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Supplementary Materials Online

1. Experiment-level statistical analysis

Value information. In all four experiments, we manipulated whether value information was present or absent during sampling. Table S1 contains the key non-hierarchical frequentist statistics for each experiment. Note that for Experiments 3 and 4 the estimates are based on the trials from the no-salience condition, since these trials are most similar to those in Experiments 1 and 2.

Comparing the first three columns of Table S1¹, we see that the proportion of risky choices was larger in the Value-Ignorance condition than in the Standard condition for all experiments, with estimates of effect sizes varying from 0.12 to 0.69. Columns 4 and 5 contain the *t* statistics and associated one-sided *p*-values for each between-subjects comparison of the two sampling conditions. The difference was statistically significant in just one experiment, using a type I error rate of 0.05.

Table S1. Descriptive and inferential statistics comparing the Standard and Value-Ignorance conditions in each of the four experiments. Note that for Experiment 3 and 4, only the data from No-Salience conditions are used.

Experiment	Proportion of Risky Choices		Effect Size	<i>t</i> (<i>df</i>)	<i>p</i> (one-tailed)
	Standard	Value-ignorance			
1	0.42	0.45	0.12	0.52 (78)	0.30
2	0.42	0.50	0.36	1.61 (78)	0.06
3	0.27	0.45	0.69	3.14 (72)	0.001
4	0.36	0.42	0.25	1.19 (87)	0.12

Salience. In Experiments 3 and 4, for Type 1 (*best-outcome salient*) problems (see Section 2 for an analysis of Type 2 problems) we also manipulated whether the rare reward was highlighted (Salience vs. No-Salience). This manipulation was crossed with the sampling manipulation (Standard vs. Value-Ignorance), and Table S2 presents the key descriptive statistics, as well as inferential statistics resulting from submitting risky choice proportions to a 2 (sampling) x 2 (salience) between-subjects analysis of variance (ANOVA). In Experiment 3, we see evidence for both main effects of sampling and salience. Though the interaction between salience and sampling was not significant, the cell means suggest that highlighting rare rewards in the Standard condition encouraged more risky choices ($M = 0.43$ vs. $M = 0.27$). However, the effect of salience was minimal in Experiment 4.

¹ Note that the numbers in Tables S1, S2, and S3 are raw means. In the main article we plot median and central 95% of the posterior distribution of the population-level mean of the proportion of risky choices, thus the numbers in the table are not directly comparable to those in the figures in the main article.

Table S2. Descriptive and inferential statistics for Type 1 (*Best-Outcome Salient*) problems in Experiments 3 and 4.

Exp	Proportion of Risky Choices				Sampling		Saliency		Interaction		df
	No-Saliency		Saliency		F	p	F	p	F	p	
	Standard	Value-Ignorance	Standard	Value-Ignorance							
3	0.27	0.45	0.43	0.45	6.38	0.01	4.06	0.05	2.28	0.13	144
4	0.36	0.42	0.37	0.44	2.94	0.09	0.27	0.61	0.01	0.95	173

2. Type 2 (*Worst-Outcome Salient*) analysis

Our saliency manipulation carried the risk of introducing a demand characteristic whereby participants were encouraged to choose the riskier option, regardless of which outcome was highlighted. Type 2 problems therefore served as a manipulation check because saliency highlighted an outcome of \$0, rather than a rare reward. We expected that saliency would operate at the level of outcome, rather than option, and therefore expected saliency to have the opposite effect on Type 2 problems. Table S3 presents the key descriptive statistics, and inferential statistics resulting from the same 2 (sampling) x 2 (saliency) ANOVA used to analyze Type 1 problems above. Overall, there is little evidence for an effect of the saliency manipulation for Type 2 problems. This suggests that participants may have treated \$0 outcomes differently from rewards – perhaps viewing them as ‘non-events’ – though future work is needed to test this interpretation.

Table S3. Descriptive and inferential statistics for Type 2 (*Worst-Outcome Salient*) problems in Experiments 3 and 4.

Exp	Proportion of Risky Choices				Sampling		Saliency		Interaction		df
	No-Saliency		Saliency		F	p	F	p	F	p	
	Standard	Value-Ignorance	Standard	Value-Ignorance							
3	0.52	0.53	0.51	0.54	0.23	0.63	0.01	0.96	0.02	0.89	144
4	0.55	0.47	0.45	0.48	0.33	0.56	0.93	0.34	2.07	0.15	173

3. Complete list of decision problems

Table S4. Choice problems used in Experiment 1. *Reward* indicates the value of blue balls. *Sample* indicates the number of blue and red balls observed during sampling. For Example, *Reward* = 12 and *Sample* = 2:10 means that participants observed two blue balls worth \$12 and ten red balls worth \$0.

Problem	Riskier Option			Safer Option		
	Reward	Sample	EV	Reward	Sample	EV
1	21	1:11	1.75	7	10:2	5.83
2	18	4:8	6	2	10:0	2
3	4	5:5	2	2	10:0	2
4	16	1:9	1.6	2	8:2	1.6
5	21	3:9	5.25	7	8:4	4.67
6	14	3:7	4.2	6	7:3	4.2
7	12	2:10	2.4	3	7:5	1.75
8	9	3:9	2.25	3	10:2	2.5
9	5	8:2	4	3	10:0	3
10	10	2:10	1.67	3	11:1	2.75
11	4	7:5	2.33	5	10:2	4.17

Table S5. Choice problems for Experiment 2. All participants completed these five trials. Additionally, each participant was presented with six additional trials. For these, gamble pairs were drawn from a larger set of random gambles. These random gambles were generated by a factorial combination of reward values from \$1 to \$20 (in steps of \$1) and reward probabilities from $p = .0833$ to $p = .9163$ (in steps of .0833). Identical gambles and dominated gambles (i.e. where both value and probability were higher for one option) were excluded. Random gamble sets were matched across conditions to assure that participants in both conditions were presented with the same stimuli.

Problem	Riskier Option			Safer Option		
	Reward	Sample	EV	Reward	Sample	EV
1	16	1:9	1.6	2	8:2	1.6
2	21	3:9	5.25	7	8:4	4.67
3	14	3:7	4.2	6	7:3	4.2
4	12	2:10	2	3	7:5	1.75
5	9	3:9	2.25	3	10:2	2.5

Table S6. Choice problems used in Experiments 3 and 4.

Problem	Riskier Option			Safer Option		
	Reward	Sample	EV	Reward	Sample	EV
1	16	1:9	1.6	2	8:2	1.6
2	12	3:9	3	4	9:3	3
3	20	1:11	1.67	2	10:2	1.67
4	12	2:10	2	3	8:4	2
5	8	2:8	1.6	4	4:6	1.6
6	15	2:10	2.5	5	5:7	2.5
7	12	1:11	1	3	4:8	1
8	9	2:10	1.5	1	11:1	0.92
9	4	4:6	1	2	11:1	1.83
10	12	2:8	2.4	2	9:1	1.8
11	6	3:9	1.5	3	9:3	2.25
12	11	1:11	0.92	5	5:7	2.08
13	10	1:11	0.83	3	4:8	1
14	12	2:10	2	4	5:7	1.67
15	3	7:5	1.75	2	10:2	1.67
16	6	6:4	3.6	4	9:1	3.6
17	4	8:4	2.67	3	11:1	2.75
18	2	7:5	1.17	1	10:2	0.83
19	4	7:5	2.33	3	11:1	2.75
20	4	8:4	2.67	2	11:1	1.83

4. Cumulative prospect theory analyses

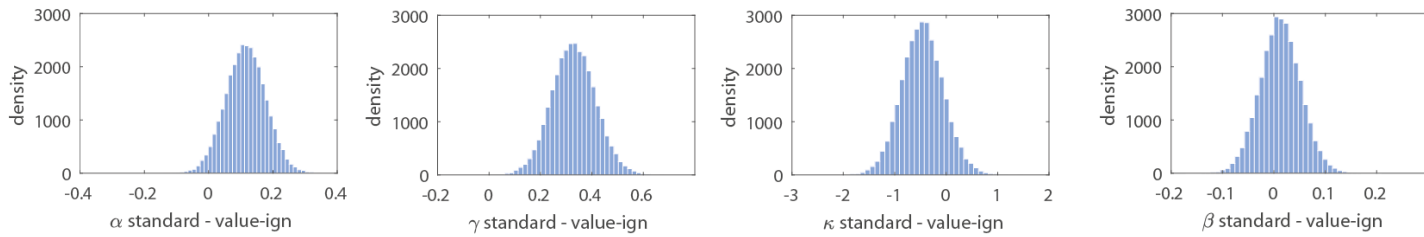


Figure S2. Posterior distributions of differences in population-level parameters between the Standard and the Value-Ignorance conditions plotted to maximize distribution coverage.

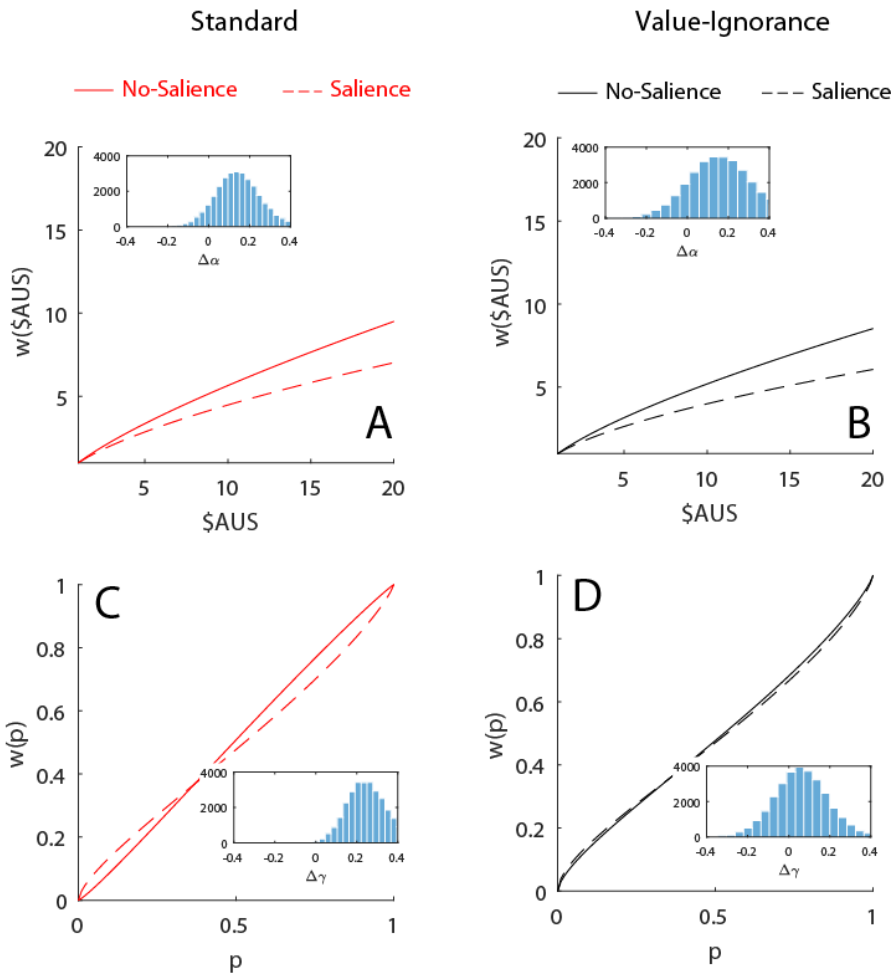


Figure S3. Value and probability weighting functions for the salience manipulation including both Type 1 and Type 2 problems. Red lines represent risk preferences when value information was available at the time of sampling (Standard). Black lines represent risk preferences when value information was revealed at the time of choice (Value-Ignorance). The functions show best-fit population-level utility functions (Panel A,B) and probability weighting functions (Panel C,D), for the No-Salience (solid line) and the Salience (dashed line) conditions. Histograms show the posterior distribution of population-level differences in parameters (i.e., No-Salience - Salience).

5. Description data

The original plan for this project was to investigate the impact of presenting value information at different points in the sampling process. This focus led to the development of the Value-Ignorance condition to be compared to the Standard condition. However, we had some limited opportunity to also collect description data, which was collected to explore whether choices made under Value-Ignorance would be more like those made in the Standard condition, or more like those made with described versions of the same gambles.

In Experiment 1 these data were collected via a brief computerized task displaying the same gambles used in the Experience conditions (Table S4) using a convenience sample of 40 participants who had finished other experiments being run in the lab. The choice options were presented side-by-side (with both probability and value information in numerical format) and participants indicated which of the two options they would prefer to play for real. In Experiment 2 we aimed for more controlled sampling of participants, though a wholly separate description condition was not practicable. We therefore used a within-subject design, in which each participant would perform the Description task after the experienced-based task (Value-Ignorance / Standard, displaying the same gambles – see Table S5). In other words, due to constraints on data collection, neither data set was collected under ideal circumstances (Exp 1 - convenience sample across many different experiments, Exp 2 order effects) and were somewhat noisy, and we therefore abandoned this condition in favor of focusing the remaining data collection resources on the two key conditions (Exp3-4).

For completeness, we nonetheless performed the hierarchical Bayesian prospect theory analysis on the Description data, pooling across experiments as in the main analyses (N=120, with each N contributing choices for 11 gambles). Figure S4 shows the result of this analysis, alongside Standard and Value-Ignorance conditions (reported in Fig 5).

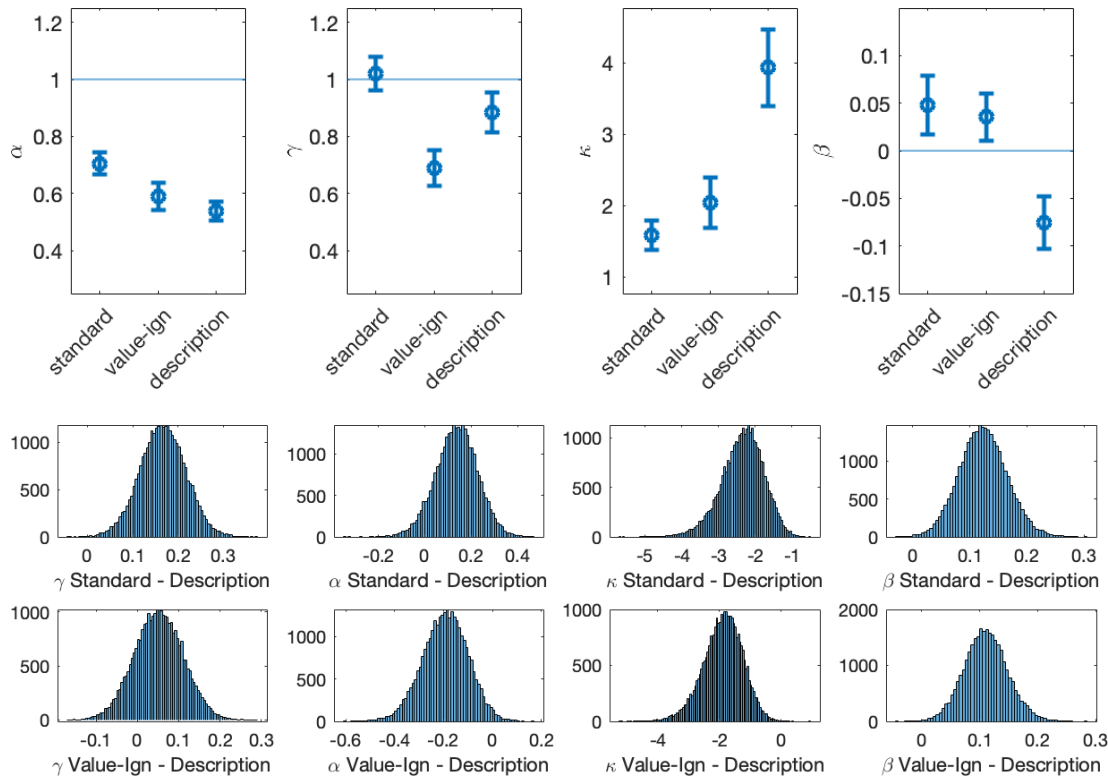


Figure S4. Hierarchical Bayesian Prospect Theory – ‘Description’. Top row: Posterior means and standard deviations of group-level prospect theory parameters. Bottom two rows: Posterior differences in parameters between the two key conditions and ‘Description’.

As can be seen (Fig S4), Description resulted in α parameters that were closer to Value-Ignorance than to Standard, in-between Standard and Value-Ignorance for γ , and closer to Value-Ignorance than to Standard for κ , with a bias (β) in favor of the right rather than left option. For the parameter with the least clear pattern, γ , the posterior distribution of differences (second panel from left, two bottom rows, Fig S4), suggests (albeit not conclusively) that Description resulted in more overweighting (of small probabilities) than Standard, and that it resulted in less overweighting than Value-Ignorance.

Overall, the Description data provide tentative evidence that having to integrate probability and value at the time of choice, in an experienced-based task (Value-Ignorance), results in risk preferences that are more similar to decisions-from-description than to the standard experienced-task where such integration is not strictly necessary. However, given the noted shortcomings, these results should be confirmed with more rigorously collected data.