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Is There a Description–Experience Gap in Choices Between a Described and an Experienced Option?

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Decision makers seem to evaluate risky options differently depending on the learning mode—that is, whether they learn about the options' payoff distributions from a summary description (*decisions from description*) or by drawing samples from them (*decisions from experience*). Are there also discrepancies when people choose between a described and an experienced option? In two experiments, we compared people's behavior in a condition with mixed learning modes (i.e., one option described, the other experienced with the sampling paradigm) to that in conditions where both options were either described or experienced. Using cumulative prospect theory's value and probability weighting functions to characterize how observed outcome and probability information was subjectively distorted in people's choices, we found clear differences between the pure description and pure experience conditions. In the mixed-mode condition, however, the value and probability weighting functions did not differ between the described and the experienced options, suggesting that people evaluated them based on a joint representation despite the different learning modes. Participants' choices were not biased toward the described or the experienced option. Finally, per-option search effort for an experienced option tended to be higher in the mixed-mode condition than in the purely experience-based condition. Our findings demonstrate that how people evaluate described and experienced options depends on the learning mode of the other option in the choice set, highlighting a previously overlooked boundary condition of discrepancies between description- and experience-based choice.

Keywords: risky choice, decisions from experience, description–experience gap, cumulative prospect theory, hierarchical Bayesian modeling

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Traditionally, it has been assumed that choices between risky options are primarily driven by the specific attributes of the options (e.g., size of outcomes and their probabilities) as well as the decision maker's risk propensity (e.g., Bernoulli, 1954; Edwards, 1962; Savage, 1972). Research in the last two decades, however, has highlighted that risky choices are also influenced by the learning mode, that is, the way people learn about the possible outcomes of each option and their probabilities (Hertwig et al., 2004; for a meta-analysis, see Wulff et al., 2018). Outcomes and probabilities can either be described explicitly in summary form (*decisions from*

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The data and analysis scripts for all experiments are available on the Open Science Framework (Tiede et al., 2024a). The materials used in the experiments are provided in the Supplemental Materials. Experiment 2 was preregistered.

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description) or learned from sequential samples from the options (*decisions from experience*). Decisions from experience can differ from decisions from description in systematic ways, a phenomenon that is commonly referred to as the *description–experience gap*. Specifically, the weight that rare events of an option (based on the underlying payoff distribution) seem to receive in decisions from experience differs from that in decisions from description (e.g., Hertwig et al., 2004; Wulff et al., 2018).

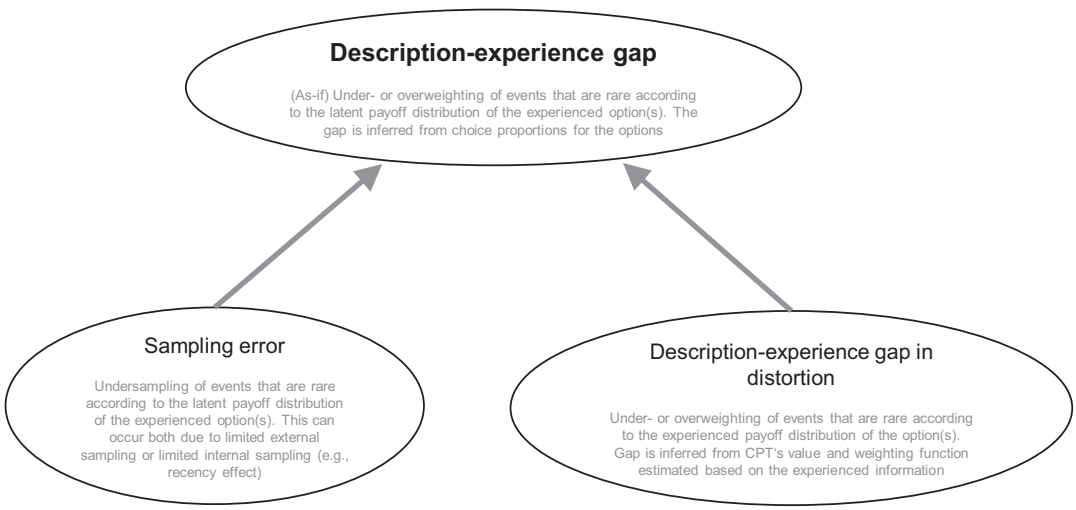
Research on the description–experience gap has investigated decisions from experience with different experimental paradigms (see Hertwig & Erev, 2009). In the *sampling paradigm*, decision makers first learn about the options' payoff distributions by drawing samples from them and make a consequential choice once they have terminated sampling. In the *feedback paradigm*, decision makers learn about the payoff distributions by repeatedly making consequential choices between the options and obtaining feedback on each choice (which means that information search is usually more costly in the feedback paradigm than in the sampling paradigm). Several factors have been identified to contribute to the description–experience gap as investigated with the sampling paradigm (for reviews on the description–experience gap with the feedback paradigm, see Erev & Plonsky, 2023; Erev et al., 2017). One key explanation is that because in the sampling paradigm people usually draw only a relatively small number of samples, sampling error often results in having systematically different information about the options than in description (note that this can also occur from limited internal sampling, e.g., recency; see section "The Description–Experience Gap in Risky Choice" below for details), distorting their choices in systematic ways. Typically, sampling error manifests in rare events being underrepresented in the options' actually experienced payoff distribution, and people choose as if they underweight events that are rare according to the option' objective, underlying payoff distribution.

Another important factor seems to be that decision makers also represent information they have available about the options differently in experience than in description. This is suggested by analyses that used cumulative prospect theory (CPT; Tversky & Kahneman, 1992) to model people's decisions from experience based on the actually experienced information and compared the estimated model parameters to those obtained for decisions from description (Glöckner et al., 2016; Kellen et al., 2016; Wulff et al., 2018). In CPT, choices are modeled based on a value function and a probability weighting function, which indicate how outcome and probability information, respectively, are distorted in people's choices (e.g., R. Gonzalez & Wu, 1999). Analyses of decisions from experience and description with CPT have found discrepancies in the estimated value and probability weighting functions; in the following, we will refer to such discrepancies as the *description–experience gap in distortion*. These discrepancies in distortion include differences in the weighting of rare events (but here referring to events that are rare according to the options' actually experienced payoff distribution). As illustrated in Figure 1 (cf. Haines et al., 2023), both sampling error and a description–experience gap in distortion can independently contribute to the description–experience gap as characterized by the weighting of rare events according to the options' latent payoff distribution.

What drives the description–experience gap in distortion? And does learning about risky options from experience or description necessarily lead to differences in how outcomes and probabilities are subjectively distorted? We address these questions by studying risky choices between options that are presented in either the same or in different learning modes—that is, whether the choice is between two described or two experienced options or between a described and an experienced option (i.e., a *mixed learning mode*). Research has shown that processes of judgment and preference are influenced by the extent to which options can be structurally aligned (Hsee, 1996; Lichtenstein & Slovic, 1971; Tversky et al., 1988; see also Markman & Gentner, 1993). The alignability between options is inevitably limited when options in a choice problem are presented in different learning modes. For instance, options that are both described are easier to align on probability information than a described option

Figure 1

Factors Contributing to the Description–Experience Gap in the Sampling Paradigm



Note. The description–experience gap is characterized based on the weighting of rare events according to the options' latent payoff distribution. CPT = cumulative prospect theory.

and an experienced one. Further, having different representations of the options in a choice problem might hinder the relative evaluation of the outcomes and probabilities. In choices between options with different learning modes, discrepancies between the evaluation of described and experienced options might therefore be smaller than when comparing choices where both options are described with choices where both options are experienced.

To date, research on the description–experience gap has primarily focused on comparing situations in which all options are described with situations in which all options are experienced (e.g., Hertwig et al., 2004; Wulff et al., 2018). It is therefore unclear how discrepancies in the evaluation of a described versus an experienced option depend on whether the options in a choice problem are presented in the same or in different learning modes. If the learning mode of an option affects only its own evaluation, people should evaluate a described and an experienced option differently regardless of the learning mode of the other option in the choice problem. To illustrate, in a choice problem with two options that both offer as best possible outcome \$50 with a probability of 10%, that probability would be distorted differently, and thus the rare event weighted differently for the two options. If, by contrast, the learning mode of an option also affects the evaluation of the alternative option—for instance, because people might strive for a common representation of both options—people might subjectively distort and weight the 10% chance of winning \$50 in similar ways in description and experience.

The goal of this article is to examine these possibilities: Do people's evaluations of options also differ between description and experience when one option is described and the other is experienced? Or are differences in the subjective distortion of outcomes and probabilities between description and experience reduced in such a mixed-mode condition? We also investigate information search in decisions from experience in a mixed-mode condition.

In the following, we first summarize previous findings on the differences between description- and experience-based risky choice and describe in more detail the difference between the description–experience gap in terms of the apparent weighting of rare events according to the options' latent payoff distribution and the description–experience gap in distortion (which is based on the experienced payoff distribution). Subsequently, we outline different scenarios for how people may choose and how outcome and probability information might be distorted in choices between a described and an experienced option. We then report two experiments that compare choice patterns, CPT's value and probability weighting functions, and search behavior in a mixed-mode condition with those in purely description- or experience-based conditions. Our results demonstrate that the evaluation of and search effort for an option indeed depend on whether it is presented in a choice problem that includes options with the same or different learning modes.

The Description–Experience Gap in Risky Choice

Empirical research on decision making under risk often employs paradigms involving options that offer monetary outcomes with some probability. The most frequently used approach is to ask people to choose between two lotteries whose outcomes and probabilities are explicitly described—for example, between a risky option that offers a 10% chance of winning \$10 (otherwise nothing) and a safe option that guarantees \$1. These descriptions resemble those that people encounter in weather forecasts or medication package inserts and usually summarize information and experiences gathered by others to communicate information about future events. In most of everyday life, however, probabilities are rarely explicitly stated: When choosing whether to lend someone money, cross the road at a red light, or eat food past its expiration date, there are no summary statistics available. Instead, the possible outcomes and information about their probabilities have to be gleaned from one's own previous experiences. This notion is reflected in the aforementioned *sampling paradigm* (Hertwig & Erev, 2009; Hertwig et al., 2004), in which the decision maker can learn in an initial exploration phase about the payoff distributions of the available options (i.e., the outcomes and their probabilities) by drawing individual samples. For instance, someone drawing 10 samples from the risky option above might see "0,0,0,0,0,0,0,10,0,0," while 10 samples from the safe option will show "1,1,1,1,1,1,1,1,1,1." In the sampling paradigm, people can usually draw as many samples as they want before making a consequential choice.

In studies comparing decisions from description and decisions from experience, participants are most commonly asked to choose repeatedly between two described options in one condition and two experienced options in another, and choice behavior is then compared between these two conditions. Studies have consistently found differences in choice patterns between conditions (for a meta-analysis on the description–experience gap investigated with the sampling paradigm, see Wulff et al., 2018). In decisions from description, people choose as if they overweight rare events (Tversky & Kahneman, 1992). When choosing between the risky and the safe option described in the example above (a 10% chance of winning \$10, otherwise nothing vs. \$1 for sure), overweighting the rare event (i.e., \$10) would be reflected in choosing the risky option. In decisions from experience, however, people choose as if they underweight rare events according to the latent payoff distribution, choosing the safe over the risky option (Barron & Erev, 2003; Hertwig et al., 2004; Wulff et al., 2018). Research with the sampling paradigm (Hertwig et al., 2004) has identified boundary conditions of the description–experience gap: It seems to be larger in choices between a safe and a risky option (vs. between two risky options) and in choices in which the smallest probability is smaller (vs. larger; Glöckner et al., 2016; Wulff et al., 2018). In addition, the gap is larger in problems in which people draw fewer samples in experience (Glöckner et al., 2016).

One key factor leading to the apparent underweighting of rare events in experience is sampling error, the deviation of the experienced relative frequency of an event from the latent, underlying probability. In the sampling paradigm, people typically draw relatively small samples (Mdn = 10 draws per option; Wulff et al., 2018). When a risky option has two outcomes—as in our and most previous studies—the nature of the binomial distribution means that rare events tend to be underrepresented in experienced payoff distributions when only a small number of samples are drawn; this underrepresentation is stronger the fewer the samples. People making decisions from experience in the sampling paradigm thus often have different information about the options than do people making decisions from description (e.g., they might not have sampled the rare event at all and thus not know about it), and therefore end up choosing differently.

However, sampling error does not seem to be the only reason for the description–experience gap. Several analyses have controlled for sampling error by analyzing only those choices where the options' experienced payoff distributions matched the described ones (Camilleri & Newell, 2011; Wulff et al., 2018) or by incentivizing people to draw a large number of samples (which largely eliminates sampling error; Hau et al., 2008). With these approaches, the description–experience gap is reduced but does not disappear (Wulff et al., 2018). Another way to take sampling error into account when comparing decisions from description and experience is to model choices based on the information about the payoff distributions that people have actually been exposed to—that is, using the experienced outcomes and their relative frequencies—and to compare description-based and experience-based choices on the model's theoretical constructs abstracted from the choices. Several analyses have used CPT (Tversky & Kahneman, 1992) as a computational model for this purpose (e.g., Abdellaoui et al., 2011; Glöckner et al., 2016; Jarvstad et al., 2013; Kellen et al., 2016; Lejarraga et al., 2016; Ungemach et al., 2009). CPT models decisions under risk by using nonlinear functions to transform outcome information into subjective values and probability information into decision weights. These functions are parameterized, and by estimating the parameters from the choices, one can measure how people subjectively distort outcome and probability information (a more detailed and formal description of CPT is provided in the section Computational Modeling below).

Using CPT to compare decisions from description and experience, Kellen et al. (2016) and Glöckner et al. (2016) found that people choose as if they overweight rare events with both learning modes, but this overweighting is stronger in experience than in description. Note that such *over*weighting of experienced rare events can occur simultaneously with an apparent *under*weighting of possible but underexperienced rare events (as reflected in the description–experience gap found by Hertwig et al., 2004; see Table 1 in Kellen et al., 2016; for further discussion, see Pachur & Hertwig, 2019). A more pronounced overweighting in experience than in description could occur because in decisions from experience, people's subjective decision weights are noisier and more uncertain and thus more strongly regressed toward the mean than in decisions from description (Fennell & Baddeley, 2012; Glöckner et al., 2016). Moreover, Glöckner et al. (2016) and Kellen et al. (2016) found a steeper value function (implying greater sensitivity to differences in outcomes) in experience than in description. To differentiate the characterization of the description–experience gap based on the latent payoff distribution from the discrepancies between decisions from description and decisions from experience as measured with CPT (based on the experienced payoff distribution), we will refer to the former as the description–experience gap in distortion. Figure 1 illustrates the relationship between these two types of description–experience gap.

Analyzing discrepancies between decisions from description and experience with CPT can be instrumental in pinpointing possible differences in how outcome and probability information is processed. For instance, an apparently stronger overweighting of rare events in experience can result from reduced attention to probability information (Pachur et al., 2017, 2018), biases in attention allocation across options (Zilker & Pachur, 2022, 2023), memory processes (Hotaling et al., 2022), or asymmetric probability learning (Haines et al., 2023). When comparing description and experience exclusively in terms of whether events that are rare according to the options' latent payoff distribution are over- or underweighted (i.e., the description–experience gap), it is not possible to identify potential distortions in how available information is processed (which might then inspire investigations into the underlying cognitive processes). After all, the discrepancies in choice might to an unknown degree be due to sampling error, and a rare event might be "underweighted" because the decision maker does not know it exists. Analyses with CPT, by contrast, allow one to capture and measure differences in the distortion of described and experienced payoff distributions.

Choice and Search Behavior in Choices Between a Described and an Experienced Option

How might options be processed and evaluated in situations in which the options in a choice problem are presented in different learning modes? For instance, when deciding between different medications, a patient may compare their usual medication, with which they have ample experience, with a new medication that they read about in a leaflet from their doctor. Do people evaluate described and experienced options differently in this choice situation with mixed learning modes? To our knowledge, only one previous study has examined decisions where participants learned about one option through description and another option by drawing outcomes as in the sampling paradigm. In Ert and Trautmann (2014, Study 1), one option was described explicitly (e.g., "You receive 2 shekels with probability 0.2; otherwise nothing"), and participants sampled the outcomes from another option (with the same payoff distribution). It emerged that the higher the probability of winning the money, the more likely participants were to choose the experienced option. This pattern reflected overweighting of rare events in the described option and/or underweighting in the experienced option. However, because the information that participants actually experienced was not taken into account in the analysis, it is not clear whether this description–experience gap was caused by sampling error or by differences in the subjective distortion of outcome and probability information.

Is There a Description–Experience Gap in Choice With Mixed Learning Modes?

Does the description–experience gap as characterized by weighting of rare events according to the latent distribution also hold when people choose between a described and an experienced option—such that a rare event is overweighted in the described option but underweighted in the experienced option? Consider again the choice between the risky option "10% chance of winning $10, otherwise $0" and the safe option "$1 for sure." If the risky option is experienced and the safe option is described, a description–experience gap would be reflected in a predominant preference for the safe option, due to an underweighting of the rare event. If the risky option is described and the safe option is experienced, a description–experience gap would be reflected in a predominant preference for the risky option, due to an overweighting of the rare event. A description–experience gap would thus be indicated by differences in choice proportions between trials in which the option that has a rare event is described compared to when it is experienced.

Is There a Description–Experience Gap in Distortion With Mixed Learning Modes?

Is there also a description–experience gap in distortion based on the experienced payoff distribution when people choose between an experienced and a described option?[1] Many theories and models of description- and experienced-based choice assume that people evaluate options independently from each other and subsequently choose the option with the superior subjective value (e.g., Birnbaum & Chavez, 1997; C. Gonzalez & Dutt, 2011; Hertwig & Pleskac, 2010; Tversky & Kahneman, 1992). In the mixed-mode condition, if people evaluate the described option and the experienced option independently of each other, the value and probability weighting functions for them should resemble those in the description and experience conditions, respectively. Thus, in a *separate-representations* scenario, people may show lower sensitivity to differences in probability and higher sensitivity to outcomes in the experienced than in the described option (Glöckner et al., 2016; Kellen et al., 2016).

Alternatively, people may evaluate the attribute values of an option relative to the values of the other option (rather than independently). Several theories and models of decision making assume relative evaluation, such as decision-by-sampling (Stewart et al., 2006), decision field theory (Busemeyer & Townsend, 1993), and the mixture-of-theories model (Peterson et al., 2021), and it also underlies the notion that preferences are constructed (Lichtenstein & Slovic, 2006; Payne et al., 1999). If people evaluate the attributes of an option relative to the values of other available options, different representations of the options would make a comparison difficult. To avoid a mismatch and make the options more comparable, people may align the representations across the two learning modes, thus distorting the outcome and probability information of the described and the experienced options in a similar fashion. If so, in turn, such a joint representation could take different forms.

In a *joint-as-description* scenario, the subjective distortions of probabilities and outcomes would resemble those observed in purely description-based choices. Consistent with that possibility, a study by Fox et al. (2013) showed that experience-based choices resembled description-based ones when participants were prompted to "repack" the sampled outcomes: They were asked to draw colored cards but were only told the assignment of colors to outcome values after completing the sampling process. Participants therefore had to recall the probabilities of the cards in order to evaluate the options and make their choices. In this condition, the level of risk seeking was similar to that observed in description-based choices, but differed from that observed in experience-based choices as well as a fourth condition in which the color assignment was presented before sampling.

In a *joint-as-experience* scenario, the subjective distortions of probabilities and outcomes would resemble those observed in purely experience-based choices. Different models of decision making assume that people take mental samples from a payoff distribution (Busemeyer & Townsend, 1993; Stewart et al., 2006); taking samples from the described option and comparing it with drawn outcomes may therefore be one way people deal with mixed-mode choices. The joint-as-experience scenario is supported by research showing that when both types of information are provided for all options, people tend to primarily rely on the experienced information (Lejarraga & Gonzalez, 2011; Weiss-Cohen et al., 2016, 2018, 2021).

In a *joint-compromise scenario*, each option's subjective representation is affected by the other option's learning mode in a reciprocal fashion, leading to a convergence on a common representation for the described and experienced options. The subjective distortions of outcomes and probabilities would reflect a compromise between those observed in purely description- or experience-based choices. This possibility is suggested by recent findings by Peterson et al. (2021), where the best-performing model was the one in which the subjective distortion of outcome and probabilities in one option was driven by the outcomes and probabilities of the other option and vice versa. Potentially, such context sensitivity also extends to other properties of the options, such as their learning mode.

Finally, depending on the role of the ease with which the two options can be compared or aligned, a *joint-shifted* scenario is also possible. People give more weight to attributes whose values can be evaluated more easily (Hsee, 1996; Hsee et al., 1999); arguably, it is easier to evaluate an attribute value that can be compared with another value that is presented in the same learning mode. In the mixed-mode condition, the format of probability information differs between the described and the experienced options, which might lead to probability information being given less weight in people's choices than in pure description or experience. As a consequence, probability sensitivity could be lower than in problems where both options are presented in the same learning mode.[2]

Do Differences in Learning Mode Bias Choice?

Choices in a mixed-mode condition may be influenced not only by differences in how outcome and probability information is distorted, but also by differences in the certainty of the available information. In description, probabilities are provided as explicit information and are thus in principle error-free (except for potential ambiguity when the provided described information is not fully trusted). In experience, in contrast, probabilities can only be estimated from the sampled outcomes; the information is thus inherently more ambiguous. Given the evidence for ambiguity aversion (Ellsberg, 1961; Trautmann & van de Kuilen, 2015), people may display a systematic preference for a described option over a more ambiguous experienced option. Furthermore, Lejarraga

[1] Although several cognitive models have been proposed to account for experience-based choice and for discrepancies between experience-based and description-based choice (e.g., C. Gonzalez & Dutt, 2011; Haines et al., 2023; Hotaling et al., 2022; Spektor et al., 2019), here we do not commit to a specific cognitive model to derive possible scenarios for the mixed-mode condition. The reason is that none of the existing cognitive models can accommodate all of the possible scenarios that are conceivable based on previous empirical and theoretical work. Instead, for comparability with previous computational analyses and comparisons of experience-based and description-based choice (Glöckner et al., 2016; Kellen et al., 2016), we formulate the predictions using CPT's elements of a probability weighting function and a value function (and the common interpretations of the respective parameters)—but acknowledge that CPT does not constitute a cognitive theory.

[2] We also considered the possibility of an experience-neglect scenario, where people make choices based solely on the valence of the described option's expected value. This scenario seems conceivable in light of findings by Garcia et al. (2023), who investigated choices between a described option and an option that participants learned about through feedback prior to seeing the described option. Because the conceptualization of experience in this work differed from ours and because we did not find any evidence for this scenario, we do not consider it further.

(2010) found that when given the opportunity to choose whether to make decisions on the basis of description or experience, people preferred description.

However, it is also possible that people show a general preference for an experienced option, given that they have to actively sample from it and thus may pay more attention to it. Because people tend to choose the option they spent more time looking at (Bhatnagar & Orquin, 2022; Krajbich et al., 2010; Krajbich & Rangel, 2011; Zilker & Pachur, 2022), this could lead to a bias toward choosing the experienced option (but see Ert & Trautmann, 2014, who found no evidence that a particular learning mode was preferred).

How Extensively Do People Sample With Mixed Learning Modes?

Another behavioral dimension to examine in a mixed-mode condition is people's sampling effort for the experienced option. In decisions from description, both options' possible outcomes and their probabilities are precisely characterized. In decisions from experience, by contrast, knowledge of outcomes and probabilities is uncertain, but the uncertainty can be reduced by drawing samples from the options. Is people's search effort for an experienced option affected by properties of the option with which it is paired in a choice problem? If the amount of information people search about an experienced option depends only on the properties of the option itself (e.g., its variance; Pachur & Scheibehenne, 2012), then search effort per option should not differ between the mixed-mode and the experience condition.

However, if search, like choice, is influenced by comparative processes, search in an experienced option might depend on whether it is paired with a described or an experienced option. For one, if people have a preference for an option in a particular learning mode (Lejarraga, 2010; Trautmann & van de Kuilen, 2015), they may draw fewer samples from an experienced option in the mixed-mode than in the experience condition. Alternatively, if people try to compare the described and experienced option based on a joint representation, they might aim to align the options (Markman & Gentner, 1993) and try to match the level of certainty about the payoff distributions across both options. This could lead to greater sampling efforts, relative to a situation with two experienced options. The same could result because in a mixed-mode condition, all sampling efforts can be invested into one option (and do not have to be distributed across two options). We test the hypothesis that the number of samples drawn per option is larger in the mixed-mode than in the experience condition.

As an additional and exploratory research question, we examine how the influence of properties of the options in a choice problem on search effort is affected by whether the options are in the same or in different learning modes. Research on experience-based choices has shown that people sample more when the variance of the options is larger and when the differences in expected value (EV) between the options are smaller (Lejarraga et al., 2012; Mehlhorn et al., 2014; Pachur & Scheibehenne, 2012; Wulff et al., 2018). It is currently unclear, however, to what extent this holds in a mixed-mode condition.

The Current Research

In two experiments, we investigated the scenarios and hypotheses described in the previous section in order to address three main questions. First, is there a description–experience gap in choice patterns (based on the latent payoff distribution) and a description–experience gap in distortion (based on the experienced payoff distribution) in a mixed-mode condition? If not, how do choice behavior and the subjective distortion of outcome and probability information in this condition relate to that in a purely description or experience condition? Second, do people have a preference for options presented in one of the learning modes? Third, how much search effort do people invest in the mixed-mode condition relative to a purely experience-based condition?

Experiment 1 was a lab experiment with undergraduate students. Experiment 2 was a preregistered replication of Experiment 1 with a more diverse online participant sample. Prior to these experiments, we had conducted an initial experiment to test whether choices in the mixed-mode condition depended on whether the described option was on the left or right side (it did not). Because the set of choice problems was considerably smaller and not well suited for CPT parameter estimation, we report the methods and results of this initial experiment in the Supplemental Section S1. While the results on the description–experience gap, choice bias, and search in the mixed-mode condition were very similar to those found in the two main experiments, we discuss differences between the initial experiment and main experiments in the General Discussion.

Experiment 1

Method

Participants

Participants were students (mostly undergraduates) from the University of Konstanz, Germany, who participated in return for either €10 (equivalent to about $11.14 at the time of the experiment) or course credit. In addition, all participants received a performance-contingent bonus of, on average, €1.12 ($SD = 0.53$; see section Procedure below for details). Data were collected from 229 participants. We excluded six participants who did not choose the dominant option in at least three out of four attention check trials (i.e., failed to choose the dominant option more than once) and four participants who did not sample any outcomes in at least a quarter of the trials, because we considered these criteria to indicate low engagement in the task.[3] The final sample ($N = 219$) comprised 167 women, 49 men, and three people who identified as nonbinary, with a mean age of $M = 22.8$ years ($SD = 4.1$; range: 18–45).

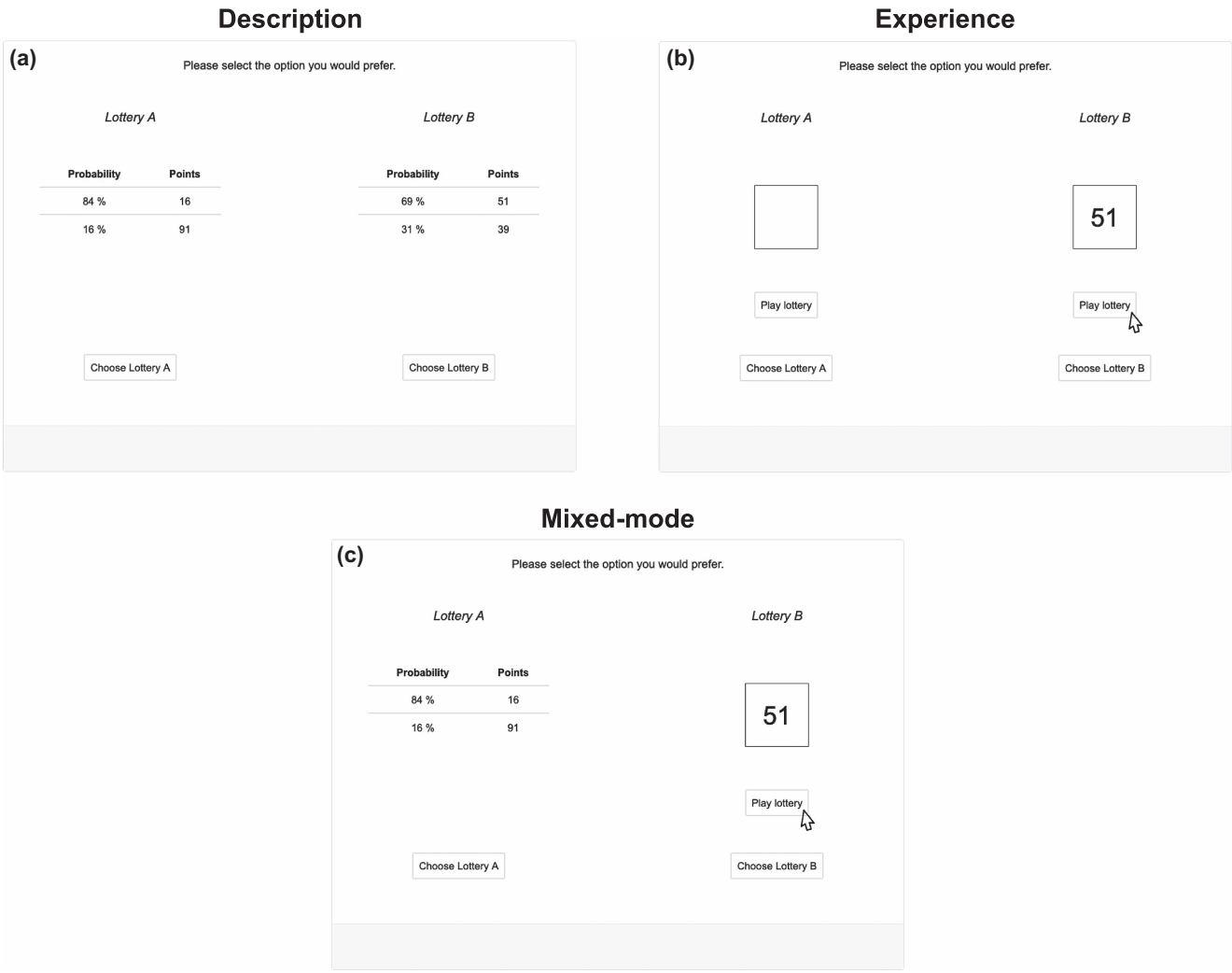
Design

The main task was a choice task in which participants made 112 choices between two monetary lotteries, each of which had either one or two outcomes. The experiment's three between-subjects conditions (see Figure 2 for screenshots) differed in the learning mode—that is, in how participants learned about the payoff distributions of the two options in each choice problem. In the *description condition*, outcomes and their probabilities (as

[3] To test whether our results were robust to different exclusion criteria, we also performed all analyses and modeling procedures with all participants and including the attention-check choice problems. The key conclusions were largely the same compared to when using the specified exclusion criterion (the results are presented in the Supplemental Section S2).

Figure 2

Screenshots of Trials in the (Panel a) Description, (Panel b) Experience, and (Panel c) Mixed-Mode Condition (Translated From the Original German)



percentages) were presented in summary format. In the *experience condition*, participants could draw samples from the options' payoff distributions by pressing a "play lottery" button. Each time the button was pressed, one outcome of the distribution was drawn randomly (based on its probability). The drawn outcome was presented until the next sample was drawn (i.e., until the "play lottery" button was pressed again); participants were free to sample as quickly and as many outcomes as they wanted from each option before making a final choice by pressing the associated "choose lottery" button. In the *mixed-mode condition*, one option (chosen randomly) was presented as in the description condition and the other as in the experience condition. In this condition, the side (left vs. right) of the described option was randomized across participants but kept constant across the experiment. The left/right ordering of the options and, in the description condition, the order in which an option's outcomes were displayed was randomized on the trial level for all participants and conditions.

Materials

We used choice problems that had been shown to allow for accurate estimation of CPT parameters in previous studies (e.g., Glöckner & Pachur, 2012; Kellen et al., 2016; see Broomell & Bhatia, 2014): These included 81 randomly generated choice problems covering the gain, loss, and mixed domains (Rieskamp, 2008), as well as six problems constructed to measure risk aversion (Holt & Laury, 2002), and 10 problems constructed to measure loss aversion (Gächter et al., 2007). Further, we included the six choice problems used in the original study on the description–experience gap (Hertwig et al., 2004), as well as the five choice problems between two identical options used by Ert and Trautmann (2014). Finally, four choice problems with one stochastically dominant option were included as attention checks, for a total of 112 problems. All choice options had one or two possible outcomes, which ranged from −100 to 100 (some problems were scaled to this range). A table

listing all choice problems used in this experiment can be found in the Supplemental Section S3.

Procedure

After providing informed consent, participants were randomly assigned to one of the three conditions. They were informed that at the end of the experiment, one of the choice problems would be randomly chosen and the chosen option played out to determine their bonus, with the points earned being converted to cents and added to a starting amount of €1 (in the choice task, no feedback was given on the individual trials). Following instructions and a questionnaire measuring subjective numeracy (i.e., preference for numbers and numeric confidence; see Appendix A and Supplemental Section S4, for details), participants completed two practice trials and the main task. They then completed an unrelated task not reported here that took, on average, 4.3 min (SD = 1.6). Finally, participants answered a questionnaire measuring objective numeracy (i.e., the ability to use probabilistic and mathematical concepts; see Appendix A and Supplemental Section S4, for details), were informed about their bonus, and were debriefed.

Computational Modeling

To measure participants' subjective distortion of outcome and probability information, we modeled their responses in the choice using CPT (Tversky & Kahneman, 1992). In CPT it is assumed that decision makers choose as if they nonlinearly transform outcomes and probability information into subjective values and decision weights, respectively, which determine the subjective valuation, V, of each option. For an option with outcomes $x_1 \leq \ldots \leq x_k \leq 0 \leq x_{k+1} \leq \ldots \leq x_n$ and corresponding probabilities $p_1 \ldots p_n$, the subjective valuation V is defined as:

$$V = \sum_{i=1}^{k} \pi_i^- v(x_i) + \sum_{j=k+1}^{n} \pi_j^+ v(x_j), \tag{1}$$

with v as a value function satisfying $v(0) = 0$ and π^+ and π^- as decision weights for gains and losses, respectively. In other words, V is the sum of all subjective values v assigned to each outcome weighted by the respective decision weights.

The value function describes the nonlinear transformation of an outcome into a subjective value and is defined as:

$$\begin{aligned} v(x) &= x^{\alpha} && \text{if } x \geq 0 \\ v(x) &= -\lambda(-x)^{\alpha} && \text{if } x < 0, \end{aligned} \tag{2}$$

where the parameter α governs the curvature of the value function and reflects the sensitivity to differences in outcomes (with smaller values indicating lower sensitivity).[4] If $\alpha < 1$, the value function has a concave curvature for gains and a convex curvature for losses (and vice versa if $\alpha > 1$). The parameter λ indicates how much higher the subjective weight of a loss is relative to the weight of a gain of the same magnitude. When $\lambda > 1$, the value function is steeper for losses than for gains, indicating loss aversion.

Furthermore, CPT assumes that the transformation of probability information into subjective decision weights depends on the rank of the outcome with which the probability is associated. The resulting decision weights are defined as:

$$\begin{aligned} \pi_1^- &= w^-(p_1) \\ \pi_n^+ &= w^+(p_n) \\ \pi_i^- &= w^-(p_1 + \ldots + p_i) - w^-(p_1 + \ldots + p_{i-1}) \text{ for } 1 < i \leq k \\ \pi_j^+ &= w^+(p_j + \ldots + p_n) - w^+(p_{j+1} + \ldots + p_n) \text{ for } k < j < n, \end{aligned} \tag{3}$$

with w^+ and w^- being the probability weighting functions for gains and losses, respectively. In other words, the decision weight π^+ (π^-) given to a positive (negative) outcome is the difference between the weight—as defined by the probability weighting functions—based on the probability of receiving an outcome as good (bad) as or better (worse) than x and the weight based on the probability of receiving an outcome better (worse) than x.

The probability weighting function w describes the transformation of probabilities:

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}. \tag{4}$$

The parameter γ governs the probability weighting function's curvature and indicates the sensitivity to probability differences (with smaller values indicating lower sensitivity). Values of $\gamma < 1$ lead to an inverse S-shaped probability weighting function and reflect overweighting of small probabilities and underweighting of moderate-to-large probabilities. The smaller $\gamma < 1$, the stronger the curvature of the function and the more overweighted small probabilities become. Values of $\gamma > 1$ reflect underweighting of small probabilities.

To derive a predicted choice probability based on the valuations determined by CPT, we used the probabilistic choice rule softmax (see Stott, 2006), which defines the probability of the option with the higher valuation V (i.e., Option A) being chosen as:

$$p(\text{A}, \text{B}) = \frac{e^{\varphi V(\text{A})}}{e^{\varphi V(\text{A})} + e^{\varphi V(\text{B})}}, \tag{5}$$

where V(A) and V(B) are the subjective valuations of Options A and B, respectively. The parameter $\phi > 0$ reflects the sensitivity to differences in valuations. When $\phi = 0$, choices are random. With higher values of ϕ, the probability of choosing the option with the higher valuation approaches 1, making choices more deterministic.

Note that CPT is not assumed to model the cognitive process generating people's choices itself. Therefore, in line with other applications of CPT (Pachur et al., 2017, 2018; Suter et al., 2016; Zilker et al., 2020; Zilker & Pachur, 2022), we employ it as a measurement model to characterize people's choices (e.g., in terms of probability sensitivity and outcome sensitivity), not as a model of the generating process.

We used two variants of CPT in order to test whether subjective distortions of outcomes and probabilities differed within a choice problem in the mixed-mode condition and if not, to compare the joint subjective distortion to that in the purely description- or experience-based condition. In the *separate-representations CPT model*, separate parameter sets were estimated for the described

[4] Note that whereas separate outcome sensitivity and probability sensitivity parameters have often been estimated for gains and losses in applications of CPT (e.g., Tversky & Kahneman, 1992), subsequent research has shown that this approach can lead to distortions in parameter estimation (Nilsson et al., 2011, 2020). We therefore estimated a common α and γ for gains and losses.

option (i.e., α_d, λ_d, and γ_d) and the experienced option (i.e., α_e, λ_e, and γ_e) in the mixed-mode conditions. We tested whether the separate-representations CPT model could reliably capture differences in CPT parameters between options within a choice problem using parameter and model recovery analyses (reported in detail in the Supplemental Section S4). The results of these analyses showed that the separate-representations CPT model is able to successfully recover such differences. In the *joint-representation CPT model*, parameter values are constrained to be the same for both options in a choice problem.

To test the extent to which in the mixed-mode condition participants had a general preference for an option depending on its learning mode, we also tested a variant of the choice rule in Equation 5 that includes an additive choice-bias parameter (e.g., Walasek & Stewart, 2015):

$$p(\mathrm{D},\ \mathrm{E}) = \frac{e^{\varphi V(\mathrm{D})+\beta}}{e^{\varphi V(\mathrm{D})+\beta} + e^{\varphi V(\mathrm{E})}}, \tag{6}$$

where β is a bias parameter; it captures a tendency to choose the described option (D) over the experienced option (E) irrespective of the subjective valuation of the options. Values of $\beta > 0$ indicate a bias toward the described option; values of $\beta < 0$ indicate a bias toward the experienced option. When $\beta = 0$, there is no bias. In our analyses, we first used this choice rule to test whether in the mixed-mode condition there was a bias toward either the described or the experienced option. If this was not the case (i.e., β did not differ from 0), we implemented the standard choice rule (Equation 5).

We used a hierarchical Bayesian approach (Nilsson et al., 2011; Scheibehenne & Pachur, 2015) to estimate the CPT parameters. In Bayesian parameter estimation, parameters are initially represented in terms of prior distributions that are then updated to posterior distributions based on the observed data (for an introduction, see Lee & Wagenmakers, 2013). In the hierarchical approach, the individual parameters are assumed to be drawn from a group-level distribution that is simultaneously estimated. Hierarchical Bayesian modeling has been shown to yield more reliable and accurate estimates compared to modeling individual data (Kruschke & Vanpaemel, 2015; Nilsson et al., 2011; Scheibehenne & Pachur, 2015).

Both the individual-level and the group-level parameters were assumed to be normally distributed; they were then inverse probit-transformed (yielding uniform priors across the parameter range) and mapped on the respective parameter range (see Rouder & Lu, 2005; Scheibehenne & Pachur, 2015); the ranges were 0–2 for the parameters α and γ and 0–5 for the parameters λ and ϕ. Two parameter values are considered credibly different if the 95% highest density interval (HDI) of the differences between distributions does not include 0. As a measure of model performance, we report the deviance information criterion (DIC), which takes into account model complexity; lower values reflect better model performance. A difference in DIC of more than 10 is considered to indicate that one model performs reliably better than the other (Spiegelhalter et al., 2002).

We estimated the individual-level and group-level posterior distributions for all CPT parameters using JAGS 4.3.0 and the R package R2jags (Su & Yajima, 2020). We ran three chains, each with 310,000 samples and with a burn-in period of 10,000 samples. To reduce autocorrelations, the chains were thinned such that only every 50th sample was recorded, resulting in 6,000 recorded samples per chain. We assessed chain convergence using the potential scale reduction factor $\hat{R}$ (Gelman & Rubin, 1992). For most estimated parameters, $\hat{R}$ was smaller than 1.01 (for all, $\hat{R} < 1.068$), indicating overall good convergence (Brooks & Gelman, 1998).

Availability of Data, Analysis Scripts, and Materials

The data and analysis scripts for the initial experiment and Experiments 1 and 2 are available on the Open Science Framework (Tiede et al., 2024a). The materials used in the studies are provided in the Supplemental Materials. Experiment 1 was not preregistered, but Experiment 2 was (Tiede et al., 2024b).

Results

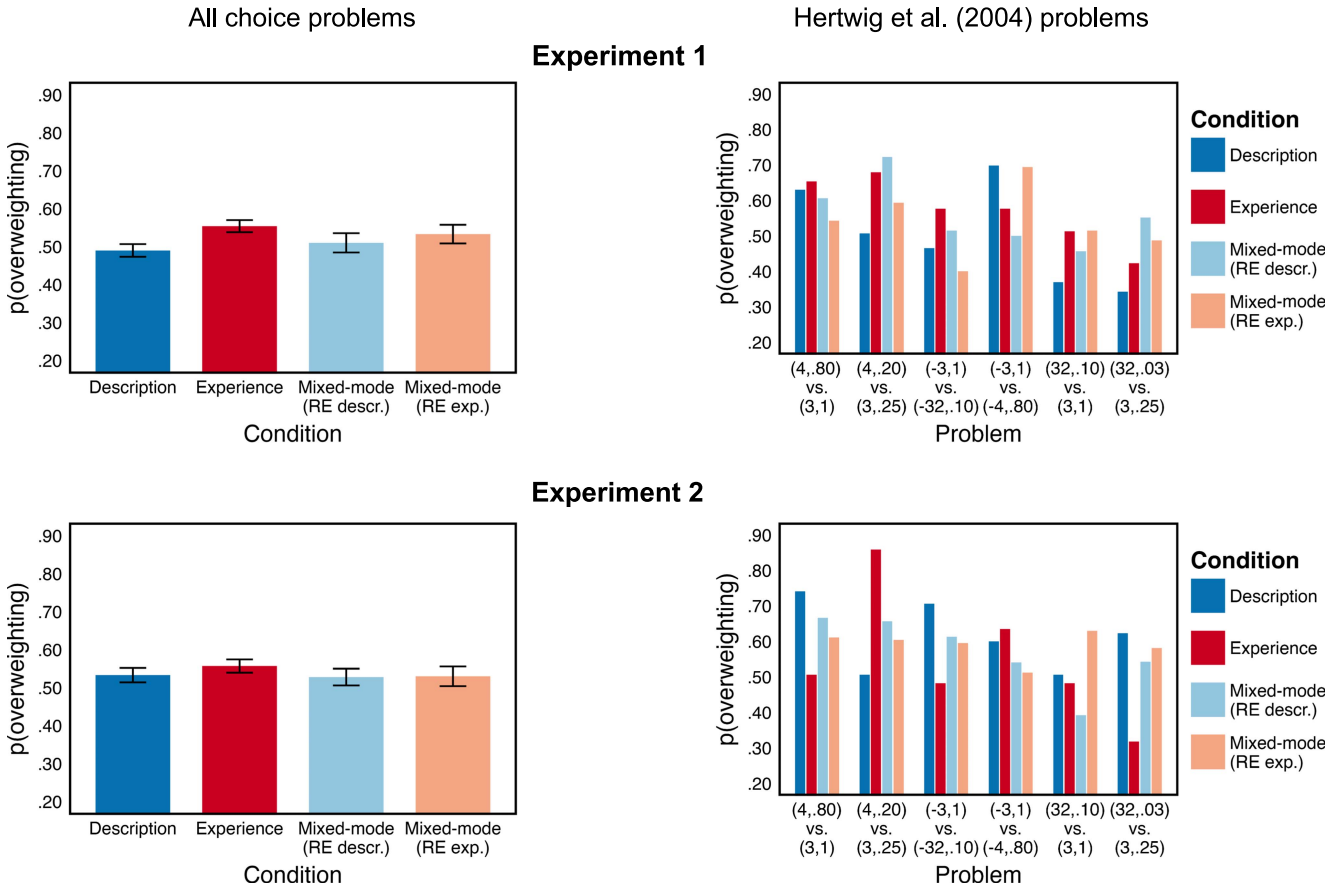
The analysis included data on 108 choice problems (i.e., excluding the four attention-check problems). Analysis and modeling for Experiment 1 was the same as for Experiment 2, which was a preregistered experiment. For all analyses of Experiment 1 that differ from the preregistration of Experiment 2, we additionally report the results of the preregistered analyses for Experiment 1 in the Supplemental Section S5. Moreover, we present results on numeracy and maximization of EV/sampled mean in Appendix A and Supplemental Section S4.

Description–Experience Gap

Description and Experience Conditions. To examine the description–experience gap as characterized by the weighting of rare events according to the latent payoff distribution, we tested whether the degree to which participants behaved as if they over- or underweighted rare events—with rarity defined based on the options' latent, ground-truth payoff distribution (i.e., not taking sampling error into account)—differed between the pure description and the pure experience conditions. Following previous research (Glöckner et al., 2016; Wulff et al., 2018), we considered a choice as reflecting overweighting of rare events if (a) the rarest event of the choice problem represented the most attractive outcome within that option and the option with the rarest event was chosen or (b) the rarest event represented the least attractive outcome within that option and the option without the rarest event was chosen. Note that we operationalize overweighting by focusing on the rarest event (as in Wulff et al., 2018), rather than only focusing on "rare" events, defined as events with $p \leq .20$ (Hertwig et al., 2004; in our experiments, 32% of choice problems did not include a "rare" event with $p \leq .20$). The resulting proportion of choices consistent with overweighting are shown in Figure 3; the figure shows the results across all choice problems and, to facilitate comparison with previous findings, separately for the six choice problems that Hertwig et al. (2004) employed in their seminal investigation. To compare whether overweighting differed between description and experience, we ran a multilevel logistic regression with random intercepts for participants. The dependent variable was whether the choice was in line with overweighting of rare events and the independent variable was condition (dummy-coded as 0 = *description*, 1 = *experience*). The results showed that overweighting was more pronounced in experience ($M = 0.55$, $SD = 0.07$) than in description ($M = 0.49$, $SD = 0.07$; $b = 0.26$, $SE = 0.05$, $p < .001$). As illustrated in Figure 3, this was also the case descriptively for five of the six choice problems

Figure 3

Proportions of Choices in Line With Overweighting of Rare Events



Note. Left panel: All choice problems. Right panel: Subset of choice problems studied by Hertwig et al. (2004). Error bars represent 95% confidence intervals. RE = rare event. See the online article for the color version of this figure.

studied by Hertwig et al. (2004). This differs from the conclusions of several other studies on the description–experience gap, which found less overweighting in experience than in description (e.g., Hertwig et al., 2004; Wulff et al., 2018). Additional analyses, which we describe in more detail in the General Discussion, showed that this discrepancy is due to the fact that our participants sampled more extensively than those in the previous studies and that our set of choice problems consisted primarily of two risky options (rather than a safe and a risky option; for details, see Supplemental Section S6).

Mixed-Mode Condition. Next, we tested whether there was a description–experience gap in the mixed-mode condition, where participants chose between a described and an experienced option. Specifically, we examined to what extent choice behavior consistent with overweighting of the rarest event differed between trials in which the rarest event was part of the described option versus the experienced option. We tested this with a multilevel logistic regression with random intercepts for participants; the latent, underlying payoff distribution was used to define which outcome constituted the rarest event. The dependent variable was whether the choice was in line with overweighting the rare events and the independent variable was the learning mode of the option with the rarest event (dummy-coded as 0 = *rarest event experienced*, 1 = *described*). The choice proportions are shown in Figure 3. Overweighting did not differ between trials in which the option with the rarest event was described ($M = 0.51$, $SD = 0.11$) versus experienced ($M = 0.53$, $SD = 0.10$; $b = -0.10$, $SE = 0.05$, $p = .065$). The overall level of overweighting in the mixed-mode condition ($M = 0.52$, $SD = 0.08$) was higher than in the description condition ($b = 0.16$, $SE = 0.06$, $p = .015$) and lower than in the experience condition ($b = -0.17$, $SE = 0.05$, $p = .007$).

Is There a Description–Experience Gap in Distortion?

Next, we report the estimated value function and probability weighting function when participants' choices in the different conditions were modeled with CPT, using for the experienced option the actually experienced payoff distributions (thus taking sampling error into account). Because the experienced payoff distribution could not be determined for trials in which no samples were drawn from at least one option, these trials were excluded for CPT parameter estimation (0.7% of trials). For the CPT parameter estimates, we report means of the group posterior distribution and

the respective 95% HDI. The 95% HDI contains 95% of the distribution such that parameter values outside the interval have lower probability than parameter values inside the interval. Posterior predictive checks showed that the estimated CPT model matched, on average, 73.2% of participants' choices. The results concerning the shapes of CPT's value function and probability weighting function were qualitatively the same when we used Prelec's (1998) one-parameter variant of the probability weighting function (for details, see Supplemental Section S7).

Description and Experience Conditions. First, we compare the value function and probability weighting function obtained in the description and the experience conditions. The parameter estimates are reported in Table 1; the resulting value function and probability weighting function are plotted in Figure 4. Outcome sensitivity α was higher, probability sensitivity γ was lower, loss aversion λ was higher, and choice sensitivity ϕ was lower in the experience than in the description condition. This description–experience gap in distortion replicates and extends findings by Glöckner et al. (2016) and Kellen et al. (2016; this research only found differences in sensitivity to outcomes and probabilities).

Mixed-Mode Condition. Next, we tested whether there was a description–experience gap in distortion in the mixed-mode condition. To this end, we first estimated a CPT model with separate sets of parameters for the described and the experienced options. The parameter estimates are reported in Table 2. The estimated values for the described and experienced options were considerably more similar to each other than those for the description and experience conditions. For instance, in the mixed-mode condition, the probability sensitivity parameters γ for the described and the experienced options were 0.74 and 0.66, respectively, relative to 0.81 in the description condition and 0.62 in the experience condition. Similarly, the respective outcome sensitivity parameters α for the described and the experienced options were 1.00 and 1.01, respectively, relative to 0.80 in the description condition and 1.11 in the experience condition. Although the parameter values of the described and the experienced options differed somewhat from each other, the differences were not credible (i.e., the 95% HDI of the difference between the two options did not include 0). As an additional test of whether one should assume different parameter values for the described and the experienced option, we conducted a model comparison (based on DIC) with a CPT model that assumed the same parameter for the described and the experienced option. The DIC of this constrained model was considerably lower (indicating better model performance) than that allowing for differences between the described and the experienced options, DIC = 8,040.2 versus 8,158.1. We therefore conclude that in the mixed-mode condition the way people subjectively distorted outcome and probability information—as measured by CPT's value and probability weighting functions—did not differ between the described and the experienced options.

Because the CPT parameters did not differ between the described and the experienced options, in the following we relied on the joint-representation CPT model (which assumes the same sets of parameters for the described and the experienced options). The estimated parameters of that model are reported in Table 1 and plotted in Figure 4. For all parameters, the mean of the group-level posterior distribution of the mixed-mode condition fell between that of the description and the experience condition. With regard to the outcome sensitivity parameter α, the probability sensitivity

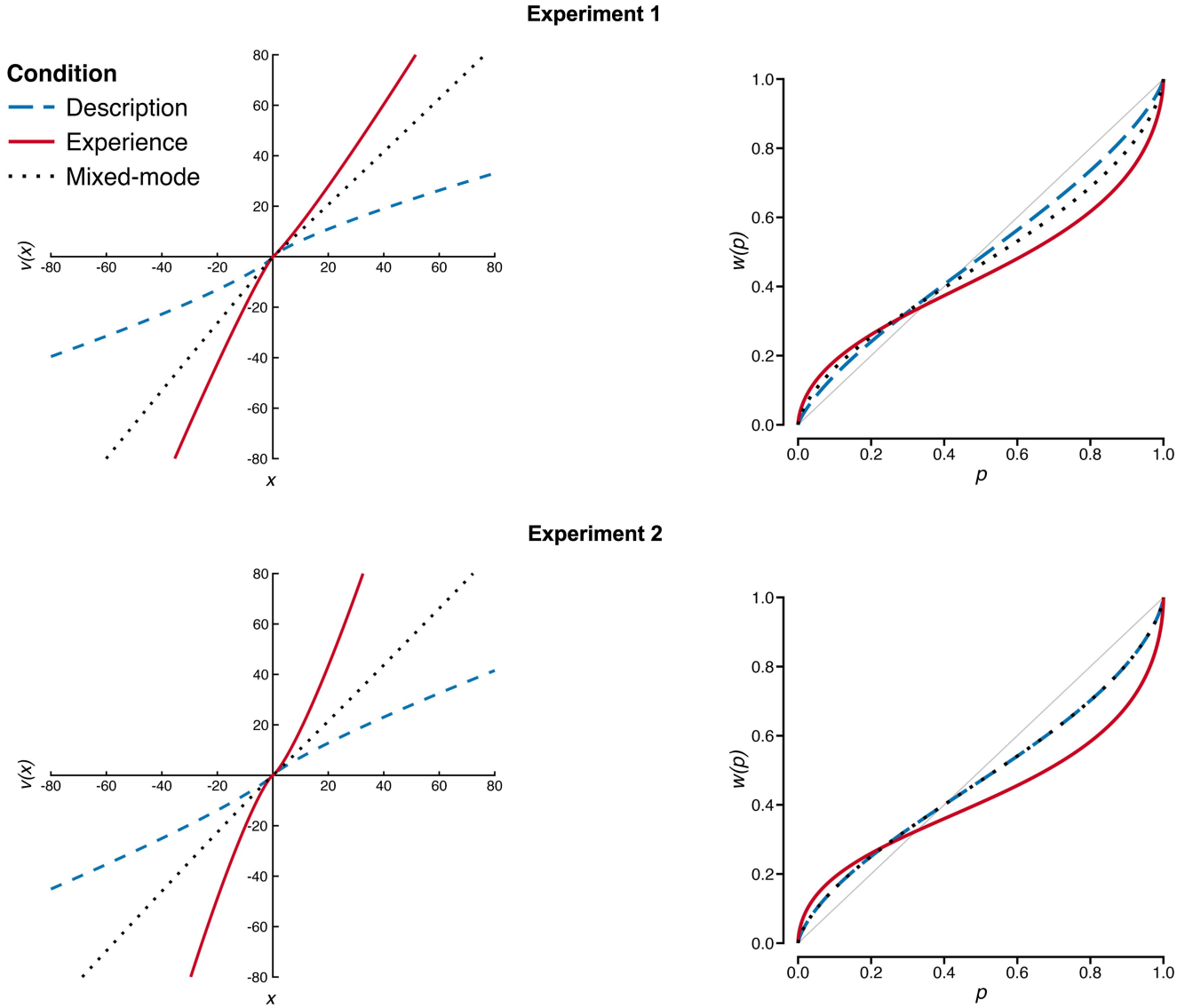
Table 1
Posterior Group-Level Mean Parameters of the CPT Model [95% HDI]

Parameter	Description condition	Experience condition	Mixed-mode condition	Difference descr. − exp.	Difference mixed − descr.	Difference mixed − exp.
Experiment 1						
Outcome sensitivity α	0.80 [0.76, 0.84]	1.11 [1.06, 1.17]	1.01 [0.96, 1.06]	**−0.31 [−0.38, −0.26]**	**0.21 [0.15, 0.27]**	**−0.10 [−0.17, −0.03]**
Probability sensitivity γ	0.81 [0.74, 0.88]	0.62 [0.59, 0.66]	0.72 [0.67, 0.77]	**0.19 [0.11, 0.26]**	**− 0.09 [−0.17, −0.00]**	**0.10 [0.03, 0.16]**
Loss aversion λ	1.20 [1.07, 1.32]	1.52 [1.29, 1.76]	1.28 [1.14, 1.42]	**−0.32 [−0.59, −0.06]**	0.08 [−0.10, 0.28]	−0.24 [−0.52, 0.03]
Choice sensitivity ϕ	0.21 [0.17, 0.26]	0.05 [0.04, 0.06]	0.08 [0.06, 0.10]	**0.16 [0.12, 0.21]**	**−0.13 [−0.18, −0.08]**	**0.03 [0.01, 0.06]**
Experiment 2						
Outcome sensitivity α	0.85 [0.81, 0.89]	1.26 [1.20, 1.32]	1.02 [0.98, 1.07]	**−0.41 [−0.48, −0.34]**	**0.17 [0.11, 0.24]**	**−0.23 [−0.31, −0.16]**
Probability sensitivity γ	0.74 [0.67, 0.81]	0.58 [0.53, 0.64]	0.74 [0.67, 0.82]	**0.16 [0.07, 0.25]**	0.00 [−0.10, 0.11]	**0.16 [0.07, 0.26]**
Loss aversion λ	1.09 [0.97, 1.20]	1.13 [0.93, 1.32]	1.05 [0.89, 1.22]	−0.04 [−0.27, 0.18]	−0.03 [−0.24, 0.17]	−0.07 [−0.33, 0.19]
Choice sensitivity ϕ	0.17 [0.14, 0.21]	0.03 [0.02, 0.04]	0.08 [0.06, 0.09]	**0.14 [0.10, 0.18]**	**−0.10 [−0.14, −0.06]**	**0.04 [0.02, 0.06]**

Note. HDI = highest density intervals; CPT = cumulative prospect theory; descr. = description condition; exp. = experience condition; mixed = mixed-mode condition. Values in bold indicate credible differences.

Figure 4

CPT's Value Functions (Left Panels) and Probability Weighting Functions (Right Panels)



Note. The functions are based on the posterior distribution of the group-level mean of the CPT parameters. CPT = cumulative prospect theory. See the online article for the color version of this figure.

parameter γ, and the choice sensitivity parameter ϕ, the values in the mixed-mode condition differed credibly from those in both the description and the experience conditions. In contrast, the loss aversion parameter λ in the mixed-mode condition was not credibly different from that in either the description or the experience condition.

Taken together, the results suggest that in the mixed-mode condition, outcome and probability information of the described and the experienced options was distorted similarly (as per participants' choices), despite their different learning modes. The degree of the distortion seemed to represent a compromise between how outcomes and probabilities are subjectively distorted in the description and the experience conditions.

Is There a Choice Bias in the Mixed-Mode Condition?

To test whether participants in the mixed-mode condition preferred an option with a particular learning mode, we modeled their choices using a variant of the choice rule that included an additive parameter β reflecting a bias toward one of the options, irrespective of its subjective valuation (Equation 6). A positive (negative) value indicates a bias toward the described (experienced) option. We estimated the parameter using the joint-representation CPT model, which showed the best model performance in the analysis above. The estimated β parameter was positive (indicating a slight preference for the described option) but did not credibly differ from 0 (group-level posterior mean = 0.08 [−0.00, 0.16]). We thus

Table 2
Posterior Group-Level Mean Parameters of the CPT Model With Separate Parameters for Each Option in the Mixed-Mode Condition [95% HDI]

Parameter	Described option	Experienced option	Difference described − experienced option
Experiment 1			
Outcome sensitivity α	1.00 [0.96, 1.04]	1.01 [0.96, 1.05]	−0.01 [−0.01, 0.00]
Probability sensitivity γ	0.74 [0.68, 0.81]	0.66 [0.63, 0.72]	0.07 [−0.00, 0.14]
Loss aversion λ	1.25 [1.16, 1.34]	1.27 [1.18, 1.36]	−0.02 [−0.06, 0.02]
Choice sensitivity ϕ	0.08 [0.06, 0.10]		
Experiment 2			
Outcome sensitivity α	1.03 [0.98, 1.07]	1.04 [0.99, 1.08]	−0.01 [−0.02, 0.00]
Probability sensitivity γ	0.77 [0.68, 0.87]	0.69 [0.63, 0.76]	0.08 [−0.04, 0.19]
Loss aversion λ	1.14 [1.06, 1.23]	1.09 [1.00, 1.19]	0.05 [−0.01, 0.10]
Choice sensitivity ϕ	0.07 [0.06, 0.09]		

Note. CPT = cumulative prospect theory; HDI = highest density intervals.

conclude that in the mixed-mode condition participants did not show a bias toward the described or the experienced option.

How Do People Search for Information in the Mixed-Mode Condition?

Next, we compared sampling behavior between the mixed-mode and experience conditions. As described above, participants might draw a larger number of samples per option in the mixed-mode than in the experienced condition (e.g., in an attempt to align the level of certainty between the two options, or because search effort does not have to be distributed across two options). Because the number of samples drawn was not normally distributed (but was best described by a negative binomial distribution), we ran a negative binomial generalized multilevel regression model with number of samples drawn per option as dependent variable and a dummy condition variable (coded as 0 = *experience*, 1 = *mixed-mode*) as independent variable, with random intercepts for participants (this is different from the preregistration of Experiment 2). The coefficients of a negative binomial generalized multilevel regression model represent the change in the log of the expected count per one-unit increase in the respective predictor variable. In the mixed-mode condition, the number of samples from the experienced option ($Mdn = 19$, $M = 22.2$, $SD = 12.2$) was indeed larger than the number of per-option samples in the experience condition ($Mdn = 13$, $M = 16.5$, $SD = 8.1$; $b = 0.24$, $SE = 0.11$, $p = .029$).

We also explored whether the influence of the properties of the choice problems on search depends on whether the experienced option is paired with another experienced option or with a described option. We refer to the option whose search effort we analyze as the *target* option and the other option as the *context* option. We ran two negative binomial generalized multilevel regression models with the number of samples drawn from the target option as the dependent variable and random intercepts for participants (this again is different from the preregistration of Experiment 2). In the first model, we analyzed search in the mixed-mode condition, and the dependent variable was the number of samples drawn from the experienced option. In the second model, we analyzed search in the experience condition, and the dependent variable was the number of samples drawn from one of the two experienced options; here, each option was treated once as target option and once as context option. As fixed effects, we included the EV, the number of unique observed outcomes, and the standard deviation (*SD*) of both the target and the context option (for the experienced options, both the EV and the *SD* were computed based on the actually experienced information) as well as absolute difference between the two options in terms of EV and *SD*. We did not include the coefficient of variance (i.e., *SD* normalized by EV; Weber et al., 2004) in the model because the inclusion of coefficient of variance caused issues of multicollinearity (this is different from the preregistration of Experiment 2). Because EV and *SD* of the experienced payoff distribution could not be determined for the experienced option(s) when no samples were drawn from at least one option, trials in which no samples were drawn from at least one option were excluded in these models.

The results are reported in Table 3. In the mixed-mode condition, the number of samples drawn from the experienced option was higher when the described option had a lower EV and a higher *SD*. The number of samples drawn was also higher when the experienced option itself had a higher EV and two (vs. one) outcomes were drawn. Furthermore, the number of samples drawn was higher with smaller absolute difference between the options in EV and *SD*. In the experience condition, the number of samples drawn from an experienced option was higher when the context option had a lower EV, a higher *SD*, and when two (vs. one) unique outcomes were sampled. The number of samples drawn was also higher when only one (vs. two) unique outcome from the target option itself was sampled. Furthermore, the number of samples drawn was higher the smaller the absolute difference between the options in EV (but not *SD*). In conclusion, information search from an experienced option was affected by the EV and *SD* of the context option as well as the difference in EV, independent of whether the context option was described or experienced.

Discussion

In Experiment 1, we examined choice and search behavior in choices between a described and an experienced option and compared it with choices between two described or two experienced options. When defining a rare event based on the latent, underlying payoff distribution of the options (i.e., irrespective of what information participants actually sampled), there was more overweighting of rare events in the experience than in the description condition—consistent with a "reversed" description–experience gap (Glöckner et al., 2016). Importantly, however, there was no evidence for differential

Table 3
Effect of Context Option, Target Option, and Choice Problem Properties on Number of Samples Drawn From the Target Option

Predictor	Experiment 1		Experiment 2	
	Mixed-mode condition (context option is described)	Experience condition (context option is experienced)	Mixed-mode condition (context option is described)	Experience condition (context option is experienced)
Intercept	**2.894 (0.089)**, $p < .001$	**2.684 (0.068)**, $p < .001$	**2.556 (0.109)**, $p < .001$	**2.225 (0.066)**, $p < .001$
$EV_{context}$	**−0.002 (0.000)**, $p < .001$	**−0.001 (0.000)**, $p < .001$	**−0.002 (0.000)**, $p < .001$	**−0.001 (0.000)**, $p < .001$
EV_{target}	**0.001 (0.000)**, $p = .004$	0.000 (0.000), $p = .052$	**0.001 (0.000)**, $p = .005$	−0.000 (0.000), $p = .085$
Number of $outcomes_{context}$	−0.047 (0.027), $p = .080$	**0.036 (0.014)**, $p = .009$	0.018 (0.027), $p = .512$	**0.150 (0.013)**, $p < .001$
Number of $outcomes_{target}$	**0.082 (0.020)**, $p < .001$	**−0.059 (0.013)**, $p < .001$	**0.069 (0.020)**, $p < .001$	**0.072 (0.013)**, $p < .001$
$SD_{context}$	**0.002 (0.000)**, $p < .001$	**0.001 (0.000)**, $p < .001$	**0.002 (0.000)**, $p < .001$	**0.001 (0.001)**, $p = .001$
SD_{target}	−0.002 (0.000), $p = .879$	0.000 (0.000), $p = .798$	0.001 (0.000), $p = .073$	**−0.001 (0.000)**, $p = .006$
Absolute EV difference between options	**−0.006 (0.001)**, $p < .001$	**−0.004 (0.000)**, $p < .001$	**−0.008 (0.001)**, $p < .001$	**−0.007 (0.000)**, $p < .001$
Absolute *SD* difference between options	**−0.002 (0.000)**, $p < .001$	−0.000 (0.000), $p = .222$	**−0.001 (0.000)**, $p = .035$	**0.003 (0.000)**, $p < .001$

Note. Shown are *b* (*SE*) values and *p* values. The context option is described in the mixed-mode condition and experienced in the experience condition. context = context option; target = target option; EV = expected value; *SE* = standard error. Values in bold indicate significant regression weights. Coefficients represent the change in the log of the expected count per one-unit increase in the respective predictor variable.

overweighting of rare events based on the options' latent payoff distribution for the described versus the experienced option in the mixed-mode condition. When modeling choices using CPT based on the experienced payoff distribution, the estimated value function and probability weighting function differed between the description and experience conditions. However, there was no description–experience gap in distortion in the mixed-mode condition. The results suggest that when making choices between a described and an experienced option, people evaluate the options based on a common representation across both learning modes. Further, there was no choice bias toward either of the learning modes in the mixed-mode condition. Finally, people drew a higher number of samples per option in the mixed-mode condition than in the experience condition, and characteristics of both the described and experienced options influenced search in the mixed-mode condition.

Experiment 2

The goal of Experiment 2 was to corroborate the findings of Experiment 1 and to generalize them to an online setting. Experiment 2 was preregistered (Tiede et al., 2024b). In a nutshell, Experiment 2 replicated the main findings of Experiment 1. First, there was no description–experience gap in the mixed-mode condition, neither in terms of the choice patterns based on the latent payoff distribution nor in terms of the estimated CPT functions based on the experienced payoff distribution (i.e., description–experience gap in distortion). As in Experiment 1, CPT's value and probability weighting functions in the mixed-mode condition were different from and fell in between those in the description and experience conditions. Second, there was again no credible choice bias. However, in contrast to Experiment 1, search effort per option was not greater in the mixed-mode condition than in the experience condition. In the following, we describe the methods and results of Experiment 2 in more detail. Methods and analysis were the same as in Experiment 1 unless noted otherwise.

Method

Participants

Participants were recruited via the platform Prolific Academic. They received £4.50 (equivalent to about $5.47 at the time of the experiment) and a bonus of, on average, £1.10 (SD = 0.54; the determination of the bonus was similar to that in Experiment 1). We based our target sample sizes on the largest of the three conditions in Experiment 1 (n = 78). Anticipating data exclusions, we collected data from 271 participants. As preregistered, we excluded participants who did not choose the dominant option in at least three out of four attention check trials (n = 19) and participants who did not sample any outcomes in at least a quarter of the trials (n = 4). The final sample (N = 248) comprised 108 women, 135 men, and two people who identified as nonbinary, with a mean age of M = 37.6 years (SD = 11.8; range: 19–76).

Choice Task, Procedure, and Computational Modeling

As Experiment 2 was a direct replication of Experiment 1, the choice task, the procedure, and the computational modeling approach were the same as in Experiment 1, with four exceptions.

First, the experiment was conducted online, rather than in the lab. Second, the language of the experiment was English, not German, and participants resided in the United States rather than Germany. Third, due to differences in the currency of the remuneration, the bonus was based on the conversion of points into pounds sterling, not euros, and it was a larger amount relative to the participation fee in Experiment 1. Fourth, there was no unrelated task between the choice task and the numeracy measure, and we did not assess subjective numeracy.

Results

Additional results on numeracy and maximization of EV/sampled mean are available in Appendix A and Supplemental Section S8.

Description–Experience Gap

The proportion of choices consistent with overweighting of rare events based on the options' latent payoff distribution are shown in Figure 3.

Description and Experience Conditions. Choice behavior in line with overweighting did not differ between the experience (M = 0.56, SD = 0.08) and the description conditions (M = 0.53, SD = 0.09; b = 0.10, SE = 0.05, p = .069). Overweighting of rare events was descriptively more pronounced in description than in experience in four of the six problems studied by Hertwig et al. (2004), but less pronounced in the other two.

Mixed-Mode Condition. As in Experiment 1, in the mixed-mode condition, the proportion of choices consistent with overweighting did not differ between cases where the rarest event was part of the described (M = 0.53, SD = 0.10) or the experienced option (M = 0.53, SD = 0.12; b = 0.00, SE = 0.05, p = .924). An exploratory analysis showed that the overall level of overweighting (M = 0.53, SD = 0.08) was less pronounced than in the experience condition (b = −0.14, SE = 0.07, p = .038), but did not differ from that in the description condition (b = 0.02, SE = 0.07, p = .799).

Is There a Description–Experience Gap in Distortion?

As in Experiment 1, for CPT parameter estimation, we excluded trials in which no samples were drawn from at least one option because the experienced payoff distribution could not be determined for these trials (0.6% of trials).

Description and Experience Conditions. The CPT parameter estimates based on the options' actually experienced payoff distribution are reported in Table 1; the resulting value functions and probability weighting functions are plotted in Figure 4. Posterior predictive checks showed that the estimated CPT model matched, on average, 74.1% of participants' choices. As in Experiment 1, outcome sensitivity α was higher, probability sensitivity γ was lower, and choice sensitivity ϕ was lower in the experience than in the description condition. Loss aversion λ did not credibly differ between the description and the experience conditions.

Mixed-Mode Condition. The parameter estimates of the separate-representations model of CPT in the mixed-mode condition are reported in Table 2. As in Experiment 1, there were no credible differences in any of the estimated parameter values between the described and the experienced option in the mixed-mode condition. Model performance of the separate-representations model of CPT (DIC = 9,356.1) was considerably worse than that of the joint-representation model (DIC = 8,973.9). The estimated parameters of the joint-representation CPT model applied to the mixed-mode condition are reported in Table 1 and illustrated in Figure 4. With regard to the outcome sensitivity parameter α and the choice sensitivity parameter ϕ, the values in the mixed-mode condition fell between those for the description and experience conditions and differed credibly from both. With regard to the probability sensitivity parameter γ, the mean of the group-level posterior distribution of the mixed-mode condition was higher than in the experience condition, but did not differ credibly from the description condition. The value of the loss aversion parameter λ was not credibly different from those in the description or experience conditions.

Is There a Choice Bias in the Mixed-Mode Condition?

As in Experiment 1, there was no choice bias toward either the described or the experienced option in the mixed-mode condition. The estimated β parameter did not credibly differ from 0 (group-level posterior mean = −0.03 [−0.13, 0.07]).

How Do People Search for Information in the Mixed-Mode Condition?

Analogous to Experiment 1 (but deviating from the preregistration), we ran a negative binomial generalized multilevel regression model. Overall, participants took slightly fewer samples than in Experiment 1 (on average, around three fewer samples per option). In Experiment 2, the number of samples drawn per option (Mdn = 15, M = 19.3, SD = 13.4) was not significantly higher than in the experience condition (Mdn = 10, M = 13.2, SD = 7.8; b = 0.23, SE = 0.13, p = .081).

Results on how search was influenced by properties of the choice problems are reported in Table 3. We deviated from the preregistration by not including the coefficient of variance in the model and by running negative binomial generalized multilevel regression models. As in Experiment 1, trials in which no samples were drawn from at least one option were excluded in these models because EV and SD of the experienced payoff distribution could not be determined for these trials. In the mixed-mode condition, results were similar to those in Experiment 1: The number of samples drawn from the experienced option was higher when the described option had a lower EV and a higher SD. The number of samples drawn was also higher when the experienced option itself had a higher EV and two (vs. one) unique outcomes were sampled. Furthermore, the number of samples drawn was higher the smaller the absolute difference between the options in EV and SD. For the experience condition, the results deviated somewhat from those of Experiment 1: The number of samples drawn from an experienced option was higher when the context option had a lower EV, a higher SD, and when two (vs. one) unique outcomes were sampled. The number of samples drawn was also higher when the target option itself had a lower SD and two (vs. one) unique outcomes were sampled. Furthermore, the number of samples drawn was higher the smaller the absolute difference between the options in EV and the larger the absolute difference in SD.

Discussion

Experiment 2 replicated the main findings of Experiment 1. Again, there was no description–experience gap (based on the options' latent payoff distribution) in choices between a described and an experienced option. The estimated shapes of the value function and the probability weighting function (based on the options' experienced payoff distribution) in the mixed-mode condition were similar for the experienced and the described option. The patterns of the functions were more consistent with the joint-compromise scenario than with the other outlined scenarios (although this was not as clear-cut as in Experiment 1). Experiment 2 did not replicate the finding that people draw more samples when they compared the experienced option to a described option (i.e., in the mixed-mode condition) than when they compared it to another experienced option (i.e., in the experience condition).

General Discussion

When people are faced with options whose payoff distribution they learn from experience, they evaluate the options differently than when they choose between options whose payoff distribution they learn from description. Here, we tested in two experiments whether such discrepancies between learning modes also emerge when people choose between a described and an experienced option. For that purpose, we studied differences between description and experience (a) in terms of whether choice behavior is in line with overweighting of rare events based on the latent payoff distribution and (b) in terms of the subjective distortions of outcome and probability information estimated with CPT based on the observed payoff distributions. Further, we tested whether choices in a mixed-mode condition are biased toward an option with a particular learning mode. Finally, we studied to what extent information sampling for an experienced option depends on the learning mode of the context option in a choice problem.

Our most important finding is that although people clearly showed differences in preference and distortion when choosing between described options than when choosing between experienced options, there were no such discrepancies when choosing between a described and an experienced option. This pattern emerged both in Experiment 1 and Experiment 2. The estimated value functions and probability weighting functions in the mixed-mode condition suggest that people converge on a common representation of the described and experienced options that seems to represent a compromise between the representations observed in the description and experience conditions. There was no evidence that people have a bias for an option when it is presented in a particular learning mode. Finally, people tended to draw more samples per option when the experienced option was compared with a described option than when it was compared with another experienced option (although nominally present, this difference was not reliable in Experiment 2). The influence of option and choice problem properties on search was largely unaffected by whether the context option was described or experienced.

Preference Construction of Mixed-Mode Choices

In the introduction, we outlined various scenarios for how people might evaluate the described and the experienced options (based on the experienced payoff distribution) in a mixed-mode condition. From these scenarios, our results are mostly consistent with the joint-compromise scenario, although this pattern was less pronounced in Experiment 2 than in Experiment 1. We motivated the joint-compromise scenario from findings that options in a choice problem are evaluated relative to each other (e.g., Madan et al., 2021; Peterson et al., 2021; Stewart et al., 2003). Note that studies have found that differences in evaluation between description and experience do arise when described and experienced options are evaluated individually (e.g., in pricing decisions; Golan & Ert, 2015; Pachur & Scheibehenne, 2017) rather than in the context of a choice task. This suggests that the lack of a description–experience gap in the mixed-mode condition is due to comparative processes—that are triggered in a choice task but not in an evaluation task—aimed at aligning the representations of the options. To illustrate, in the mixed-mode condition, the explicitly described probabilities of the described option could have led participants to represent probability information for the experienced option in a way that makes the options more comparable—leading to similar probability weighting functions for both options (but note that even if probability weighting seems to be similar, this does not necessarily mean that the same mechanisms are involved in processing the information).

How can the CPT parameters estimated for the choices in the mixed-mode condition, which mostly fell between those in the pure description and the pure experience conditions, be interpreted psychologically? Although CPT is not a cognitive theory, based on analyses that have related cognitive processes to patterns in CPT's probability weighting function and value function (Pachur et al., 2017, 2018; Zilker & Pachur, 2022), the estimated parameters allow one to constrain possible types of cognitive processing. For instance, based on findings in Zilker and Pachur (2023), the pattern in the mixed-mode condition is consistent with either more attention to probability (vs. outcome) information or more attention to the more risky option in the mixed-mode condition than in a situation in which both options are experienced.

Our results provided no evidence for a separate-representations scenario, under which in the mixed-mode condition people would show a more strongly curved probability weighting function for the experienced option than for the described option. We motivated the separate-representations scenario from considerations that due to the higher ambiguity in experience than in description, there might be a more strongly curved probability weighting function in experience, leading to more strongly regressive decision weights (e.g., Fennell & Baddeley, 2012).[5] A possible reason that this scenario did not materialize is that in the mixed-mode condition, participants drew a rather large number of samples, reducing the differences in ambiguity between the experienced and the described option.

[5] To model choices in our experiments, we used the experienced payoff distributions (e.g., Glöckner et al., 2016; Kellen et al., 2016). However, it is possible that participants estimated the probabilities following a Bayesian updating process (see, e.g., Fennell & Baddeley, 2012; Hoffart et al., 2019), which could at least partly explain why decisions weights were more strongly distorted in purely experience-based (vs. description-based) choices. As we describe in detail in the Supplemental Section S9, due to the overall relatively high number of samples drawn in our experiments, probabilities derived from a Bayesian updating model closely corresponded to the observed probabilities (r = .976 and r = .982 in the mixed-mode and experience conditions, respectively). Hence, we did not additionally model choices separately based on probabilities derived from a Bayesian updating process.

Our results also showed no evidence for the joint-shifted scenario, which we motivated from evaluability theory (Hsee & Zhang, 2010). To recap, research on evaluability theory has shown that decision makers are more sensitive to an attribute when they can evaluate an option's value on the attribute more easily. For instance, when evaluating the attractiveness of a dictionary with 10,000 entries, people seem to weight that attribute more when they can compare the number of entries to that of a reference option (another dictionary with 20,000 entries; Hsee, 1996). Although in our mixed-mode condition the format of probability information differed between the described and experienced options, we did not find lower sensitivity for probabilities in this than in all the other conditions, in which probability information was in the same format for both options in a choice problem. It is possible that the different learning modes in the mixed-mode condition did not reduce the weight of probabilities because probabilities have a clear upper and lower bound (0 and 1), allowing people to evaluate probabilities even without an explicit reference (but see Park et al., 2021).

As laid out in the introduction, the description–experience gap is nourished both by sampling error in experience and by differences in how outcome and probability information seems to be subjectively distorted (description–experience gap in distortion; see Figure 1). Participants in the mixed-mode condition of our experiments drew a relatively large number of samples, and this alone might explain why overweighting of rare events did not differ between trials in which the option that includes the rarest event was described versus experienced. However, should one expect a description–experience gap in the mixed-mode condition when only few samples are drawn? Based on our results, what quantitative predictions can be made regarding the size of the description–experience gap in the mixed-mode condition?

To address this question, we conducted a computer simulation in which we generated choices with CPT for the choice problems used in Experiments 1 and 2, separately for the description condition, the experience condition, and the mixed-mode condition. To generate the choices, we used the respective CPT parameters obtained in Experiment 1 for each condition. For the mixed-mode condition, we further manipulated whether the option that included the rarest event was described or experienced. For the experienced options, we varied the number of samples drawn, implementing a relatively small and a relatively large number of samples drawn per option (5 vs. 20 samples). Figure 5 shows that when the number of samples drawn was large (i.e., 20 per option), the description–experience gap in the mixed-mode condition was negligible (1.5% points), with choices in line with overweighting of rare events being only slightly more pronounced when the option which included the rarest event was described (vs. experienced). When the number of samples drawn was small (i.e., 5 per option), however, this difference was considerably larger (4.9% points), with the description–experience gap amounting to more than three times the size compared to when the number of samples drawn was large. These results suggest that a description–experience gap may emerge if the number of samples drawn is sufficiently low. Future research could empirically test this prediction by manipulating the number of samples drawn in the mixed-mode condition (e.g., Hau et al., 2008). Further, by also doing so in an experience condition and comparing the results to those in a description condition, one could then carve out and quantify the relative contribution of sampling error and a description–experience gap in distortion to the "classical" description–experience gap.

Theoretical Implications

Our results have several implications for theories of learning and decision making. One of the key differences between an experience and a description learning mode is that in the former people have to learn information about the payoff distribution from sequentially encountered outcomes, whereas no such learning process is involved in the latter. Several models have been proposed to describe the learning processes in decisions from experience and have highlighted a possible role of recency effects (C. Gonzalez & Dutt, 2011; Hotaling et al., 2022), asymmetric learning after positive versus negative prediction errors (Haines et al., 2023), and the similarity between the options' payoff distributions (Spektor et al., 2019) for learning and evaluating experienced options. Current models assume that the learning processes for an option depend on the learning mode in which the option is presented, but not on the learning mode of other options in the choice context. Based on our findings, accounts of learning about an experienced option also need to accommodate that learning may be sensitive to whether the option is paired with a described or an experienced option.

Second, our results show that the choice context can affect not only choice but also search behavior: People tend to draw more samples from an experienced option when the context option is described than when the context option is experienced, resulting, for instance, in smaller sampling error. Our results suggest that theories of experience-based decision making should aim to account both for the effect of context on the subjective distortion of outcome and probability information and choice and for how context affects preference via differences in the sampled information.

Comparison of Our Results With Previous Results on the Description–Experience Gap

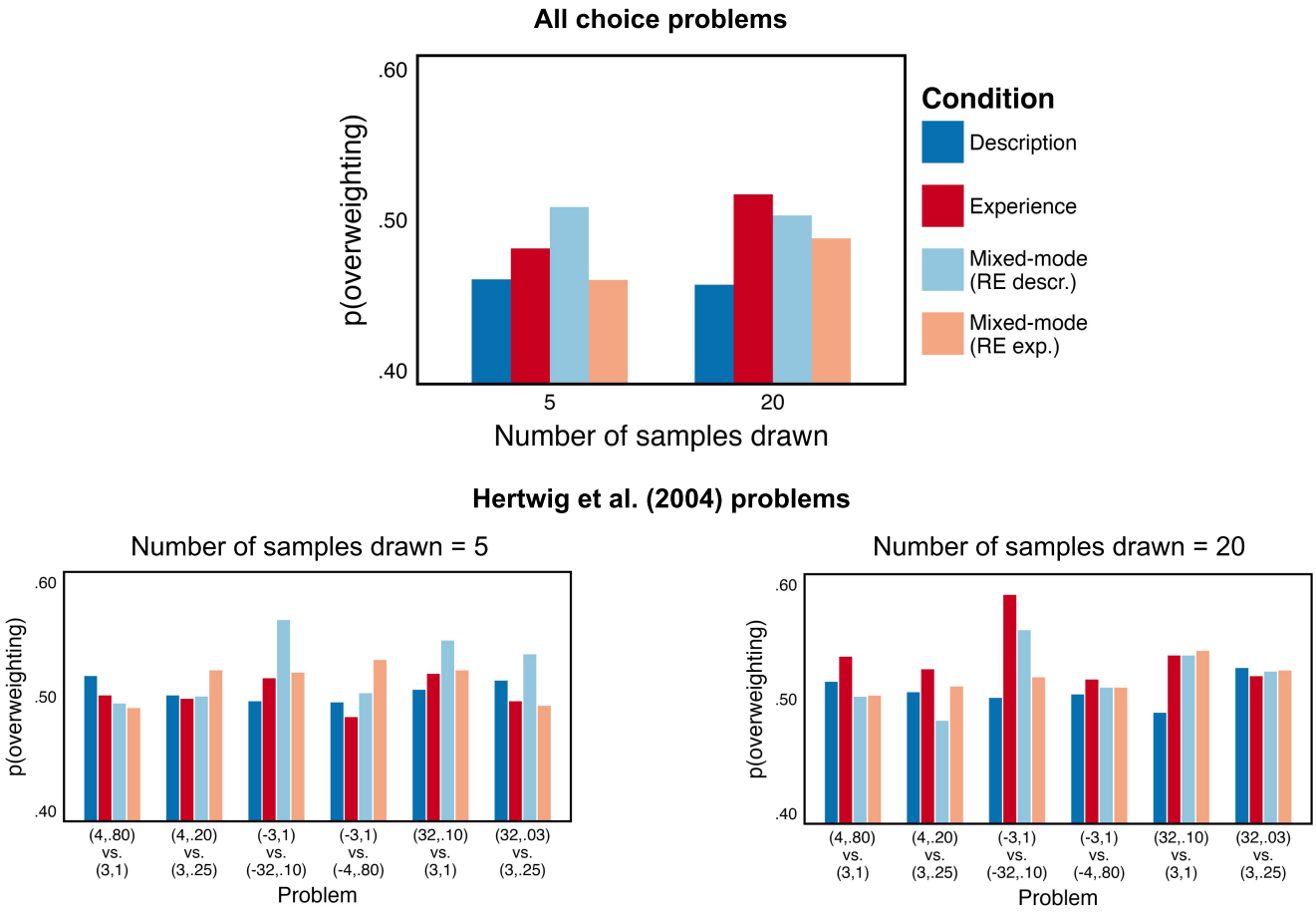
In the original analyses of the description–experience gap by Hertwig et al. (2004), a rare event was defined based on the options' latent payoff distribution, irrespective of whether people experienced the event as rare or experienced the event at all. Using this definition in our analyses, in Experiment 1 the amount of overweighting was significantly more pronounced in the pure experience than in the pure description condition, and in Experiment 2 there was no difference in overweighting. This finding contradicts conclusions on the description–experience gap in many studies (cf. Wulff et al., 2018).

There are two likely reasons for this apparent inconsistency (for details, see Appendix B). The first is that participants in our experiments drew a relatively large number of samples. In previous studies, the number of drawn samples per option was typically around 10 (Wulff et al., 2018). In our Experiment 1, by contrast, it was more than 16 (see also Glöckner et al., 2016).[6] With a higher number of samples, there is lower sampling error, and the contribution of this factor to a description–experience gap is therefore reduced. For illustration, drawing 10 samples will statistically lead to not experiencing a 10% event in 35% of all trials, whereas this probability decreases to 19% when 16 samples are drawn. Differences in the amount of sampling might also

[6] One possible reason for the larger number of samples drawn is that in our experiments participants could draw samples as quickly as they liked, which could have led to larger sample sizes compared to settings in which sampling speed is restricted (for instance, in Hau et al., 2008, each outcome was presented for 1 s before the next sample could be drawn).

Figure 5

Proportions of Choices in Line With Overweighting as a Function of Condition and Number of Samples Drawn



Note. Upper panel: All choice problems. Lower panel: Subset of choice problems studied by Hertwig et al. (2004). RE = rare event. See the online article for the color version of this figure.

explain (at least partly) why there were differences in the description–experience across our studies: there was a "reversed" description–experience gap in Experiment 1, where participants drew a relatively large number of samples; no gap in Experiment 2, where participants drew fewer samples; and an "original" description–experience gap in our initial experiment, in which participants drew even fewer samples (on average, 11.0). Analyses reported in Appendix B show that for both the data of the Wulff et al. (2018) meta-analysis and our current data, the direction and size of the description–experience gap is indeed a function of how many samples were drawn (for a similar analysis and conclusion, see Glöckner et al., 2016). In fact, in studies in which the number of samples drawn is comparable to those in our experiments, the description–experience gap disappears or even "reverses."[7]

Second, one likely reason that in contrast to previous findings on the description–experience gap we find evidence, overall, for more pronounced *over*weighting (rather than underweighting) of rare events is that our set of choice problems consisted predominantly (90%) of choice problems with two risky options (but see Erev et al., 2022, for results suggesting that there might be settings where an underweighting of rare experienced events also occurs in choices between two risky options). In Hertwig et al. (2004) and most other studies on the description–experience gap, in contrast, the majority of choice problems consisted of a risky and a safe option. Analyses in Appendix B show for the data from Wulff et al. (2018) meta-analysis that the description–experience gap in choice (i.e., less overweighting of rare events in experience than in description) is pronounced in problems involving a safe and a risky option, whereas in problems involving two risky options, there is typically no description–experience gap or a "reversed" description–experience gap (i.e., more overweighting of rare events in experience than in description). Similar conclusions were reported by Glöckner et al. (2016). This might also explain why we found an "original" description–experience gap only in our initial experiment, in which there was a smaller proportion of risky–risky choice problems.

[7] This conclusion seems to be inconsistent with an analysis in Wulff et al. (2018), in which it was concluded that the size and nature of the description–experience gap persists even when controlling for the number of samples drawn. However, note that Wulff et al. included in their analysis only those trials in which participants' experienced payoff distributions matched the described ones. This set of trials made up merely 8.9% of all trials in the database with autonomous and matched sampling. Our analyses, by contrast, used the entire database of trials with autonomous sampling.

Conclusion

The observation of a description–experience gap in risky choice has triggered a wealth of research on the impact of learning mode on preference construction. Previous analyses have mainly focused on how search and ambiguity contribute to a discrepancy between experience-based and description-based choice. Our results demonstrate that differences in learning mode do not inevitably lead to differences in how a described and an experienced option are evaluated. Instead, there are no discrepancies when information acquired in different learning modes needs to be compared across options to construct a preference. This result suggests that comparative processes play an important and previously neglected role for the emergence of the description–experience gap.

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Appendix A

Additional Analyses

Additional Analyses for Experiment 1

Maximization of Expected Value and Sampled Mean

Because some previous analyses on the impact of learning mode on risky choice have compared description- and experience-based choice in terms of how often people chose the option with the higher expected value (EV; described options) or sampled mean (SM; experienced options; based on the observed payoff distributions; e.g., Ashby, 2017; Hertwig & Pleskac, 2010; Wulff et al., 2018)—thus deciding in line with EV/SM maximization—we also analyzed this aspect of participants' choices. Full results are reported in the Supplemental Section S4. Replicating previous findings (e.g., Wulff et al., 2018), maximization of SM in the experience condition was higher than maximization of EV in the description condition. In the mixed-mode condition, maximization of EV/SM was higher than in the description condition, but did not differ from the experience condition. It seems that just one option in an experiential learning mode is enough to enhance maximization of EV/SM—and thus decision quality.

The Role of Numeracy

We examined to what extent individual differences in objective numeracy (i.e., the ability to use probabilistic and mathematical concepts) and subjective numeracy (i.e., preference for numbers and numeric confidence) were related to participants' choice and search behavior. Detailed results can be found in the Supplemental Section S4. First, we examined whether objective and subjective numeracy were related to individual-level CPT parameter values and how these associations differed between conditions. We found that the association between objective numeracy and CPT parameters differed between conditions. In particular, in the description condition, numeracy was positively related to outcome sensitivity α and probability sensitivity γ, whereas in the experience condition, numeracy was positively related to choice sensitivity ϕ. In the mixed-mode condition, numeracy was positively related to loss aversion λ. Subjective numeracy was not associated with any of the parameters. Second, we examined whether objective and subjective

(*Appendices continue*)

numeracy were associated with search effort. No such associations emerged in the experience or mixed-mode conditions. In sum, between conditions objective numeracy was associated with different CPT parameters, but it was not substantially associated with search behavior in the current experiment.

Additional Analyses for Experiment 2

Maximization of EV and SM

Maximization of SM in the experience condition was higher than maximization of EV in the description condition. In the mixed-mode condition, maximization of EV/SM was higher than in the description condition and lower than in the experience condition (for details, see Supplemental Section S8).

The Role of Numeracy

In the description condition, objective numeracy was positively associated with outcome sensitivity α and choice sensitivity ϕ. In the experience and mixed-mode conditions, it was positively associated with loss aversion λ and choice sensitivity ϕ. Further, objective numeracy was not associated with the number of samples drawn (for details, see Supplemental Section S8).

Appendix B

The Role of Search Effort and Problem Type in the Description–Experience Gap

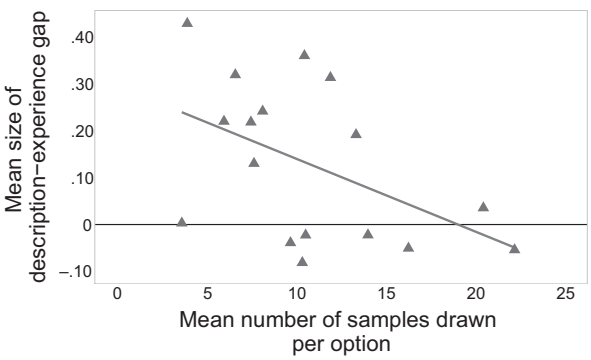
How Does the Empirical Manifestation of the Description–Experience Gap Depend on Sampling Effort and Type of Choice Problem?

Number of Samples Drawn

To test whether differences in the average number of samples drawn per option could explain differences in the size and direction of the description–experience gap between the present and previous investigations (e.g., Hertwig et al., 2004), we analyzed the meta-analytic data set on the description–experience gap compiled by Wulff et al. (2018) by regressing the size of the description–experience gap on the average number of samples for each of the 28 studies in the data set that included both description- and experience-based choices (for details, see Supplemental Section S6). As shown in Figure B1, the direction and size of the description–experience gap was a function of how many samples were drawn on average: The "original" gap (i.e., less overweighting in experience than in description) was found more often in studies in which fewer than 15 samples were drawn and the gap was diminished or reversed in studies in which more than 15 samples were drawn.

This pattern can at least partly explain why in our experiments we found a reversed description–experience gap in Experiment 1, where participants drew a relatively large number of samples, and no gap in Experiment 2, where participants drew fewer samples. In our initial experiment, participants drew even fewer samples (on average, 11.0, which is close to the mean found in the meta-analysis), and there was a significant "original" gap. Thus, the number of samples people draw seems to have a substantial effect on the size and direction of the description–experience gap and should be taken into count when interpreting results on the description–experience gap.

Figure B1
The Description–Experience Gap as a Function of Number of Samples Drawn (Reanalysis of Wulff et al., 2018)



Problem Type

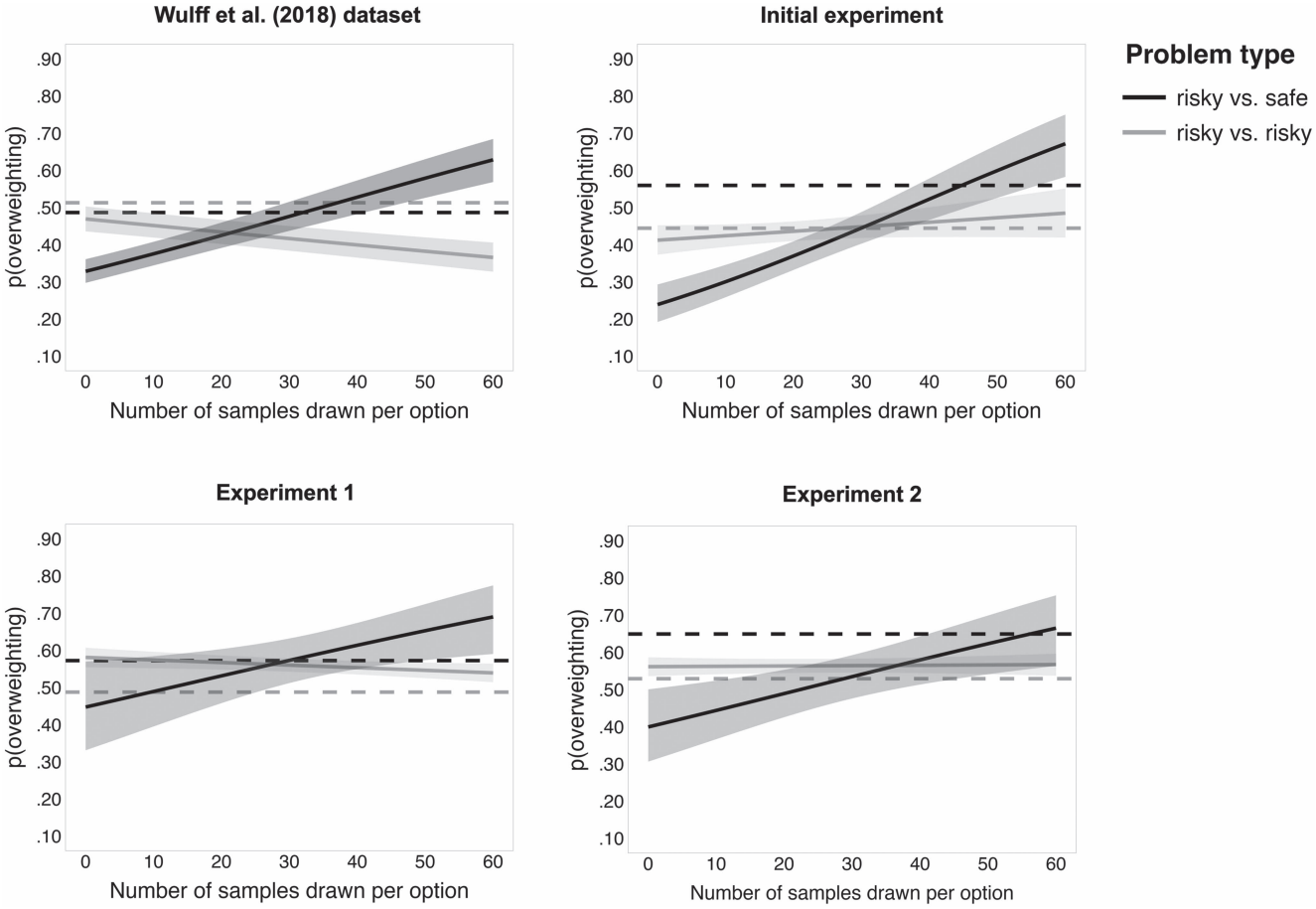
A second crucial factor governing the size and direction of the description–experience gap is the type of choice problems used—specifically, whether people choose between a safe and a risky option or between two risky options. In their meta-analysis, Wulff et al. (2018) found a substantial gap for choices between a safe and a risky option, but only a negligible gap for choices between two risky options. Most studies on the description–experience gap involved choices between a safe and a risky option and reported the "original" gap. In our experiments, choices between two risky options made up the majority of the choice problems (90%); it is therefore not surprising that we did not find a description–experience gap in its "original" direction. Corroborating the importance of problem type, there was an "original" gap in our initial experiment, which included a smaller share of risky–risky problems (68%).

Glöckner et al. (2016) found that on a problem level, the effect of number of samples drawn and problem structure seemed to interact: With a higher (vs. lower) number of samples, the description–experience gap was reduced in risky–risky problems, but this effect was more pronounced in risky–safe problems. To test whether there was such an interaction in our experiments as well as the meta-analytic data set by Wulff et al. (2018), we analyzed the degree to which participants overweighted rare events in experience-based choices (as there is no sampling in the description conditions), as preregistered for Experiment 2. To that end, we regressed choice in line with overweighting of rare events on the numbers of samples drawn, the problem type, and their interaction (for details, see Supplemental Section S6). We also included the probability of the rarest event in the regression model and describe the motivation regarding its role and the full results in Supplemental Section S6. In all four data sets, the number of samples drawn interacted with

(*Appendices continue*)

Figure B2

Estimated Probability of Choosing in Line with Overweighting of Rare Events as a Function of Numbers of Samples Drawn and Problem Type



Note. Dashed lines represent estimated probabilities of the choices in line with overweighting in the description condition.

problem type (see Figure B2): In choices between a risky and a safe option, there was a substantial positive effect of number of samples drawn on the probability to choose in line with overweighting of rare events, but this effect was nonsignificant or slightly negative in choices between two risky options.

Figure B2 also illustrates that in risky–safe problems, overweighting in experience was less prevalent than in description when relatively few samples were drawn (in line with the "original" gap), but similar or more prevalent when relatively many samples were drawn (in line with the "reversed" gap). In risky–risky problems, overweighting in experience did not deviate strongly from that in description, independent of how many samples were drawn. This interaction further underscores that our results are in line with previous findings: In Experiment 1, which included mostly choices between two risky options and where participants drew a relatively large number of samples, we found more overweighting of rare events in experience than in description; in our initial experiment, which included a smaller proportion of choice problems with two risky options (and instead more choices between a safe and a risky option) and where participants sampled less extensively—as in many previous description–experience gap studies—there was less overweighting in experience than in description.

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