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How sampling strategies shape experience-based risky choice

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ABSTRACT

Hallmark phenomena of risky choice, such as risk aversion and deviations from expected value (EV) maximization, are commonly modeled with psychoeconomic curves (e.g., utility function, probability weighting function). Yet these functions describe choices rather than the cognitive processes that generate them. Here, we examine how aspects of the oft-neglected process of information search – in particular, switching between options during sampling and stopping based on sampled evidence – can give rise to patterns in experience-based risky choice in the context of the sampling paradigm. We develop a computational framework that conceptualizes sampling strategies as consisting of three building blocks: a search rule (governing the rate of switching between options during sampling), a comparison rule (roundwise vs. summary evaluation of the options), and a stopping rule (decision threshold). In simulation analyses comparing different combinations of these building blocks, we show that frequent switching increases EV-maximizing choices for strategies with a summary comparison rule, but decreases maximization for strategies with a roundwise comparison rule. Further, frequent switching promotes an apparent underweighting of rarely experienced events found under the roundwise comparison rule, and curtails overweighting found under the summary comparison rule. We also reveal how the sampling strategies give rise to different risk attitudes depending on the existence and attractiveness of rare events. Finally, an empirical analysis suggests that people combine switching behavior and comparison rules in a way that fosters EV-maximizing choices. Our results underscore the possible contribution of search processes to patterns in risky choice.

1. Introduction

Many decisions involve risky options that can lead to several possible outcomes with some probability. For example, it is often possible to choose between short or long connection times when booking a train trip. While a short wait between trains can save time, it also carries a higher risk of missing the connection altogether. According to a classical view, the rational way to make such risky decisions is to choose the option with the higher expected value (EV),

$$EV = \sum_{i=1}^{m} x_i p_i \ , \tag{1}$$

and thus to consider all of an option's m possible outcomes x, weighted by their probabilities p. Often, however, people's decisions do not maximize the EV. In the St. Petersburg paradox, for instance, people are willing to pay only a moderate amount of money to play a game that offers an infinite EV—they seem to be risk averse (Bernoulli, 1954; Hayden & Platt, 2009).

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To account for violations of EV theory, it is assumed in expected utility theory that people choose as if they maximize an option's expected utility (EU). The EU is defined similarly to the EV, but the objective outcomes x are transformed into subjective utilities $u(x)$ using a nonlinear utility function u that typically indicates diminishing sensitivity (e.g., Bernoulli, 1954; Friedman & Savage, 1952). Neo-Bernoullian models such as prospect theory (Kahneman & Tversky, 1979) and its subsequent development into cumulative prospect theory (CPT; Tversky & Kahneman, 1992) further assume nonlinear probability weighting. Specifically, the utilities of an option's outcomes are not weighted by objective probabilities p, but by subjective decision weights π, which follow from a nonlinear transformation of the probabilities. CPT's parameterized value function and probability weighting function can capture a range of phenomena in risky choice that violate EU theory, and measure variability in risky choice across people and contexts (e.g., Bruhin et al., 2010; Fehr-Duda et al., 2010, 2006, 2011; Kellen et al., 2016; Schley & Peters, 2014; Suter et al., 2016; Tiede et al., 2025; Zilker et al., 2020). Psychoeconomic curves – such as utility and probability weighting functions – have thus been a powerful theoretical element in accounting for human preference under risk.

Despite their descriptive success (but see Birnbaum, 2008; Cohen et al., 2020; Rieskamp, 2008), neo-Bernoullian models have been challenged on conceptual grounds. Simon (1955, 1978) pointed out that decision makers rarely have immediate access to complete information about each option's payoff distribution (which would be necessary to compute an option's EU) and instead have to actively search for information. Decision making therefore requires strategies that contain not only a procedure for evaluating options, but also procedures for guiding and stopping information search. Search processes, however, are not considered in neo-Bernoullian models, and their potential role in contributing to hallmarks of human preference in decisions under risk is therefore unclear.

In this article, we study the potential contribution of search processes to risky choice phenomena – such as deviations from EV maximization, risk aversion, and over- and underweighting of rare events – that have traditionally been accounted for using psychoeconomic curves. (We do not study what drives the search process itself; for such an analysis, see Spektor & Wulff, 2024). We address this issue in the context of experience-based decisions as they are investigated with the *sampling paradigm* (Hertwig & Erev, 2009). Unlike in description-based decision making, where information about the options' payoff distributions is complete and directly available (but see, e.g., Pachur et al., 2013; Payne & Braunstein, 1978; Russo & Dosher, 1983), in experience-based decision making people have to learn about the options by sequentially drawing samples from their payoff distributions—reflecting typical situations in real-world decision making, where decisions have to be made based on limited information and thus under uncertainty (Simon, 1978). In the sampling paradigm, information search is explicitly separated from choice: To learn about the options' payoff distributions, people are free to decide when to sample from which option, and have to decide when to stop information search and make a single, consequential choice. The outcomes drawn from the options during predecisional sampling are inconsequential and have no impact on the decision maker's payoff.[1]

We first develop a computational framework of sampling strategies. Extending previous ideas and analyses by Hills and Hertwig (2010), we conceptualize the sampling strategies in terms of three building blocks: a search rule, a comparison rule, and a stopping rule. The sampling strategies are formalized as sequential sampling models (e.g., Busemeyer & Townsend, 1993; Diederich & Trueblood, 2018; Ratcliff, 1978), where sampled outcomes are integrated into a decision variable that dynamically accumulates evidence in favor of or against an option. The search rule governs the degree to which sampling switches between the options, the comparison rule translates the specific sequence of sampled outcomes into evidence by governing how the outcomes are integrated into the decision variable, and the stopping rule determines when enough evidence is gathered to stop information search. Our modeling framework thus includes search processes as a fundamental element of the decision-making process and allows us to examine the impact of switching and stopping on the emerging choice pattern and how this impact may depend on the type of comparison rule.

Our computational framework of sampling strategies has parallels with the instance-based learning (IBL; Gonzalez & Dutt, 2011) model in the sense that it also describes choice and search behavior in the sampling paradigm. In contrast to the sampling strategies, however, the IBL model focuses on the contribution of memory processes to experience-based choice and is couched within the framework of the cognitive architecture ACT-R (Anderson & Lebiere, 1998). As a consequence, the two approaches differ substantially in how they conceptualize the search, comparison, and stopping mechanisms and their interplay. For instance, the IBL model treats the decision to draw a new sample during search similarly to the final choice and uses previously sampled outcomes to guide search.[2] This allows the model to predict dynamic changes in the switching behavior over the course of a trial, while the sampling strategies assume a fixed switch rate. Unlike the sampling strategies, which are equipped with a stopping rule that defines the amount of evidence necessary to make a choice in a given choice problem, IBL has no such psychological stopping rule and predicts stopping without relying on the sampled outcomes. Thus, our framework of sampling strategies and IBL offer complementary avenues to study experience-based risky choice.

Another related modeling approach is the Choice from Accumulated Samples of Experience (CHASE) model (Markant et al., 2015), which, like the sampling strategies, assumes a sequential sampling (i.e., diffusion) process to describe decisions from experience in the sampling paradigm. An important difference is that in CHASE the drift coefficient of the diffusion process is defined by CPT. The model thus relies on a neo-Bernoullian psychoeconomic function as a stand-in for a comparison mechanism,

[1] This is different from decisions from experience studied with feedback paradigms, where people can only learn about options by choosing them, thereby combining search and choice (Hertwig & Erev, 2009).

[2] In the IBL model, it is assumed that people store each sampled outcome as an instance in memory. When considering whether to sample from or choose the options, the options' instances are retrieved from memory and summed up in blended values, where each instance is weighted by its activation in memory, which depends on the sampled frequency and the recency of similar instances. It is assumed that the option with the higher blended value is selected.

without specifying where the modeled distortions of probabilities and outcomes come from. In contrast, the comparison rules of the sampling strategies are defined in terms of specific mechanistic and psychologically plausible operations for evaluating options based on the sampled outcomes. Another difference to the sampling strategies is that CHASE does not explicitly accommodate switching between options during sampling.

In the following, we first describe our computational framework, which allows us to derive a continuum of sampling strategies, each representing a combination of different settings of the search rule, comparison rule, and stopping rule. We then report a simulation study examining how different settings of these building blocks can give rise to different patterns in risky choice. We opted for a simulation approach because it allowed us to vary the different building blocks independently, combine them orthogonally, and observe the resulting patterns in choice and sampling. While Hills and Hertwig (2010) focused on the extent to which sampling strategies can lead to an apparent underweighting of objectively rare events, here we provide a more comprehensive picture of the sampling strategies choice behavior. Specifically, we characterize the risky choices generated by the sampling strategies by focusing on two commonly studied behavioral characteristics in research on decision making under risk, EV maximization and risk attitudes (e.g., risk aversion and risk seeking), which we examine independently of each other. In addition, we characterize the choice behavior of the sampling strategies through the lens of CPT, allowing us to connect the sampling strategies' behavior to CPT's prominent concepts of nonlinear probability weighting and outcome sensitivity. This analysis is also informative for research on decision from experience, which has frequently relied on CPT (e.g., Glöckner et al., 2016; Hotaling et al., 2019; Jarvstad et al., 2013; Tiede et al., 2025). Previous studies have observed a wide range of patterns of probability weighting, including both an underweighting and an overweighting of rarely experienced events (Abdellaoui et al., 2011; Kellen et al., 2016; Wulff et al., 2018). Our analyses with CPT help illuminate how different patterns of over- and underweighting might arise from differences in information search and processing. Finally, we examine the interplay between the sampling strategies and the structure of the environment by testing how the strategies' risk attitude depends on whether there are rare events and, if so, how attractive they are.

2. Computational framework

In a first step toward conceptualizing possible strategies for searching and integrating information on the options in the sampling paradigm, Hills and Hertwig (2010) highlighted two key elements of sampling strategies. The first element distinguishes between two types of information search: *piecewise search*, where sampling constantly switches between options, and *comprehensive search*, where multiple consecutive samples are taken from each option (Fig. 1A). The second element specifies how the sampled outcomes are integrated and processed to evaluate the options. Here, Hills and Hertwig (2010) distinguished between *summary comparison* and *roundwise comparison* (Fig. 1B, C). In summary comparison, all sampled outcomes of an option are integrated in an option-specific summary score (e.g., sampled means), which is compared against that of the other option. In roundwise comparison, options are evaluated over multiple comparison rounds, with each round involving only a small subset of the sampled outcomes from each option.[3] In the simplest case described by Hills and Hertwig (2010), a round involves only one outcome drawn from each option and the option with the higher sampled outcome wins the round. The option with more round wins in total is chosen.

In empirical analyses, Hills and Hertwig (2010) found evidence that piecewise search tends to co-occur with roundwise comparison, whereas comprehensive search tends to co-occur with summary comparison. Moreover, in formal analyses the authors showed that piecewise search (i.e., frequent switching) and roundwise comparison lead to more apparent underweighting of rare events (i.e., rare events receive less weight in the decision than their objective probability warrants) than comprehensive search (i.e., infrequent switching) and summary comparison, respectively.

However, although Hills and Hertwig (2010) emphasized that "many empirical strategies will fall on the continuum between" (p. 1788) the stylized strategies of piecewise search combined with roundwise comparison and comprehensive search with summary comparison, they did not examine this continuum. The impact that different switching levels have under either comparison rule therefore remained unclear. In addition, a complete computational model of sampling strategies also requires a mechanism that specifies when sampling is stopped and a "good enough" option has been identified—an issue that was not addressed by Hills and Hertwig (2010). Previous research suggests that people tend to rely on optional stopping rules that are sensitive to the sampled evidence in a given trial (e.g., Markant et al., 2015), rather than setting a fixed number of samples beforehand that they will draw in each of a series of trials (also see Spektor & Wulff, 2024).

To address these points, we developed a computational framework of sampling strategies consisting of three building blocks – a search rule, a comparison rule, and a stopping rule – and formalized the sampling strategies as sequential sampling models (Fig. 1, right panel). In sequential sampling models, the decision-making process is conceptualized as an accumulation of sampled evidence over time and it is assumed that a choice is made once the accumulated evidence in favor of an option reaches a decision threshold (e.g., Diederich & Busemeyer, 2003; Ratcliff & Smith, 2004). Here we model the accumulation process as a dynamic decision variable D, which accumulates the sampled evidence obtained about the options in the sampling paradigm (Fig. 1D). For the following formal descriptions of the sampling strategies, let the choice problems consist of two options A and B, each representing probability distributions over finite sets of outcomes.

[3] The summary and roundwise comparison rules echo the common distinction between interdimensional (option-wise) and intradimensional (attribute-wise) processing, respectively (e.g., Payne & Braunstein, 1978; Russo & Dosher, 1983; Tversky, 1969). In interdimensional processing, options are evaluated separately from each other; in intradimensional processing, they are evaluated by comparing them on each attribute.

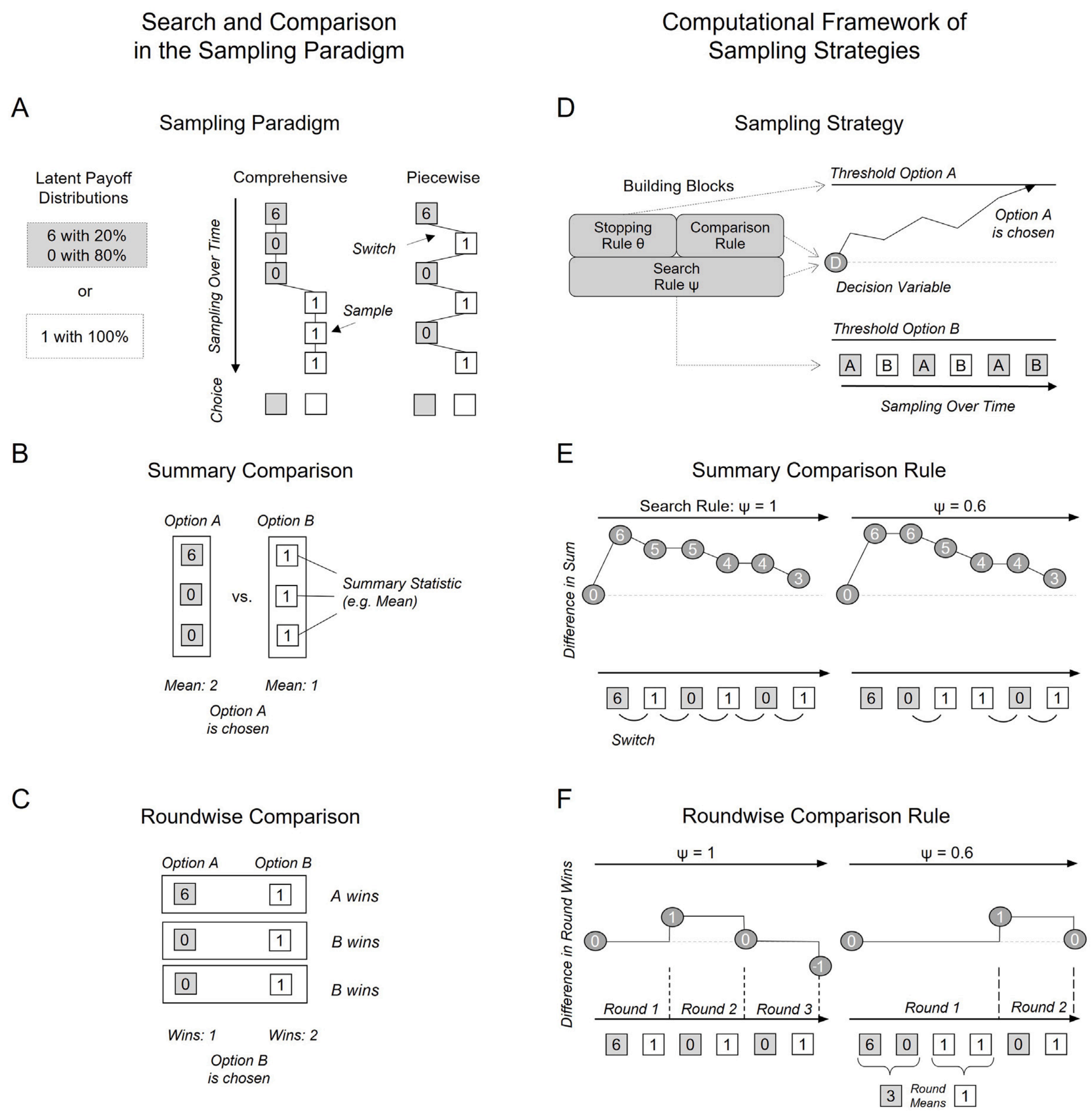

Fig. 1. Sampling strategies for decisions from experience in the sampling paradigm.
Note. (A) In the sampling paradigm, people learn about options by sampling from their payoff distributions; during sampling they may switch rarely (comprehensive sampling) or often (piecewise sampling) between options. (B, C) The comparison rule specifies how samples are integrated for option evaluation. (D) Sampling strategies conceptualized as sequential sampling models; the strategies' building blocks (search, comparison, stopping) map onto several aspects of the sampling and accumulation process. (E, F) Different settings of the search rule (ψ) lead to different accumulation processes for the summary and the roundwise comparison rule.

2.1. Search rule

In each choice trial, S is the set of all samples drawn, $s_j \in S$ (i.e., s_j are the individually sampled outcomes), and $j \in \mathbb{N}$ indicates the position of the sample within the sampling sequence. A choice trial starts with the first sampled outcome s_1 being drawn from one of the two options, determined randomly. The search rule specifies the extent to which consecutive samples are taken from the same or a different option. We quantify the rule as a switch rate ψ, representing the probability that the jth sample is drawn from a different option than the previous (i.e., $j-1$th) sample. Specifically, the probability that the jth sample is drawn from option A

can be written as

$$p(\text{sample } j \text{ is drawn from A}) = \begin{cases} .5 & \text{if } j = 1 \text{ (i.e., 1st sample)}, \\ \psi & \text{if } j-1\text{th sample is drawn from B}, \\ 1-\psi & \text{if } j-1\text{th sample is drawn from A}. \end{cases} \tag{2}$$

We assume that the switch rate is constant across a choice trial.

2.2. Comparison rule

The comparison rule describes how the decision maker processes the sampled outcomes in order to compare and evaluate the options. The rule specifies which information is fed into the decision variable D, which expresses the relative amount of evidence gathered for the options in terms of a difference score. A positive value for D favors option A; a negative value favors option B. Following Hills and Hertwig (2010), we distinguish two types of comparison rules: summary comparison and roundwise comparison.

2.2.1. Summary comparison

As shown in Fig. 1E, under the summary comparison rule the accumulated evidence about an option is expressed as the sum of the sampled outcomes from the option, and the decision variable D_n is defined as the difference between the options on this evidence after n samples have been drawn[4]:

$$D_n = d \sum_{j=1}^{n} s_j (-1)^{(I_j+1)} , \tag{3}$$

where d is a constant (here set to .01) that scales the amount of accumulated evidence and I is an indicator variable that specifies whether a sample was drawn from option A or option B:

$$I_j = \begin{cases} 1 & \text{if } j\text{th sample is drawn from A}, \\ 0 & \text{if } j\text{th sample is drawn from B}. \end{cases} \tag{4}$$

2.2.2. Roundwise comparison

As shown in Fig. 1F, under the roundwise comparison rule the decision variable D_q is defined as the difference between the options in terms of the number of their respective round wins after q comparison rounds. In a given choice trial, each comparison round starts on the option from which the initial sample in the choice trial was drawn and is defined as a single uninterrupted sampling sequence from both options (i.e., it includes a single switch from the initially sampled option to the other). A comparison round therefore ends when sampling switches back to the initially sampled option (note that the comparison rounds will, on average, be shorter the higher the switch rate). Let S_r' be the set of indices for the outcomes sampled in comparison round r. In each comparison round the options are compared to each other with regard to the average sampled outcomes for each option:

$$\mathcal{M}_r = \frac{1}{\ell_r} \sum_{j \in S_r'} s_j \cdot I_j - \frac{1}{h_r} \sum_{j \in S_r'} s_j \cdot (1 - I_j) , \tag{5}$$

where ℓ_r and h_r are the number of samples from option A and B, respectively, in comparison round r. At the end of each round, the round win indicator

$$\mathcal{W}_r = \begin{cases} 1 & \mathcal{M}_r > 0, \\ -1 & \mathcal{M}_r < 0, \\ 0 & \text{else} , \end{cases} \tag{6}$$

is fed into the decision variable

$$D_q = \sum_{r=1}^{q} \mathcal{W}_r , \tag{7}$$

expressing the difference between the options in terms of the number of round wins after q comparison rounds.

2.3. Stopping rule

Under both settings of the comparison rule, the sampling process continues until the decision variable D reaches a decision threshold $\pm\theta$. The decision threshold serves as a stopping rule, determining both when information search is stopped and which of the two options is chosen. Option A is chosen if the decision variable exceeds the positive threshold $D \geq \theta$ and option B is chosen if the decision variable exceeds the negative threshold $D \leq -\theta$. The point at which the decision threshold is crossed also indicates the amount of information (number of samples) that the sampling strategy had to acquire to make a choice in a given trial.

[4] In Hills and Hertwig (2010), the sampled outcomes for each option are averaged for a summary comparison. Here, we use a different approach because averaging is ill-suited to implement sequential evidence accumulation: If the decision variable at each time step is computed based on the average sampled outcome for each option, the decision variable will stabilize around the EV difference, which may be below a threshold. In contrast, summing ensures that the accumulated evidence will build up sequentially and approach one of the thresholds.

Table 1
Simulated levels of the search rule, comparison rule, and stopping rule.

Building block	Levels
Comparison rule	summary, roundwise
Search rule (switch rate ψ)	$.1, .4, .7, 1$
Stopping rule (decision threshold θ)	$1, 2, 3$

Note. We implemented all possible combinations of the indicated levels of the search, comparison, and stopping rule, resulting in 24 sampling strategies. The decision threshold for sampling strategies with a summary comparison rule determines the required difference in sums across all sampled outcomes, scaled by .01. For sampling strategies with a roundwise comparison rule, the decision threshold indicates the required difference in round wins.

3. Method

To examine how the building blocks contribute to choice patterns, we conducted a simulation analysis. We constructed sampling strategies by combining different settings of the search and stopping rule with either the summary comparison rule or the roundwise comparison rule. In total, we analyzed 4 (search rules) × 3 (stopping rules) × 2 (comparison rules) = 24 sampling strategies (Table 1). We simulated the choice behavior of each sampling strategy for a set of 60 binary choice problems.

3.1. Choice problems

We focus on choice problems consisting of a risky and a safe option (but see Supplements S1, S2 for analyses of problems consisting of two risky options). The risky option contained one outcome that was less valuable than that of the safe option and one outcome that was more valuable than that of the safe option. This ensured that there would be no dominant option that gave a strictly better outcome. In order to cover a wide range of probability levels and to enable us to subsequently also examine the possible impact of the existence of a rare event (which has been shown to play an important role in shaping experience-based risky choice; e.g., Fox & Hadar, 2006; Hertwig et al., 2004) on the strategies' behavior, the problem set contained three types of choice problems. The choice problems differed in terms of the presence or absence of a rare event (defined as $p \leq .2$; cf. Hertwig et al., 2004; Wulff et al., 2018) and in terms of whether the rare event was attractive (i.e., better than the outcome of the safe option) or unattractive (i.e., worse than the outcome of the safe option). Of the 60 problems, 40 contained a rare event and 20 did not. Of the 40 problems with a rare event, 20 had an attractive rare event ($p_{high} \leq .2$) and 20 had an unattractive rare event ($p_{low} \leq .2$). The probabilities of the rare events were set to $p \in \{.1, .125, .15, .175, .2\}$. Of the 20 problems without a rare event, 10 had a more probable attractive event ($p_{high} = .6$), and 10 had a more probable unattractive event ($p_{low} = .4$). For each problem type (and across all 60 problems), the safe and the risky option had the better EV in 50% of the cases and the magnitude of EV differences between options was held constant across problems (6 reward units). The outcomes ranged from 0 to 200 reward units.

As the choice behavior of the sampling strategies may differ as a function of the specific properties of a given choice problem, the problem set was designed such that the aggregate behavior across all problems reflects the general choice characteristics of a sampling strategy. That is, key properties of the choice problem, such as the probability levels, the attractiveness of rare events, the options' riskiness, and the direction of EV differences are counterbalanced and uncorrelated in the overall problem set. However, to obtain insights into how the strategies' behavior is affected by specific properties of choice problems, we also examined the strategies' behavior on subsets of the problems that differed in terms of whether there is a rare event and how attractive it is (see Section 4.4).

We also conducted additional analyses on problem sets with smaller EV differences, on problem sets including only risky options, and on a problem set with more and more varied option pairs. The results, which are reported in Supplements S1 and S2, show that the key conclusions obtained in the main analyses also hold for these problem sets.[5]

3.2. Simulations

We simulated the behavior of each of the 24 sampling strategies on the 60 choice problems. Each run of a strategy on a given problem was repeated 300 times to take into account the stochastic nature of the search rule and the sampling process. The simulations were programmed in R (R Core Team, 2024); the code and choice problems can be found in the supplementary GitHub repository (https://github.com/linushof/sampling-strategies).

To illustrate the accumulation dynamics of the sampling strategies, Fig. 2 displays the accumulation processes of six sampling strategies, in a choice problem where either the safe option or the risky option has a better EV. The plots show how, for a given choice problem, different combinations of the search rule and the comparison rule lead to different accumulation trajectories. For

[5] The behavior of all sampling strategies was virtually the same for risky–risky problems, whereas in problems with smaller EV differences, strategies with a summary comparison rule and high switch rates produced substantially larger sample sizes while also achieving higher rates of EV maximization. The strategies with a roundwise comparison rule were not affected by the size of EV differences.

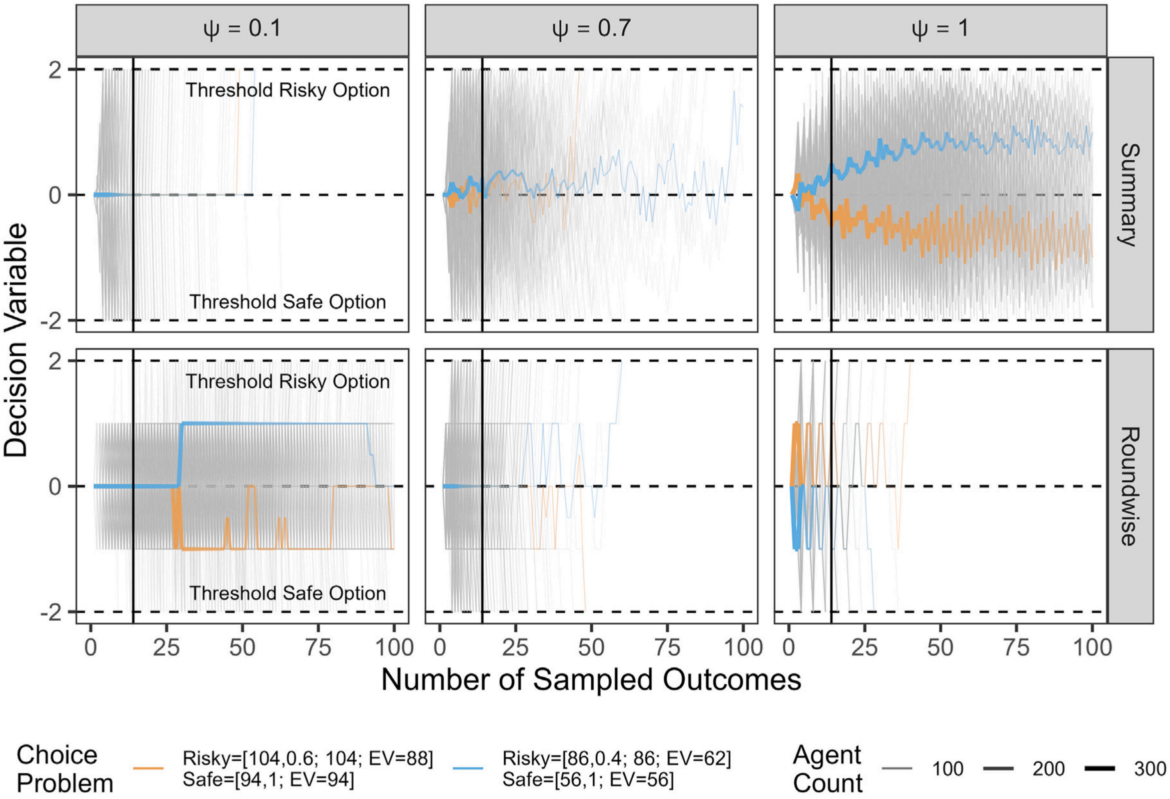

Fig. 2. Evidence accumulation trajectories for sampling strategies in a choice problem offering a safe and a risky option.
Note. Each plot shows the median trajectory for a specific combination of a search rule (switch rate ψ) and a comparison rule as a colored line. Orange (blue) trajectories refer to a problem where the safe (risky) option has a higher EV. Color intensity and line thickness indicate the number of simulated agents for whom the decision threshold was not reached after the respective number of sampled outcomes. Gray lines represent the trajectories of individual agents. Decision thresholds are set to $\theta = 2$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

instance, for sampling strategies with a summary comparison rule and a low switch rate ($\psi = .1$), the trajectories drift toward the decision threshold for the risky or the safe option with similar frequency, without a clear overall trend toward one of the two options. In contrast, for sampling strategies with a summary comparison rule and a high switch rate ($\psi = 1$), most trajectories drift toward the threshold of the option with the better EV. The sampling strategies with a roundwise comparison rule also give rise to different trajectories depending on whether they are combined with a low or a high switch rate. Here, most trajectories drift toward the decision threshold of the option with the better EV when the switch rate is low, while a large number of trajectories drift toward the decision threshold of the option with the lower EV when the switch rate is high.

4. Results

We analyzed the choice behavior of the sampling strategies in three respects. First, for each sampling strategy we determined the proportion of trials where the option with the higher EV was chosen. This provided insights into how the sampling strategies' building blocks and their interplay gave rise to (deviations from) EV maximization. Second, we analyzed the proportion of trials where the risky option was chosen over the safe one. This shed light on how the sampling strategies' building blocks and their interplay gave rise to different risk attitudes. These two behavioral facets of risky choice are commonly analyzed in research on decisions from experience (e.g., Hertwig et al., 2004; Weber et al., 2004; Wulff et al., 2018). Third, we modeled the choices of each sampling strategy with CPT to see whether and how different settings of the building blocks are reflected in differences in the probability weighting function and the value function.

While our analyses focus on the sampling strategies' choice behavior, the strategies also differ in the amount of sampling effort they typically give rise to (as we show in Appendix A). Yet most of the sampling strategies tended to require 25 or fewer samples to reach the decision threshold—which falls within the range typically observed in empirical studies (e.g., Wulff et al., 2018).

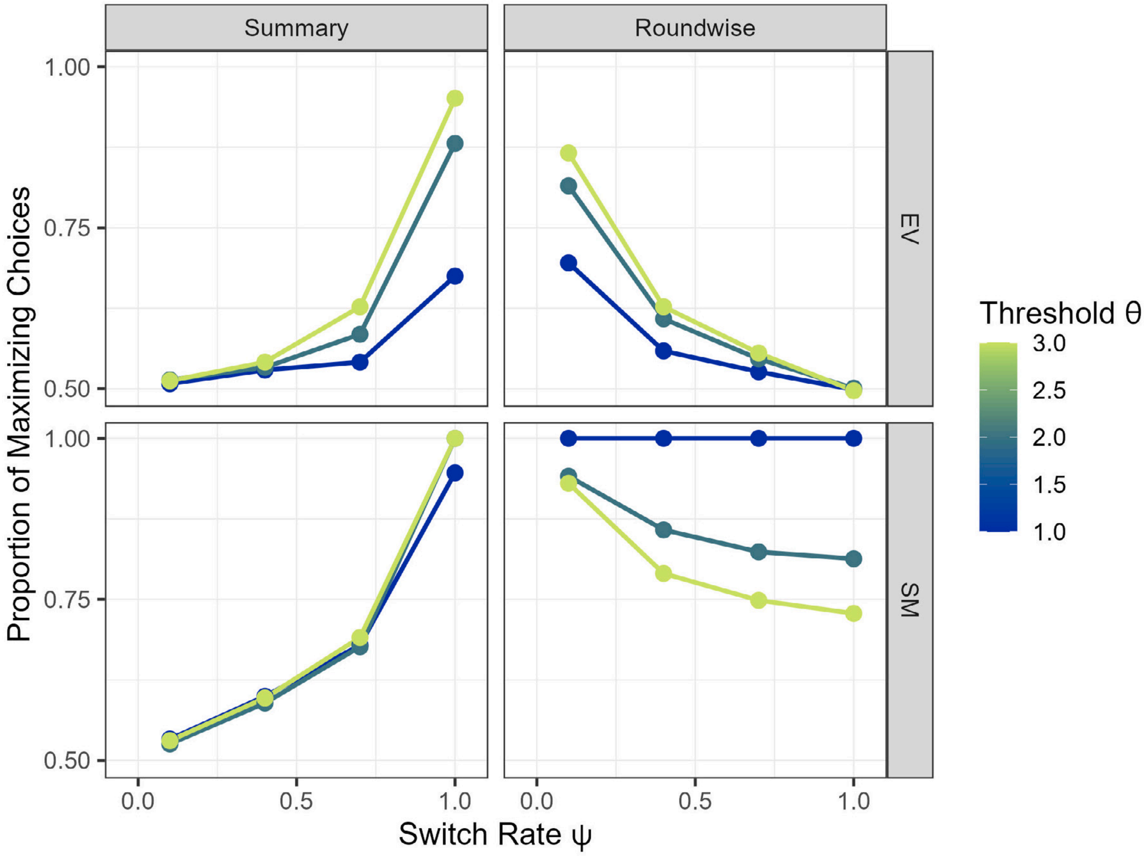

Fig. 3. Sampling strategies' maximization behavior as a function of their search, comparison, and stopping rules.
Note. Points represent sampling strategies with different switch rates ψ (search rule; x-axis) and different decision thresholds θ (stopping rule; color coding). Left panels show the results for sampling strategies with a summary comparison rule; right panels show the results for sampling strategies with a roundwise comparison rule. Top panels show the proportion of choices maximizing the expected value (EV maximization); bottom panels show the proportion of choices maximizing the sampled mean outcome (SM maximization).

4.1. EV maximization

The top row of Fig. 3 shows, separately for different settings of the search and stopping rules, the proportion of cases in which the option with the higher EV was chosen.

4.1.1. Sampling strategies with summary comparison

For sampling strategies with a summary comparison rule, both a lower switch rate and a lower decision threshold led to stronger deviations from EV maximization (Fig. 3, top-left panel). In other words, the less frequently a strategy switched between options during sampling and the less evidence it required before stopping search, the more it deviated from choosing the option that yielded the higher reward in the long run.

To assess the contribution of sampling error – that is, when the distribution of sampled outcomes deviates from the options' actual payoff distribution due to limited sampling – to the observed patterns in EV maximization, the bottom row of Fig. 3 shows the *sampled mean* (SM) maximization—that is, how frequently the sampling strategies chose the option with the higher mean of the sampled outcomes. This analysis yielded a qualitatively similar pattern for the effects of the switch rate and the decision threshold, suggesting that the differences in EV maximization were not predominantly driven by sampling error. By implication, they must be due to differences between the sampling strategies in how they processed the sampled information. One factor in information processing could be that a low switch rate can lead to a *primacy bias* in choice: When the switch rate is low and it takes longer for sampling to switch from one option to the other, the initially sampled option has an advantage over the other option in terms of the number of sampled outcomes that drive the accumulated evidence when relying on a summary comparison rule. This temporary imbalance in the accumulated evidence increases the probability that the decision threshold for the initially sampled option is reached first (for details on the primacy bias, see Appendix B). Crucially, since the option that was sampled first was determined randomly on each choice problem, the rates of EV maximization and SM maximization were close to the chance level of .5 for sampling strategies with a low switch rate.

4.1.2. Sampling strategies with roundwise comparison

The top-right panel of Fig. 3 shows that higher switch rates and lower decision thresholds led to stronger deviations from EV maximization. In other words, the more frequently a strategy switched between options and the less evidence it required before search was stopped, the less frequently it chose the option that yielded the higher reward in the long run. Hence, compared to strategies with a summary comparison rule, the same differences in the switch rate had the opposite effect on EV maximization—higher switch rates led to more maximization for strategies with a summary comparison rule but less maximization for strategies with a roundwise comparison rule.

As shown in the bottom-right panel of Fig. 3, the analysis of the sampling strategies' SM maximization yielded a qualitatively different effect of the decision threshold than for EV maximization, indicating that sampling error played a prominent role here. However, SM maximization also varied between different settings of the switch rate and the decision threshold, indicating that information processing had an impact as well.[6] Specifically, the SM maximization rate was smaller with higher switch rates and higher decision thresholds.

One plausible explanation for the effect of the switch rate on EV maximization and SM maximization is that with a high switch rate, comparison rounds are relatively short, such that in each round, rare outcomes tend to be undersampled. As a consequence, rare outcomes had disproportionately little impact in most of the comparison rounds and round wins were typically driven by high-probability outcomes. The resulting tendency to choose the "frequent winner" (i.e., the option that leads to a higher outcome most of the time; see also Olschewski et al., 2024) led to more deviations from EV maximization. Because the undersampling of rare events occurs less frequently when the number of comparison rounds (and thus the total number of samples) is high, sampling strategies with higher decision thresholds led to less SM maximization (for an analysis of undersampling within comparison rounds and details, see Appendix C).

In sum, the analyses highlight that search processes can play a key role in producing differences in EV maximization. Frequent switching during information sampling fostered EV maximization for sampling strategies with a summary comparison rule, but hindered EV maximization for sampling strategies with a roundwise comparison rule.

4.2. Risk attitude

We next examined the extent to which different settings of the search rule, comparison rule, and stopping rule led to specific risk attitudes (i.e., risk aversion or risk seeking) in the resulting choices (note that by virtue of the design of the choice problems, we were able to examine risk attitudes independently of deviations from EV maximization). Fig. 4 plots the proportion of choices of the safe option, separately for sampling strategies with a summary or a roundwise comparison rule and for different settings of the switch rate and the decision threshold. Sampling strategies with a summary comparison rule and sampling strategies with a roundwise comparison rule chose the safe option in 50% of the trials, with no discrepancies between different settings of the switch rate and the decision threshold. Given that the choice problems were designed such that the risky option had the higher EV in half of the cases, this is the expected pattern under risk neutrality.

For strategies with a summary comparison rule, the observed risk neutrality can be explained by the tendency to maximize the EV when the switch rate was high (see Fig. 3) and by the impact of the primacy bias (which randomly affected the safe or the risky option) when the switch rate was low. The risk neutrality found for strategies with a roundwise comparison rule can be explained by the tendency to maximize the EV when the switch rate was low and by the tendency to choose the frequent winner (which was the risky option in half of the cases) when the switch rate was high.

Aggregated across different types of choice problems, the building blocks of the sampling strategies thus did not produce systematic deviations from risk neutrality. However, as we will show in Section 4.4, the sampling strategies gave rise to different degrees of risk aversion and risk seeking as a function of whether there was a rare event and how attractive it was.

4.3. Characterizing the sampling strategies' choices with CPT

We now turn to the question of how the preference patterns generated by the sampling strategies were reflected in the shapes of CPT's probability weighting function and value function. As mentioned in Section 1, CPT has been widely used to describe choice behavior and variations thereof between individuals and across contexts. Analyzing the sampling strategies' choices with CPT allowed us to connect the mechanistic underpinnings of the sampling strategies to CPT's psychoeconomic functions, and thereby to indicate to which degree aspects of search might give rise to the choice regularities underlying nonlinear probability weighting and diminishing outcome sensitivity.

The probability weighting function specifies how the probability of an outcome is translated into a subjective decision weight. Its shape is determined by the parameters γ and δ. γ governs the function's curvature, with $\gamma < 1$ (>1) leading to an overweighting (underweighting) of low-probability events relative to their probability; δ governs the function's elevation, with $\delta < 1$ (>1) leading to overall more underweighting (overweighting; Goldstein & Einhorn, 1987). The value function specifies how outcomes are translated into subjective values; its curvature is governed by the outcome sensitivity parameter α, with $\alpha = 1$ leading to a linear function and $\alpha < 1$ ($\alpha > 1$) leading to concave (convex) functions. Values of $\alpha < 1$ indicate increasingly lower sensitivity to differences in outcomes. A full description of the CPT model we used in our analyses is presented in Appendix D.

[6] As an exception, at a threshold value of 1, the SM maximization rate was always 1, irrespective of the setting of the switch rate. This is because only one comparison round was required to reach the threshold and round wins were determined by comparing the sampled average outcome within a round.

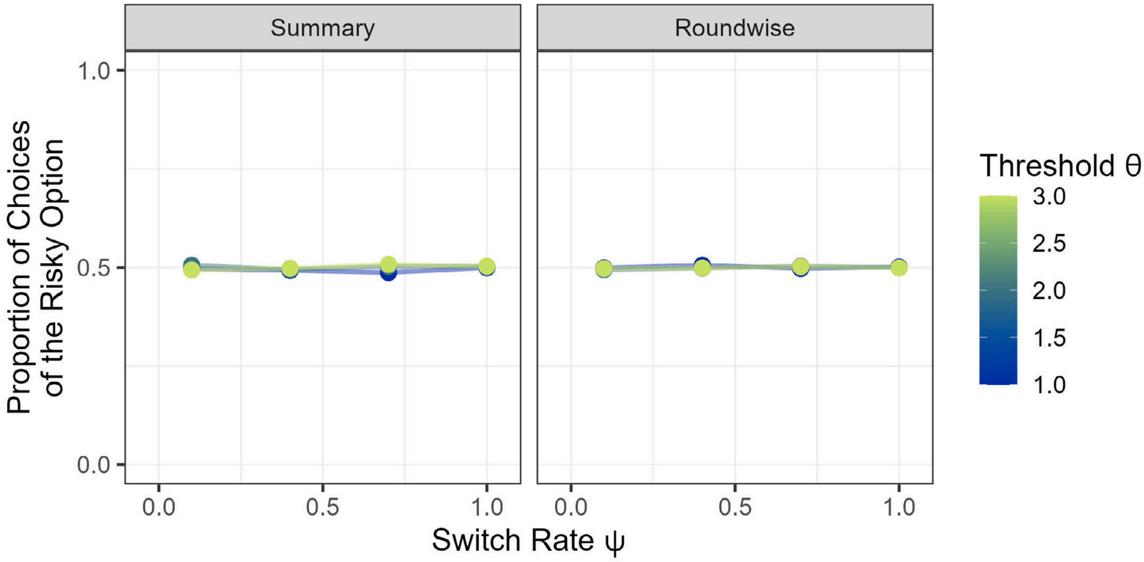

Fig. 4. Sampling strategies' risk attitude as a function of search, comparison, and stopping rules.
Note. Each point represents the proportion of choices of the risky over the safe option, separately for each sampling strategy.

We estimated a separate CPT model for each strategy.[7] Importantly, as in previous applications of CPT to decisions from experience, we estimated the probability weighting function on the basis of the sampled relative frequency with which each outcome was sampled (e.g., Glöckner et al., 2016; Hotaling et al., 2019; Jarvstad et al., 2013; Kellen et al., 2016; Lejarraga et al., 2016; Tiede et al., 2025; Zilker & Pachur, 2022). The estimated probability weighting functions thus provide insights into how the sampled information about the options' payoff distributions was distorted in the resulting choices—that is, how the information processing led to a nonlinear treatment of the sampled outcomes and their relative frequencies.

4.3.1. Probability weighting

Sampling strategies with summary comparison. The top row of Fig. 5 displays the probability weighting functions estimated for the choices of the sampling strategies with a summary comparison rule. It can be seen that across many settings of the search rule and the stopping rule, the strategies gave rise to an apparent overweighting of the higher risky outcome, indicated by an inverse S-shaped probability weighting function. Importantly, the degree of overweighting was strongly modulated by the search rule: Overweighting was most pronounced for strategies with a low switch rate, whereas strategies with a high switch rate gave rise to approximately linear probability weighting. The middle row of Fig. 5 shows the means and 95% credibility intervals of the posterior distributions of CPT's curvature parameter γ; the bottom row shows the same metrics for the elevation parameter δ. Both parameters were close to 1 for sampling strategies with a high switch rate, reflecting approximately linear probability weighting patterns, but deviated considerably from 1 for sampling strategies with a lower switch rate, reflecting nonlinear probability weighting: The curvature parameter γ was lower and the elevation parameter δ was higher for lower switch rates. This pattern held irrespective of the level of the decision threshold, though it was more pronounced for strategies with a low decision threshold.

Why did sampling strategies with a summary comparison rule give rise to strong overweighting (which boosted the attractiveness of the risky option, since the higher risky outcome was overweighted; see Eq. (D.4))? Primacy bias – which is strongest with a low switch rate and a low decision threshold – could be the main reason: If the safe option was sampled first, only a relatively small number of samples were drawn from the risky option, increasing the chance that only one of the two risky outcomes would be drawn—that is, the sampled probabilities were either $p_{high} = 0$ or $p_{high} = 1$. Because trials with sampled probabilities of 0 and 1 did not influence the shape of the probability weighting function (the transformed probability is 0 or 1 irrespective of the function's parameters), the estimation of the shape of the probability weighting function was predominantly determined by trials in which the risky option was sampled first – that is, where sampled probabilities deviated from 0 and 1 – and then also typically chosen. As a result, the probability weighting function showed an overweighting pattern, which boosted the attractiveness of the risky option, even though the sampling strategy actually behaved in a risk-neutral manner, choosing the safe option equally often (for details on the effect of primacy bias on the estimated CPT parameters, see Appendix B).

[7] To assess how well the choices of the sampling strategies were captured by CPT, we conducted posterior predictive checks (see Appendix D). Overall, the results show that for strategies with roundwise comparison, CPT captured the choices well, whereas for strategies with a summary comparison, the predictive accuracy was more modest.

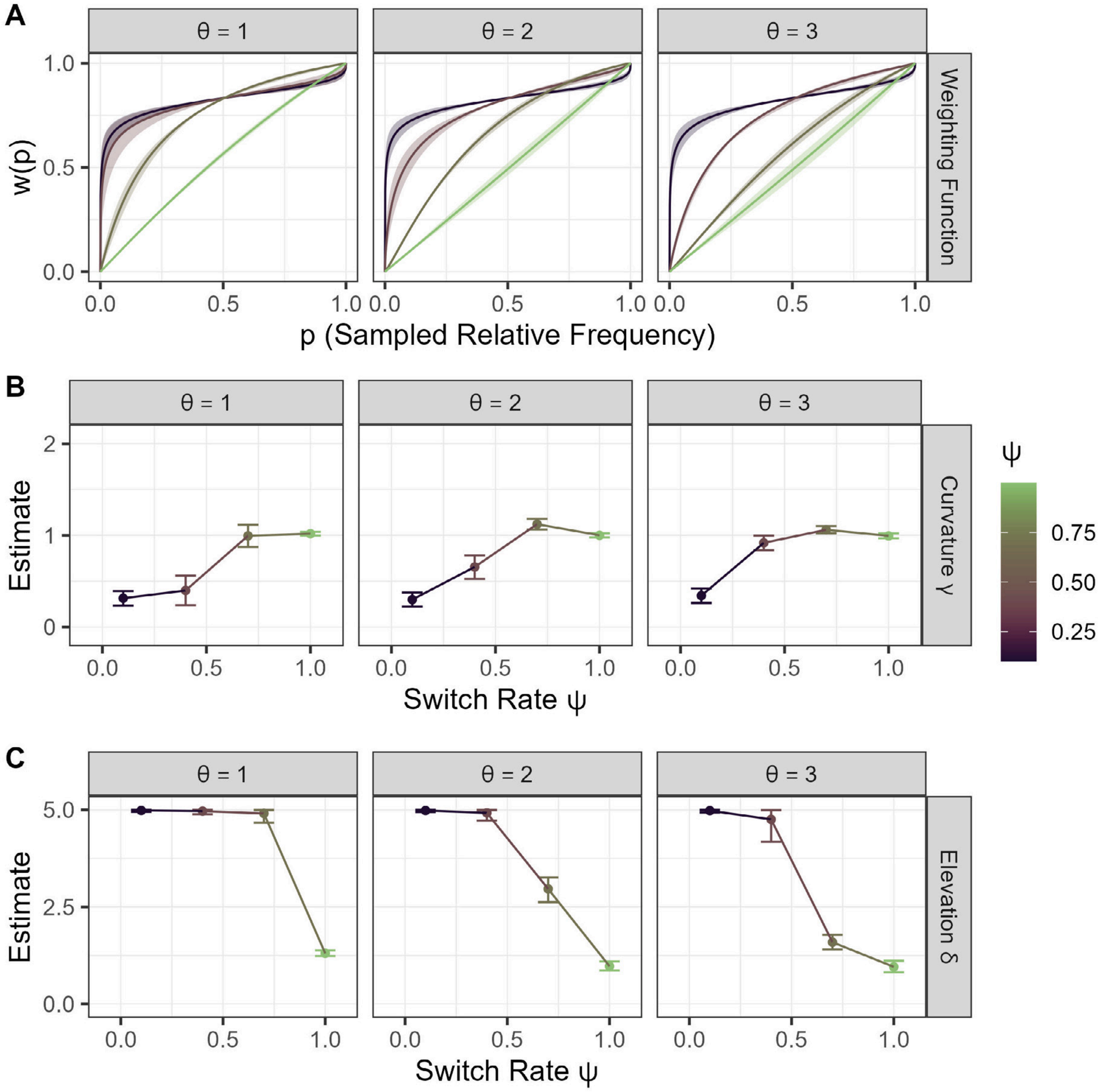

Fig. 5. Probability weighting functions and estimated probability weighting parameters for sampling strategies with a summary comparison rule. *Note.* (A) The probability weighting functions are based on the means of the posterior distributions of the curvature parameter γ and the elevation parameter δ, separately for different settings of the switch rate ψ and the decision threshold θ. (B) Means and 95% credibility intervals of the posterior distribution of γ. (C) Means and 95% credibility intervals of the posterior distribution of δ.

Sampling strategies with roundwise comparison. Fig. 6 shows the estimated probability weighting functions and corresponding parameters for the sampling strategies with a roundwise comparison rule. The top row of the figure shows that the resulting probability weighting patterns were markedly different from those of strategies with a summary comparison rule: Across many settings of the search rule and the stopping rule, the strategies gave rise to an underweighting of rare events, indicated by an S-shaped probability weighting function. Importantly, the degree of underweighting was modulated by the switch rate. Whereas strategies with a low switch rate gave rise to approximately linear probability weighting, the underweighting of rarely sampled outcomes was increasingly pronounced for strategies with a higher switch rate.

The likely reason for the S-shaped probability weighting functions is that common outcomes have a disproportionately large impact on evidence accumulation in sampling strategies with a roundwise comparison rule, and this effect becomes larger the higher the switch rate. With higher switch rates, comparison rounds are shorter, and most of the rounds are won by the safe option when the risky option's higher outcome was infrequently sampled ($p < .5$), but are won by the risky option when its higher outcome was

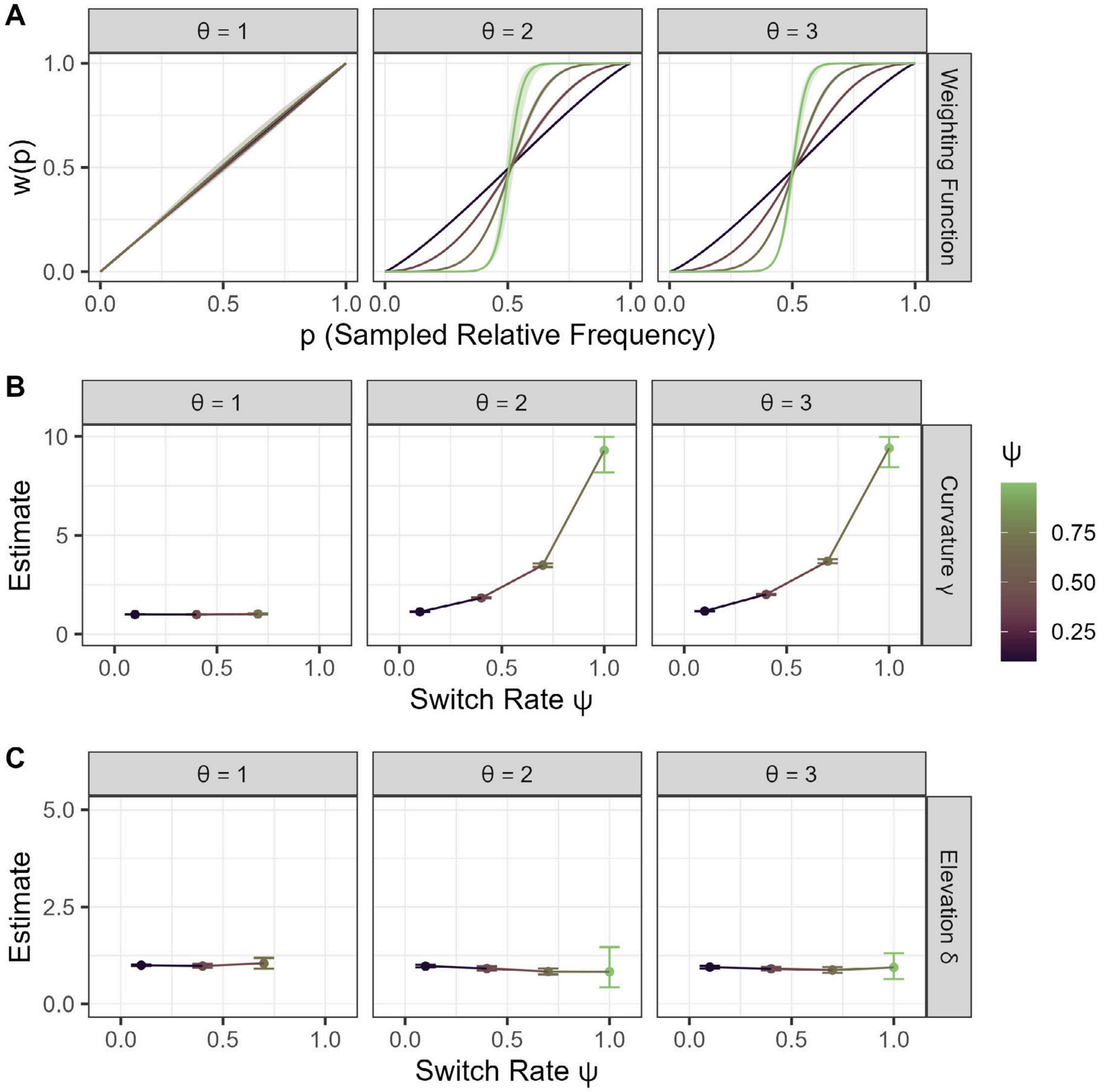

Fig. 6. Probability weighting functions and estimated weighting parameters for sampling strategies with a roundwise comparison rule.
Note. (A) The probability weighting functions are based on the means of the posterior distributions of the curvature parameter γ and the elevation parameter δ, separately for different settings of the switch rate ψ and decision threshold θ. (B) Means and 95% credibility intervals of the posterior distribution of γ. (C) Means and 95% credibility intervals of the posterior distribution of δ. Results for the sampling strategy with the decision threshold set at $\theta = 1$ and the switch rate set at $\psi = 1$ are not shown, as with this setting, only one sample is drawn per option, resulting in sampled probabilities of either 0 or 1; based on these probability levels, it is not possible to estimate a probability weighting function.

frequently sampled ($p > .5$). According to Eq. (D.3), this choice pattern is captured by an S-shaped probability weighting function where the curvature parameter γ is larger than 1, since the function underweights the high risky outcome when it is infrequently sampled ($p < .5$), but overweights it when it is frequently sampled.

To summarize, the analysis of the sampling strategies' choice behavior with CPT's probability weighting function showed that search processes can have a strong influence on probability weighting. Infrequent switching between options (i.e., a low switch rate) can promote apparent overweighting for sampling strategies with a summary comparison rule. By contrast, frequent switching between options (i.e., a high switch rate) can promote apparent underweighting of rare events for sampling strategies with a roundwise comparison rule.

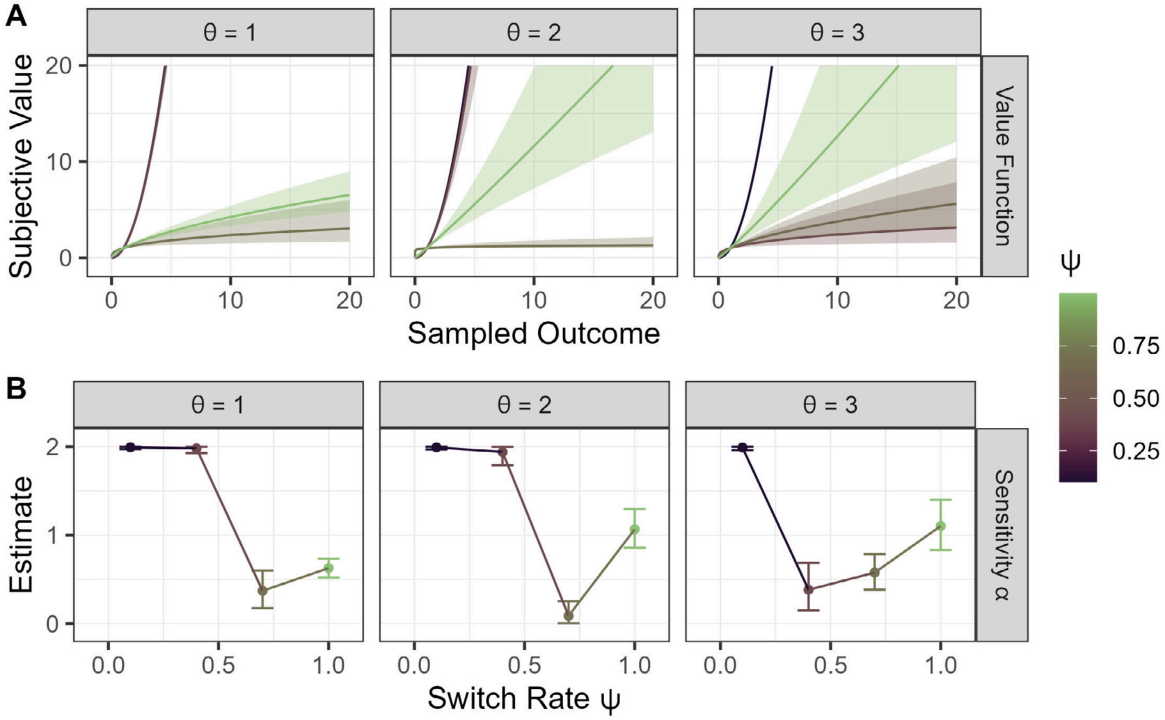

Fig. 7. Value functions and estimated outcome sensitivity parameters for sampling strategies with a summary comparison rule.
Note. (A) The value functions are based on the means of the posterior distributions of the outcome sensitivity parameter α, separately for different settings of the switch rate ψ and the decision threshold θ. (B) Means and 95% credibility intervals of the posterior distribution for α.

4.3.2. Outcome sensitivity

How was the choice behavior of the sampling strategies reflected in CPT's value function? Figs. 7 and 8 display the estimated value functions, separately for the sampling strategies with a summary and a roundwise comparison rule. The lower rows show the estimates of the outcome sensitivity parameter α.

Sampling strategies with summary comparison. For sampling strategies with a summary comparison rule, the value function was approximately linear (i.e., $\alpha \approx 1$) if the switch rate was high and became increasingly concave (i.e., $\alpha < 1$) for lower switch rates. This finding implies that sampling strategies with a summary comparison rule and a low switch rate are relatively insensitive to differences in the magnitude of the sampled outcomes. This low outcome sensitivity likely reflects that a low switch rate usually leads to a strong primacy bias, where more samples and thus evidence tends to be accumulated for the initially sampled option. As a consequence, that option ends up being chosen, irrespective of the magnitude of its outcomes.[8]

Sampling strategies with roundwise comparison. Fig. 8 shows that the search rule had a different effect on the shape of the value function than for sampling strategies with a summary comparison rule: Low switch rates led to more linear value functions (i.e., $\alpha = 1$), while high switch rates led to more concave value functions (i.e., $\alpha < 1$).[9] The reason for this pattern is that sampling strategies with a roundwise comparison rule accumulate round wins without keeping track of the absolute differences in the average sampled outcome—that is, whether an option won a round by a narrow or wide margin. Intuitively, this neglect of the outcome magnitudes in the accumulation process is reflected in a concave value function (i.e., limited outcome sensitivity). When the switch rate is high, this neglect is amplified due to an undersampling of rare outcomes. As a consequence, the accumulated number of round wins is driven more by the sampled frequency of the high risky outcome than by its exact magnitude.

To summarize, the analysis of the sampling strategies' choice behavior with CPT's value function indicates how sampling strategies can foster diminished outcome sensitivity and give rise to the empirically common concave value function.

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8 Yet Fig. 7 also shows that for low switch rates, the value function can be convex ($\alpha > 1$). A likely reason for this pattern is that the impact of very strong levels of primacy bias can be further amplified by large outcomes. Especially when the decision threshold is low, large outcomes increase the probability with which the initially sampled option reaches the threshold first. Higher thresholds counteract this interplay: While the imbalance in the number of sampled outcomes continues to drive choices, the exact magnitude of each sampled outcomes becomes less relevant. (The convexity did not lead to substantially different posterior predictions; see Appendix D).

9 Given the wide posterior interval for $\psi = 1$, we tested the robustness of the pattern of decreasing outcome sensitivity in Supplements S1 and S2. The additional analysis corroborate this pattern. Particularly in Supplement S2, which is based on the broadest problem set with more and more varied option pairs, one finds a clear decreasing pattern that also sets in at smaller switch rates.

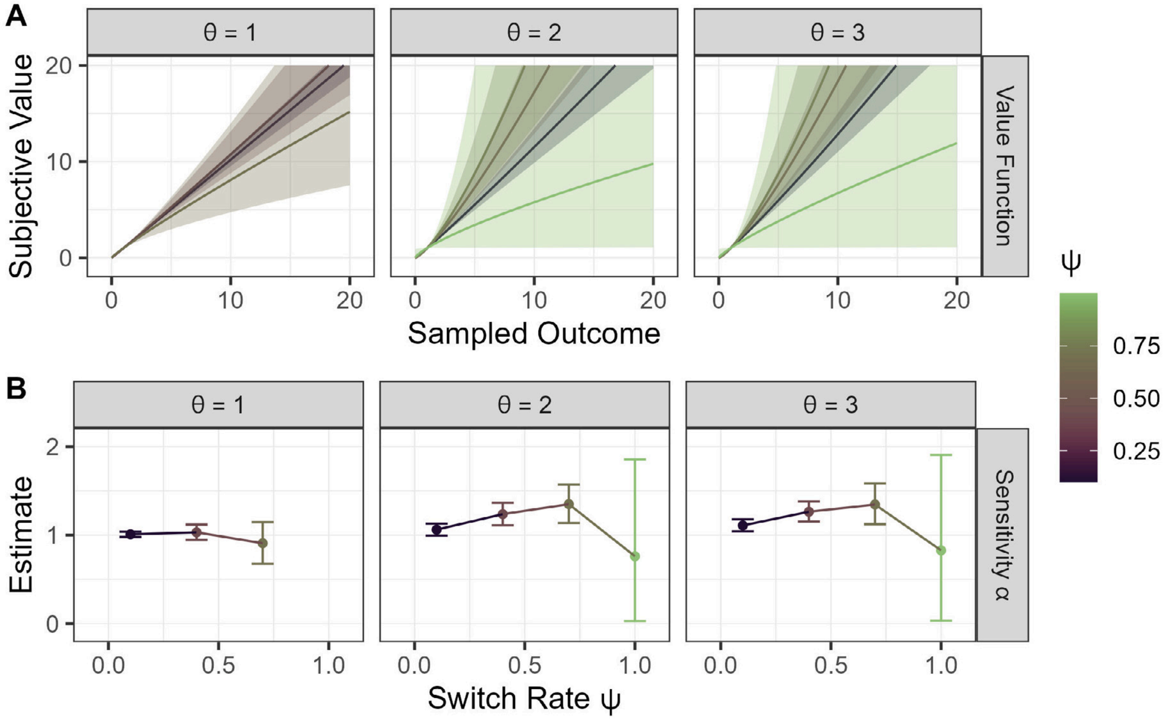

Fig. 8. Value functions and estimated outcome sensitivity parameters for sampling strategies with a roundwise comparison rule.
Note. (A) The value functions are based on the means of the posterior distributions of the outcome sensitivity parameter α, separately for different settings of the switch rate ψ and the decision threshold θ. (B) Means and 95% credibility intervals of the posterior distribution for α. The estimation results for the sampling strategy with the decision threshold set at $\theta = 1$ and the switch rate set at $\psi = 1$ are not shown, as with this setting only one sample per option is drawn, resulting exclusively in sampled probabilities of 0 and 1, for which the probability weighting function cannot be estimated.

4.4. *Sampling strategies and the structure of the choice ecology*

In our analyses of the sampling strategies' EV maximization and risk attitude, we aggregated across a wide range of different types of choice problems. Yet it is possible that the sampling strategies' behavior is affected by properties of the choice ecology, which remains invisible when aggregating across the choice problems. We therefore examined the sampling strategies' choice behavior for different subsets of the choice problems, distinguishing problems depending on whether they contain an option with a rare event or not (i.e., whether the ground-truth probability of the outcome was $\leq .2$)—an aspect that has received considerable attention in analyses of decisions from experience (e.g., Hertwig et al., 2004). In addition, we distinguished between problems where the rare event is attractive or unattractive (i.e., better or worse than the outcome of the safe option), since people choosing between a safe and a risky option in decisions from experience seem to be risk averse when the rare event is attractive but risk seeking when it is unattractive (Wulff et al., 2018).

Fig. 9 plots the strategies' risk attitude, separately for choice problems in which the risky option did not contain a rare event and for those in which it did (for a similar analysis of EV maximization, see Supplement S1). It shows that whereas for sampling strategies with a summary comparison rule the existence of a rare event had virtually no impact on the risk attitude, for sampling strategies with a roundwise comparison rule the risk attitude differed critically between the choice ecologies: In contrast to the risk neutrality in choice problems without a rare event, the strategies produced risk-averse choices in problems with an attractive rare event (i.e., right-skewed environment). Importantly, the switch rate and the decision threshold also affected risk attitude: Risk aversion was higher with higher switch rates and with higher decision thresholds. This occurred because with a higher switch rate, comparison rounds were shorter, increasing the chance that the rare event was undersampled and thus not considered—leading to an undervaluation of the risky option. For choice problems in which the risky option had an unattractive rare event (i.e., left-skewed environment), the same ecological dependency emerged, but the pattern was flipped toward risk seeking rather than risk aversion for these strategies. The risk attitude patterns of the strategies with a roundwise comparison rule thus mirror the common finding of risk aversion for attractive rare events and risk seeking for unattractive rare events in decisions from experience, which is typically interpreted as indicating an underweighting of rare events (e.g., Barron & Erev, 2003; Hertwig et al., 2004). Overall, these analyses further highlight the potential impact of search processes in shaping risky choice.

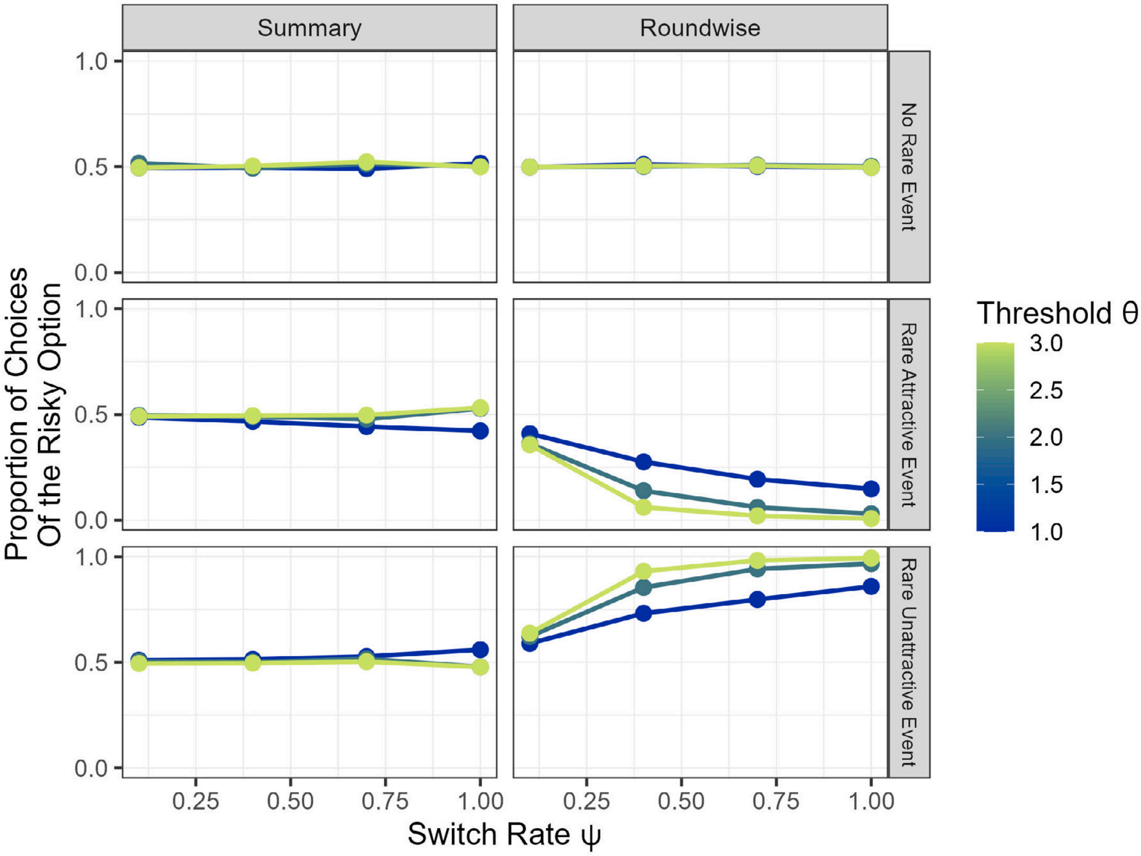

Fig. 9. Sampling strategies' risk attitude, separately for choice problems without a rare event and choice problems with an attractive/unattractive rare event.

Note. Each point represents the proportion of choices of the risky option, separately for each sampling strategy and separately for choice problems without a rare event (p_{low} > .2 and p_{high} < .8; top row), problems with an attractive rare event (p_{high} ≤ .2; middle row), and problems with an unattractive rare event (p_{low} ≤ .2; bottom row).

5. General discussion

To account for human preference deviating from EV theory and EU theory, descriptive models of risky choice have traditionally invoked psychoeconomic curves—which are mute with regard to the underlying cognitive processing. Inspired by Herbert Simon's call for more focus on processes of search in the study of decision making, we examined how aspects of information search can contribute to patterns in risky choice. To that end, we developed a computational framework of sampling strategies that extends ideas on strategies for decisions from experience in the sampling paradigm sketched by Hills and Hertwig (2010). Our sampling strategies, which are formalized as sequential sampling models, highlight two aspects of information search: switching between options and stopping based on sampled evidence (i.e., optional stopping). The sampling strategies consist of three building blocks: a search rule, specifying the extent to which sampling oscillates between options during search; a comparison rule, specifying whether the options are evaluated based on evidence derived from a summary of all drawn outcomes or a series of ordinal comparisons; and a stopping rule, which determines when sufficient evidence has been accumulated to make a choice.

We used the framework to analyze how combinations of different settings of the building blocks give rise to commonly studied properties of risky choice. We found that a low switch rate produces high EV maximization for sampling strategies with a roundwise comparison rule, whereas a high switch rate produces high EV maximization for sampling strategies with a summary comparison rule. Our analyses further show that while the sampling strategies are risk-neutral in general, they can yield risk seeking or risk aversion in environments in which there is a rare event. Sampling strategies with a roundwise comparison rule (but not those with a summary comparison rule) produce risk-averse choices when the rare event is attractive and risk-seeking choices when the rare event is unattractive—echoing empirically observed patterns in experience-based choice (Wulff et al., 2018). Modeling the choices generated by the sampling strategies with CPT further showed that the two comparison rules give rise to markedly different patterns in probability weighting: Sampling strategies with a summary comparison rule lead to an apparent overweighting of rarely sampled outcomes, which was amplified by a low switch rate, whereas sampling strategies with a roundwise comparison rule lead to an apparent underweighting of rarely sampled outcomes, which was amplified by a high switch rate. Moreover, conservative decision thresholds often made these patterns more pronounced.

Our framework not only complements Hills and Hertwig's (2010) strategies with a stopping rule; by allowing for an examination of the full continuum of sampling strategies that can be constructed by combining different settings of the building blocks (Hills and Hertwig had focused on only two particular combinations of a search and a comparison rule), the framework also enables us to study how the building block interact in shaping risky choice. In addition, by scrutinizing the strategies' in terms of EV maximization, risk attitude, and CPT's constructs, we provide a more general characterization of the strategies than Hills and Hertwig (2010)—who only analyzed the sampling strategies' apparent underweighting of rare events.

Overall, our analyses show that switching between options during sampling and optional stopping can substantially influence preference in risky choice. Behavior that has traditionally been explained by reference to psychoeconomic curves could thus, at least to some extent, be mechanistically explained by these aspects of information search, without having to assume distortions of outcomes or probabilities (cf. Zilker & Pachur, 2022). In the following, we discuss theoretical implications of our results, link the sampling strategies to empirical data, and point to limitations of our analyses as well as avenues for future research.

5.1. Theoretical implications

5.1.1. Sampling strategies as models of bounded rationality

Simon (1978, 1990) argued that the study of search processes must take the natural constraints of human information processing into account in order to shed light on how people achieve what he called *bounded rationality*. At least three aspects of the sampling strategies represent simplifications of the decision-making process relative to the traditional neo-Bernoullian calculus (which implies a transformation and multiplicative integration of complete information on an option's outcomes and probabilities): sequential and additive processing, evaluation by ordinal comparison, and limited search.

Sequential and additive processing. Relative to the multiplicative calculus of neo-Bernoullian models, the accumulation process of the sampling strategies is based on two simple computations, addition and subtraction, and merely requires that the decision variable is remembered and updated (similar to reinforcement learning models; Sutton & Barto, 2018). It is generally assumed that additive integration is cognitively easier than multiplicative integration (e.g., He & Bhatia, 2023; Juslin et al., 2008, 2009).

Evaluation by ordinal comparison. To evaluate options, the roundwise comparison rule uses ordinal comparisons of the average outcome sampled during a comparison round. Research in psychophysics shows that people can compare stimuli with high accuracy, but are markedly worse at judging the absolute magnitude of the same stimuli (e.g., Miller, 1956; Shiffrin & Nosofsky, 1994; Stewart et al., 2005)—suggesting that relative comparison comes at lower cognitive costs than absolute evaluation. The roundwise comparison rule keeps track of the number of round wins by simply updating the decision variable sequentially by increments of ± 1. Since monitoring frequencies is assumed to be an automatic process (e.g., Hasher & Zacks, 1984), choosing between options based on multiple ordinal comparisons of *small* samples can be expected to incur relatively low cognitive costs.[10] By contrast, for evidence accumulation under the summary comparison rule the decision variable must be updated based on the magnitude of each sampled outcome and might thus be more complex.

Limited search. Equipped with a decision threshold as a stopping rule, the sampling strategies feature an important aspect of bounded rationality: an aspiration level, which, based on the sampled outcomes, indicates when a "good enough" (i.e., satisficing) option has been identified (Simon, 1978). The stopping rule allows the sampling strategies to curtail the number of samples drawn from the options and thus helps to avoid unnecessarily extensive search. Drawing a relatively small number of samples from the options reduces the time spent on information search and keeps cognitive costs manageable, because only a small amount of information has to be remembered and processed into the decision variable.

Overall, the sampling strategies provide a modeling framework consisting of information processing mechanisms that are likely more cognitively feasible than a neo-Bernoullian calculus. In that sense, they could offer another inroad to the question of how human decision makers might implement bounded rationality.

5.1.2. Sampling strategies as mechanisms underlying probability weighting in decisions from experience

Decisions from experience have frequently been analyzed in terms of probability weighting (e.g., Glöckner et al., 2016; Jarvstad et al., 2013; Pachur & Scheibehenne, 2017). Investigations that have estimated probability weighting functions for decisions from experience based on the experienced distribution of outcomes have observed a wide range of probability weighting patterns—including both substantial underweighting and substantial overweighting of rare events (e.g., Kellen et al., 2016; Zilker & Pachur, 2022). What cognitive mechanisms might be behind patterns of apparent under- or overweighting, and their heterogeneity? Previous discussions of potential cognitive processes underlying apparent patterns of probability weighting in decisions from experience have mostly focused on memory processes, such as selective activation and recency (e.g., Haines et al., 2023; Hotaling et al., 2019; Wulff et al., 2018). Our analyses suggest a possible mechanistic explanation for the observed heterogeneity in probability weighting in

[10] Since the roundwise comparison rules requires outcomes to be averaged in rounds involving more than one outcome per option, it should be noted that the advantage gained from ordinal comparisons and the sequential accumulation of evidence hinges on the round length (and thus the switch rate). An advantage in terms of cognitive costs should be expected at least with low to moderate switch rates, where the comparison rounds are relatively short and the number of outcomes to be considered for a comparison are manageable.

Table 2
Predictive performance of the summary and roundwise comparison rules in the dataset compiled by Wulff et al. (2018).

		Roundwise			
		Correct	False	Indifferent	Total
Summary	Correct	.572	.080	.068	.720
	False	.100	.122	.045	.267
	Indifferent	.005	.004	.006	.015
	Total	.677	.206	.119	

Note. We distinguish three cases of the comparison rules' predictions: correct (i.e., the prediction matches the empirically observed choice), incorrect (i.e., the prediction does not match the empirically observed choice), or indifferent (the prediction is ambiguous). Each cell represents one of the possible cases when jointly considering the predictions of both strategies. The cell entries summarize the observed proportions of these cases among all analyzed trials.

decisions from experience—namely, that it reflects the use of different types of sampling strategies. For instance, sampling strategies with a roundwise comparison rule and moderate to high switch rate may be a mechanism that underlies choices that seem to reflect underweighting, whereas a summary comparison rule may lead to apparent overweighting.

5.2. How do decision makers combine the building blocks? An exploratory empirical analysis

Our computational framework describes a broad space of possible sampling strategies. To explore how actual decision makers might combine settings of the building blocks, and whether some combinations are more common than others, we analyzed the meta-analytic dataset on search and choice in the sampling paradigm compiled by Wulff et al. (2018). We first determined a subset of 1877 participants who were presented with choice problems consisting of a safe and a risky option with two possible positive outcomes—that is, problems of the same type used in our simulation. For further comparability with our simulation, only trials with random and autonomous sampling (i.e., no yoked design or restrictions on switching and sample size) were considered in the analysis. Based on participants' sequence of sampled outcomes in each trial, we determined the predicted choices under the summary comparison rule and under the roundwise comparison rule. Table 2 summarizes the performance of the two comparison rules in terms of proportions of trials in which the predictions were correct, incorrect, or indifferent.[11] In 4638 (82.4%) of 5627 analyzed trials, participants made a choice that was consistent with the prediction of at least one of the two comparison rules (72.0% summary comparison; 67.7% roundwise comparison), indicating that the comparison rules provide a reasonably good approximation of how people evaluate options based on sampled outcomes. However, the predictions for the two comparison rules also showed a strong overlap, such that the data often did not allow to clearly distinguish between the two strategies.

Next, we examined whether the use of a roundwise or a summary comparison rule might be linked to a particular setting of the search rule. Focusing on the 1010 (18%) trials in which the comparison rules did not make the same choice predictions, we determined, for each participant, the proportion of choices that were consistent with the roundwise and the summary comparison rule as well as the average switching frequency across trials (as an indicator of their sampling strategy's switch rate). The switching frequency on each trial was computed as $N_{Switches}/(N_{Samples}-1)$. As shown in Fig. 10, a higher proportion of choices consistent with the roundwise comparison rule tended to be associated with a lower switching frequency. This pattern was corroborated statistically with a Bayesian logistic multilevel regression (using brms; Bürkner, 2017), in which we predicted whether the choice in each trial was consistent with a roundwise comparison rule from the switching frequency at that trial—showing a clear negative association ($\beta = -0.80$, $CI_{95\%}$: -1.19, -0.40).

Note that our simulations had shown that for strategies with roundwise comparison, EV maximization is higher the lower the switch rate, and for strategies with summary comparison, EV maximization is higher the higher the switch rate. One intriguing interpretation of the (admittedly approximate) empirical analysis is thus that people might select sampling strategies that combine a comparison rule and a search rule in a way that fosters EV-maximizing choices.[12]

5.3. Understanding the selection among sampling strategies

In light of the wide range of sampling strategies that can be described with our framework, an interesting question for future research is when different types of sampling strategies might be used. To guide applications of the sampling strategy framework to

[11] Predictions are indifferent when, on the basis of the sampled outcomes, the accumulated evidence is the same for both options. Because the number of round wins is a coarser-grained metric than sums across outcomes, the roundwise comparison rule tends to be indifferent more often. Moreover, when applying the roundwise comparison rule to data, the final comparison round of a trial is incomplete if samples were drawn from only one option. In this case, we treated the sampled option as a round winner. For details and an alternative approach yielding a qualitatively similar result, see Supplement S3.

[12] In a similar analyses, Hills and Hertwig (2010) observed the opposite pattern—namely, that the choices of frequent (infrequent) switchers are more consistent with the roundwise (summary) comparison rule. In Supplement S3, we report additional analyses suggesting that these apparent discrepancies are partly due to the smaller subset of data analyzed by Hills and Hertwig as well as different integration mechanisms assumed for the summary comparison rule (averaging vs. summing).

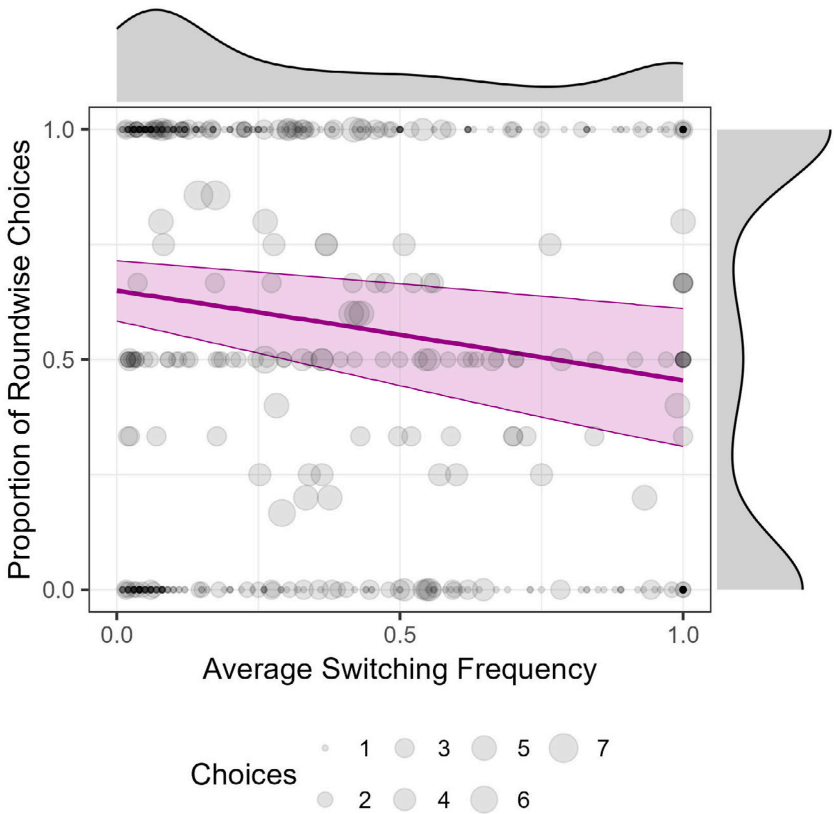

Fig. 10. Proportion of choices consistent with a roundwise or a summary comparison rule and their association to switching frequency in the dataset compiled by Wulff et al. (2018).
Note. Points represent individual participants' average switching frequency (x-axis) and the proportion of their choices that were consistent with the choice predicted by the roundwise comparison rule but not the summary comparison rule (y-axis). Only gain problems with a safe and a risky option and with diverging predictions (correct or false) for the two comparison rules were analyzed. Circle diameter reflects the number of trials underlying the participants' switching frequencies and choice proportions. Regression lines are derived from a Bayesian logistic multilevel model that predicts the choice in each trial from the switching frequency in that trial, assuming random intercepts for papers. The solid line represents the posterior means of the intercept and the slope. The upper and lower dashed lines represent the upper and lower boundaries of the 95% credibility intervals.

help understand strategy selection, we next sketch possible psychological and ecological factors that might influence the setting of the search, comparison, and stopping rules.

5.3.1. Goals

Decision-makers choosing between risky options can pursue different goals. Some might aim to maximize returns in the long run, while others might prefer to minimize the risk of facing long periods with low returns and thus focus on the results obtained in the short run (Olschewski et al., 2024; Wulff et al., 2015). The selection of sampling strategies might differ depending on whether a long-term or a short-term goal is pursued. Wulff et al. (2015) manipulated participants' aspiration toward a long-term (vs. short-term) goal and found that this led to more extensive sampling, suggesting that goal-setting impacts the decision threshold. Further, one might expect that a decision maker who pursues a short-term goal would select the frequent winner—that is, the option that provides the better outcome most of the time (assuming pairwise random draws from each option; Olschewski et al., 2024). Within our framework, identifying this option would be achieved most effectively with a sampling strategy that has a roundwise comparison rule and a high switch rate.

5.3.2. Working memory and cognitive resources

During sampling, a decision maker needs to keep track of and process the sequence of sampled outcomes in order to evaluate and compare options. A possible factor influencing the sampling strategies they select may therefore be their working memory capacity. In Rakow et al. (2008), people with lower working memory capacity drew samples in smaller "batches" from the options – corresponding to shorter comparison rounds – compared to people with higher working-memory capacity; they also drew fewer samples overall (but see Kopsacheilis, 2018; Wulff et al., 2015). Lower working memory capacity might thus lead decision makers to select sampling strategies with a higher switch rate and a lower decision threshold, allowing them to process fewer samples of a given option simultaneously and to generally consider fewer samples when comparing options. Working memory might also affect the comparison rule. Bröder and Schiffer (2006) found that under higher working memory load, decision makers were more likely to select a decision strategy that relies on a simple tally of the number of positive attributes rather than a strategy that computes the weighted sum of the amount of evidence. Applied to the selection of sampling strategies, this might suggest that lower working memory capacity increases the adoption of a roundwise comparison rule (rather than a summary comparison rule). A similar pattern of strategy selection might be observed in situations where cognitive resources are constrained, such as under time pressure or in dual task conditions (e.g., Payne et al., 1993).

5.3.3. Problem structure

An ecological factor that might influence the selection of sampling strategies is the number of distinct outcomes that each option can have, which makes a choice problem more or less complex (Erev et al., 2017; Huck & Weizsäcker, 1999; Spiliopoulos & Hertwig, 2023; Zilker et al., 2020). For instance, a problem consisting of a risky and a safe option (which has only one outcome) is less complex than a problem consisting of two risky options. Because repeated sampling from a safe option leads to redundant information, people might focus their search on the options with multiple distinct outcomes and thus select sampling strategies with a lower switch rate than in risky–risky problems (for evidence that people sample more from options with higher outcome variability, see Gershman, 2019; Spektor & Wulff, 2024; Tiede et al., 2025). Yet, such estimation-driven search might be preceded by discovery-driven search, where people first aim to sample as many distinct outcomes as they are expecting the options to have based on previous experience with similar problems (Spektor & Wulff, 2024). All things being equal, switching might thus be more prevalent in more complex problems, which not only have more outcomes but also invoke more epistemic states.

5.3.4. External search costs

How people search for information might also depend on the specific costs associated with sampling. If consecutive draws can be taken relatively quickly (e.g., because there is no fixed viewing time for each sample), people might select sampling strategies with higher decision thresholds than in situations in which the time costs of sampling are relatively high. Kopsacheilis (2018) found that people sampled more extensively when there was less waiting time between consecutive samples. In a similar vein, higher switch costs can lead decision makers to select sampling strategies with a lower switch rate. In a repeated choice paradigm, Ashby and Teodorescu (2019) found that people switch less between options when there are monetary switch costs. In the sampling paradigm, switch costs could, for example, depend on how far apart the options are presented on the screen. It is also possible that strategy selection is not driven by search costs directly, but by the trade-off between search costs and the expected payoff (cf. Lieder & Griffiths, 2020; Payne et al., 1993).

5.4. Limitations and future directions

Our main goal in this article was conceptual: to explore the effects of the search, comparison, and stopping rules on choice behavior. An important next step is to develop the sampling strategy framework such that it can be fitted to empirical data, to see which combination of a comparison rule, search rule, and stopping rule best accounts for a person's search and choice data. A current limitation of our framework is that it does not yet provide an explicit likelihood function for the choice and sample size data. A canonical approach to address this issue would be to model a diffusion process, for which various solutions to derive a likelihood exist (e.g., Diederich & Busemeyer, 2003; Ratcliff, 1978). One of the challenges in applying this approach to our framework, however, is that a diffusion process requires a drift coefficient, which captures the mean rate of evidence accumulation. While in many applications the drift coefficient is a free parameter that is estimated from the data, in the context of our framework the coefficient also depends on the combination of the search and comparison rules (see Fig. 1). The challenge is thus to compute the drift coefficient as a function of the sequence of sampled outcomes – including the observed switch rate – such that it adequately approximates the integration mechanism assumed in the respective comparison rule of our framework.[13] Alternatively, recent developments in model-fitting approaches based on machine learning that use simulated data from a model to train neural networks to learn the inverse mapping from data to model parameters could help address the issue of fitting the strategies to empirical data (see, e.g., Boelts et al., 2022; Elsemüller et al., 2024; Kvam et al., 2025).

Having an estimation approach for the sampling strategies would also allow for a model comparison with alternative modeling frameworks that have been proposed for decisions from experience in the sampling paradigm. Similar to IBL, some of these models emphasize the possible role of memory storage and retrieval. For instance, the MEM-EX model (Hotaling et al., 2022) assumes that sampled outcomes are represented as exemplars, and the evaluation of options based on the stored exemplars can be modulated by serial position effects, confusion of memory traces, and salience effects. Other approaches highlight learning processes (e.g., Ashby & Rakow, 2014; Hertwig et al., 2006). For instance, Haines et al. (2023) proposed a reinforcement learning model with

[13] The Wiener diffusion process is just one of several sequential sampling models that have been proposed to simultaneously model choice and response time data (see Ratcliff & Smith, 2004, for a comparison). To accommodate both comparison rules in our sampling strategy framework, it might be necessary to build on a mixture of the assumptions from the different sequential sampling models. For instance, the Wiener diffusion process assumes that varying amounts of evidence are gathered in continuous time, whereas other approaches, such as the Poisson counter model, assume that evidence is collected in fixed amounts (e.g., counts). While the former model seems to fit the assumption of the summary comparison rule, the latter seems to better fit the assumption of the roundwise comparison rule. However, all sequential sampling models require a coefficient that specifies the rate of evidence accumulation.

asymmetric learning of outcome probabilities after positive or negative prediction errors and showed how this can lead to apparent overweighting and underweighting of experienced rare events. An empirical comparison to these models and their assumed cognitive mechanisms can help to clarify the unique contribution of the search processes in our sampling strategy framework and point to possible avenues for future model integration and development.

Our framework and analyses have several limitations. First, in our implementation of the sampling strategies, a given switch rate was constant during sampling. This allowed us to compare sampling strategies that differed along a continuum of switch rates in order to specifically work out the impact that different switch rates have on choice. Yet analyses of empirical switching behavior suggest that the switch rate may change during sampling, typically with more switching at the beginning than the end of a trial (cf. Gonzalez & Dutt, 2011; Hills & Hertwig, 2012; Yechiam, 2020). It will therefore be informative to equip sampling strategies with changing switch rates. To this end, our framework could be adapted to include a dynamic search rule—for example, in the form of a switch rate that decreases with the number of samples. Related, sequential sampling models with collapsing boundaries have been shown to better explain peoples' behavior in the face of speed-accuracy trade-offs compared to models with fixed thresholds (Glickman & Usher, 2019).

Second, a related limitation is that our framework does not specify genuine cognitive mechanisms for the decision to stay with an option or to switch to a different one during sampling. Spektor and Wulff (2024) identified three types of search: discovery-driven, value-driven, and estimation-driven. Each type is meant to reduce a different source of uncertainty in the decision-making process. This work suggests that search can be an adaptive response to the structure of the choice ecology and the computational demands of the choice task (but also see Cohen & Teodorescu, 2022, showing that participants searched in an nonadaptive manner by following spurious outcome patterns). Future work could therefore flesh out potential cognitive mechanisms underlying switching behavior that are responsive to the experienced structure of the choice problem as well as the learned value of the options (see also Gonzalez & Dutt, 2011).

Third, in order to isolate the potential effects of aspects of information search on choice behavior, in our analyses of sampling strategies we intentionally excluded memory and reinforcement learning processes. Future modeling could integrate these processes into the sampling strategies. For instance, forgetting or serial order effects could be accommodated in the computation of the decision variable by weighting the outcomes according to their position in the sampling sequence (e.g., as in MEM-EX and IBL; Gonzalez & Dutt, 2011; Hotaling et al., 2022).

Finally, our ecological analysis addressed only one specific facet of environmental structure, the presence and attractiveness of rare events (but see Footnote 5 for a summary of the effects of EV differences between the options and problems with versus without a safe option). Future work could take a broader ecological perspective and also examine the sampling strategies' behavior in environments in which outcomes and probabilities are negatively correlated (i.e., in risk-reward environments; Pleskac & Hertwig, 2014) or in environments with skewed distributions of outcomes and probabilities (as observed in the real world; Stewart et al., 2006). Another extension would be to also consider problem sets with mixed lotteries, thus making it possible to investigate loss aversion.

6. Conclusion

Research on experience-based risky choice aims to capture decisions as they often occur in real life—under uncertainty, where making a choice requires information search (Hertwig et al., 2004; Olschewski et al., 2023). Unlike neo-Bernoullian models, our sampling strategy framework explicitly incorporates information search into the process of preference construction. Our analyses show how aspects of search interact with evaluation operations and the environmental structure, and can generate behavioral patterns that have traditionally been "explained" through psychoeconomic curves. A comprehensive account of human preferences under risk therefore requires not only studying and measuring search processes, but also embedding them within formal models of choice. By doing so, the present framework provides a process-level explanation for key characteristics of risky choice, complementing existing descriptive theories and accommodating factors that frequently arise in real-world situations, such as time pressure, search costs, and switching costs.

CRediT authorship contribution statement

Linus Hof: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Veronika Zilker:** Writing – review & editing, Methodology, Conceptualization. **Thorsten Pachur:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

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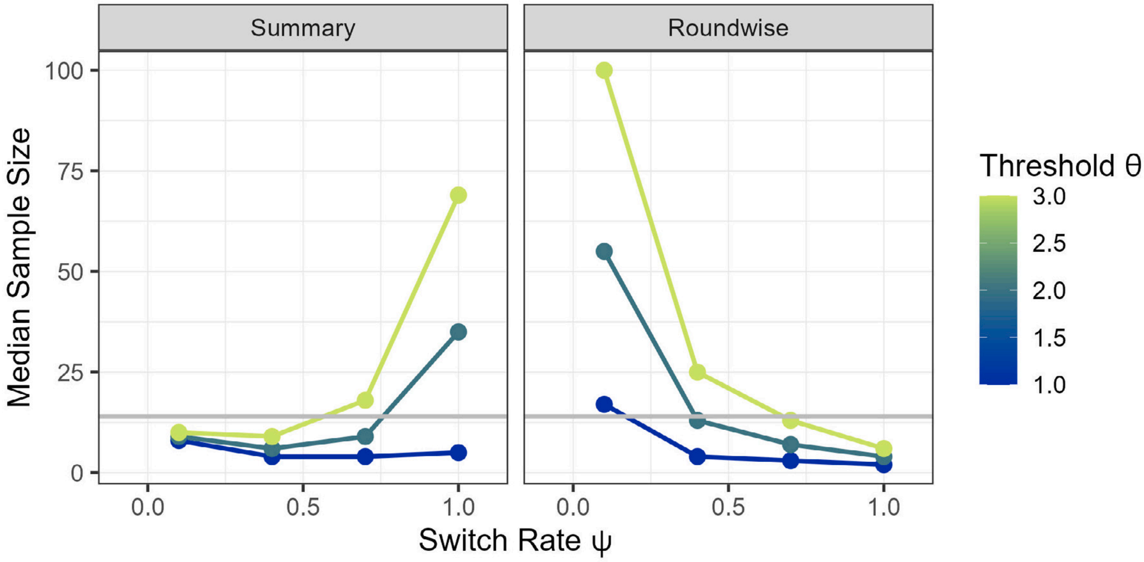

Fig. A.1. Median search effort of sampling strategies.
Note. Each point represents the median sample size across all simulated trials for a sampling strategy. The horizontal line represents the empirical median (14) for safe–risky problems reported in Wulff et al. (2018).

Appendix A. Search effort of the sampling strategies

Our analyses in the main text focused on the sampling strategies' choice behavior. Yet the strategies also differ in the search effort they require. Fig. A.1 shows that higher decision thresholds led, as could be expected, to more extensive sampling, irrespective of the comparison rule. However, the switch rate also had a pronounced effect on the sample size. For sampling strategies with a summary comparison rule, search was more extensive the higher the switch rate; for sampling strategies with a roundwise comparison rule, by contrast, search was more extensive the lower the switch rate. Overall, as illustrated in Figs. A.1 and A.2, most of the sampling strategies produced strongly right-tailed sample size distributions and tended to require only a rather small number of samples (25 or less) to reach the decision threshold, in line with observations in empirical studies (e.g., Gonzalez & Dutt, 2011; Hertwig & Pleskac, 2010; Wulff et al., 2018).

Appendix B. Primacy bias of sampling strategies with a summary comparison rule

Fig. B.1 shows that sampling strategies with a summary comparison rule, a low switch rate, and a low decision threshold draw more samples from the initially sampled option than from the other option (primacy bias). As a result, they are more likely to choose the initially sampled option (Fig. B.2). In addition, when the initial sample in a choice trial is drawn from the safe option, often only one of the two risky outcomes is sampled, leading to sampled probabilities of $p_{high} = 0$ or $p_{high} = 1$ (Fig. B.3). Conversely, if the initial sample is drawn from the risky option, more samples were drawn from the risky option, increasing the chance that both outcomes of the risky option would be experienced; as a consequence, the sampled probabilities could vary more gradually between 0 and 1. Keeping only these trials would leave a subset of predominantly risky choices and seemingly risk-seeking behavior (Fig. B.4).

B.1. *Why primacy bias leads to overweighting*

Following Eq. (D.3), CPT's decision weights for outcomes with sampled probabilities of 0 and 1 invariably equal $w(0) = 0$ and $w(1) = 1$, respectively, independent of the parameter setting of the probability weighting function. Trials in which the sampled relative frequencies are $p_{high} = 0$ or $p_{high} = 1$ therefore have no influence on and do not constrain the shape of the probability weighting function. In turn, for sampling strategies with a low switch rate and a low decision threshold, the estimated probability weighting pattern accommodates the peculiar subset of trials in which the risky option was sampled first and typically chosen (Fig. B.5 shows that the proportion of risky choices is very high when $0 < p_{high} < 1$, but substantially smaller for the cases $p_{high} = 0$ and $p_{high} = 1$). This is achieved by a high elevation of the probability weighting function (i.e., high δ), because it strongly overweights the higher risky outcome and thus boosts the attractiveness of the risky option (see Eq. (D.4)).

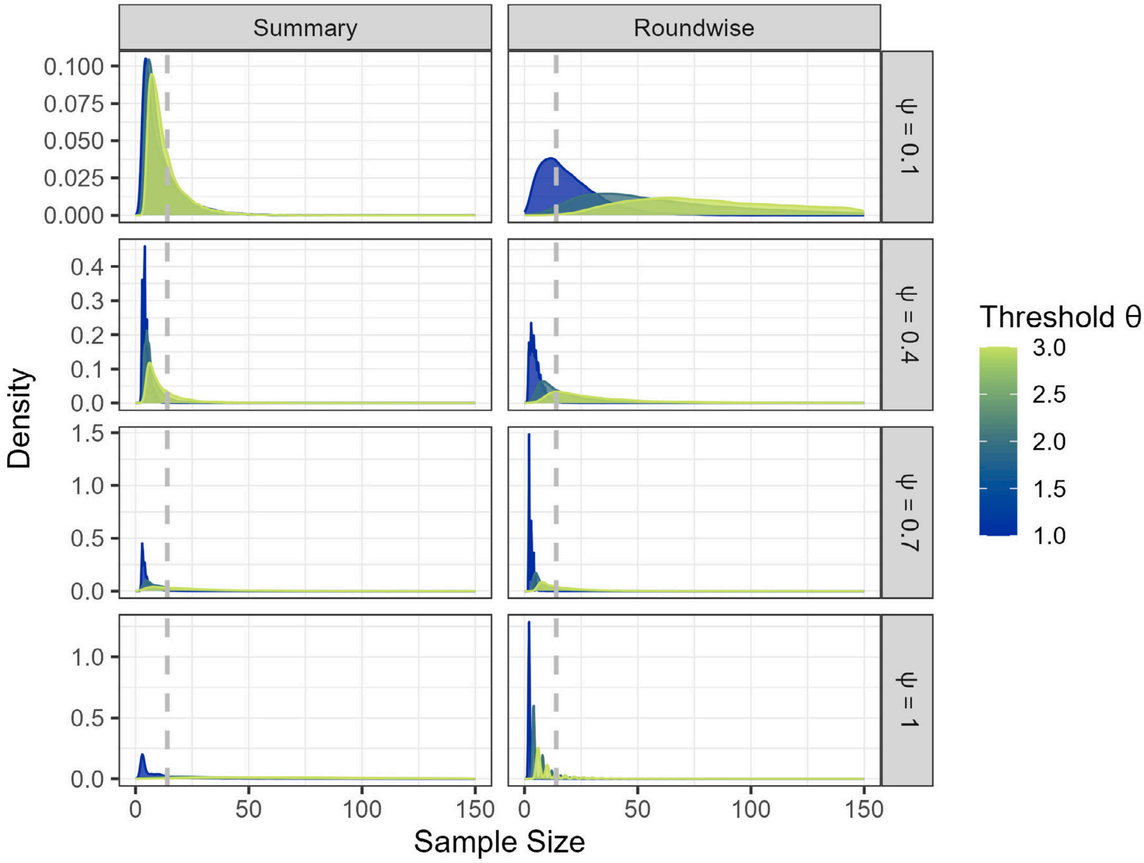

Fig. A.2. Sample size distributions of the sampling strategies.
Note. Each distribution represents the sample sizes from all simulated trials for a sampling strategy. The dashed vertical line represents the empirical median (14) for safe–risky problems reported in Wulff et al. (2018).

Appendix C. Undersampling of rare events in short comparison rounds

Because each comparison round of the roundwise comparison rule starts on the option from which the first sample was drawn and ends when sampling switches back to this option, a high switch rate leads to shorter comparison rounds. Crucially, the binomial distribution for the number of occurrences of outcomes, $B(n, p)$, is positively skewed for a low n (i.e., small sample sizes) and small p (i.e., low probabilities). Hence, given a high switch rate, rare events tend to be undersampled in a comparison round. This effect of undersampling of rare events is illustrated in Fig. C.1, which shows that at a high switch rate, rare outcomes were sampled less frequently within a round than would be expected based on their ground-truth probability (top row) and their relative frequency across all rounds (bottom row).

Appendix D. Modeling the sampling strategies' choices with CPT

D.1. CPT specification

We estimated a separate CPT model for each sampling strategy. CPT implements a rank-dependent transformation of outcomes and probabilities into subjective values $v(x_i)$ and decision weights π_i, which are then integrated to obtain an option's overall valuation,

$$V = \sum_{i}^{m} v(x_i)\pi_i. \tag{D.1}$$

Outcomes are transformed by a value function,

$$v(x) = x^{\alpha}\ , \tag{D.2}$$

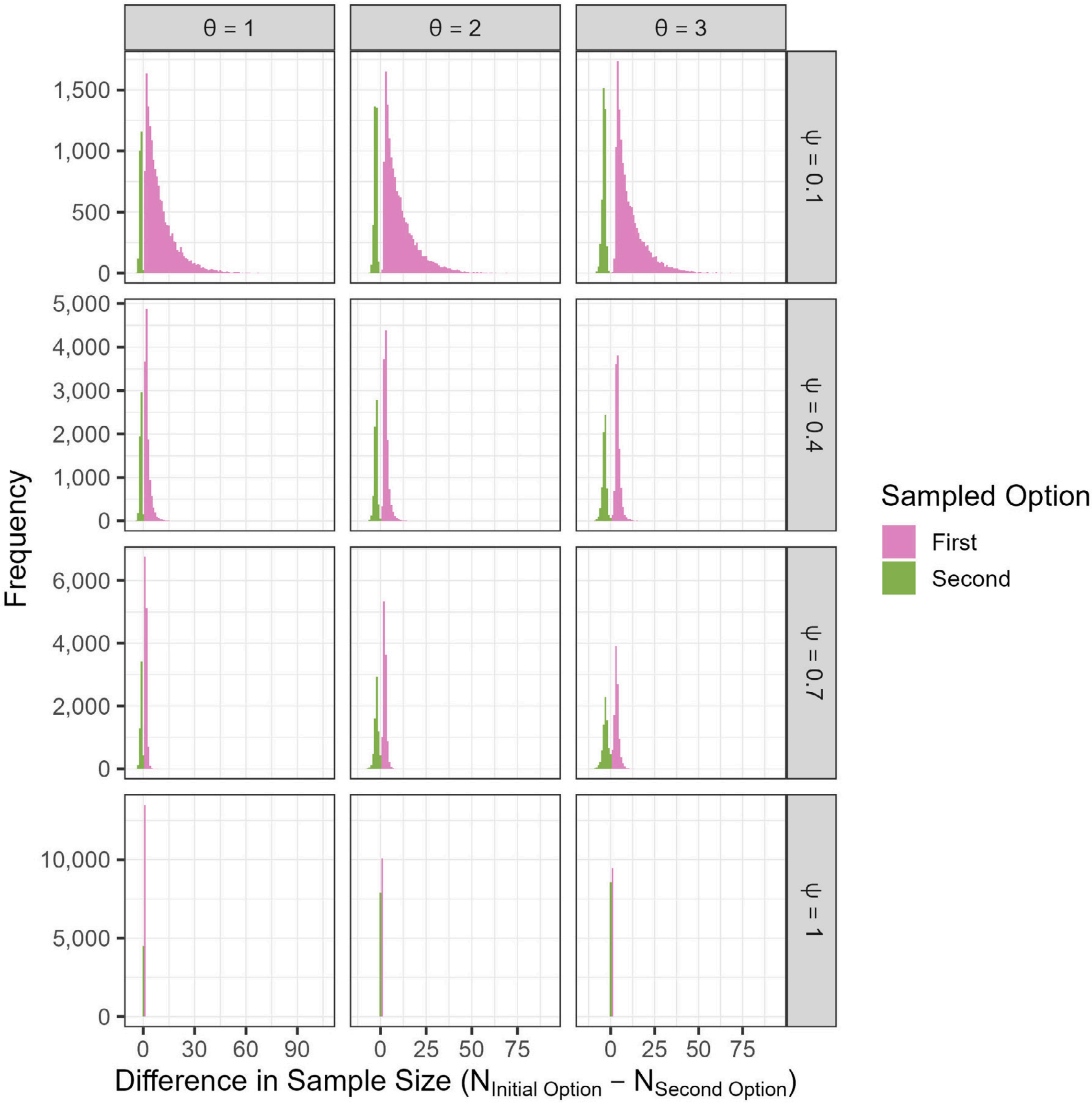

Fig. B.1. Difference in the number of sampled outcomes between the initially sampled option and the other option.
Note. Each plot shows the observed differences in the number of samples from the initially sampled option and the other option, separately for different settings of the switch rate ψ and decision threshold θ. More samples from the initially sampled option are indicated by positive values and pink bars. More samples from the other option are indicated by negative values and green bars. For better resolution and comparability of the individual plots, all frequencies are log-transformed. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where the parameter $\alpha \in [0, 2]$ governs the curvature of the value function and indicates the level of outcome sensitivity (lower values indicating lower outcome sensitivity).

The decision weight for each outcome is determined based on the probability weighting function

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}} , \quad \text{(D.3)}$$

where the parameter γ governs the function's curvature and the parameter δ governs its elevation (Goldstein & Einhorn, 1987). In the original formulation of CPT, $w()$ is an inverse S-shaped probability weighting function (Tversky & Kahneman, 1992). Here, we allow

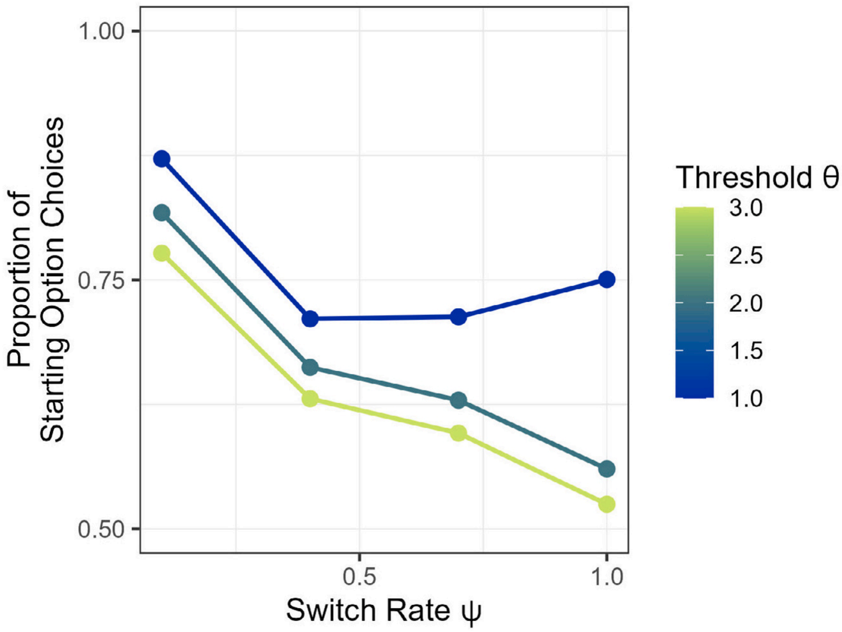

Fig. B.2. Proportion of choices of the initially sampled option.
Note. Each point represents the proportion of trials in which the initially sampled option was chosen, separately for different settings of the switch rate ψ and decision threshold θ.

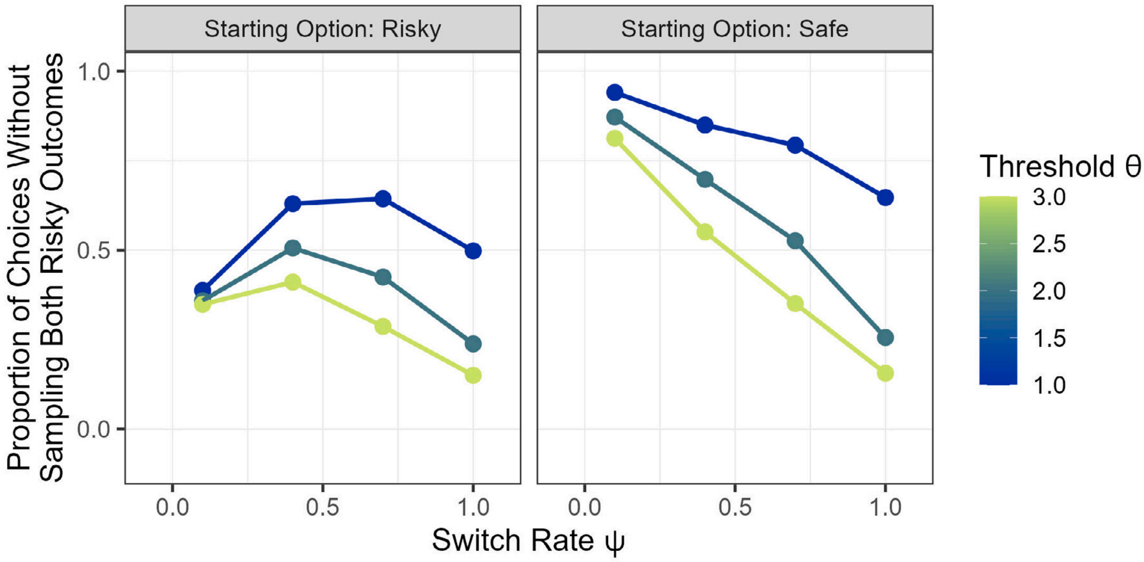

Fig. B.3. Proportion of choices without sampling both risky outcomes.
Note. Each point represents the proportion of trials where only one of the two risky outcomes was sampled (i.e., the sampled probability p_{high} is either 0 or 1). This is the proportion of trials that do not affect the estimation of the probability weighting function. ψ: Switch rate. θ: Decision threshold.

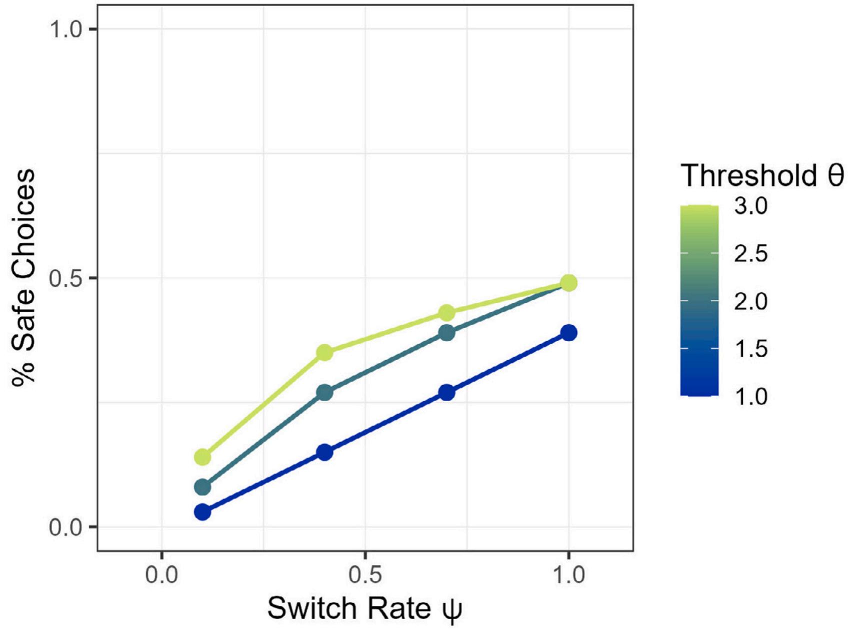

Fig. B.4. Proportion of choices of the safe option.
Note. Each point represents the proportion of choices of the safe option, separately for strategies with different switch rate ψ and decision thresholds θ. In contrast to the risk-attitude analysis reported in the main text, trials in which the risky option was not experienced as such (because only one of the risky outcomes was sampled) were discarded from the analysis.

for greater flexibility – including S-shaped probability weighting functions – by assuming $\gamma \in [0, 10]$ and $\delta \in [0, 5]$.[14] Importantly, we modeled the choices using the relative frequencies of the sampled outcomes rather than the latent probabilities as inputs to the probability weighting function. The resulting shapes of the probability weighting function therefore reflect how information about the options' payoff distribution as it was experienced is distorted in the agents' choices. In the current analyses, where the choice problems consisted of a safe option with one outcome and a risky option with two, the decision weights are defined as follows:

$$\begin{aligned} \pi_{safe} &= 1, \\ \pi_{high} &= w(p_{high}), \\ \pi_{low} &= 1 - \pi_{high}. \end{aligned} \tag{D.4}$$

To determine the probability of choosing the safe option over the risky option in a given choice problem, the valuations of the options were entered into a logit choice rule (also known as softmax):

$$p(safe, risky) = \frac{1}{1 + e^{-\varphi\left(V_{safe}^{\frac{1}{\alpha}} - V_{risky}^{\frac{1}{\alpha}}\right)}}. \tag{D.5}$$

Accordingly, the more favorable an option's valuation is relative to that of the other option, the higher the probability that the more favorable option is chosen. The parameter φ governs the sensitivity of this mapping of differences in valuations onto choice probabilities, with $\varphi = 0$ implying no sensitivity at all (i.e., random choice) and higher values of φ implying higher sensitivity. As proposed by Stewart et al. (2018), we rescaled the valuations by exponentiating them with $\frac{1}{\alpha}$ to counteract the common parameter interdependency between α and φ (e.g., Krefeld-Schwalb et al., 2022; Scheibehenne & Pachur, 2015). In sum, for the CPT analyses we estimated the parameters α, γ, δ, and φ.

The posterior distributions of the parameters were estimated using the No-U-Turn-Sampler (NUTS) in Stan (Stan Development Team, 2025). Uniform prior distributions were used for all four parameters: $\alpha \sim U(0, 2)$, $\gamma \sim U(0, 10)$, $\delta \sim U(0, 5)$, and $\varphi \sim U(0, 5)$. We ran 6 chains of 12,500 samples each with a warm-up period of 7500 samples, leaving 30,000 samples across chains. All scale reduction factors were $\hat{R} \leq 1.00$, indicating good convergence (Gelman & Rubin, 1992). The minimal effective sample size (ESS) was

[14] Applications of CPT that consider the possibility of an S-shaped probability weighting function often assume that $\gamma \in [0, 2]$ (e.g., Pachur et al., 2018; Zilker et al., 2020); however, some applications also assume a higher upper boundary (e.g., Kellen et al., 2016). Assuming $\gamma \in [0, 10]$ allows the curvature of the function to be equally pronounced for an S-shaped as for an inverse S-shaped curve. Moreover, in exploratory analyses we found that for some sampling strategies, the estimated values of γ were considerably larger than 2; constraining $\gamma \leq 2$ would therefore result in a distortion of the estimates of other parameters and a considerably worse model fit.

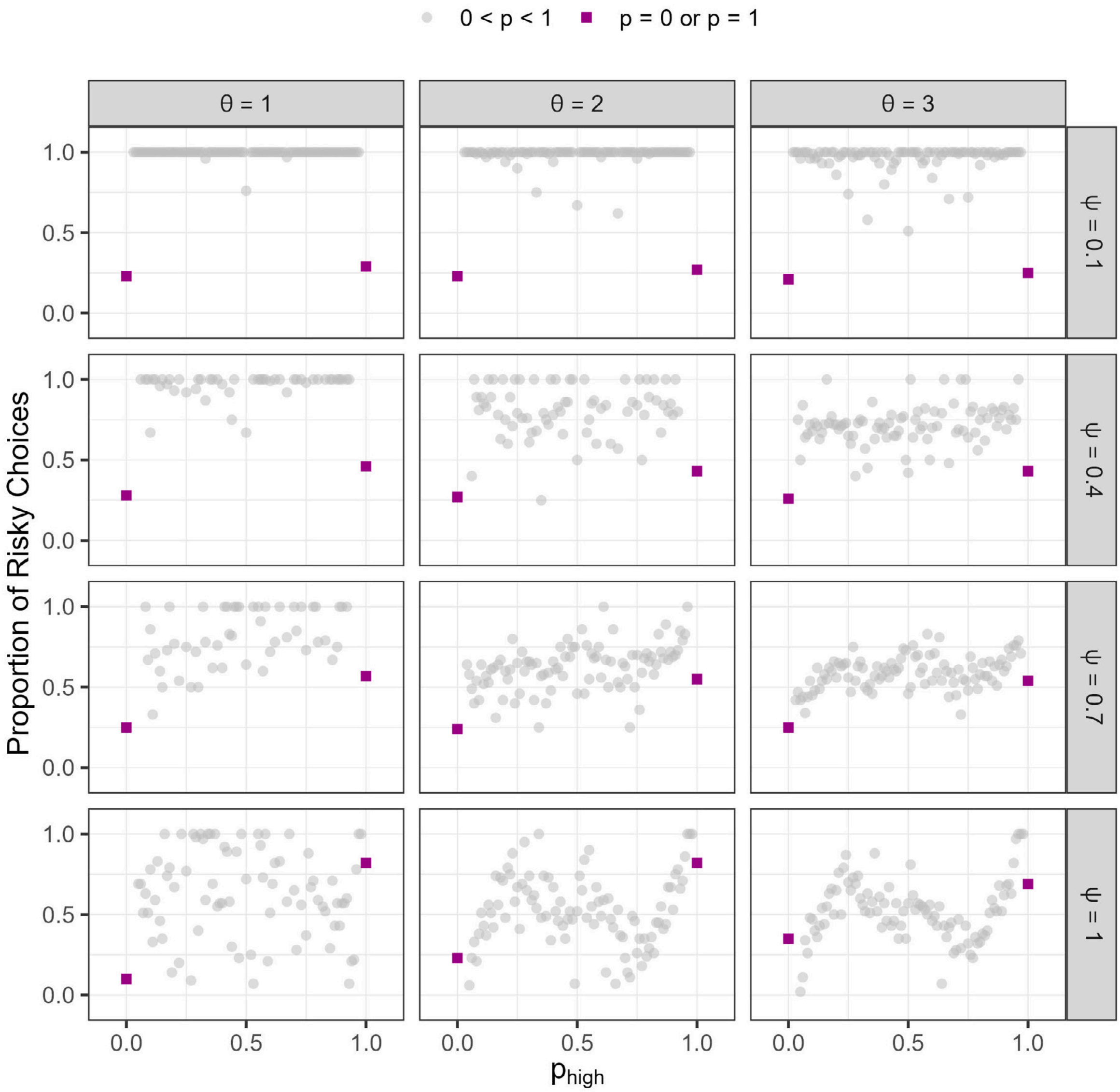

Fig. B.5. Proportion of choices of the risky option as a function of the sampled probability of the higher outcome of the risky option p_{high}.
Note. Each point represents the proportion of choices of the risky option for a given level of p_{high}, separately for strategies with different switch rates ψ and decision thresholds θ. Pink dots indicate trials where only one of the outcomes of the risky option was sampled (i.e., where the sampled probability p_{high} is either 0 or 1). Given a low switch rate and a low decision threshold, these trials often indicate that the safe option was initially sampled and chosen, explaining the low proportion of choices of the risky option. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

7202. All samples, summaries, and convergence statistics of the posterior distributions are provided in the supplementary GitHub repository (https://github.com/linushof/sampling-strategies).

D.2. CPT model performance

To assess how well CPT captures the choices of each sampling strategy, we conducted a posterior predictive check based on the estimated posterior means of the parameters, separately for each model. The results of these analyses are summarized in Figs. D.1 and D.2.

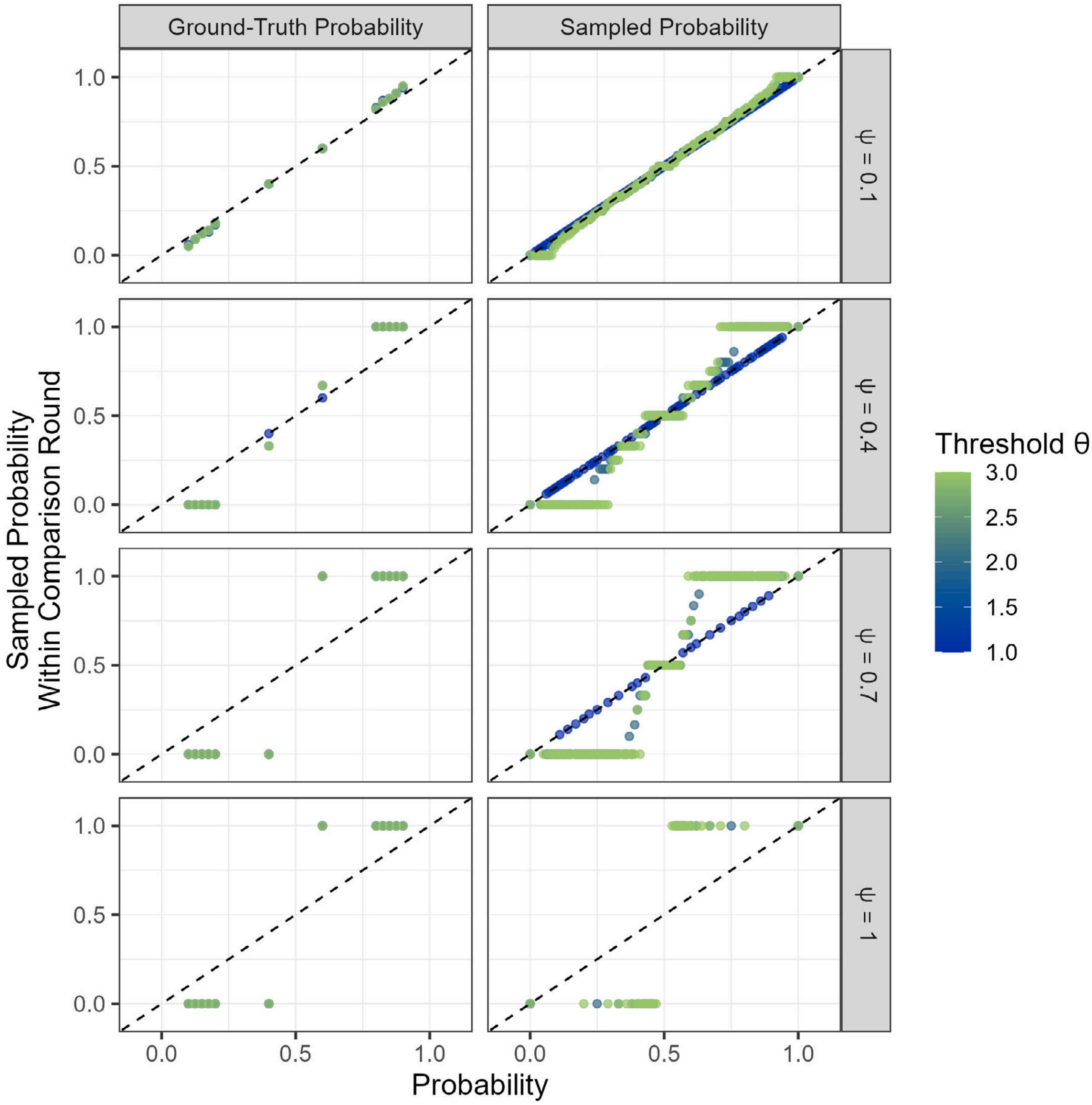

Fig. C.1. Sampled probabilities of risky outcomes in the comparison rounds of sampling strategies with a roundwise comparison rule.
Note. Each point represents the median relative frequency with which the risky option's outcomes were sampled in a comparison round as a function of the outcomes' ground-truth probability (left panel) or the outcome's relative frequency across all comparison rounds of the choice trial (right panel). The dashed diagonal line represents a perfectly linear relationship between the sampled probabilities in comparison rounds and either the ground-truth probabilities or the sampled probabilities across comparison rounds. Points below the diagonal indicate cases where an outcome tended to be undersampled; points above the diagonal indicate cases where an outcome tended to be oversampled.

Appendix E. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cogpsych.2025.101769.

Data availability

The simulations and analyses underlying this article can be reproduced using the materials from the supplementary GitHub repository (Release: v2.1-rev): https://github.com/linushof/sampling-strategies.

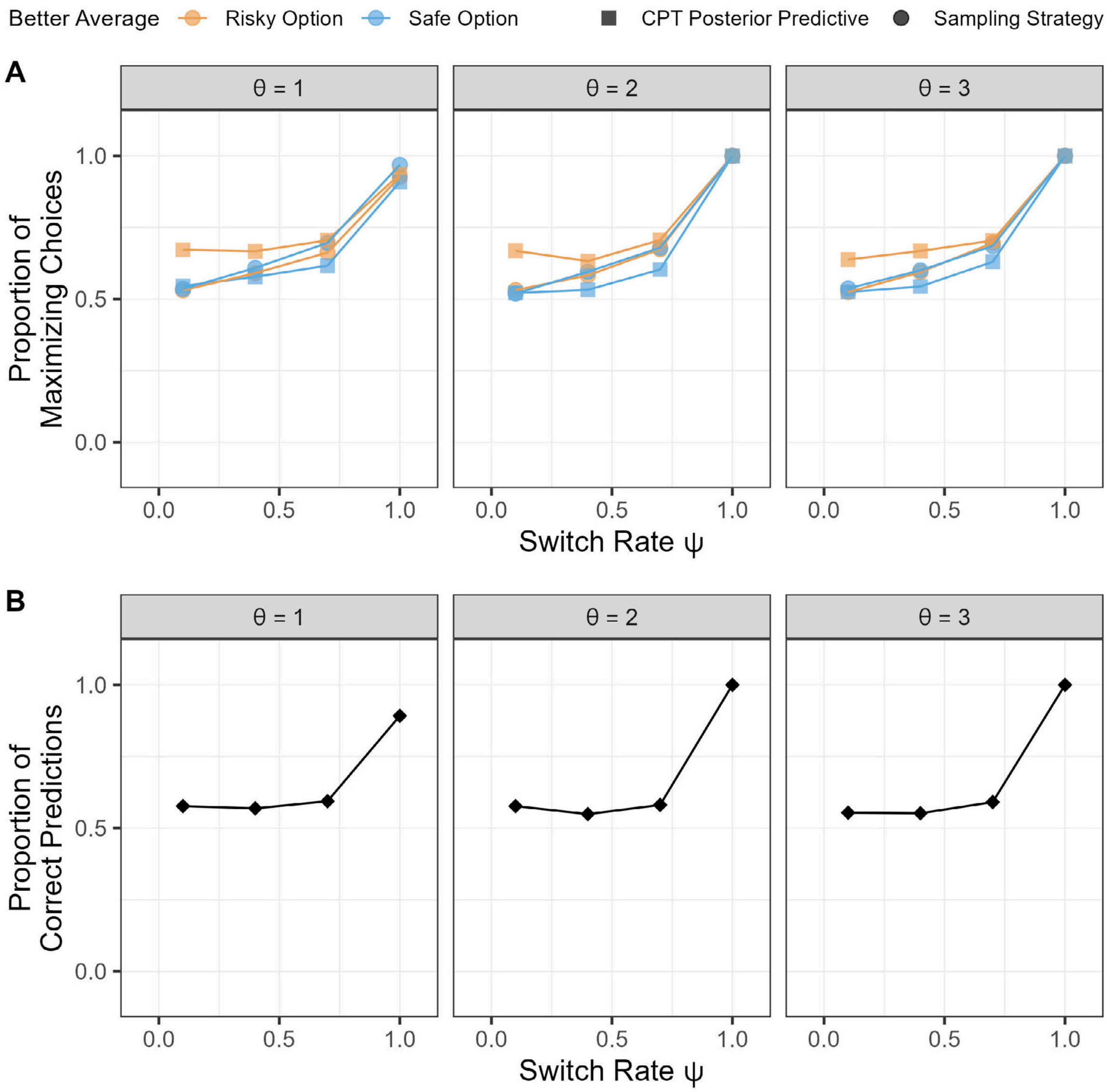

Fig. D.1. CPT posterior predictive accuracy for strategies with a summary comparison rule.
Note. Each point represents a choice proportion produced by a sampling strategy. θ: Decision threshold. (A) Proportion of choices maximizing the sample average. (B) Proportion of trials in which the CPT posterior prediction matched the choice generated by the sampling strategy.

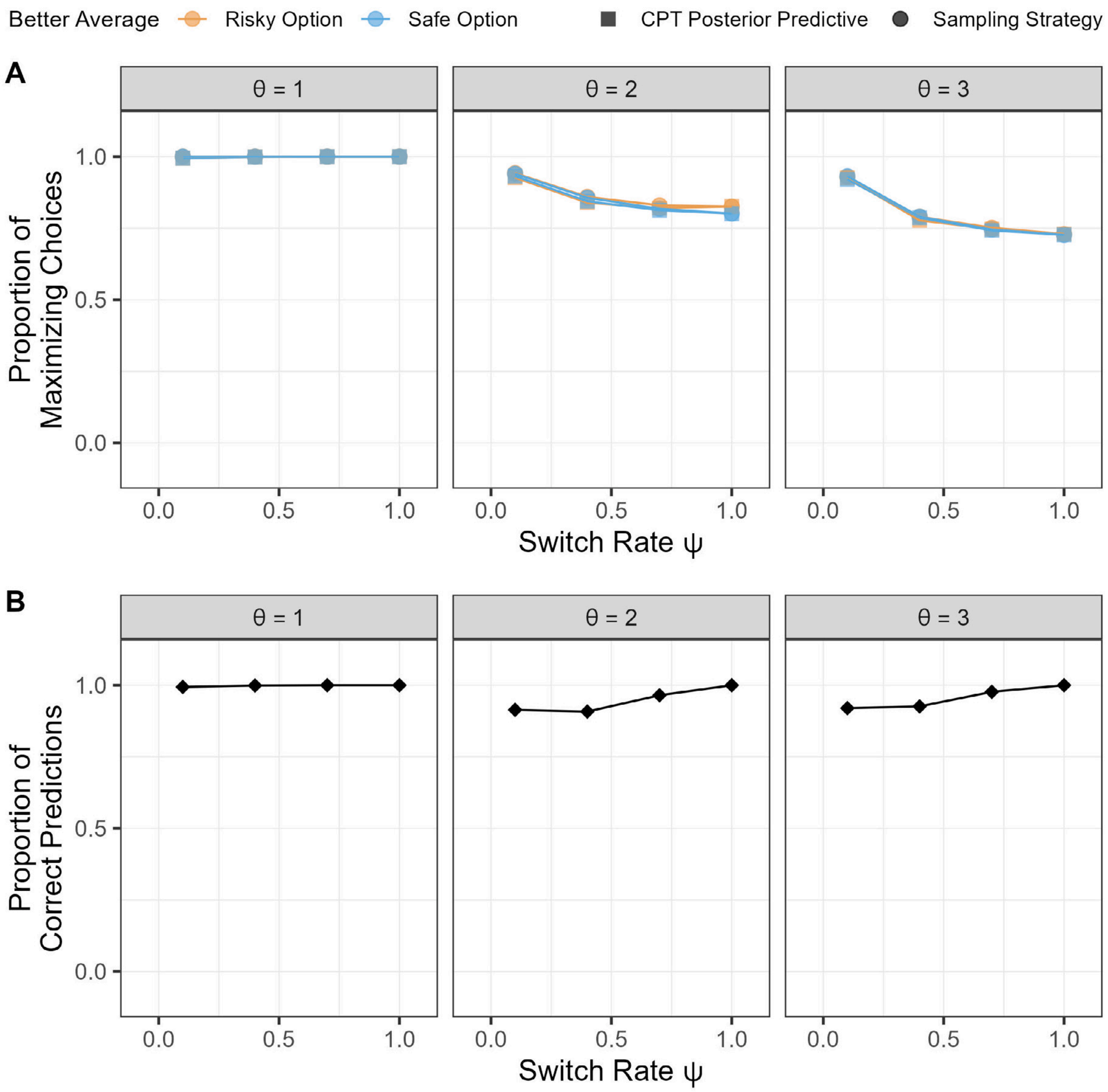

Fig. D.2. CPT posterior predictive accuracy for strategies with a roundwise comparison rule.
Note. Each point represents a choice proportion produced by a sampling strategy. θ: Decision threshold. (A) Proportion of choices maximizing the sample average. (B) Proportion of trials in which the CPT posterior prediction matched the choice generated by the sampling strategy.

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