Supplemental Materials:

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

by

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S1 Initial Experiment

We conducted an initial experiment prior to Experiments 1 and 2 to explore choice and search behavior in the mixed-mode condition. In this initial experiment, we were primarily interested to examine to what extent people would maximize expected value (EV)/sample mean (SM) and how many samples people would draw in the mixed-mode condition. For consistency, we followed the same exclusion criteria, analyses, and modeling as in Experiment 1 and the preregistered Experiment 2, unless noted otherwise.

We decided to report this experiment here rather than in the main text for several reasons: First of all, one main goal of our paper was to study differences in subjective distortions of outcome and probability information between description- and experience-based learning modes. However, the initial experiment was primarily designed to provide insights into choice behavior. As a result, our set of choice problems was considerably smaller than that of Experiments 1 and 2 which makes CPT parameter estimation less reliable. Moreover, the choice problems of the pilot experiment were hand-picked, whereas the choice problems in Experiments 1 and 2 have 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). In addition, we only used problems in the gain domain, making it impossible to measure loss aversion. Second, because were mainly interested in choice behavior in the mixed-mode condition and the test whether allocation of the described option to the left or right side had an impact on choice behavior, we oversampled participants for the mixed-mode condition by a ratio of 2:1, leaving us with unequal group sizes. Although the total sample size was larger than those of Experiments 1 and 2, the group sizes of the description and experience conditions were smaller than in Experiments 1 and 2.

Method

A total of $N = 246$ participants (116 females, 130 males; $M_{\text{age}} = 36.6$ years; $SD_{\text{age}} = 11.5$ years; 45.1% bachelor's degree or more) recruited via Amazon Mechanical Turk each made 50 choices between two monetary gambles in one of three conditions. The design of the initial experiment was similar to that of Experiments 1 and 2. All choice problems involved options offering gains and were taken from a variety of sources. There were 38 target problems, eight problems consisting of choices between the identical option, and four attention-check problems. A table listing all choice problems can be found in Section S10 of the Supplemental Materials. In the *description* and the *experience* conditions, participants made purely experience- and description-based choices. In the *mixed-mode* condition, participants made choices between a described and an experienced option. We recruited twice as many participants for the mixed-mode condition (n = 122) than for the description (n = 57) and the experience (n = 67) condition. Following the choice task, participants filled out the same 7-item objective numeracy questionnaire as in Experiment 2. For one randomly selected choice problem the participant's chosen option was played out and the participant received the resulting outcome as a performance-contingent bonus (1 point = \$0.01; M = \$0.48, SD = \$0.24) in addition to their baseline compensation of \$3.00.

Results

Analogously to the preregistered Experiment 2, we analyzed and modeled the data of the 46 choice problems excluding the attention-check problems. Unless stated otherwise, the computational modeling and analyses were conducted in the same way as in Experiments 1 and 2 (for details, see main article and section S3 of the Supplemental Materials). We excluded 0.9% of the trials from the analysis because no outcomes were drawn from at least one option. Posterior predictive checks indicated that the estimated CPT model matched, on average, 72.6% of participants' choices.

Description–Experience Gap

Description and Experience Conditions. The proportion of choices in line with overweighting was greater in the description condition (M = .48, SD = .14) than in the experience condition (M = .43, SD = .11; b = −0.23, SE = 0.09, p = .011). Of the four gain-domain choice problems studied by Hertwig et al. (2004) which were used in this experiment, overweighting of rare events was descriptively more pronounced in description (vs. experience) in three problems, but less pronounced in one problem.

Mixed-Mode Condition. In the mixed-mode condition the proportion of choices consistent with overweighting of rare events did not differ between cases where the rarest event was included in the described (M = .47, SD = .16) or the experienced option (M = .46, SD = .17; b = 0.01, SE = 0.06, p = .919). An exploratory analysis showed that the overall level of overweighting (M = .47, SD = .12) was more pronounced than in the experience condition (b = −0.19, SE = 0.09, p = .031) but did not differ from that in the description condition (b = 0.08, SE = 0.09, p = .381).

Is There a Description-Experiment Gap in Distortion?

Description and Experience Conditions. The CPT parameter estimates are reported in Table S1. There was a credible difference between the two conditions for outcome sensitivity α and probability sensitivity γ: In the experience (vs. description) condition, outcome sensitivity α was higher and probability sensitivity γ was lower. There was no credible difference in choice sensitivity φ between conditions. Note that because we only used gain-domain choice problems, we did not estimate a loss aversion parameter λ.

Mixed-Mode Condition. The parameter estimates of the separate-representations model in the mixed-mode condition are reported in Table S2. There were no credible differences between the two options in terms of outcome sensitivity α and probability sensitivity γ. Model performance of that separate-representation CPT model was considerably lower than that of the simpler joint-representation model, DIC = 6358.1 versus 6490.8. The estimated parameters of the joint-representation CPT model applied to the mixed-mode condition are reported in Table S1. For all three parameters (i.e., α, γ, and φ) the group-level posterior means of the mixed-mode condition fell descriptively between those of the description and the experience conditions. In addition, in the mixed-mode condition outcome sensitivity (i.e., α parameter) was credibly different from that in the experience condition and probability sensitivity (i.e., γ parameter) was credibly different from that in the description condition.

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

There was no credible choice bias towards either the described or experienced option in the mixed-mode condition. The estimated β parameter did not credibly differ from 0 (group-level posterior mean = 0.08[−0.03–0.19]).

Table S1

Posterior Group-Level Mean Parameters of the CPT Model [95% HDI] (Initial Experiment)

Parameter	Description condition (n = 57)	Experience condition (n = 67)	Mixed-mode condition (n = 122)	Difference Descr. – Exp.	Difference Mixed – Descr.	Difference Mixed – Exp.
Outcome sensitivity α	0.70 [0.62–0.78]	0.93 [0.83–1.04]	0.76 [0.71–0.81]	**−0.23 [−0.37–−0.10]**	0.06 [−0.03–0.16]	**−0.17 [−0.29–−0.05]**
Probability sensitivity γ	1.14 [0.84–1.45]	0.71 [0.65–0.78]	0.78 [0.72–0.83]	**0.42 [0.11–0.74]**	**−0.36 [−0.68–−0.06]**	0.06 [−0.02–0.15]
Choice sensitivity φ	0.63 [0.37–0.92]	0.47 [0.27–0.69]	0.51 [0.39–0.64]	0.16 [−0.19–0.52]	−0.12 [−0.44–0.17]	0.04 [−0.22–0.28]

Note. Descr. = Description condition, Exp. = Experience condition, Mixed = Mixed-mode condition. Credible differences are printed in boldface.

Table S2

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

Parameter	Described option	Experienced option	Difference described – experienced option
Outcome sensitivity α	0.78 [0.73–0.84]	0.78 [0.73–0.83]	0.00 [−0.00–0.00]
Probability sensitivity γ	0.81 [0.74–0.88]	0.79 [0.74–0.86]	0.02 [−0.07–0.11]
Choice sensitivity φ	0.49 [0.35–0.63]		

Note. None of the differences between the parameters for the described and experienced option were credible.

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

Analogously to Experiments 1 and 2, we deviated from the preregistration of Experiment 2 by log-transforming the number of samples drawn per option (instead of using the raw values) because the raw values were not normally distributed. Further, in contrast to the preregistration we did not include the options' CV and the number of observed outcomes because they increased multicollinearity and are conceptually closely related to SD. Overall, participants drew fewer samples than in Experiments 1 and 2. The number of samples drawn per option (M = 17.9, SD = 10.7) was higher than in the experience condition (M = 11.0, SD = 7.8; $t(187)$ = 2.84, p = .003; one-sided test due to directional hypothesis).

Results on how search was influenced by properties of the choice problems are reported in Table S3. The number of samples drawn from an experienced option depended mostly on the context option's EV and SD, on the target option's EV and SD, and on the difference in EV between the options, irrespective of whether the context option was described (mixed-mode condition) or experienced (experience condition).

In sum, the results from the initial experiment largely replicate the findings of Experiments 1 and 2. When comparing the effects of the options' properties across experiments, however, note that the choice problems used in the initial experiment differed from those in Experiments 1 and 2 (e.g., there were only gain-domain problems in the initial experiment).

Maximization of EV and Sampled Mean (SM)

We also examined choice behavior in terms of maximization of EV and SM (for details on motivation and analysis, see Section S3 of the Supplemental Materials). The results showed that the proportion of choices in line with maximizing SM in the purely experience-based condition (M = .80; SD = .11) was higher than the proportion of choices in line with

Table S3

Effect of Context Option and Target Option Properties and of Choice Problem on Number of Samples Drawn From the Target Option (Initial Experiment)

Predictor	Mixed-mode condition (context option is described)	Experience condition (context option is experienced)
Intercept	2.522 [2.333–2.711]	2.064 [1.831–2.297]
$EV_{context}$	**-0.004 [-0.005–-0.002]**	**-0.002 [-0.003–-0.001]**
EV_{target}	**0.001 [0.000–0.002]**	−0.000 [-0.001–0.001]
$SD_{context}$	**0.005 [0.004–0.007]**	**0.004 [0.002–0.005]**
SD_{target}	**0.004 [0.003–0.006]**	**0.002 [0.001–0.003]**
Absolute EV difference between options	**-0.008 [-0.010–-0.007]**	**−0.009 [-0.010–-0.008]**
Absolute SD difference between options	**−0.004 [-0.006–-0.003]**	0.000 [-0.001–0.002]

Note. The context option described in the mixed-mode condition and experienced in the experience condition. context = context option, target = target option, EV = expected value, SD = standard deviation. Values in brackets are 95% confidence intervals. Results in boldface indicate significant predictors.

maximization of EV in the description-based condition (M = .58; SD = .10; t(122) = 11.70, p < .001). EV/SM maximization in the mixed-mode condition (M = .68; SD = .11) fell between that of purely description-and experience choices and was higher than in the description condition (b = −.10, SE = .02, p < .001) and lower than in the experience condition (b = .13, SE = .02, p < .001).

Numeracy

We further tested whether participants higher (vs. lower) in objective numeracy drew more samples (in the mixed-mode condition and the experience condition; for details on motivation, methods, and analysis, see Section S3 of the Supplemental Materials). Mean objective numeracy was 3.66 (range = 0–7; SD = 1.52). Participants with higher (vs. lower) numeracy drew more samples per option than those with lower numeracy (b = 0.27, SE = 0.08, p < .001). This association did not differ between conditions (interaction: b = −0.02, SE = 0.10, p = .842).

Further, we examined the correlations of individual-level posterior estimates of the CPT parameters with objective numeracy. Table S4 presents the bivariate correlations. In the description condition, outcome sensitivity α was positively associated with objective numeracy. In the experience condition, no CPT parameter was associated with objective numeracy. In the mixed-mode condition, outcome sensitivity α and choice sensitivity γ were positively associated with objective numeracy.

Table S4

Bivariate Pearson Correlations of Individual-Level Posterior Means of CPT Parameters and Objective Numeracy, Separately for Each Condition (Initial Experiment)

Parameter	r	p
Description condition		
Outcome sensitivity α	**.312**	**.018**
Probability sensitivity γ	−.174	.197
Choice sensitivity φ	.156	.248
Experience condition		
Outcome sensitivity α	−.087	.484
Probability sensitivity γ	−.075	.547
Choice sensitivity φ	−.079	.524
Mixed-mode condition		
Outcome sensitivity α	**.257**	**.004**
Probability sensitivity γ	−.046	.614
Choice sensitivity φ	**.229**	**.011**

Note. Results in boldface indicate significant correlations.

S2 Robustness Check: Results Based on Analysis Without Exclusion of Participants and Trials

In the analyses of the initial experiment, Experiment 1, and Experiment 2, we excluded participants based on the exclusion criteria which were stated in the preregistration of Experiment 2. This led to exclusions of participants who did not pass the attention check and/or did not draw at least one sample from at least one option in at least a quarter of the trials (for the number of participants excluded, see main text and Section S1 of the Supplemental Materials). To test the robustness of our results against these exclusions, we ran all analysis and modeling including all participants. Moreover, we also did not include the four attention-check choice problems in the analysis presented in the main text as one option in each of those choice problems was stochastically dominated. For the robustness check, we also included these attention-check trials. In the following, we present the results of the robustness check for each experiment.

Experiment 1

Description–Experience Gap

Description and Experience Conditions. The proportions of choices in line with overweighting of rare events was higher in the experience condition (M = .55, SD = .07) than in the description conditions (M = .49, SD = .07; b = 0.24, SE = 0.04, p < .001).

Mixed-Mode Condition. In the mixed-mode condition, the proportion of choices consistent with overweighting was lower when the rarest event was part of the described option (M = .51, SD = .10) compared to when it was part of the experienced option (M = .54, SD = .10; b = −0.11, SE = 0.05, p = .034). An exploratory analysis showed that the overall level of overweighting (M = .52, SD = .08) was less pronounced than in the experience condition (b = 0.11, SE = 0.05, p = .020) and more pronounced than in the description condition (b = −0.13, SE = 0.05, p = .007).

Is There a Description–Experience Gap in Distortion?

Description and Experience Conditions. The CPT parameter estimates are reported in Table S5. In the experience condition, outcome sensitivity α was higher, probability sensitivity γ was lower, loss aversion λ was higher, and choice sensitivity φ was lower than in the description condition.

Mixed-Mode Condition. The parameter estimates of the separate-representations model of CPT in the mixed-mode condition are reported in Table S6. The only credible difference in parameter values between the described and the experienced option was the difference in probability sensitivity γ, which was higher in the described option. Otherwise, there were no credible differences. Model performance of the separate-representations model of CPT was still considerably lower than that of the simpler joint-representation model, DIC = 8,445.1 versus 8,553.7, indicating a better model performance of the joint-representation model. The estimated parameters of the joint-representation CPT model applied to the mixed-mode condition are reported in Table S5. 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 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 value of the loss aversion parameter λ was not credibly different in the mixed-mode condition from that in either the description or the experience condition.

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

There was no choice bias towards 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 = 0.06[−0.04–0.15]).

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

The number of samples drawn per option (Md = 18, M = 21.3, SD = 12.2) was not higher than in the experience condition (Md = 13, M = 16.5, SD = 9.4; b = 0.22, SE = 0.12, p

= .062).

Results on how search was influenced by properties of the choice problems are reported in Table S7. 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 experience option was higher when the context option had a lower EV, a higher SD, and when two (vs. one) unique outcomes were observed. The number of samples drawn was also higher when the target itself option had a higher EV and only one (vs. two) outcome from the target option were drawn. Furthermore, the number of samples drawn was higher with smaller absolute difference between the options in EV (but not SD).

Table S5

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 [1.05−1.16]	1.01 [0.97−1.06]	**−0.31 [−0.38–−0.24]**	**0.21 [0.15–0.27]**	**−0.09 [−0.17–−0.02]**
Probability sensitivity γ	0.80 [0.74−0.87]	0.62 [0.58−0.65]	0.72 [0.67−0.77]	**0.19 [0.11–0.26]**	**−0.08 [−0.17–−0.00]**	**0.10 [0.04–0.17]**
Loss aversion λ	1.19 [1.07−1.31]	1.45 [1.22−1.68]	1.26 [1.12−1.40]	**−0.26 [−0.53–−0.01]**	0.07 [−0.11–0.25]	−0.20 [−0.45–0.09]
Choice sensitivity φ	0.21 [0.17−0.25]	0.05 [0.04−0.06]	0.08 [0.06−0.10]	**0.16 [0.12–0.21]**	**–0.13 [−0.18–−0.09]**	**0.03 [0.01–0.05]**
Experiment 2						
Outcome sensitivity α	0.85 [0.81−0.89]	1.25 [1.20−1.31]	1.03 [0.99−1.08]	**−0.41 [−0.48–−0.33]**	**0.19 [0.12–0.25]**	**−0.22 [−0.30–−0.15]**
Probability sensitivity γ	0.74 [0.68−0.81]	0.59 [0.53−0.64]	0.73 [0.66−0.81]	**0.16 [0.07–0.24]**	−0.01 [−0.12–0.09]	**0.15 [0.06–0.24]**
Loss aversion λ	1.09 [0.97−1.21]	1.13 [0.94−1.31]	1.04 [0.87−1.19]	−0.04 [−0.25–0.19]	−0.06 [−0.26–0.14]	−0.09 [−0.35–0.14]
Choice sensitivity φ	0.16 [0.13−0.20]	0.03 [0.02−0.04]	0.06 [0.05−0.08]	**0.13 [0.09–0.17]**	**−0.10 [−0.14–−0.06]**	**0.03 [0.01–0.05]**

Note. Descr. = Description condition, Exp. = Experience condition, Mixed = Mixed-mode condition. Credible differences are printed in boldface.

Table S6

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	1.01 [0.97−1.04]	1.01 [0.98−1.05]	−0.01 [−0.01–0.00]
Probability sensitivity γ	0.75 [0.69−0.81]	0.67 [0.63−0.71]	**0.08 [0.01–0.15]**
Loss aversion λ	1.25 [1.16−1.33]	1.26 [1.17−1.35]	−0.01 [−0.06−0.03]
Choice sensitivity φ	0.08 [0.06−0.10]		
Experiment 2			
Outcome sensitivity α	1.04 [0.99−1.09]	1.05 [1.00−1.10]	**−0.01 [−0.02–-0.00]**
Probability sensitivity γ	0.76 [0.67−0.85]	0.70 [0.63−0.77]	0.06 [−0.04–0.17]
Loss aversion λ	1.14 [1.06−1.22]	1.07 [0.99−1.17]	**0.06 [0.00–0.12]**
Choice sensitivity φ	0.06 [0.04−0.08]		

Note. Credible differences are printed in boldface.

Table S7

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

Predictor	Experiment 1: Mixed-mode condition (context option is described)	Experiment 1: Experience condition (context option is experienced)	Experiment 2: Mixed-mode condition (context option is described)	Experiment 2: Experience condition (context option is experienced)
Intercept	2.831 [2.663–2.999]	2.618 [2.476–2.760]	2.300 [2.074–2.526]	2.225 [2.096−2.353]
$EV_{context}$	**−0.002 [−0.002–−0.001]**	**−0.001 [−0.001–−0.001]**	**−0.002 [−0.002–−0.001]**	**−0.001 [−0.002–−0.001]**
EV_{target}	**0.001 [0.000–0.001]**	**0.001 [0.000−0.001]**	0.000 [−0.000–0.001]	−0.000 [−0.001–0.000]
Number of $outcomes_{context}$	−0.046 [−0.099–0.007]	**0.052 [0.026−0.078]**	0.012 [−0.041–0.065]	**0.150 [0.124–0.176]**
Number of $outcomes_{target}$	**0.114 [0.075–0.152]**	**−0.033 [−0.058–−0.007]**	**0.118 [0.081–0.155]**	**0.072 [0.047–0.097]**
$SD_{context}$	**0.002 [0.001–0.003]**	**0.002 [0.001–0.002]**	**0.002 [0.002–0.003]**	**0.001 [0.000–0.001]**
SD_{target}	−0.000 [−0.001–0.001]	0.000 [−0.000–0.001]	0.000 [−0.000–0.001]	**−0.001 [−0.001–−0.000]**
Absolute EV difference between options	**−0.007 [−0.008–−0.006]**	**−0.005 [−0.005–−0.004]**	**−0.008 [−0.009–−0.007]**	**−0.007 [−0.008–−0.007]**
Absolute SD difference between options	**−0.002 [−0.002–−0.001]**	0.000 [−0.000–0.001]	−0.001 [−0.002–0.000]	**0.003 [0.002–0.003]**

Note. The context option described in the mixed-mode condition and experienced in the experience condition. context = context option, target =

target option, EV = expected value, SD = standard deviation. Values in brackets are 95% confidence intervals. Results in boldface indicate significant predictors.

Experiment 2

Description–Experience Gap

Description and Experience Conditions. Choice behavior in line with overweighting did not differ between the experience (M = .55, SD = .08) and the description conditions (M = .53, SD = .08; b = 0.09, SE = 0.05, p = .082).

Mixed-Mode Condition. 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 = .53, SD = .10) or the experienced option (M = .52, SD = .11; b = 0.05, SE = 0.04, p = .312). An exploratory analysis showed that the overall level of overweighting (M = .53, SD = .07) did not differ from that in the experience condition (b = 0.09, SE = 0.05, p = .020) or description condition (b = 0.00, SE = 0.05, p = .007).

Is There a Description–Experience Gap in Distortion?

Description and Experience Conditions. The CPT parameter estimates are reported in Table S5. In the experience condition, outcome sensitivity α was higher, probability sensitivity γ was lower, and choice sensitivity φ was lower 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 S6. In the described option, outcome sensitivity α was credibly higher and loss aversion λ was credibly lower than in the experience option. There was no credible in probability sensitivity γ between the described and the experienced option. Model performance of the separate-representations model of CPT was still considerably lower than that of the simpler joint-representation model, DIC = 10,368.3 versus 10,627.8, indicating a better model performance of the joint-representation model. The estimated parameters of the joint-representation CPT model applied to the mixed-mode condition are reported in Table S5. 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 and the choice sensitivity parameter φ, the values in the mixed-mode condition fell between those of 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?

There was no choice bias towards 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 = −0.04[−0.14–0.06]).

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

The number of samples drawn per option (Md = 13, M = 16.9, SD = 13.6) was not higher than in the experience condition (Md = 10, M = 12.8, SD = 8.3; b = 0.07, SE = 0.18, p = .708).

Results on how search was influenced by properties of the choice problems are reported in Table S7. 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 two (vs. one) unique outcomes from the experienced option itself were observed. 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 observed. The number of samples drawn were also higher when the target experienced option itself had a lower SD and two (vs. one) unique outcomes were observed. Furthermore, the number of samples drawn was higher with smaller absolute difference between the options in

EV.

Initial Experiment

Description and Experience Conditions. Choice behavior in line with overweighting was less pronounced in the experience condition (*M* = .43, *SD* = .10) than in the description condition (*M* = .47, *SD* = .12; *b* = −0.19, *SE* = 0.08, *p* = .011).

Mixed-Mode Condition. 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* = .46, *SD* = .14) or the experienced option (*M* = .46, *SD* = .15; *b* = −0.02, *SE* = 0.05, *p* = .706). An exploratory analysis showed that the overall level of overweighting (*M* = .46, *SD* = .10) was higher than in the experience condition (*b* = −0.14, *SE* = 0.06, *p* = .019), but did not differ from that in the description condition (*b* = 0.05, *SE* = 0.06, *p* = .411).

Is There a Description–Experience Gap in Distortion?

Description and Experience Conditions. The CPT parameter estimates are reported in Table S8. In the experience condition, outcome sensitivity α was higher and probability sensitivity γ was lower. There was no credible difference in choice sensitivity φ.

Mixed-Mode Condition. The parameter estimates of the separate-representations model of CPT in the mixed-mode condition are reported in Table S9. There were no credible differences in any of the CPT parameter between the described and the experienced option. Further, model performance of the separate-representations model of CPT was considerably lower than that of the simpler joint-representation model, DIC = 7290.8 versus 7,459.0, indicating a better model performance of the joint-representation model. The estimated parameters of the joint-representation CPT model applied to the mixed-mode condition are reported in Table S8. 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 values in the mixed-mode condition fell between those of 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 credibly lower than in the description condition, but did not differ credibly from the experience condition.

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

There was no choice bias towards 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 = 0.04[−0.09–0.17]).

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

The number of samples drawn per option (*Md* = 12, *M* = 14.9, *SD* = 11.4) was not higher than in the experience condition (*Md* = 8, *M* = 10.2, *SD* = 8.3; *b* = 0.20[-0.20-0.59], *p* = .330).

Results on how search was influenced by properties of the choice problems are reported in Table S10. 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 and when two (vs. one) unique outcomes were observed. The number of samples drawn was also higher when the experienced option itself had a higher SD. 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 and when two (vs. one) unique outcomes were observed. The number of samples drawn were also higher when one (vs. two) unique outcomes were observed in the experienced option itself. Furthermore, the number of samples drawn was higher with smaller absolute difference between the options in EV.

Table S8

Posterior Group-Level Mean Parameters of the CPT Model [95% HDI] (Initial Experiment)

Parameter	Description condition	Experience condition	Mixed-mode condition	Difference Descr. – Exp.	Difference Mixed – Descr.	Difference Mixed – Exp.
Outcome sensitivity α	0.64 [0.55–0.73]	0.91 [0.83–1.00]	0.75 [0.70–0.81]	**−0.27 [−0.39–−0.14]**	**0.11 [0.00–0.22]**	**−0.16 [−0.26–−0.06]**
Probability sensitivity γ	1.06 [0.80–1.35]	0.71 [0.64–0.78]	0.78 [0.72–0.84]	**0.34 [0.07–0.64]**	**−0.28 [−0.57–−0.00]**	0.06 [−0.02–0.15]
Choice sensitivity φ	0.62 [0.31–0.95]	0.44 [0.27–0.63]	0.48 [0.35–0.60]	0.17 [−0.20–0.55]	−0.14 [−0.50–0.19]	0.03 [−0.21–0.24]

Note. Descr. = Description condition, Exp. = Experience condition, Mixed = Mixed-mode condition. Credible differences are printed in boldface.

Table S9

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

Parameter	Described option	Experienced option	Difference described – experienced option
Outcome sensitivity α	0.78 [0.73–0.83]	0.78 [0.73–0.83]	−0.00 [−0.01–0.00]
Probability sensitivity γ	0.82 [0.75–0.90]	0.79 [0.74–0.86]	0.03 [−0.06–0.12]
Choice sensitivity φ	0.44 [0.32–0.57]		

Note. None of the differences between the parameters for the described and experienced option were credible.

Table S10

Effect of Alternative Option and Target Option Properties and of Choice Problem on Number of Samples Drawn From the Target Option (Initial Experiment)

Predictor	Mixed-mode condition (context option is described)	Experience condition (context option is experienced)
Intercept	2.117 [1.914–2.320]	1.883 [1.646−2.120]
$EV_{context}$	**−0.003 [−0.004–−0.002]**	**−0.002 [−0.003–−0.001]**
EV_{target}	−0.000 [−0.001–0.001]	−0.001 [−0.001–0.000]
Number of $outcomes_{context}$	**0.082 [0.044–0.120]**	**0.118 [0.080–0.156]**
Number of $outcomes_{target}$	0.016 [−0.021–0.053]	**−0.061 [−0.099–−0.023]**
$SD_{context}$	**0.002 [0.000–0.004]**	−0.001 [−0.003–0.001]
SD_{target}	**0.002 [0.001–0.004]**	0.002 [−0.000–0.004]
Absolute EV difference between options	**−0.008 [−0.009–−0.007]**	**−0.009 [−0.010–−0.008]**
Absolute SD difference between options	**−0.003 [−0.005–−0.001]**	−0.001 [−0.003–0.000]

Note. The context option described in the mixed-mode condition and experienced in the experience condition. context = context option, target = target option, EV = expected value, SD = standard deviation. Values in brackets are 95% confidence intervals. Results in boldface indicate significant predictors.

S3 Choice Problems Used in Experiments 1 and 2

Table S11

Choice Problems Used in Experiments 1 and 2 and Choice Proportions in Each Condition

									Proportion choosing Option A							
									Experiment 1				Experiment 2			
	Option A				Option B						Mixed-Mode				Mixed-Mode	
ID	p1	o1	p2	o2	p1	o1	p2	o2	Des	Exp	A-des	A-exp	Des	Exp	A-des	A-exp
1	.34	24	.66	59	.42	47	.58	64	.27	.13	.19	.11	.13	.09	.06	.16
2	.88	79	.12	82	.20	57	.80	94	.41	.50	.50	.41	.40	.44	.35	.48
3	.74	62	.26	0	.44	23	.56	31	.51	.63	.72	.66	.52	.68	.62	.58
4	.05	56	.95	72	.95	68	.05	95	.48	.60	.45	.50	.51	.60	.56	.62
5	.25	84	.75	43	.43	7	.57	97	.74	.76	.58	.57	.72	.62	.74	.64
6	.28	7	.72	74	.71	55	.29	63	.37	.27	.36	.38	.29	.40	.32	.45
7	.09	56	.91	19	.76	13	.24	90	.37	.22	.29	.33	.31	.20	.31	.31
8	.63	41	.37	18	.98	56	.02	8	.12	.08	.10	.13	.20	.07	.07	.11
9	.88	72	.12	29	.39	67	.61	63	.52	.44	.5	.53	.53	.49	.44	.67
10	.61	37	.39	50	.60	6	.40	45	.93	.99	.94	.91	.94	.94	.90	.92
11	.08	54	.92	31	.15	44	.85	29	.85	.69	.77	.62	.85	.81	.68	.85
12	.92	63	.08	5	.63	43	.37	53	.58	.68	.6	.67	.65	.62	.51	.69
13	.78	32	.22	99	.32	39	.68	56	.44	.63	.51	.58	.49	.65	.48	.62
14	.16	66	.84	23	.79	15	.21	29	.96	.92	.91	.94	.95	.92	.90	.97
15	.12	52	.88	73	.98	92	.02	19	.21	.13	.03	.06	.18	.12	.09	.21
16	.29	88	.71	78	.29	53	.71	91	.51	.69	.66	.70	.53	.59	.61	.65
17	.31	39	.69	51	.84	16	.16	91	.89	.77	.76	.85	.82	.71	.80	.97
18	.17	70	.83	65	.35	100	.65	50	.51	.41	.37	.48	.46	.32	.37	.58
19	.91	80	.09	19	.64	37	.36	65	.82	.85	.90	.85	.87	.89	.83	.86
20	.09	83	.91	67	.48	77	.52	6	.96	.91	.88	.94	.92	.81	.86	.98
21	.44	14	.56	72	.21	9	.79	31	.79	.90	.91	.91	.86	.87	.94	.86
22	.68	41	.32	65	.85	100	.15	2	.16	.26	.16	.06	.27	.21	.12	.38
23	.38	40	.62	55	.14	26	.86	96	.08	.12	.16	.07	.25	.11	.17	.10
24	.62	1	.38	83	.41	37	.59	24	.14	.37	.32	.39	.15	.52	.27	.21
25	.49	15	.51	50	.94	64	.06	14	.10	.06	.06	.03	.14	.00	.11	.09
26	.05	60	.95	76	.84	95	.16	17	.66	.47	.50	.43	.52	.47	.52	.55
27	.73	75	.27	34	.90	56	.10	82	.32	.40	.42	.53	.40	.46	.35	.61
28	.16	-15	.84	-67	.72	-56	.28	-83	.74	.73	.62	.65	.72	.79	.69	.62
29	.13	-19	.87	-56	.70	-32	.30	-37	.07	.14	.03	.03	.13	.14	.05	.21
30	.29	-67	.71	-28	.05	-46	.95	-44	.64	.45	.80	.68	.72	.67	.71	.60
31	.82	-40	.18	-90	.17	-46	.83	-64	.59	.58	.62	.56	.55	.55	.74	.56
32	.29	-25	.71	-86	.76	-38	.24	-99	.36	.64	.63	.34	.45	.62	.36	.40

33	.60	-46	.40	-21	.42	-99	.58	-37	.82	.95	.94	1	.93	.99	.81	.97
34	.48	-15	.52	-91	.28	-48	.72	-74	.52	.51	.58	.56	.46	.64	.66	.50
35	.53	-93	.47	-26	.80	-52	.20	-93	.44	.60	.82	.47	.31	.76	.59	.54
36	.49	-1	.51	-54	.77	-33	.23	-30	.59	.47	.65	.50	.54	.64	.69	.58
37	.99	-24	.01	-13	.44	-15	.56	-62	.84	.83	.90	.86	.93	.75	.80	.88
38	.79	-67	.21	-37	.46	0	.54	-97	.37	.47	.55	.47	.55	.56	.49	.57
39	.56	-58	.44	-80	.86	-58	.14	-97	.47	.56	.54	.59	.47	.58	.58	.52
40	.63	-96	.37	-38	.17	-12	.83	-69	.19	.12	.09	.25	.08	.13	.09	.20
41	.59	-55	.41	-77	.47	-30	.53	-61	.12	.09	.06	.06	.09	.07	.19	.05
42	.13	-29	.87	-76	.55	-100	.45	-28	.75	.81	.77	.67	.76	.64	.81	.73
43	.84	-57	.16	-90	.25	-63	.75	-30	.10	.03	.06	.08	.05	.07	.10	.13
44	.86	-29	.14	-30	.26	-17	.74	-43	.81	.78	.83	.84	.81	.66	.79	.97
45	.66	-8	.34	-95	.93	-42	.07	-30	.55	.33	.71	.49	.49	.41	.61	.33
46	.39	-35	.61	-72	.76	-57	.24	-28	.11	.12	.14	.17	.08	.16	.15	.25
47	.51	-26	.49	-76	.77	-48	.23	-34	.32	.22	.38	.33	.29	.28	.29	.32
48	.73	-73	.27	-54	.17	-42	.83	-70	.30	.26	.26	.38	.28	.31	.29	.31
49	.49	-66	.51	-92	.78	-97	.22	-34	.62	.49	.61	.46	.66	.53	.64	.57
50	.56	-9	.44	-56	.64	-15	.36	-80	.73	.83	.72	.66	.81	.89	.78	.71
51	.96	-61	.04	-56	.34	-7	.66	-63	.21	.19	.10	.26	.15	.08	.20	.26
52	.25	-94	.75	-37	.83	-49	.17	-11	.19	.21	.17	.27	.20	.15	.20	.32
53	.93	-55	.07	-17	.27	-88	.73	-35	.44	.63	.58	.35	.53	.64	.50	.50
54	.56	-4	.44	-80	.04	-46	.96	-58	.74	.69	.80	.67	.69	.74	.77	.54
55	.43	-91	.57	63	.27	-83	.73	24	.44	.37	.50	.26	.45	.47	.62	.52
56	.06	-82	.94	54	.91	38	.09	-73	.92	.78	.68	.72	.82	.82	.64	.77
57	.79	-70	.21	98	.65	-85	.35	93	.49	.68	.42	.63	.45	.65	.47	.42
58	.37	-8	.63	52	.87	23	.13	-39	.81	.78	.78	.77	.84	.78	.77	.83
59	.61	96	.39	-67	.50	71	.50	-26	.52	.35	.54	.43	.48	.42	.49	.51
60	.43	-47	.57	63	.02	-69	.98	14	.32	.35	.35	.40	.35	.46	.42	.60
61	.39	-70	.61	19	.30	8	.70	-37	.64	.29	.62	.42	.62	.39	.59	.33
62	.59	-100	.41	81	.47	-73	.53	15	.23	.42	.52	.29	.40	.52	.51	.35
63	.92	-73	.08	96	.11	16	.89	-48	.21	.23	.23	.24	.25	.33	.12	.42
64	.89	-31	.11	27	.36	26	.64	-48	.38	.6	.54	.52	.52	.60	.61	.60
65	.86	-39	.14	83	.80	8	.20	-88	.44	.65	.69	.38	.42	.60	.49	.51
66	.74	77	.26	-23	.67	75	.33	-7	.44	.27	.28	.41	.35	.29	.26	.29
67	.91	-33	.09	28	.27	9	.73	-67	.84	.86	.83	.87	.78	.88	.84	.91
68	.93	75	.07	-90	.87	96	.13	-89	.44	.49	.29	.43	.42	.38	.39	.48
69	.99	67	.01	-3	.68	74	.32	-2	.86	.82	.62	.9	.87	.66	.55	.71
70	.48	58	.52	-5	.40	-40	.60	96	.45	.49	.59	.50	.51	.47	.54	.49
71	.07	-55	.93	95	.48	-13	.52	99	.82	.69	.64	.86	.69	.58	.64	.67
72	.97	-51	.03	30	.68	-89	.32	46	.29	.55	.48	.46	.34	.44	.61	.28
73	.86	-26	.14	82	.60	-39	.40	31	.38	.63	.45	.54	.46	.68	.58	.55
74	.88	-90	.12	88	.80	-86	.20	14	.62	.45	.57	.48	.55	.54	.50	.53
75	.87	-78	.13	45	.88	-69	.12	83	.07	.23	.38	.11	.16	.15	.26	.23
76	.96	17	.04	-48	.49	-60	.51	84	.73	.68	.65	.71	.60	.54	.56	.62

77	.38	-49	.62	2	.22	19	.78	-18	.41	.14	.19	.19	.20	.18	.32	.28
78	.28	-59	.72	96	.04	-4	.96	63	.19	.24	.30	.39	.21	.35	.39	.28
79	.50	98	.5	-24	.14	-76	.86	46	.62	.63	.59	.74	.72	.72	.67	.56
80	.18	-19	.82	73	.94	58	.06	-54	.73	.58	.51	.69	.60	.67	.59	.79
81	.39	76	.61	-7	.06	-65	.94	37	.32	.47	.51	.42	.52	.53	.29	.57
82	.50	-20	.50	60	1	0			.79	.65	.79	.67	.74	.60	.81	.73
83	.50	-30	.50	60	1	0			.63	.54	.79	.50	.65	.55	.73	.65
84	.50	-40	.50	60	1	0			.49	.47	.59	.48	.56	.54	.61	.55
85	.50	-50	.50	60	1	0			.49	.38	.50	.48	.55	.45	.66	.49
86	.50	-60	.50	60	1	0			.44	.44	.50	.56	.46	.45	.52	.43
87	.50	-70	.50	60	1	0			.27	.21	.27	.23	.35	.35	.44	.38
88	.10	40	.90	32	.10	77	.90	2	.96	.81	.94	.94	.95	.85	.86	.98
89	.20	40	.80	32	.20	77	.80	2	.88	.79	.74	.91	.89	.75	.77	.89
90	.30	40	.70	32	.30	77	.70	2	.84	.74	.75	.83	.88	.71	.79	.81
91	.40	40	.60	32	.40	77	.60	2	.79	.67	.77	.67	.85	.61	.73	.78
92	.50	40	.50	32	.50	77	.50	2	.68	.65	.80	.63	.71	.59	.71	.75
93	.60	40	.40	32	.60	77	.40	2	.58	.65	.70	.37	.64	.53	.59	.57
94	.70	40	.30	32	.70	77	.30	2	.41	.55	.37	.36	.58	.42	.45	.34
95	.80	40	.20	32	.80	77	.20	2	.30	.36	.36	.16	.27	.29	.27	.27
96	.90	40	.10	32	.90	77	.10	2	.21	.26	.24	.1	.21	.21	.18	.22
97	1	40			1	77			.01	.00	.04	.02	.00	.00	.02	.03
98	.80	4	.20	0	1	3			.37	.35	.41	.44	.26	.49	.33	.38
99	.20	4	.80	0	.25	3	.75	0	.51	.68	.68	.64	.51	.86	.74	.50
100	1	-3			.10	-32	.90	0	.47	.58	.37	.59	.71	.48	.56	.64
101	1	-3			.80	-4	.20	0	.3	.42	.37	.43	.40	.36	.36	.57
102	.10	32	.90	0	1	3			.37	.51	.71	.30	.51	.48	.53	.43
103	.03	32	.97	0	.25	3	.75	0	.34	.42	.76	.29	.62	.32	.73	.35
104	.10	20	.90	0	.10	20	.90	0			.53	.24			.58	.36
105	.20	20	.80	0	.20	20	.80	0			.47	.38			.48	.43
106	.50	20	.50	0	.50	20	.50	0			.53	.29			.48	.32
107	.80	20	.20	0	.80	20	.20	0			.58	.26			.48	.40
108	.90	20	.10	0	.90	20	.10	0			.66	.47			.39	.34
109	.80	91	.20	63	.60	15	.40	22	.99	1	1	.96	.98	1	1	.97
110	.45	57	.55	63	.70	23	.30	12	.97	.99	1	.97	.96	1	1	1
111	.61	-24	.39	-19	.48	-78	.52	-59	.96	.99	1	1	.99	.99	1	1
112	.60	-3	.40	-22	.37	-50	.63	-60	1	1	1	.92	.98	.99	.95	.95

Note. Descr = Description condition, Exp = Experience condition, A-des = Mixed-mode condition with described Option A, A-exp = Mixed-mode condition with experieneced Option A. Choice problems taken from Rieskamp (2008; IDs 1–81); Gächter et al. (2007; IDs 82–87); Holt & Laury (2002; IDs 88–97); Hertwig et al. (2004; IDs 98–103); and Ert & Trautmann (2014; IDs 104–108). Attention-check problems (IDs 109–112) were developed by the authors. For choice problems 104–108, no choice proportions are reported in the description and experience conditions because options were identical.

S4 Additional Analyses for Experiment 1

In this section, we present further analyses of the data of Experiment 1. We report results on maximization of EV/sampled mean (SM) across conditions and the role of numeric abilities in choice and search behavior in the mixed-mode condition.

Maximization of EV/SM

A meta-analysis comparing purely description- and purely experienced-based choices has found that EV/SM maximization is higher in experienced-based choices than in description-based choices (Wulff et al., 2018). This effect can at least partly be attributed to the choice amplification, the amplification of the differences between the options' SM when fewer samples are drawn (Hertwig & Pleskac, 2010). To test whether the choice amplification effect also occurred in our experiment, we computed the ratio between the larger absolute EV/SM and the smaller absolute EV/SM for each choice problem as an indicator of difficulty (cf. Brandstätter et al., 2006, 2008), based on the actually experienced information. As expected, in the expectation condition choices were on average easier ($M_{\text{SMratio}} = 1.99$; $SD_{\text{SMratio}} = 0.59$) than in the description condition ($M_{\text{EVratio}} = 1.34$; $SD_{\text{EVratio}} = 0.00$; because choice problems were presented descriptively, there was no variation in EV ratio in this condition). In the mixed-mode condition, EV/SM ratio fell between that of the description and the experience conditions ($M_{\text{EV/SMratio}} = 1.59$; $SD_{\text{EV/SMratio}} = 0.33$). All comparisons between conditions were significant (ps < .001).

Next, we examined how often participants chose the option with the higher EV or SM—thus deciding in line with EV/SM maximization—in the different conditions. In the experienced and the mixed-mode conditions, the SM of the experienced options was calculated as the mean of the sampled outcomes (as in e.g., Wulff et al., 2018). In this analysis, we excluded trials in which EVs/SMs were the same for both options (2.6% of trials). The results showed that when participants chose between two experienced options, they chose the option with the higher SM more often than participants chose the option with the higher EV when choosing between two described options ($M_{\text{experience}}$ = .70, $SD_{\text{experience}}$ = .08 vs. $M_{\text{description}}$ = .65, $SD_{\text{description}}$ = .07; $t(149) = 4.03$, $p < .001$). Next, we compared EV/SM maximization of the mixed-mode condition ($M_{\text{mixed-mode}}$ = .70, $SD_{\text{mixed-mode}}$ = .08) with EV and SM maximization of the description and experience conditions. For that purpose, we conducted a linear regression with two condition dummy variables as predictors (first variable coded as 0 = mixed, 1 = description; second variable coded as 0 = mixed, 1 = experience) and proportion of choices in line with EV/SM maximization as dependent variable. Participants in the mixed-mode condition chose the option with the higher EV/SM significantly more often than in the description condition ($b = -.04$, $SE = .01$, $p < .001$), but not more or less often than in the experience condition ($b = .00$, $SE = .01$, $p = .706$).

These results replicate previous findings on differences between description- and experience-based choices (Wulff et al., 2018) and suggest that decision quality in the mixed-mode condition is comparable to that in the experience condition. However, this finding is difficult to reconcile with the amplification effect (Hertwig & Pleskac, 2010). As sample size per option was higher in the mixed-mode condition than in the experience condition and thus choices become more difficult, an amplification effect should lead to even worse choices in the mixed-mode condition than in the experience condition. Nevertheless, our findings suggest that information integration in the mixed-mode condition does not incur particularly high cognitive costs, but instead that including an experienced option in a choice set even improves decision quality in comparison to purely description-based choices.

The Role of Numeracy

In the following, we study the role of numeracy in choice and search behavior.

Objective and Subjective Numeracy and Sample Size

People with higher objective numeracy (the ability to use probabilistic and mathematical concepts; Peters et al., 2006) have been shown to draw more samples in purely experience-based choices than people with lower numeracy (Ashby, 2017; Lejarraga, 2010;

Traczyk et al., 2018). We tested whether this effect holds in the mixed-mode condition with only one experienced option. In addition, we examined also the role of subjective numeracy, a combination of numeric confidence and preferences for numbers (Fagerlin et al., 2007). All previous studies on the effect of numeracy on the number of samples drawn—including our initial experiment—only measured the actual numeric abilities (i.e., objective numeracy; Ashby, 2017; Lejarraga, 2010; Traczyk et al., 2018), and it is therefore unclear whether these objective abilities or instead people's numeric confidence and subjective preferences for numbers are responsible for that effect. Subjective numeracy has been shown to correlate with objective numeracy but explains unique variance (Nelson et al., 2013; Peters & Bjalkebring, 2015; Peters et al., 2019). Because in the sampling paradigm participants can choose how much information they want to gather, it is possible that sample size rather depends on a person's subjective numerical abilities and the preference for numbers (i.e., subjective numeracy) rather than her objective numeracy. To examine this possibility, participants were asked to fill out the German translation of the subjective numeracy scale (Fagerlin et al., 2007) before starting the choice task. This 7-item measure asked people to rate their numerical abilities and their preference for numbers on a 6-point scale (Cronbach's α = .76; one item of the original 8-item scale was not used because it was specific to the US; see Galesic & Garcia-Retamero, 2010). Objective numeracy was assessed after the choice task using the German translation of a 7-item questionnaire that combined the measures by Schwartz et al. (1997) and a variation of the Berlin Numeracy Test (Cokely et al., 2012).

To test the effect of objective and subjective numeracy on sample size per option, we ran a negative binomial generalized multilevel with number of samples drawn per option as the dependent variable (in the experience condition, this was the mean sample size across both options). The independent variables were objective numeracy, subjective numeracy (both mean-centered), condition (dummy-coded as 0 = experience condition, 1 = mixed-mode condition), and their interactions.

Mean objective numeracy was 4.34 (*SD* = 1.50) and mean subjective numeracy was 4.10 (*SD* = 0.83). The results showed that participants sampled more outcomes per option in the mixed-mode condition than in the experience condition (b = 0.31, *SE* = 0.12, p = .007). However, neither objective numeracy (b = 0.05, *SE* = 0.05, p = .331) nor subjective numeracy (b = 0.02, *SE* = 0.09, p = .824) affected sample size. There were no significant interactions.

Our study thus did not replicate the finding that people higher (vs. lower) in objective numeracy draw more samples (Ashby, 2017; Lejarraga, 2010; Traczyk et al., 2018). Possibly, our participant sample (mainly undergraduate students) was too homogeneous with regard to level of education and thus numeracy to detect effects of objective or subjective numeracy.

Numeracy and CPT Parameters

Previous studies have found objective numeracy to be related to some of CPT's parameters. Specifically, people with higher (vs. lower) numeracy have been found to be more sensitive to outcomes and probabilities (Pachur et al., 2017, 2018; Patalano et al., 2015; Schley & Peters, 2014), although these relations were not consistent across studies. Further, three studies which also examined a possible link of numeracy with loss aversion did not find a significant correlation (Pachur et al., 2017, 2018; Schley & Peters, 2014). Finally, Pachur et al. (2017) reported numeracy to be positively related to choice sensitivity, with people with higher (vs. lower) numeracy choosing less noisily.

Table S12 presents for Experiment 1 the bivariate correlations of individual-level posterior estimates of the individual-level CPT parameters with objective and subjective numeracy. The associations between numeracy and CPT parameters differed between conditions. In the description condition, objectively numeracy was positively related to outcome sensitivity α and probability sensitivity γ. In the experience condition, objective numeracy was positively associated with choice sensitivity φ. In the mixed-mode condition, objective numeracy was positively associated with loss aversion λ. No CPT parameter was significantly associated with subjective numeracy.

Table S12

Bivariate Pearson Correlations of Individual-Level Posterior Means of CPT Parameters and Objective and Subjective Numeracy, Separately for Each Condition (Experiment 1)

	Objective Numeracy		Subjective Numeracy	
	r	*p*	*r*	*p*
Description condition				
Outcome sensitivity α	**.234**	**.046**	.078	.511
Probability sensitivity γ	**.248**	**.035**	.154	.194
Loss aversion λ	.153	.196	.084	.480
Choice sensitivity φ	.195	.098	.178	.133
Experience condition				
Outcome sensitivity α	.141	.218	.086	.453
Probability sensitivity γ	.010	.934	-.050	.666
Loss aversion λ	.163	.155	.096	.401
Choice sensitivity φ	**.276**	**.015**	.221	.052
Mixed-mode condition				
Outcome sensitivity α	.118	.337	.076	.536
Probability sensitivity γ	−.092	.456	−.018	.882
Loss aversion λ	**.301**	**.011**	−.030	.811
Choice sensitivity φ	.044	.725	.053	.671

Note. Results in boldface indicate significant correlations.

Parameter and Model Recovery Analysis

We tested whether the separate-representations CPT model, which allowed for separate parameter sets for the experienced and described option in the mixed-mode condition, could reliably capture differences in participants' subjective distortions of outcomes and probabilities between options. The goal was to examine whether the estimated parameter values of that model, which in the analyses of the empirical data did not credibly differ between options, might be the result of limited parameter recoverability of that model variant. We first conducted a parameter recovery analysis in which we tested whether parameter values that objectively differed between options and were used to simulate choices could be recovered. In addition, we conducted a model recovery analysis to test whether the separate-representations CPT model would perform better than the joint-representation CPT model when applied to the choice data that were generated using parameter values that differed between options.

For the parameter recovery analysis, we tested whether we could detect differences in CPT parameter estimates between the described option and the experienced option if participants in the mixed-mode condition were subjectively distorting the outcomes and probabilities of the described and the experienced options to the same degree as the participants in the description and the experience conditions, respectively (for parameter values, see Table 1 in the main text). Note that the values of almost all CPT parameters estimated in Experiments 1 and 2 credibly differed between the description and the experience conditions (except for loss aversion in Experiment 2) and thus we would also expect credible differences between options in our parameter recovery.

Specifically, we created 68 (the number of participants in the mixed-mode condition of Experiment 1) synthetic participants in the mixed-mode condition. To that end, we drew individual-level parameter estimates (i.e., the means of the individual-level posterior distributions) of 68 randomly selected participants from the purely description-based condition of Experiment 1 (as the parameter values for the described option); and we did the same for 68 randomly selected participants from the purely experience-based condition of Experiment 1 (as the parameter values for the experienced condition). Using these parameters, for the choice problems of the mixed-mode condition (i.e., based on the actually experienced information in Experiment 1) we next generated choices for these 68 synthetic participants using the separate-representations CPT model. For the choice sensitivity parameter φ, we used the values of participants in the description condition.[1] Finally, we applied the separate-

[1] When using the φ values of participants in the experience condition (which were lower than in the description condition), choices became noisier and, as expected, parameter estimates became less accurate. However, the overall pattern of results was similar to that when using φ values of the description condition.

representations CPT model to the synthetic data and estimated the parameters. We repeated the approach to create 100 synthetic experiments.

We next analyzed in how many of the 100 synthetic experiments the recovered group-level parameter values indicated credible differences in CPT parameters between the described and the experienced option. For outcome sensitivity α, parameter values differed credibly between options in all 100 synthetic experiments. For probability sensitivity γ, parameter values differed credibly between options in 78 out of the 100 synthetic experiments. For loss aversion λ, parameter values differed credibly between options in 96 out of the 100 synthetic experiments.

For the model recovery analysis, we applied both the separate-representations CPT model and the joint-representation CPT model to the simulated data and tested whether the separate-representations model would outperform the latter in terms of DIC. The DIC of the separate-representations model was considerably lower (i.e., difference > 10; indicating better model performance) than the joint-representation model in all 100 synthetic experiments.

Overall, the results of our parameter and model recovery analysis demonstrate that the separate-representations variant of the CPT model would in principle be able to capture differences in subjective distortions of outcomes and probabilities between options and that it performs better than the joint-representation model if the generated data is based on different subjective distortions between options.

S5 Results of Preregistered Analysis

For the analyses with regard to the number of samples drawn, we deviated from the preregistration for different reasons. First, because the number of samples drawn did not follow a normal distribution but closely followed a negative binomial distribution, we ran negative binomial generalized multilevel models (instead of preregistered t-test and linear multilevel models). Second, in the analysis on how the number of samples drawn depends on the properties of the choice problems, we found that including all preregistered predictors caused serious issues of multicollinearity (for VIF values, see Table S13). Therefore, we excluded the options' coefficient of variance (CV) as well as the absolute difference between the options in CV from the models. Third, we included also trials in which no samples were drawn from an option instead of excluding them as preregistered. For transparency, in the following we present the results of the preregistered analysis.

Experiment 1

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

The number of samples drawn per option (*Md* = 19, *M* = 22.2, *SD* = 12.2) was significantly higher than in the experience condition (*Md* = 13, *M* = 16.5, *SD* = 8.1; $t(114.8) = 3.36$, $p = .001$).

The results on the number of samples drawn as a function of the properties of the choice problem are presented in Table S14.

Experiment 2

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

The number of samples drawn per option (*Md* = 15, *M* = 19.3, *SD* = 13.4) was significantly higher than in the experience condition (*Md* = 10, *M* = 13.2, *SD* = 7.8; $t(121.0) = 3.51$, $p < .001$).

The results on the number of samples drawn as a function of the properties of the choice problem are presented in Table S14.

Initial Experiment

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

The number of samples drawn per option (Md = 15, M = 17.3, SD = 10.5) was significantly higher than in the experience condition (Md = 9, M = 10.6, SD = 7.6; $t(173.3) = 5.06$, $p < .001$).

The results on the number of samples drawn as a function of the properties of the choice problem are presented in Table S15.

Table S13

Variance Inflation Factor (VIF) Values of Predictors in Preregistered Model and Model as Presented in the Paper

	Experiment 1				Experiment 2				Initial experiment			
	Mixed-mode		Experience		Mixed-mode		Experience		Mixed-mode		Experience	
Predictor	pre reg.	final	pre reg.	final	pre reg.	final	pre reg.	final	pre reg.	final	pre reg.	final
$EV_{context}$	7.74	8.82	5.63	6.40	6.51	8.09	4.54	5.48	6.12	3.23	3.60	2.73
EV_{target}	7.83	8.90	5.64	6.41	5.60	8.19	4.54	5.48	6.08	3.27	3.60	2.75
Number of $\text{outcomes}_{context}$	1.17	1.16	1.44	1.44	1.17	1.16	1.52	1.50	1.56	1.49	1.97	1.97
Number of outcomes_{target}	1.43	1.38	4.44	1.43	1.46	1.43	1.52	1.50	1.96	1.93	1.97	2.02
$SD_{context}$	1.69	1.42	1.91	1.62	1.77	1.44	1.87	1.70	2.90	2.02	3.03	2.48
SD_{target}	1.64	1.47	1.91	1.60	1.68	1.51	1.87	1.68	2.93	2.32	3.03	2.52
$CV_{context}$	4.73	-	92.77	-	6.79	-	40.58	-	3.92	-	2.28	-
CV_{target}	50.90	-	92.77	-	20.54	-	50.58	-	2.16	-	2.28	-
Absolute EV difference between options	1.09	1.07	1.10	1.09	1.08	1.07	1.10	1.10	1.17	1.06	1.07	1.07
Absolute SD difference between options	1.61	1.40	1.62	1.44	1.69	1.45	1.52	1.39	3.39	1.82	3.01	1.76
Absolute CV difference between options	55.34	-	183. 41	-	26.71	-	80.41	-	5.43	-	3.09	-

Note. The context option described in the mixed-mode condition and experienced in the experience condition. prereg. = model as preregistered, final = final model as reported in the paper, context = context option, target = target option, EV = expected value, SD = standard deviation, CV = coefficient of variance.

Table S14

Effect of Alternative Option and Target Option Properties and of Choice Problem on Number of Samples Drawn From the Target Option (As Preregistered)

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	22.21 [19.31−25.12]	16.52 [12.92−17.21]	18.39 [15.18−21.61]	13.14 [12.92−17.21]
$EV_{context}$	**−0.05 [−0.07–−0.03]**	**−0.02 [−0.03–−0.01]**	**−0.05 [−0.06–−0.03]**	**−0.01 [−0.02–−0.01]**
EV_{target}	0.02 [0.00–0.04]	0.01 [−0.00–0.02]	**0.02 [0.01–0.04]**	−0.00 [−0.01–0.00]
Number of $outcomes_{context}$	−0.44 [−1.88–1.00]	0.28 [−0.30–0.85]	1.06 [−0.24–2.37]	**1.02 [0.56–1.48]**
Number of $outcomes_{target}$	**1.09 [0.00–2.17]**	**−1.03 [−1.60–−0.46]**	−0.04 [−0.99–0.92]	−0.43 [−0.89–0.03]
$SD_{context}$	**0.05 [0.03–0.07]**	**0.02 [0.01–0.03]**	**0.04 [0.02–0.06]**	**0.02 [0.01–0.03]**
SD_{target}	0.01 [−0.02–0.03]	0.01 [−0.01–0.02]	**0.02 [0.00–0.04]**	−0.00 [−0.01–0.01]
$CV_{context}$	−0.06 [−0.22–0.10]	0.11 [−0.02–0.23]	0.11 [−0.05–0.27]	0.02 [−0.06–0.10]
CVtarget	0.04 [−0.12–0.20]	0.11 [−0.01–0.23]	0.05 [−0.10–0.21]	0.01 [−0.07–0.09]

Absolute EV difference between options	**−0.11 [−0.13–−0.08]**	**−0.05 [−0.06–−0.03]**	**−0.09 [−0.12–−0.07]**	**−0.06 [−0.07–−0.05]**
Absolute SD difference between options	**−0.04 [−0.06–−0.02]**	−0.01 [-0.02–0.00]	**−0.02 [−0.05–−0.00]**	**0.02 [0.01–0.03]**
Absolute CV difference between options	−0.04 [−0.21–0.12]	−0.11 [−0.24–0.01]	−0.06 [−0.22–0.10]	−0.01 [−0.10–0.07]

Note. The context option described in the mixed-mode condition and experienced in the experience condition. context = context option, target = target option, EV = expected value, SD = standard deviation, CV = coefficient of variance. Values in brackets are 95% confidence intervals. Results in boldface indicate significant predictors.

Table S15

Effect of Context Option and Target Option Properties and of Choice Problem on Number of Samples Drawn From the Target Option (Initial Experiment; as Preregistered)

Predictor	Mixed-mode condition (context option is described)	Experience condition (context option is experienced)
Intercept	15.06 [12.92−17.21]	10.65 [8.95−12.36]
$EV_{context}$	**−0.06 [−0.09–−0.03]**	−0.00 [−0.02–0.01]
EV_{target}	**0.05 [0.02–0.08]**	0.01 [−0.01–0.02]
Number of $\text{outcomes}_{context}$	**3.14 [2.07–4.20]**	**1.65 [1.04–2.27]**
Number of outcomes_{target}	−0.50 [−1.53–0.54]	**−0.87 [−1.49–−0.26]**
$SD_{context}$	**0.06 [0.01–0.12]**	−0.01 [−0.04–0.02]
SD_{target}	0.02 [−0.04–0.07]	0.03 [−0.01–0.06]
$CV_{context}$	**−1.17 [−1.91–−0.44]**	0.09 [−0.41–0.59]
CV_{target}	**2.20 [1.48–2.92]**	0.22 [−0.28–0.71]
Absolute EV difference between options	**−0.12 [−0.15–−0.08]**	**−0.05 [−0.07–−0.03]**
Absolute SD difference between options	**−0.08 [−0.14–−0.02]**	**−0.04 [−0.08–−0.01]**
Absolute CV difference between options	**2.24 [1.34–3.15]**	**1.99 [1.44–2.55]**

Note. The context option described in the mixed-mode condition and experienced in the experience condition. context = context option, target = target option, EV = expected value, SD = standard deviation, CV = coefficient of variation. Values in brackets are 95% confidence intervals. Results in boldface indicate significant predictors.

S6 Details of Analysis Presented in Appendix B

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

Number of Samples Drawn. To examine whether the mean size of the description–experience gap across studies depends on the mean sample size across studies, we analyzed all 17 datasets in the database compiled by Wulff et al. (2018) which had both a description and an experience condition. Overall, this included 28,932 trials (71.9% of all trials in the database with autonomous sampling). For each dataset, we determined the size of the description–experience gap and the mean log-transformed number of samples drawn in the experience condition (because of the skewed distribution of the number of samples drawn). The size of the description–experience gap and the mean sample were negatively correlated ($r(15) = -.52$, $p = .034$; for an illustration, see Figure A1 of Appendix B). This correlation was also significant when we used the raw (i.e., untransformed) number of samples drawn.

Problem Type. Next, we tested whether choice in line with overweighting of rare events was associated with the number of samples drawn, the problem type (two risky options vs. one risky and one safe option), and rarity (i.e., probability of rarest event). We chose problem type and rarity as problem characteristics because in the meta-analysis by Wulff et al. (2018), both characteristics affected the size of the description–experience gap. Because there is no sampling in the description condition, we only analyzed data from the experience conditions. For this analysis, we separately analyzed the meta-analytic database by Wulff et al. (2018; here, we used the whole database with autonomous sampling; $N = 40,246$) and the datasets from our initial experiment, Experiment 1, and Experiment 2. This analysis was preregistered for Experiment 2. As described in the main text, we deviated from the pre-registration by log-transforming the number of samples drawn because that variable showed a right-skewed distribution.

For each dataset, we ran a multilevel logistic regression. The dependent variable was choice in line with overweighting of rare events and the independent variables were log-transformed number of samples drawn (centered), problem type (0 = risky vs. risky, 1 = risky vs. safe) and rarity (centered). In the datasets from our experiments, there was a random intercept for participants, in the meta-analytic dataset there was a random intercept for participants nested within datasets. The results are presented in Table S16. In sum, we found a positive interaction of sample size and problem type in every dataset, indicating that in problems with a safe and a risky option, there is stronger positive effect of the number of samples drawn on the propensity to overweight rare events compared to problems with two risky options (the interaction is illustrated in Figure A2 of Appendix B). This interaction was also significant in all datasets when we used the raw (i.e., untransformed) number of samples drawn.

Table S16

Effect of Number of Samples Drawn and Problem Characteristics on choice in Line With Overweighting of Rare Events in Four Datasets (Wulff et al. (2018) Dataset, our Initial Experiment, our Experiment 1, and our Experiment 2).

	Wulff et al. dataset	Initial experiment	Exp. 1	Exp. 2
Predictor	*b*	*b*	*b*	*b*
Intercept	−0.11 [−0.25–0.03]	−0.27 [−0.37–−0.17]	0.42 [0.34–0.49]	0.40 [0.32–0.48]
Number of samples drawn	**−0.06 [−0.09–−0.02]**	**0.15 [0.05–0.24]**	0.03 [−0.06–0.12]	**0.16 [0.09–0.24]**
Problem type	**−0.47 [−0.54–−0.39]**	**−0.33 [−0.54–−0.13]**	−0.16 [−0.54–0.22]	**−0.45 [−0.83–−0.07]**
Rarity	**1.88 [1.62–2.14]**	**1.11 [0.10–2.12]**	**4.15 [3.63–4.66]**	**4.01 [3.52–4.50]**
Number of samples drawn × Problem Type	**0.31 [0.25–0.37]**	**0.44 [0.25–0.63]**	**0.70 [0.14–1.25]**	**0.66 [0.21–1.11]**
Number of samples drawn × Rarity	−0.03 [−0.28–0.21]	**−0.01 [−0.95–0.94]**	**1.83 [1.17–2.48]**	**1.44 [0.91–1.96]**
Problem type × Rarity	**0.47 [0.12–0.81]**	2.08 [−0.46–3.70]	−1.71 [−6.92–3.50]	−2.07 [−7.23–3.10]
3-way interaction	−0.13 [−0.48–0.23]	**−1.95 [−3.45–−0.45]**	0.64 [−6.47–7.75]	3.11 [−2.49–8.72]

Note. Exp. 1 = Experiment 1, Exp. 2 = Experiment 2. Values in brackets are 95% confidence intervals. Significant predictors are printed in boldface.

S7 Testing the Robustness of the CPT Results Using an Alternative Probability-Weighting Function

For the modeling presented in the main text, we implemented CPT with the one-parameter weighting function proposed by Tversky & Kahneman (1992), with one probability sensitivity parameter for both gains and losses (see Eq. 4 in the main text). To test the robustness of the results concerning the shapes of CPT's value function and probability weighting function, we exploratorily also modeled choices implementing Prelec's (1998) variant of the probability weighting function. Specifically, the weighting function is defined as

$$w(p) = e^{-(-\log(p))^{\gamma}} \quad . \tag{1}$$

When we modeled choices implementing this probability weighting function, the results were similar as presented in the main text. In Tables S17 and S18, we present CPT parameter estimates for all conditions implementing the joint-representation CPT model and for the mixed-mode condition implementing the separate-representation CPT model, respectively (analogous to Tables 1 and 2 in the main text). The qualitative patterns of estimates are similar to those found in Experiments 1 and 2, except for the following differences.

In the CPT joint-representation model, the only difference is that in Experiment 1 the difference in the probability sensitivity parameter γ between the mixed-mode and description condition is not credible.

In the separate-representations CPT model, the only difference is the difference in the outcome sensitivity parameter α credibly differs between the described and experienced conditions in Experiments 1 and 2, although this difference is negligible in absolute terms. Examination of model performance also indicated that the credible differences in the outcome sensitivity parameter α should be interpreted with caution as the joint-representation CPT model performed better than the separate-representations CPT model in Experiments 1 and 2 (Experiment 1: DIC = 8,019.5 versus 8,122.9; Experiment 2: DIC = 9,105.6 versus 9,306.0), indicating that also when implementing Prelec's (1998) variant of the probability weighting function, the results favor a joint-representation scenario.

With respect to choice bias, in Experiment 1 the estimated β parameter was positive and credibly differ from 0 (group-level posterior mean = 0.08 [0.00–0.17]), indicating that there was a bias toward the described option which was not credible with the original specification of the probability weighting function, although descriptively the values of the bias parameter were very similar across specifications. In Experiment 2, the estimated β parameter did not differ from 0 (group-level posterior mean = −0.03 [−0.13–0.07]).

Table S17

Posterior Group-Level Mean Parameters of the CPT Model [95% HDI] With Prelec's (1998) Weighting Function

Parameter	Description condition	Experience condition	Mixed-mode condition	Difference Descr. – Exp.	Difference Mixed – Descr.	Difference Mixed – Exp.
Experiment 1						
Outcome sensitivity α	0.76 [0.73−0.80]	1.04 [0.99−1.09]	0.97 [0.93−1.02]	**−0.28 [−0.34–−0.27]**	**0.21 [0.15–0.27]**	**−0.07 [−0.14–−0.00]**
Probability sensitivity γ	0.76 [0.66−0.76]	0.47 [0.41−0.53]	0.65 [0.57−0.74]	**0.28 [0.17–0.40]**	−0.10 [−0.23–0.03]	**0.18 [0.08–0.28]**
Loss aversion λ	1.21 [1.09−1.33]	1.52 [1.31−1.73]	1.30 [1.16−1.44]	**−0.31 [−0.56–−0.07]**	0.09 [−0.09–0.28]	−0.22 [−0.48–0.02]
Choice sensitivity φ	0.25 [0.20−0.30]	0.07 [0.05−0.08]	0.10 [0.07−0.12]	**0.18 [0.13–0.24]**	**−0.16 [−0.21–−0.10]**	**0.03 [0.00–0.06]**
Experiment 2						
Outcome sensitivity α	0.80 [0.76−0.84]	1.13 [1.08−1.17]	0.93 [0.89−0.97]	**−0.33 [−0.39–−0.27]**	**0.13 [0.08–0.19]**	**−0.19 [−0.25–−0.13]**
Probability sensitivity γ	0.63 [0.51−0.74]	0.40 [0.32−0.47]	0.69 [0.55−0.82]	**0.23 [0.09–0.36]**	0.06 [−0.11–0.24]	**0.29 [0.13–0.44]**
Loss aversion λ	1.14 [1.03−1.25]	1.26 [0.07−1.44]	1.09 [0.93−1.27]	−0.12 [−0.35–0.08]	-0.04 [−0.24–0.17]	−0.16 [−0.41–0.09]
Choice sensitivity φ	0.23 [0.18−0.28]	0.06 [0.05−0.07]	0.11 [0.09−0.14]	**0.17 [0.12–0.22]**	**−0.11 [−0.16–−0.06]**	**0.06 [0.03–0.09]**

Note. Descr. = Description condition, Exp. = Experience condition, Mixed = Mixed-mode condition. Credible differences are printed in boldface.

Table S18

Posterior Group-Level Mean Parameters of the CPT Model with Separate Parameters for Each Option in the Mixed-Mode Condition [95% HDI] With Prelec's (1998) Weighting Function

Parameter	Described option		Experienced option	Difference described – experienced option
Experiment 1				
Outcome sensitivity α	0.97 [0.93–1.01]		0.98 [0.93–1.02]	**−0.01** **[−0.01–−0.00]**
Probability sensitivity γ	0.67 [0.58–0.76]		0.58 [0.51–0.65]	0.09 [−0.02–0.19]
Loss aversion λ	1.27 [1.18–1.36]		1.29 [1.20–1.38]	−0.02 [−0.06–0.02]
Choice sensitivity φ		0.10 [0.08–0.12]		
Experiment 2				
Outcome sensitivity α	0.94 [0.90–0.98]		0.95 [0.90–0.99]	**−0.01** **[−0.02–−0.00]**
Probability sensitivity γ	0.71 [0.57–0.84]		0.59 [0.47–0.70]	0.12 [−0.05–0.29]
Loss aversion λ	1.30 [1.12–1.28]		1.16 [1.07–1.25]	0.04 [−0.01–0.09]
Choice sensitivity φ		0.11 [0.08–0.13]		

Note. Credible differences are printed in boldface.

S8 Additional Analyses for Experiment 2

In this section, we present further analyses of the data of Experiment 2. We report results on maximization of EV/SM across conditions and the role of numeric abilities in choice and search behavior in the mixed-mode condition.

Maximization of EV/SM

Again, in this analysis we excluded trials in which EVs/SMs were the same for both options (2.6% of trials). As in Experiment 1, in the experience condition choices were on average easier ($M_{\text{SMratio}} = 2.05$; $SD_{\text{SMratio}} = 0.61$) than in the description condition ($M_{\text{EVratio}} = 1.32$; $SD_{\text{EVratio}} = 0.00$; because choice problems were presented descriptively, there was no variation in EV ratio in this condition). In the mixed-mode condition, EV/SM ratio fell between that of the description and the experience conditions ($M_{\text{EV/SMratio}} = 1.70$; $SD_{\text{EV/SMratio}} = 0.39$). All comparisons between conditions were significant (*p*s < .001).

When participants chose between two experienced options, they chose the option with the higher SM more often than participants chose the option with the higher EV when choosing between two described options ($M_{\text{experience}} = .73$, $SD_{\text{experience}} = .09$ vs. $M_{\text{description}} = .66$, $SD_{\text{description}} = .09$; $t(168) = 5.50$, $p < .001$). In the mixed-mode condition, participants in the mixed-mode condition chose the option with the higher EV/SM significantly more often than in the description condition ($M_{\text{mixed-mode}} = .69$, $SD_{\text{mixed-mode}} = .08$; $b = -.04$, $SE = .01$, $p = .007$), but less often than in the experience condition ($b = .04$, $SE = .01$, $p = .003$).

The Role of Numeracy

In the following, we examine the role of numeracy in choice and search behavior.

Objective Numeracy and Sample Size

In Experiment 2, we assessed objective numeracy following the choice task using the same questionnaire as in Experiment 1, but in English (i.e., the original language of the items). Mean objective numeracy was 3.42 (range = 0–7; $SD = 1.78$). We did not assess subjective numeracy in this experiment.

We again ran a negative binomial generalized multilevel model with the number of samples drawn per option. Here, we deviated from the preregistration (for the rationale, see main text). People with higher objective numeracy did not draw more samples (b = 0.08, SE = 0.05, p = .071) than people with lower objective numeracy.

Thus, Experiment 2 seems to replicate the association of objective numeracy and numbers of samples drawn found in previous studies (Ashby, 2017; Lejarraga, 2010; Traczyk et al., 2018) and in our initial experiment. One possible explanation for the differences in results between Experiments 1 and 2 could be the differences in study population. In Experiment 1, participants were mostly undergraduate students who may have had relatively high levels of objective numeracy, which may have restricted the variance and thus the possibility to find significant associations. In Experiment 2, in contrast, participants were from the general population and numeracy was more normally distributed.

Numeracy and CPT Parameters

Table S19 presents the bivariate correlations of individual-level posterior estimates of the individual-level CPT parameters with objective numeracy. In the description condition, objective numeracy was positively associated with outcome sensitivity α and choice sensitivity φ. In the both the experience condition and the mixed-mode condition, objective numeracy was positively associated with loss aversion λ and choice sensitivity φ.

Table S19

Bivariate Pearson Correlations of Individual-Level Posterior Means of CPT Parameters and Objective Numeracy, Separately for Each Condition (Experiment 2)

	Objective Numeracy	
	r	*p*
Description condition		
Outcome sensitivity α	**.290**	**.007**
Probability sensitivity γ	.170	.120
Loss aversion λ	.048	.660
Choice sensitivity φ	**.371**	**< .001**
Experience condition		
Outcome sensitivity α	.061	.576
Probability sensitivity γ	−.145	.174
Loss aversion λ	**.307**	**.004**
Choice sensitivity φ	**.215**	**.048**
Mixed-mode condition		
Outcome sensitivity α	.201	.078
Probability sensitivity γ	−.125	.274
Loss aversion λ	**.308**	**.006**
Choice sensitivity φ	**.405**	**< .001**

Note. Results in boldface indicate significant correlations.

S9 Comparing Observed Relative Frequencies with Probability Estimates Derived From a Bayesian Updating Process

To model choices in our experiments, we used the experienced payoff distributions (as in 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 probabilities were more strongly distorted in purely experience-based (vs. description-based) choices. To test how strongly the observed probabilities and the probability estimates derived from a Bayesian updating process were associated, we determined a probability estimate derived from a Bayesian updating process for each observed probability. Following the approach by Hoffart et al. (2019), we assumed that probability estimates were based on the mean of a Beta distribution, $p \sim Beta(a, b)$. Initially, people have a uniform prior ($a = b = 1$) and with every sample they draw, the distribution is updated. If a particular outcome is drawn, 1 is added to parameter a, whereas 1 is added to parameter b if the other is drawn. Thus, the probability estimate approaches the observed probabilities as overall more samples are drawn. The probability estimate is represented by the mean of the beta distribution ($p = \frac{a}{a+b}$). For this analysis, we used the data of Experiment 1.

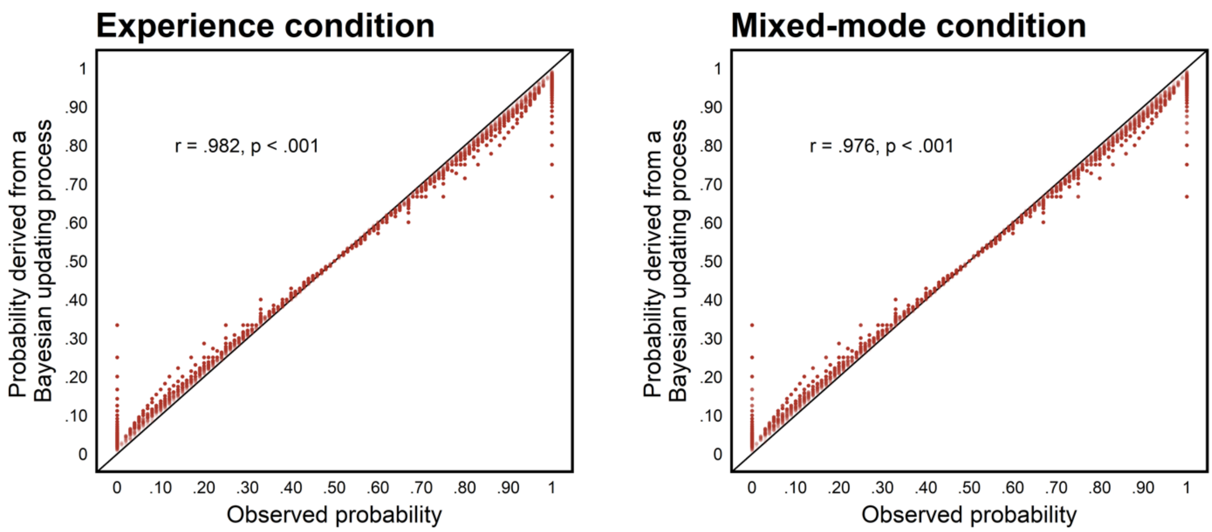
In Figure S1, we illustrate the association between the observed probabilities and the probability estimates, separately for the experience and the mixed-mode conditions. It becomes visible that the probability estimates closely match the observed probabilities, also demonstrated by very high correlations (experience condition: $r(33{,}486) = .982$, $p < .001$; mixed-mode condition: $r(14{,}408) = .976$, $p < .001$). One reason for this high correlation is the relatively high numbers of samples drawn from the experienced options.

Note that this is the most conservative test of the association because it assumes that participants expected two outcomes for each option, although they were instructed (and had the chance to learn) that options had either one or two outcomes. If only those options were analyzed for which participants had observed two outcomes and thus knew that there were two outcomes, the correlations became even larger (mixed-mode condition: $r(11{,}938) = .998$, $p < .001$; experience condition: $r(27{,}460) = .997$, $p < .001$).

In sum, the observed probabilities closely match the probability estimates derived from a Bayesian updating process. Hence, we did not additionally model choices separately based on probabilities derived from a Bayesian updating process.

Figure S1

Association between the observed probabilities and probability estimates derived from a Bayesian updating process. Each data point represents one outcome of one option of one participant. The diagonal line represents a perfect correspondence of the observed probabilities and the probability estimates.



S10 Choice Problems Used in the Initial Experiment

Table S20

Choice Problems Used in the Initial Study and Choice Proportions in Each Condition

	Option A				Option B				Proportion choosing Option A			
											Mixed-Mode	
ID	p1	o1	p2	o2	p1	o1	p2	o2	Des	Exp	A-des	A-exp
1	.80	40	.20	0	1	30			.32	.43	.37	.42
2	.20	40	.80	0	.25	30	.75	0	.51	.63	.69	.66
3	.10	32	.90	0	1	3			.46	.34	.40	.52
4	.03	32	.97	0	.25	3	.75	0	.58	.40	.79	.36
5	.90	50	.10	0	1	45			.23	.58	.35	.43
6	.11	55	.89	0	1	5			.40	.40	.46	.41
7	.07	42	.93	6	1	8			.61	.39	.74	.48
8	.92	90	.08	36	1	86			.26	.52	.49	.45
9	1	53			1	53					.22	.18
10	1	22			1	22					.22	.31
11	.50	40	.50	0	.50	40	.50	0			.36	.36
12	.30	78	.70	43	.30	78	.70	43			.61	.51
13	.90	40	.10	0	.90	40	.10	0			.46	.44
14	.05	80	.95	8	.05	80	.95	8			.43	.31
15	.08	12	.92	69	.08	12	.92	69			.52	.51
16	.90	0	.10	40	.90	0	.10	40			.36	.44
17	.91	21	.09	54	.61	10	.39	72	.51	.30	.42	.42
18	.90	44	.10	8	.35	6	.65	84	.33	.28	.12	.31
19	.91	27	.09	64	.45	40	.55	25	.46	.49	.46	.47
20	.09	7	.91	52	.40	74	.60	30	.4	.42	.4	.47
21	.68	41	.32	65	.85	96	.15	2	.23	.30	.12	.29
22	.93	37	.07	2	.54	27	.46	22	.60	.75	.66	.75
23	.92	35	.08	97	.35	22	.65	53	.56	.49	.39	.45
24	.80	54	.20	21	.49	98	.51	3	.74	.48	.51	.64
25	.05	56	.95	72	.95	68	.05	95	.46	.66	.53	.50
26	.05	60	.95	76	.84	95	.16	17	.46	.43	.35	.51
27	.12	52	.88	73	.98	92	.02	19	.18	.07	.10	.2
28	.98	76	.02	37	.82	49	.18	50	.89	.96	.89	.91
29	.19	30	.81	97	.14	85	.86	82	.35	.57	.32	.45
30	.88	79	.12	82	.20	57	.80	94	.32	.28	.35	.49
31	.08	54	.92	31	.15	44	.85	29	.81	.73	.71	.70
32	.10	45	.90	14	.14	25	.86	27	.16	.13	.16	.16
33	.05	95	.95	68	1	71			.37	.19	.49	.29

34	.05	95	.95	68	.05	90	.95	70	.35	.24	.35	.27
35	.05	56	.95	72	1	71			.25	.64	.56	.38
36	.09	7	.91	52	.09	95	.91	43	.28	.51	.42	.44
37	.09	7	.91	52	.09	1	.91	53	.61	.46	.46	.65
38	.09	95	.91	43	.40	74	.60	30	.70	.76	.50	.67
39	.50	59	.50	12	.30	41	.70	47	.12	.19	.09	.21
40	.42	20	.58	80	.45	30	.55	60	.72	.66	.76	.78
41	.33	99	.67	56	.60	70	.40	60	.58	.57	.53	.69
42	.77	23	.23	11	.51	14	.49	28	.32	.27	.32	.19
43	.50	44	.50	77	1	55			.54	.66	.80	.67
44	.27	68	.73	35	1	51			.21	.22	.08	.16
45	.40	92	.60	10	1	34			.46	.63	.59	.61
46	.39	23	.61	26	1	25			.42	.45	.39	.36
47	.50	61	.50	78	1	34			.89	1.00	.99	.96
48	.33	32	.67	22	1	68			.00	.01	.00	.02
49	.25	95	.75	57	.40	31	.60	21	.98	.97	.98	.97
50	.45	31	.55	9	.30	56	.70	.87	.00	.00	.00	.02

Note. Des = Description condition, Exp = Experience condition, A-des = Mixed-mode condition with described Option A, A-exp = Mixed-mode condition with experienced Option A. Choice problems taken and adapted from Hertwig et al. (2004; IDs 1–4); Camilleri & Newell (2011; IDs 5–6); Glöckner et al., 2016 (IDs 7–8); Ert & Trautmann (2014; IDs 11, 13, and 16); Glöckner et al. (2012; IDs 17–20 and 22–23); Rieskamp, 2008 (2008; IDs 21 and 24–32). All other choice problems (IDs 9–10, 12, 14–15, and 33–50) were developed by the authors. For choice problems 104–108, no choice proportions are reported in the description and experience conditions because options were identical.

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