participants had different evidence accumulation processes between described and experienced losses and between described and experienced gains. Most notable, the magnitude of evidence favoring the deterministic option for described gains and experienced losses increased with learning, whereas this was not the case for described losses or experienced gains. This is consistent with works showing that these decision formats (i.e., described versus experienced prospects) result in different subjective representations of outcomes and probabilities (Glöckner et al., 2012, 2016; Kellen et al., 2016). Here, we show that these differences are a result of differences in the

magnitude of evidence accumulation strengths between options which remain constant for described but change for experience-based prospects.

People rely on samples from memory (Gonzalez & Dutt, 2011; Shohamy & Daw, 2015; Stewart et al., 2006; Weber & Johnson, 2006) to help judge the probability of events occurring (Busemeyer et al., 2011). The results from *Experiment 2* provide further support that memory biases during sampling lead to systematic differences in risky choice. The most favorable experienced outcomes are sampled more often, affecting the impact of the rate of accumulation (drift rate). Since more outcomes are experienced when making risky choices (as opposed to fixed outcome choices), more outcomes provide additional memories to be sampled, thus modifying the rates of accumulation. Because extreme outcomes are overrepresented in memory, and extreme outcomes for losses and low-value rewards are perceived as occurring more frequently (Ludvig et al., 2018; Madan et al., 2014, 2021), participants are more likely to sample these extreme outcomes. As such, participants are more likely to sample the worst outcomes associated with the probabilistic option, acting as favorable evidence for the deterministic option and increasing the rate of accumulation for the deterministic over the probabilistic option. Conversely, extreme outcomes do not appear to be as overweighted in memory for gains or high-value rewards, leading to retrieved instances being equally favorable for either option, affecting the rate of evidence accumulation opposite to that of losses and low-value rewards.

The modeling results furthermore provide a novel insight into how people move in parameter space. That is, as participants gained more knowledge about their choice environment, the cognitive mechanisms associated with their decision-making adaptively changed. This is, particularly, clear in *Experiment 2,* where participants appear to rely on the same cognitive mechanism – which changed in almost perfect symmetry – for losses and low-value rewards. Although similar research has modeled how individual differences are represented as computational parameters (e.g., Navarro et al., 2006), to the best of our knowledge, we are the first to show how people move in parameter space. Although our approach is somewhat rudimentary, it still provides valuable insight into how people navigate parameter space. To obtain a comprehensive account of (human) decision-making, understanding how computational mechanisms shift with, e.g., learning will be critical. As such, we urge future research to develop and adopt approaches that allow for

understanding how people navigate parameter space to inform their decision-making processes.

In summary, we provide evidence for how temporal dynamics lead to systematic differences in risky choice based on the decision context. These data suggest that as people gain a better understanding of their choice environment, their response caution decreases, as less favorable evidence is needed before committing to a decision. Furthermore, people's evidence accumulation rates significantly change with a better understanding of their choice environment for experience-based decisions (but not description-based decisions), illustrating a clear connection between choice and biased memory sampling.

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Supplemental

Model comparison and selection.

To evaluate the goodness-of-fit, we used the Deviance Information Criterion (DIC), which is a generalization of the Akaike Information Criterion (AIC) for hierarchical modeling. The model with the lowest DIC score determines the best-fitting model. For easier comparisons between models, we also report ΔDIC to show the absolute difference between models. Model fits are reported in Table S1-2 and S3-4 for *Experiment 1* and *Experiment 2*, respectively. Note that for *Experiment 1*, the DIC scores for decisions-from-experience represent model fit for a collapsing bounds DDM, whereas DIC scores for the decisions-from-description represent model fit for a standard DDM. Different models were used because a standard DDM was unable to capture the behavioral data for the decisions-from-experience (see section on posterior predictive checks).

Table S1: Model comparison for Experiment 1

Model	Params	Gain (experience)	Loss (experience)	Gain (description)	Loss (description)	Average DIC
1	*v*	28728.6613	39878.0643	27651.6281	30502.2406	31690.1486
2	*a*	28664.9808	39917.8245	28131.6842	31865.928	32145.1044
3	*z*	28852.4518	39916.4538	27491.7431	30502.108	31690.6892
4	*va*	28649.4737	39768.2531	26997.3963	30005.5739	31355.1742
5	*vz*	28655.1259	39809.6744	26986.0547	30084.2362	31383.7728
6	*az*	28653.5162	39765.9595	26962.674	29913.2393	31323.8473
7	***vaz***	**28648.7809**	**39763.8259**	**26956.3756**	**29891.8183**	**31315.2002**

Note. Model-fit for each condition; average model-fit across all conditions for each model, using collapsing bounds models for the experience conditions and using standard DDMs for description conditions.

Table S2: ΔDIC model comparison for Experiment 1

Model	Params	ΔGain (experience)	ΔLoss (experience)	ΔHigh (description)	ΔLow (description)	Average ΔDIC
1	*v*	79.880461	114.238371	695.252527	610.422293	374.948413
2	*a*	16.199942	153.998617	1175.30857	1974.10971	829.904209
3	*z*	203.670891	152.627958	535.367471	610.28969	375.489003
4	*va*	0.692821	4.427195	41.020705	113.755563	39.974071
5	*vz*	6.345027	45.848506	29.679068	192.417863	68.572616
6	*az*	4.735316	2.133625	6.298411	21.420962	8.6470785
7	***vaz***	**0**	**0**	**0**	**0**	**0**

Note. Model fit for each condition; ΔDIC model-fit across all conditions for each model, using collapsing bounds models for the experience conditions and using standard DDMs for description conditions.

Table S3: Model comparison for Experiment 2

Model	Params	Gain	Loss	High-value	Low-value	Average DIC
1	*v*	14872.4712	17919.4212	13026.2158	15051.4822	15217.3976
2	*a*	14716.4171	17823.7633	12858.7174	14989.1433	15097.0103
3	*z*	14881.7063	17930.0711	13045.2217	15069.6919	15231.6727
4	***va***	**14711.7627**	**17744.0616**	12866.4085	14952.7463	**15068.7448**
5	*vz*	14875.2104	17885.0367	13033.1652	15052.0515	15211.366
6	*az*	14716.626	17792.7072	**12855.6271**	14962.2624	15081.8057
7	*vaz*	14711.9731	17755.7673	12861.6908	**14952.5153**	15070.4866

Note. Model-fit for each condition; average model-fit across all conditions for each model, using collapsing bounds models.

Table S4: ΔDIC model comparison for Experiment 2

Model	Params	ΔGain	ΔLoss	ΔHigh-value	ΔLow-value	Average ΔDIC
1	*v*	160.708462	175.359593	170.58864	98.966903	148.652809
2	*a*	4.654375	79.7017	3.090219	36.628075	28.2655012

3	*z*	169.943558	186.009539	189.594519	117.176582	28.2655012
4	***va***	**0**	**0**	10.781379	0.230985	**0**
5	*vz*	163.447682	140.975075	177.538098	99.536246	142.621184
6	*az*	4.863275	48.645579	**0**	9.747078	13.060892
7	*vaz*	0.210391	11.705751	6.063649	**0**	1.74185675

Note. Model fit for each condition; ΔDIC model-fit across all conditions for each model, using collapsing bounds models.

Although not all the best-fitting models in *Experiment 2* share the same freely varying parameters, we report results from the overall best-fitting model. Firstly, we do not suspect people rely on different overall cognitive processes solely based on the condition in which they are making choices given the within-subject design that was used. In addition, the fitting process itself may have affected the outcome of the overall fits, given the slight variability involved in the fitting process (e.g., for the low-value condition). Lastly, by using the average best-fitting model, the comparison between conditions allows for better inferences about the underlying cognitive processes.

Posterior predictive checks.

To assess how closely our model predictions match the observed data, we performed posterior predictive checks (PPC) of 1,000 simulations. For these simulations, parameter values for drift rate, decision threshold, and bias were randomly sampled from the posterior distributions of the obtained parameter estimates. Each simulation returned a predicted choice and reaction time for every trial for each participant. Following the 1,000 simulations, the simulated datasets were used to analyze RT densities and choice percentages.

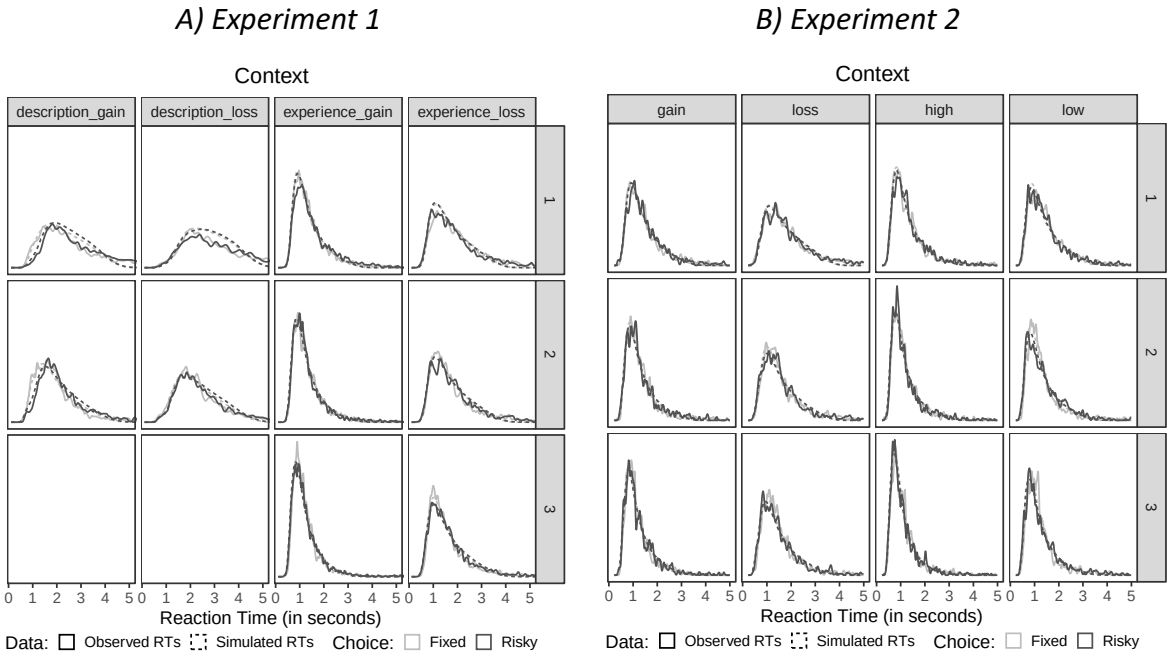
PPC: RTs.

The PPC simulated data of the RT distributions varied in how well they captured the data between the two experiments (Fig. S1). For *Experiment 1*, the model least faithfully captures the observed RT distributions for all decision contexts by overestimating the distributions in the first block. However, the model adequately captures the observed RT distribution for decisions-from-description in Block 2 and decisions-from-experience in

Blocks 2-3. For *Experiment 2*, the PPC simulated data of the RT distributions showed a good ability to capture the observed RT data across all three blocks.

This mismatch between the model predictions and observed data is likely due to an artifact in the Bayesian hierarchical fitting process. Given the inherent differences between the description and experience and the effect experience has on described prospects (e.g., Weiss-Cohen et al., 2016, 2021), we surmise this mismatch reflects individual decision strategies of a minority of participants which causes the model to down-weigh these participants' contributions to the group posterior. Thus, after the first block, all participants' strategies align closer, causing the model to better being able to capture the RT distribution.

Figure S1: Posterior predictive check of RTs



Note. Visual representation of the observed and simulated RTs for fixed and risky choices for A) *Experiment 1* and B) *Experiment 2* (experience-based choices only).

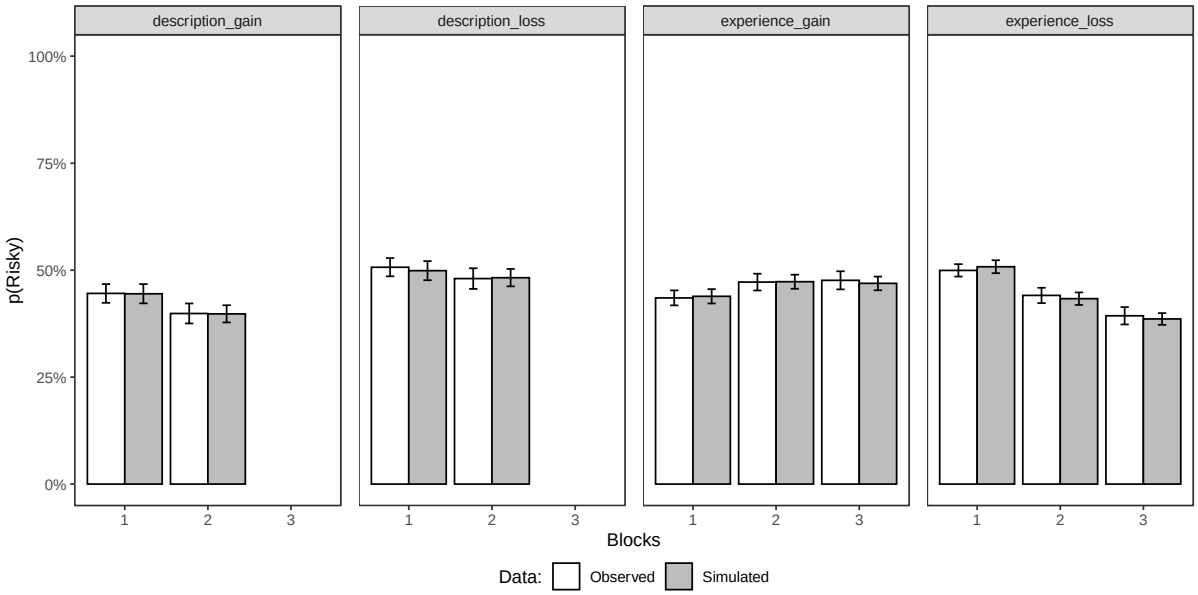
PPC: risk seeking.

Conducting the PPC simulations of participants' risk-seeking propensities, our model observes slight over- and underestimations of the simulated data. Using repeated-measures ANOVAs revealed no significant interaction between data types (empirical vs. simulated data) with the proportion of risk-seeking for the different blocks in *Experiment 1*

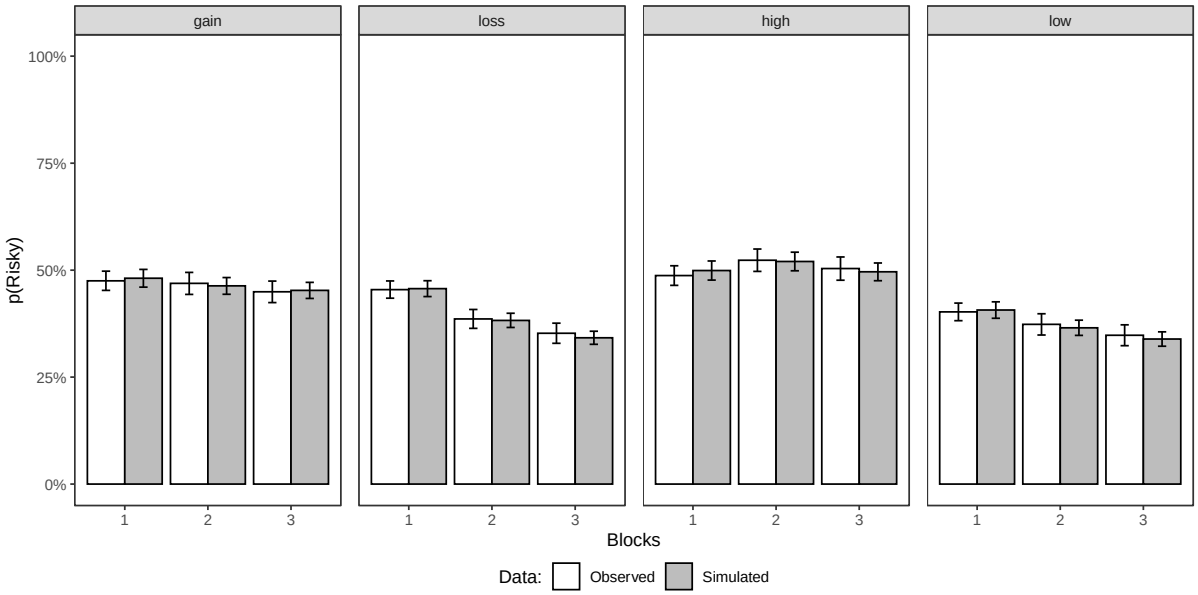
[description: $F(1, 254) = 0.16$, $p = 0.69$, $\eta^2 = 0.00001$; experience: $F(2, 508) = 0.52$, $p = 0.59$, $\eta^2 = 0.0001$] or *Experiment 2* [$F(3, 254) = 0.50$, $p = 0.61$, $\eta^2 = 0.0001$] for any of the decision contexts. Thus, we can assume that the simulated data generated under the model is consistent with the observed data in terms of patterns and variability.

Figure S2. **Posterior predictive check for proportion of risk-seeking**

A) Experiment 1



B) Experiment 2



Note. Observed and simulated proportion of risk-seeking for A) *Experiment 1* and B) *Experiment 2*. Error bars reflect ± 1 SEM.

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Discussion

The studies presented in this thesis examined the link between memory and decision-making, specifically focusing on how participants rely on past experiences to inform present choices. This work aligns with studies focusing on the interplay between memory and decision processes (e.g., Bornstein et al., 2017; Duncan & Shohamy, 2016; Gluth et al., 2015; Madan et al., 2014; Shohamy & Adcock, 2010; Shohamy & Daw, 2015) and how these systems shape each other. This work, furthermore, contrasts with prior research on decisions made from description (e.g., Kahneman & Tversky, 1979).

Examining the interplay between memory and decision-making processes, this thesis aimed to asses several questions: (1) How do people integrate and utilize information when making choices? (**Chapter 1**); (2) What can optimal stopping theory tell us about decision-making? (**Chapter 2**); (3) How is task-irrelevant information remembered in risky choice? (**Chapter 3**); (4) Can fixations and pupil dilation inform us how memories are used in choice? (**Chapter 4**); (5) What temporal computational mechanisms are associated with risky decision-making? (**Chapter 5**). For **Chapters 3-5**, a central aim was also to assess how learning influenced information processing. To address these questions, three different approaches were used. In **Chapters 1** and **2**, comprehensive literature reviews were conducted with accompanying simulations in **Chapter 2**. **Chapter 3** used a well-established risky choice task (Ludvig & Spetch, 2011) to assess how reward processing and memory formation for task-irrelevant stimuli might interact. In **Chapter 4**, the same task was used and adapted for an eye-tracking study testing whether fixation and pupil dilation data could be used to inform how memory and decision-making interact. Lastly, **Chapter 5** used pre-existing datasets (Madan et al., 2017, 2021) to assess the temporal dynamics of risky choice by fitting drift-diffusion models. This final chapter provides a summary of the theoretical contribution of the experimental work and future avenues for potential research.

Encoding of unrelated stimuli in risky choice

The results from a series of experiments presented in **Chapter 3** illustrate that encoding of task-irrelevant information may be down-regulated, whereas task-relevant incremental learning is prioritized (*Experiments 2 and 3*). Memory for task irrelevant stimuli

decreased significantly across blocks in *Experiments 2* and *3* and did not interact with reward value or uncertainty as predicted by existing literature (e.g., Rouhani et al., 2018). However, in *Experiment 3*, we did observe reward value to influence encoding of task irrelevant stimuli with better memorability for items associated with high- compared to low-value rewards (Adcock et al., 2006). Together, these results hints at the intuitive idea that as the choice environment becomes increasingly known – and perhaps subjectively perceived as less uncertain – the influence of rewards and reward prediction errors has diminishing effects on incidental encoding of unrelated stimuli. However, the inability to replicate previously robust results of curiosity-enhancing effects on memory (e.g., Fandakova & Gruber, 2021; Gruber et al., 2014) may represent a challenge to conclusions drawn from Experiments 2 and 3, despite recent evidence showing a trade-off between incremental learning and recruitment of episodic memory to guide choice (Li et al., 2022; Nicholas et al., 2022). Therefore, it is possible the results presented in *Experiments 2 and 3* may not replicate (and instead align more closely with the initial hypotheses put forth) if conducted using in-lab experiments. However, it should be noted that the curiosity-enhancing effects on memory have previously failed to replicate (e.g., see Swirsky et al., 2020). Further research should be conducted to assess if and to what extent these results show deviations between population samples (i.e., online versus in-lab).

Visual fixation and pupil dilation may provide insight into the mechanism of risky choice

Chapter 4 assessed the relationship between visual attention and risky choice in an attempt to closely link memory processes to decision-making. Results indicate that the amount of attention allocated to a fixed or risky option depends on the decision context. Risky options draw more attention for gains compared to losses and for high- compared to low-value rewards. Results from pupillometry data illustrate that the risky option is perceived as being inherently riskier for losses and low-value rewards compared to their gain and high-value reward counterparts. Similarly, a larger physiological response is observed when experiencing the best compared to the worst outcome following a risky choice but only for high- and low-value rewards. Lastly, when awaiting feedback, evidence indicates participants may rely on covert attention. Taken together, visual attention and physiological responses (i.e., pupil dilation) provide a window into how people perceive available

information – which is used in conjunction with memory of past experiences to guide choices.

Sequential sampling parameter estimates change with learning

Chapter 5 investigated the temporal dynamics involved in risky choice and how these dynamics change with more experience in their choice environment. Results show that parameters between described and experienced prospects significantly differ (*Experiment 1*), which provides additional support for why the description-experience gap arises (Garcia et al., 2021; Madan et al., 2017; Wulff et al., 2018). Moreover, mean parameter estimates also differ between different decision contexts based solely on experience. Intuitively, the results show that increased experience in a choice environment results in less information being gathered before committing to a decision. The rate of evidence accumulation also increases with experience, albeit differentially depending on the decision set. This aligns well with the idea that heuristics become more established with time, causing information acquisition to become faster with less information needed to make a choice. These results provide a novel insight into how people navigate parameter space and how people's computational – and, by extension, cognitive – mechanisms change and evolve with learning.

Future directions

The studies highlighted in this thesis provides novel insights into how memory and decision-making processes interact and how learning changes cognitive representations of risk, uncertainty, and utility. However, these results also raise several additional questions.

Recent evidence has shown how risky decisions involving risk are similar to preference-based risky choices (Mason et al., 2022, 2023); options resulting in high effort are perceived similarly to options resulting in monetary losses. But how do people make risky choices if rewards are contingent on first succeeding in an effortful task in which difficulty is directly tied to the chosen option? One approach to assess this question would be to use a multi-step decision-making paradigm, where people would first choose between a fixed or a risky option followed by a cognitively effortful task (e.g., a visual search task). The relative difficulty of the effortful task could be associated with the magnitude of the reward (i.e., the higher the reward, the higher the effort that needs to be expended) to see how this interaction might shape risky choices.

The results found in **Chapter 5** highlight an exciting avenue for fruitful research to better understand decision-making processes. Typically, when modeling human behavior using computational models (e.g., drift-diffusion modeling or reinforcement learning), researchers look at differences between two conditions and obtain singular parameter estimates describing the difference between these conditions (e.g., differences in learning rates). However, this implicitly assumes people's cognitive processes change at a constant rate and provides no possible way of seeing how different stages of interventions may cause shifts in computational parameters. The modeling results presented in this thesis clearly show how computational parameters can change with varying degrees of magnitude throughout an experiment. I argue that understanding how people move in parameter space will be paramount if we wish to obtain a comprehensive understanding of decision-making. It will allow us to better understand at what stages interventions may be most effective (e.g., at changing risk perception) and how computational parameters may interact. At present, how exactly to develop new approaches for testing how people navigate parameter space is still unclear.

Another interesting avenue is the interaction between episodic future thinking (Atance & O'Neill, 2001) and experienced regret. Episodic future thinking enables people to make predictions about the future (mental time travel), whereas experienced regret is directly tied to the experience of past outcomes. Intuitively, these two episodic memory-related concepts would interact in ways where instances of experienced regret would be used for episodic future thinking when predicting the outcomes of related choices. This could help quantify how large of an influence experienced regret has on mental time travel and potentially how this might be reflected in actual choice behavior.

Summary

Taken together, this thesis provides novel insight into how people utilize their past experiences to inform their current choices and how learning influences how information is perceived and integrated into the decision process. Cognitive resources are assigned to task-relevant information by directly prioritizing this type of information and neglecting task-irrelevant information. As people learn about their choice environments, the allocation of (visual) attention shifts, highlighting that what is perceived as task-relevant information changes over time, further supported by findings showing changes in computational

parameters with learning. These provide theoretical advances in understanding how people use memory to guide decisions and how information integration and utilization change with experience.

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