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Variability in Decision Strategies Across Description-based and Experience-based Decision Making

SANGSUK YOON,[1] KHOI VO[2] and VINOD VENKATRAMAN[1]*

[1]*Center for Neural Decision Making, Fox School of Business, Temple University, Philadelphia, PA USA*

[2]*Center for Cognitive Neuroscience, Duke University, Durham, NC USA*

ABSTRACT

Individuals are known to make systematically different decisions when the probabilities in risky choice problems are described or experienced. This difference, known as the description–experience gap, has been reliably replicated across several studies using binary choice gambles. Yet little is known whether these differences exist in more complex gambles in the absence of rare outcomes, and whether they are associated with systematic differences in the use of decision heuristics and strategies across formats. Using three-outcome mixed gambles, we found that participants showed a strong preference for alternatives that maximized the overall probability of winning when such an option was available in the description condition, and chose more randomly otherwise. In the experience condition, preferences were more homogenous across trials types, with participants choosing the alternative with extreme values more often relative to the description condition. However, when we controlled for the experienced outcomes, both natural mean heuristic (choosing the alternative with highest sampled mean or expected value) and overall probability of winning heuristic reliably predicted choice on each trial. In fact, expected value was the strongest predictor of preferences in a conditional logistic regression model that included extreme values, expected value, and overall probability of winning variables simultaneously. Yet expected value did not predict preferences in decisions from description. Together, these findings provide evidence for an explicit dissociation in decision strategies across description and experience formats. Copyright © 2017 John Wiley & Sons, Ltd.

KEY WORDS the description–experience gap; complex gambles; risky choice; heuristics; decision strategies

INTRODUCTION

The description–experience (D-E) gap refers to the inconsistent preferences observed in risky choice tasks depending on the format in which the information is presented (Camilleri & Newell, 2013; Hertwig, Barron, Weber, & Erev, 2004; Rakow & Newell, 2010). In a seminal study, Hertwig et al. (2004) asked two groups (decision from description vs. experience) of participants to choose between a risky gain (e.g., 80% chance of gaining 8¢) or a sure gain (e.g., 6¢ for sure). When the information was described completely (i.e., magnitude and probabilities of both options were known; decision from description), only 36% of the participants selected the risky option even though it was associated with higher expected value (EV; 6.4¢ vs. 6¢). When the information had to be learned through repeated sampling of each alternative (decision from experience), 88% of the participants chose the risky option instead. The difference, known as the D-E gap, has since been directly replicated using the same stimuli as the original study, although the effects (size of the gap) have been smaller (Hau, Pleskac, Kiefer, & Hertwig, 2008; Rakow, Demes, & Newell, 2008). Similarly, the D-E gap has also been shown across several other studies using different stimulus sets (for a recent review, see Camilleri & Newell, 2013; Rakow & Newell, 2010). Understanding the D-E gap is particularly important given that several real-world decisions (e.g., a doctor deciding to prescribe a certain medication to a patient while considering its potential side effects) are often better characterized by learning from experience rather than description (Gonzalez & Dutt, 2011; Hau et al., 2008; Li, Rakow, & Newell, 2009; March & Shapira, 1987; Weber, 2006; Yechiam, Barron, & Erev, 2005).

The D-E gap has historically been attributed to the inconsistent weighting of a rare event (Hertwig & Erev, 2009). People often overweight the probability of a rare event in description condition, while they underweight the probability of the rare event in experience condition. The D-E gap has been mostly reported in situations where there is a rare event, and the magnitude of the gap often decreases as the rare event becomes less extreme (e.g., Erev et al., 2010; Rakow & B Rahim, 2010). However, recent studies have also demonstrated the D-E gap in equal probability gambling tasks in the absence of rare events (Ludvig, Madan, & Spetch, 2014; Ludvig & Spetch, 2011). For example, Ludvig and Spetch (2011) showed that participants were more risk seeking for gains in description condition than in experience condition, while they were more risk averse for losses in experience condition than in description condition. Indeed, Ludvig et al. (2014) showed that the D-E gap in equal probability gamble tasks was more prominent when the gains and losses were extreme.

Another characteristic of the D-E gap literature is that a vast majority of past studies investigating the D-E gap have used binary choice tasks in which participants choose between two alternatives, with each alternative having one or two outcomes. Very little is known about how these findings extend to more complex tasks, such as risky choice involving mixed gambles with multiple outcomes and multiple alternatives (Rakow & Newell,

*Correspondence to: Vinod Venkatraman, Temple University, 1801, Liacouras Walk (Alter A562), Philadelphia, PA 19122, USA. E-mail vinod.venkatraman@temple.edu

2010). In one study, Hills, Noguchi, and Gibbert (2013) investigated the experience-based decision making using multiple alternatives (e.g., 2, 4, 8, 16, and 32 alternatives) with different presentation orders (few-to-many vs. many-to-few). They showed that participants sampled more as the set size increased, but the number of samples per gamble however decreased as the set size increased. They also found a strong effect of the order of set size change, such that participants selected higher rank EV gambles in smaller set size trials (set size 2 and 4) when the presentation order was few-to-many but not when the presentation order was many-to-few. Noguchi and Hills (2015) also found inconsistent preference for risky alternatives in an experience-based decision task depending on set size. In their study, participants preferred risky alternatives more when a set size was large (32 alternatives in the choice set) than when the set size was small (binary) for gain domain. Although these papers investigated experience-based decision making using multiple alternatives, each alternative still had a binary outcome (one gain and zero) and the decisions were not directly compared with corresponding description-based choices.

In the present study, we investigated whether people employ consistent decision strategies across description-based and experience-based decisions involving complex decision environments. There are several advantages to using non-binary mixed gambles similar to the ones used in this study (Rakow & Newell, 2010). First, they are more representative of most real-world decisions, which involve choices among different alternatives with multiple outcomes (Lopes, 1995; Lopes & Oden, 1999). Second, multiple-outcome gambles lead to the use of more diverse decision strategies across trials and individuals, providing valuable insights into the use of simplifying strategies and heuristics in decisions from experience (DFE)—a key focus of this study.

It is well known that people simplify complex tasks using simplifying heuristics owing to limited cognitive resources (Simon, 1955; Tversky, 1972; Tversky & Kahneman, 1974). In fact, it has been argued that people choose from a toolbox of heuristics based on *task environment* and *decision context* (Payne, Bettman, & Johnson, 1988). However, most of this research has utilized description-based paradigms, and little is known about how the same heuristics extend to DFE. Crucially, it remains unknown whether the D-E gap is restricted to differences in choice preferences between the two formats, or also extends to decision strategies. In one study, Hau et al. (2008) predicted preferences from an experience-based paradigm using a diverse array of choice models and heuristics. The results showed that the maximax heuristic (i.e., selecting an option that gives highest experienced maximum outcome) predicted choices in the task best, followed by others like the natural mean heuristic (i.e., choosing alternatives with higher sampled mean) and the lexicographic heuristic (i.e., identifying the most frequent outcome and selecting the alternative with the highest value for that outcome). In another study, Camilleri and Newell (2011) asked participants to report decision strategies that they used during the experience-based tasks. Participants' commonly reported strategy was similar to the natural mean heuristic, in addition to other strategies such as risk aversion, priority heuristic, and multiple composite strategies. Finally, Hills and Hertwig (2010) also showed that people used different decision strategies depending on the way they sample. Participants whose sampling patterns were frequently changing (i.e., zigzag) used round-wise decision strategy (i.e., counting how many rounds each option won and selecting an option which won more times), while people whose sampling patterns rarely changed showed summary-based decision strategy (i.e., comparing final mean values and selecting the alternative with higher final mean value). However, these studies do not compare the consistency of strategies across the two formats. Here, we used three-outcome mixed gambles in an experience-based paradigm to directly compare the use of simplifying heuristics between decisions from description and experience.

Overall probability of winning heuristic

In two independent studies, we used a modified version of the value allocation task where participants choose among three 3-outcome gambles in each trial (Venkatraman, Payne, & Huettel, 2014). One heuristic that is often employed with complex mixed gambles is the overall probability of winning (Pwin) heuristic (Payne, 2005). The Pwin heuristic refers to decisions that are based on the valence of the gamble, while often ignoring the magnitude of the individual outcomes. For example, in Payne (2005), participants were asked to choose between a gamble that provided the highest positive outcome and a gamble that maximized the Pwin. The results showed that participants preferred the option that maximized the Pwin, even when the choice was associated with a lower EV. The Pwin heuristic has since been reliably replicated in a number of studies involving three- and five-outcome gambles (Venkatraman, Payne, Bettman, Luce, & Huettel, 2009; Venkatraman et al., 2014). It has also been shown to be associated with distinct processing strategies (Venkatraman et al., 2014) and brain regions (Venkatraman et al., 2009).

Here, we sought to investigate whether the Pwin heuristic extends to DFE. Several experience-based decision making studies in the past have demonstrated a variant of the Pwin heuristic with binary gambles. For example, in one of the classic problems from Hertwig and colleagues (S: 3, 1 vs. R: 32, 0.1), participants show an increased preference for Gamble S (which has a higher probability of winning) in DFE. However, in a different problem within the same study (S: 3, 1 vs. R: 4, 0.8), participants show an increased preference for Gamble R in DFE, which runs counter to the Pwin heuristic. One problem in these two examples is that the Pwin heuristic is confounded with the maximax heuristic and the minimax heuristic (choosing an alternative that gives the greatest minimum outcome). For example, in the first example, Gamble S gives a higher probability of winning and also has greater minimum outcome than Gamble R (minimum gain of S: 3 vs. R: 0).

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Thus, it is difficult to attribute whether the higher preference for Gamble S was contributed by the greater probability of winning or by the larger minimum outcome. In the latter example, Gamble S gives a higher probability of winning but a lower greatest gain (maximum gain of S: 3 vs. R: 4). Therefore, it is not clear whether the lower preference for Gamble S is evidence against Pwin heuristic or evidence for maximax. The use of three-outcome mixed gambles in the current study enables us to isolate the Pwin heuristic from other strategies like maximax or minimax heuristics. Even in the absence of rare outcomes, Erev, Ert, and Yechiam (2008) showed that for the higher nominal magnitude condition (i.e., the magnitude of outcomes was large), participants preferred an alternative with greater number of positive outcomes over an alternative that provided a greater gain but included zero outcome in a repeated choice task where participants knew the possible outcomes and associated probabilities of alternatives. In this study, we seek to understand the role of the Pwin heuristic in a classic sampling paradigm using a three-outcome mixed gambles task.

Without any rare events for the mixed gambles used in this study, one possible prediction is that people will be more sensitive to extreme outcomes when they are learning the likelihood of an event from experience. For example, taste aversion research has shown that animals can learn associations between extreme outcomes and the causal events, even with sparse exposures and longer gaps between the causal event and its effects (Garcia, Kimeldorf, & Koelling, 1955). The peak-and-end rule also implies that peak intensity influences people's judgments on experienced events (Fredrickson, 2000). A similar focus on extreme outcome has also been shown to play an important role in experience-based paradigms with simple binary gambles (Ludvig et al., 2014). In that study, the authors found that the magnitude of outcomes in binary choice tasks contributed to distinct preferences in DFE. Specifically, participants were more risk seeking when they experienced extreme gains or losses than when they experienced less extreme outcomes. Similarly, Payne, Samper, Bettman, and Luce (2008) showed that people considered the magnitude of biggest gain when they had to learn the attractiveness of gambles by sampling. Using a sequential paradigm similar to that of DFE to study the boundary conditions of the unconscious thought effect, the authors found that the greatest proportion of participants simply selected the option that provides the greatest gain. Therefore, we seek to understand whether DFE will lead to increased preference for choices that emphasize extreme outcomes or the effect of the Pwin still significantly influences choices during experience-based decision making.

Alternatively, choices during DFE may also be explained by the natural mean heuristic, with participants being more sensitive to the experienced EV (ExpEV) of the individual alternatives (Camilleri & Newell, 2011; Hau et al., 2008). For example, Hertwig and Pleskac (2008) argued that individuals rely on small samples in experience-based decision making because it makes decisions easier by amplifying the difference between alternatives. The natural mean heuristic relies on such strength of evidence, leading to the choice of a gamble with the larger sample mean. It accounted for 77% of preferences in the choice sets used in Hertwig et al. (2004), further demonstrating an important role of this strategy in experience-based decision making. However, it remains unclear if the use of natural mean heuristics extends beyond binary gambles and whether participants will continue to choose the option with higher sample mean even in more complex gambles. Therefore, in two independent studies using three-outcome mixed gambles, we examined the role of different decision strategies like natural mean, Pwin, minimax, and maximax in explaining differences between decisions from description and experience, when information is different or matched across the two formats (Fox & Hadar, 2006; Hertwig & Pleskac, 2010).

STUDY 1

Method

A total of 69 university undergraduate students (mean age = 22.28, *SD* = 3.61, female = 36) completed the study in exchange for class credit or \$5 cash payment. Temple University's institutional review board approved the study, and all participants provided informed consent.

Materials

We used a modified version of the value allocation task used in several past studies (Venkatraman et al., 2014). In each trial, participants had to choose between three different mixed gambles, presented in a 4 × 4 grid format (Figure 1). Each gamble consisted of three outcomes (one gain, one loss, and one intermediate), each with its own probability. The three alternatives were constructed by improving one of the three base outcomes, respectively (Figure 1). Therefore, one alternative was always associated with the highest gain outcome (gain maximizing or Gmax; see G1 in Figure 1), one alternative was associated with the lowest loss outcome (loss minimizing or Lmin; see G3 in Figure 1), and the third intermediate alternative (G2 in Figure 1) was associated with superior value for the intermediate outcome. Trials were further classified into two types: Pwin available or Pwin unavailable. In the Pwin available trials, the intermediate alternative was associated with a greater Pwin compared with the other alternatives (G2 in Figure 1a). In the Pwin unavailable trials, there was no difference in Pwin across all alternatives (G2 in Figure 1b). We used these later trials to rule out the possibility that the intermediate alternative is merely a compromise option (Venkatraman et al., 2009). In both trial types, all alternatives had equal EV (Table 1).

Experimental design and procedure

We used a 2 (trial type: Pwin available vs. Pwin unavailable) × 2 (presentation format: description vs. experience) within-subject design (Camilleri & Newell, 2009; Ludvig

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		0.33 (P1)	0.33 (P2)	0.33 (P3)
Base		55 (O1)	-15 (O2)	-65 (O3)
G1	Gmax	75	-15	-65
G2	Pwin	55	5	-65
G3	Lmin	55	-15	-45

a. Pwin available trial

		0.33 (P1)	0.33 (P2)	0.33 (P3)
Base		65 (O1)	-30 (O2)	-85 (O3)
G1	Gmax	85	-30	-85
G2	Intermediate	65	-10	-85
G3	Lmin	65	-30	-65

b. Pwin unavailable trial

Figure 1. An example of Pwin available and Pwin unavailable trials. The three gambles (G1, G2, and G3) were developed by adding a constant (here 20) amount to the highest gain (O1 of G1, Gmax), intermediate (O2 of G2), and loss (O3 of G3, Lmin) outcomes of the base gamble. Adding a constant amount to the intermediate outcome changed the overall probability of winning in Pwin available trials (a), but not for Pwin unavailable trials (b). The row with base gamble is shown here for display purposes only and was not presented to participants. (P indicates probability and O indicates outcome)

et al., 2014). All participants solved the same problems in both presentation formats with a fixed block order. All trial types were randomized within each block, and the description format block was always presented second to prevent participants from familiarizing themselves with the structure of the problems (i.e., three-outcome equal probabilities). As the choice proportions in the description format were consistent with those of previous studies using a similar paradigm (Venkatraman et al., 2014), we believe that order did not critically influence the core findings presented here.

After completing two practice trials, participants completed eight main trials (Table 1). In the description format, the gambles were presented in a 4×4 table consisting of three gambles with three outcomes and their (common) probabilities (Figure 1). Participants indicated their choice by pressing the appropriate button on the keyboard. There was no time constraint for responding. For the experience format, we used a sampling paradigm similar to that of past studies of DFE (Camilleri & Newell, 2013; Hertwig et al., 2004). Three boxes (corresponding to the three gambles) were presented on the computer screen, and the three gambles were randomly allocated into those three boxes. Participants could sample one gamble at a time by pressing the corresponding button (1, left box; 2, middle box; 3, right box), and a randomly chosen outcome (based on the underlying probabilities) from that gamble was revealed within that box for 500 milliseconds. They could sample each gamble as many times as they wanted without any restriction in the sampling order. When participants felt that they had sufficient information to make their decision, they were instructed to press the number 4. This toggled the screen to an output format, where they could indicate their choice by pressing the corresponding button for the chosen gamble (1, 2, or 3). If participants wanted to continue sampling, they were given the option to toggle back to the sampling screen again by pressing 4 again. At the end of the both sessions, participants were asked to complete a demographic questionnaire.

Results

Sampling

First, we investigated the number of samples and sampling pattern (across-gamble vs. within-gamble) depending on trial types (Pwin available vs. Pwin unavailable). A total of nine trials had zero samples, so we excluded these trials and their corresponding description trials from all subsequent analyses. Participants sampled on average 36.24 times (*median* = 33.50, *SD* = 28.31), which is higher than the average number of samples reported in studies with binary gambles (a recent meta-analysis (Hertwig, 2015) showed that median number of samples in binary gambles was 16). In previous studies using a similar task in description condition, Pwin unavailable trials are associated with longer response times than Pwin available trials (Venkatraman et al., 2009; Venkatraman et al., 2014). Consistent with these studies, we found that participants took longer for Pwin unavailable trials (*M* = 12.27, *SD* = 7.54)

Table 1. Stimuli and choice proportions in Study 1

	Base gambles					Description choice (%)			Experienced choice (%)		
Trial	O1	O2	O3	Constant	EV	G1 Gmax	G2 Intermediate	G3 Lmin	G1 Gmax	G2 Intermediate	G3 Lmin
1	40	−10	−65	15	−6.67	30.88	48.53	20.59	20.59	51.47	27.94
2	60	−20	−60	25	10.00	32.35	47.06	20.59	26.47	48.53	25.00
3	55	−15	−65	20	−1.67	23.53	64.71	11.76	36.76	35.29	27.94
4	65	−10	−75	20	0.00	29.41	52.94	17.65	27.49	42.65	29.41
5	70	0	−90	20	0.00	30.30	51.52	18.18	40.91	48.48	10.61
6	45	−15	−65	15	−6.67	27.49	57.35	14.71	33.82	42.65	23.53
7	65	−30	−85	20	−10.00	47.06	25.00	27.94	45.59	23.53	30.88
8	50	10	−75	10	−1.67	29.41	35.29	35.29	26.47	35.29	38.24
9	80	−25	−70	15	0.00	27.54	30.43	42.03	44.93	15.94	39.13
10	60	5	−70	5	0.00	16.18	55.88	27.94	33.82	42.65	23.53

Trials 1–2, practice trials; Trial 3–6, Pwin available trials; Trials 7–10, Pwin unavailable trials. Constant is the amount added to each of the outcomes to form the three alternatives (G1, G2, and G3).
O1, highest gain; O2, intermediate; O3, loss outcomes.

Table 2. Choice proportions (%) by trial types in Study 1

Gamble	Choice type	Pwin available		Pwin unavailable	
		Description	Experience	Description	Experience
G1	Gmax	27.54	34.90	39.83	37.92
G2	Intermediate[a]	57.00	41.91	36.35	28.99
G3	Lmin	15.46	23.19	33.82	33.09

[a]The intermediate choice represents the Pwin alternative for Pwin available trials.

than Pwin available trials ($M = 10.40$, $SD = 6.66$) in the description condition ($t(68) = -3.05$, $p = .003$). However, there was no significant difference in the number of samples across trial types ($t(68) = -.89$, $p > .250$, $d = .059$), although participants sampled slightly more in Pwin unavailable trials ($M = 37.12$, $SD = 28.93$) than in Pwin available trials ($M = 35.37$, $SD = 29.96$).

Next, we examined the sampling pattern by looking at switching frequency—the ratio between the number of switches between the gambles and the maximum number of possible switches (Hills & Hertwig, 2010). Sampling pattern showed that participants sampled more within gamble ($M = .34$, $SD = .36$) in general. People switched across gambles more often in the Pwin unavailable trials ($M = .34$, $SD = .37$) than in the Pwin available trials ($M = .33$, $SD = .37$), but the difference in the search pattern between the two trial types was not statistically significant ($t(68) = -.67$, $p > .250$, $d = .023$). These results suggest that decisions were more homogenous across trial types in the experience condition relative to the description condition.

Choice

We examined the effect of the two presentation formats (description vs. experience) on choice, by trial types (Pwin available vs. Pwin unavailable). First, we examined whether participants showed a consistent preference for the intermediate gamble in the Pwin available trials across both formats. We showed a strong preference for the intermediate Pwin alternative in the description condition (Table 2), and the proportions were consistent with prior studies using similar paradigm (Venkatraman et al., 2014). A binomial test for the choice proportion of the Pwin alternative was significantly greater than chance level (33%, p (two-tailed) $< .001$). Further, a cross-tabulation analysis revealed that the association between presentation formats and choice was statistically significant in the Pwin available trials ($\chi^2(2, N = 540) = 11.68$, $p = .003$, Cramer's $V = .15$). In other words, we found that there was a decrease in the proportion of choices for the intermediate alternative in the experience condition relative to the description condition for Pwin available trials (Table 2, Pwin available columns).

Next, we tested whether participants showed a strong preference for the intermediate gamble even in the Pwin unavailable trials, to rule out the possibility that participants' preference for the Pwin gamble (i.e., the intermediate gamble in the Pwin available condition) was merely a compromise strategy and not related to the Pwin heuristic. A binomial test indicated that the proportion of intermediate gamble choices in the description condition was at chance level (33%, p (two-tailed) $> .250$). An additional cross-tabulation analysis revealed that there was no significant association between presentation formats and choice in the Pwin unavailable trials ($\chi^2(2, N = 546) = 4.61$, $p = .100$, Cramer's $V = .09$). These results indicated that people did not prefer the intermediate gambles in these trials, and there was no difference in choice pattern across the two presentation formats, when the intermediate gamble was not associated with an increase in Pwin (Table 2, Pwin unavailable column).

Indeed, further multilevel logistic regression analysis with random intercept for the Pwin available trials also showed a significant main effect of presentation format ($\chi^2(1) = 12.82$, $p < .001$). This indicates that participants had a strong preference for the intermediate alternative only when the intermediate alternative had a higher Pwin, and this preference for the intermediate alternative was significantly smaller in the experience condition than in the description condition. No such differences were observed between the formats for the Pwin unavailable trials ($\chi^2(1) = 3.37$, $p = .066$).

Although the choice-based analysis indicates a difference in preferences across the two formats with the three-outcome mixed gambles used in this study (similar to the traditional D-E gap observed in binary gambles), it provides little insights into the differences in the underlying decision strategies. For example, it is probable that participants' true experienced probabilities for the various gambles are significantly different from the predefined probability distributions, based on their sampling history and experienced outcomes. This could in turn lead to different probability profiles for the alternatives across the two formats. In other words, the intermediate alternatives (G2) in the Pwin available trials have two positive values, while both the extreme alternatives (G1 and G3) have only one positive value. However, if a participant experiences the positive outcomes more when sampling the extreme alternatives (especially in trials where participants sampled too little), these alternatives might be perceived as the Pwin option for those trials based on the experienced samples. Similarly, even though the EVs were set to be equal across the different alternatives, this might no longer be the case based on the experienced probabilities in the DFE. As expected, we found that the experienced Pwin and EVs were not identical with the original predefined values for the experience condition (Appendix A). Therefore, we conducted a follow-up study, where we modified the probabilities in description format to match those sampled by the participants in the experienced format. We predicted that if the differences in choice across formats were purely related to sampling errors, then these differences should be eliminated when the probabilities in

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description condition are matched to those in experience, and preferences should be more consistent across formats.

Follow-up study with matched problems across formats

A total of 66 additional participants[1] participated in a follow-up study. The procedures were largely similar to those of the main study. First, all participants completed 12 problems in the study, with six problems in Pwin available condition and another six in Pwin unavailable condition (stimuli are in Appendix B). For each participant, half of the description trials were formed based on their sampling history in the experience format (matched condition), while the other half of the description trials were formed from predefined information (original condition, similar to main study). Therefore, there were three problems of each trial type in the matched and original conditions. Second, participants completed the experience format first, followed by description format, consistent with the main study. This also allowed us to easily match the probabilities in description to those experienced in the corresponding experience trial. If a particular outcome was never experienced in the experience condition, we used a negligible probability of .01 for those outcomes in the description condition in the matched trials to maintain consistency in presentation format across individuals (Appendix C). We were primarily interested in whether preferences across description and experience formats are different, when the information is matched across the formats. Trials in both formats were randomized.

A total of 25 responses that had zero samples were excluded from this analysis. First of all, we did not find any differences in the number of samples ($M_{\text{original}} = 26.94$, $SD = 23.98$ vs. $M_{\text{matched}} = 26.98$, $SD = 22.77$; $t(65) = -.03$, $p > .500$) and in the search pattern ($M_{\text{original}} = .34$, $SD = .28$ vs. $M_{\text{matched}} = .31$, $SD = .27$; $t(65) = 1.46$, $p = .148$), indicating that there were no behavioral differences between the original and matched conditions during sampling. While we replicated the previously shown inconsistent preferences across formats in the original condition (Table 3; cross-tabulation analysis: $\chi^2(2, N = 770) = 9.55$, $p = .008$; multilevel logistic regression: $\chi^2(1) = 5.48$, $p = .019$), we found relatively consistent preferences across formats in the matched condition (Table 3; cross-tabulation analysis: $\chi^2(2, N = 764) = 4.53$, $p = .104$; multilevel logistic regression: $\chi^2(1) = 3.11$, $p = .078$). We also computed the proportion of trials where participants chose the same alternatives for the same trial across the two formats. We found significantly more consistent preferences across formats in the matched condition ($M = .46$) than in the original condition ($M = .38$; $t(65) = -2.08$, $p = .041$). In summary, matching the information across formats in a yoked experimental design diminished the differences in preference across formats (i.e., reduced the D-E gap). However, preferences were still inconsistent in more than 50% of the trials, suggesting that the gap is not completely eliminated even in the matched condition. Therefore, we next sought to explore whether these differences can be explained further by explicit differences in decision strategies across the two formats.

[1]Age information is not available owing to a computer recording error, but all students were undergraduates recruited through the subject pool at Fox School of Business, Temple University.

Table 3. Choice proportions (%) in the follow-up study across all problems

	Original		Matched	
	Description	Experience	Description	Experience
G1	36.36	35.32	30.89	37.70
G2	42.86	34.81	39.27	33.25
G3	20.78	29.87	29.84	29.06

The gambles are not mapped to specific choice types because the probabilities are based on the experienced samples in the matched condition.

Decision strategies in decisions from experience

To further investigate the decision strategies underlying DFE, we conducted two additional analyses, pooling the data across all trials in DFE. We focused our analyses on the experienced outcomes and probabilities rather than the predefined ones. We also combined the data across both the main study and the follow-up study.[2] In the first analysis, we predicted participants' choice based on four common decision heuristic strategies (maximax, minimax, natural mean, and Pwin), as these heuristics make differential predictions across the different alternatives in this study. In the second analysis, we sought to further investigate the relative importance of each of these experienced variables (extreme gain and loss values, EVs, and the Pwin) in predicting choice across all trials using a conditional logistic regression analyses.

The prediction accuracies are summarized in Figure 2. Using a one-way analysis of variance with each individual's choice prediction accuracies from the four decision strategies as a dependent variable, we found a significant main effect of decision strategy ($F(3, 134) = 13.63$, $p < .001$, $\eta_p^2 = .092$). Post-hoc analyses using the Tukey honest significant difference test showed that both the Pwin strategy (54% correct, $SD = .25$) and the natural mean strategy (55% correct, $SD = .22$) predicted choices better than the minimax strategy (42% correct, $SD = .21$) and the maximax strategy (48% correct, $SD = .27$). The comparison between the Pwin strategy and the natural mean strategy did not reveal any significant differences in prediction accuracy. In fact, we found a very strong correlation between experienced Pwin and ExpEV ($r(133) = .80$), and 42% of the choices were predicted accurately by both the Pwin and natural mean strategies. Additional one-sample t-test results showed that all of the four decision strategies predicted choices better than chance (chance = 33%; maximax: $t(134) = 6.54$, $p < .001$, minimax: $t(134) = 4.69$, $p < .001$, Pwin: $t(134) = 10.15$, $p < .001$, and natural mean: $t(134) = 11.61$, $p < .001$).

[2]We did not find a significant interaction between decision strategies and study (Study 1 vs. follow-up) for the prediction accuracies ($F(3, 399) = 0.17$, $p > .500$) and interactions between the four predictors and study code conditional in a multiple logistic regression analysis ($zs < 1.00$, $ps > .450$). In other words, the findings are largely consistent for each individual study.

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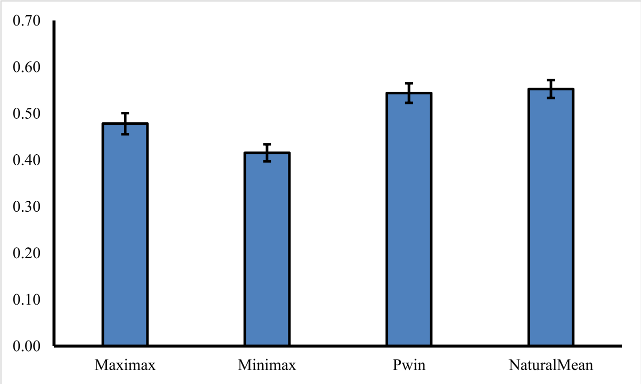

Figure 2. The prediction accuracies for the experience format from maximax, minimax, Pwin, and natural mean strategies in Study 1. [Colour figure can be viewed at wileyonlinelibrary.com]

For the conditional logistic regression analysis using standardized values of the four predictors (Table 4), we found that all four predictors positively influenced choice when modeled separately, and ExpEV explained the greatest amount of variance of the dependent variable (Table 4, Models 1–4). Considering all four predictors together (Table 4, Model 5), we found that ExpEV, experienced Pwin (ExpOP), and experienced maximum gain (MaxGain) positively influenced choices. Further linear comparisons showed that the effect of ExpEV was stronger than that of ExpOP (ExpOP vs. ExpEV: $b = -.35$, $SE = .15$, $z = -2.30$, $p = .021$) and MaxGain (MaxGain vs. ExpEV: $b = -.33$, $SE = .16$, $z = -2.07$, $p = .038$), but there was no difference between MaxGain and ExpOP (MaxGain vs. ExpOP: $b = .01$, $SE = .09$, $z = .15$, $p > .500$).

Discussion

In summary, we found inconsistent preferences across description and experience formats based on the predefined outcomes and probabilities. Participants showed a higher preference for the intermediate alternative in the description format relative to the experience format, when it was associated with higher probability of winning, consistent with the D-E gap. However, when we accounted for sampling error by matching the probabilities in the description condition to the experienced condition, we found that the magnitude of D-E gap reduced (Fox & Hadar, 2006; Hadar & Fox, 2009; Rakow et al., 2008) but was not completely eliminated. Therefore, we next sought to understand whether the differences across formats could be explained by differences in decision strategies. Although the Pwin heuristic significantly predicted choices, the natural mean heuristic also predicted choices as accurately as the Pwin heuristic did in the experience condition. Critically, the ExpEV was a stronger predictor of choices than the experienced Pwin in a multiple conditional logistic regression model that included these variables simultaneously.

Previous studies suggest that participants sacrifice EV in favor of the Pwin heuristic in decisions from description (Payne, 2005; Venkatraman et al., 2009), suggesting that the two formats may favor the use of different strategies for the same problems. However, the core problems in the description condition in this study were constructed in such a way that there were no changes in EVs across the alternatives (probabilities were always equal), precluding a more direct dissociation of strategies across formats. Therefore, we sought to replicate our findings in an independent study with greater variability across the problems.

STUDY 2

Method and materials

A total of 47 undergraduate students (mean age = 21.75, $SD = 2.98$, female = 31) participated in the study in exchange for class credit. Temple University's institutional review board approved the study, and all participants provided informed consent. Overall procedures were similar to those of Study 1. However, to provide additional variance in the problem types, we included problems where the EV was not equal across the alternatives. Across a total of 14 problems (two practice trials and 12 main trials), we varied the EV of the intermediate alternative in addition to the availability of Pwin alternative (Table 5). Similar to Study 1, participants were presented with these problems in two formats—experience and description. The description condition always

Table 4. Conditional logistic regression results predicting choice across all trials in the experience format in Study 1

	(1)	(2)	(3)	(4)	(5)
MaxGain	0.723*** (0.060)				0.269*** (0.084)
MinLoss		0.338*** (0.074)			−0.316*** (0.075)
ExpOP			0.618*** (0.067)		0.255** (0.101)
ExpEV				0.722*** (0.075)	0.602*** (0.099)
N	3705	3705	3705	3705	3705
Pseudo-R^2	.074	.026	.093	.115	.134

Models 1–4 indicate simple conditional logistic regression results using experienced maximum gain (MaxGain), minimum loss (MinLoss), overall probability of winning (ExpOP), and expected value (ExpEV) estimated from participants' sampling history as independent variables respectively. Model 5 indicates the multiple conditional logistic regression using all four variables simultaneously. Standard errors in parentheses.
$^{**}p < .01$.
$^{***}p < .001$.

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followed experience, to prevent participants from familiarizing themselves with the structure of the problems, and only included the original problems that were not matched to the experienced samples. None of the participants from Study 1 participated in Study 2.

Results

Sampling

A total of five trials had zero samples, so we excluded these trials and their corresponding description trials from all subsequent analyses. Participants sampled on average 48.23 times (*median* = 36, *SD* = 40.87), which is higher than the average number of samples reported in Study 1 and in studies with binary gambles. Consistent with Study 1, sampling pattern showed that participants sampled more within gamble (M = .20, SD = .27).

Choice

The choice proportions for each problem across decision formats are summarized in Table 5. As seen from the table, preferences varied across the different problem types. Participants showed a strong preference for the alternative that maximized the Pwin when such an alternative was available in the mix (mean choice share: .51 for Trials 3, 4, and 7 to 12). Similar to Study 1, they switched to other strategies when there were no alternatives that maximized the Pwin.

Similar to Study 1, we also found that choice preferences were different across the two formats. Although experienced EV was a strong predictor of choices in the experience condition in Study 1, we could not test the role of EV in description condition because all problems were matched for EV. Here, we examined whether participants showed a higher preference for an alternative that maximized EV in the description format, when an EV alternative was in the mix (Trials 7 to 13). The average preference for EV alternative was .30, which was not significantly different from chance (chance = 33%; $t(46) = -1.24$, $p = .222$). This suggests that maximizing EV is not a dominant strategy in the description-based decision making, consistent with previous studies using similar paradigms (Payne, 2005; Venkatraman et al., 2009).

To replicate the effect of experienced Pwin and EV on choice in the experience condition, we conducted the same two additional analyses as in Study 1. First, we predicted choices using the four decision strategies (maximax, minimax, natural mean, and Pwin strategies). The prediction accuracies are summarized in Figure 3. The results showed that the Pwin strategy and the natural mean strategy predicted choices better than the maximax and minimax strategies. Using a one-way analysis of variance with each individual's choice prediction accuracies from the three decision strategies as a dependent variable, we found a significant main effect of decision strategy ($F(3, 46) = 20.82$, $p = .006$, $\eta_p^2 = .312$). Post-hoc analyses using the Tukey honest significant difference test showed that the Pwin strategy (54% correct, $SD = .20$) and the natural mean strategy (54% correct, $SD = .18$) predicted choices better than maximax (36% correct, $SD = .18$) and minimax strategies (35% correct, $SD = .16$). Additional one-sample t-test results showed that the predictions from the maximax ($t(46) = 1.01$, $p > .250$) and minimax ($t(46) = .68$, $p > .500$) strategies were not significantly different from chance (33%), but the Pwin strategy ($t(46) = 7.33$, $p < .001$) and the natural mean strategy were ($t(46) = 8.04$, $p < .001$). However, the prediction accuracies between the Pwin strategy and the natural mean strategy were not different. Similar to Study 1, we still found a very strong correlation between experienced probability of winning and ExpEV ($r(45) = .77$). Consequently, we found that 37% of the choices were accurately and commonly predicted by the both Pwin and natural mean strategies.

Second, we ran a conditional logistic regression analysis to investigate the relative importance of extreme values, probability of winning, and EV based on experienced values, using standardized values of the four predictors (Table 6). We found that all of the four predictors positively influenced choice (Table 6, Models 1–4). In terms of the variance explained by the four predictors, ExpEV had the greatest explanatory power. Furthermore, when we considered all the four predictors together, ExpOP and ExpEV were significant predictors of choice, but maximum gain and minimum loss were not (Table 6, Model 5). Linear comparisons between predictors revealed that the effects of experienced Pwin and EV were stronger predictors than maximum gain (ExpOP vs. MaxGain: $b = .31$, $SE = .11$, $z = 2.67$, $p = .008$; ExpEV vs. MaxGain: $b = .73$, $SE = .21$, $z = 3.55$, $p < .001$) and minimum loss (ExpOP vs. MinLoss: $b = .40$, $SE = .11$, $z = 3.59$, $p < .001$; ExpEV vs. MinLoss: $b = .82$, $SE = .19$, $z = 4.28$, $p < .001$). Further linear comparison between the effect of experienced Pwin and EV showed that the effect of ExpEV was greater than that of experienced Pwin (ExpOP vs. ExpEV: $b = -.42$, $SE = .19$, $z = -2.23$, $p = .026$).

CONCLUSION AND DISCUSSION

Across two independent studies, we investigated differences in preferences and underlying decision strategies across two presentation formats (description vs. experience) using a complex risky choice task involving decisions between three 3-outcome mixed gambles. We found inconsistent preferences across formats when only considering the predefined outcomes and probabilities. Participants showed a stronger preference for the intermediate alternatives in the description relative to the experience format, only when these gambles were associated with a greater Pwin. When we matched the probability information in the description format to that experienced in the corresponding trials in the experienced format, we found that the differences between formats diminished but were not eliminated. Last, choices in the experience format were predicted significantly by both the natural mean and Pwin heuristic strategies, when accounting for the experienced probabilities and outcomes. Therefore, participants still demonstrate the use of Pwin strategy even when making DFE, which might explain some of the similarities in the matched conditions. Strikingly, however, participants' decisions in the experience format were influenced by ExpEV, and the conditional logistic regression results

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Table 5. Stimuli and choice proportions in Study 2

Trial		O1	O2	O3	EV	Choice type	Description (%)	Experience (%)
1	prob.	0.33	0.33	0.33				
	G1	75	−15	−65	−1.67	Gmax	31.11	31.11
	G2	55	5	−65	−1.67	Pwin	57.78	51.11
	G3	55	−15	−45	−1.67	Lmin	11.11	17.78
2	prob.	0.33	0.33	0.33				
	G1	85	−10	−75	0.00	Gmax	8.51	23.40
	G2	65	10	−75	0.00	Pwin	70.21	51.06
	G3	65	−10	−55	0.00	Lmin	21.28	25.53
3	prob.	0.33	0.33	0.33				
	G1	90	0	−90	0.00	Gmax	19.15	25.53
	G2	70	20	−90	0.00	Pwin	57.45	44.68
	G3	70	0	−70	0.00	Lmin	23.40	29.79
4	prob.	0.33	0.33	0.33				
	G1	60	−15	−65	−6.67	Gmax	19.15	31.91
	G2	45	0	−65	−6.67	Pwin	61.70	38.30
	G3	45	−15	−50	−6.67	Lmin	19.15	29.79
5	prob.	0.33	0.33	0.33				
	G1	85	−30	−85	−10.00	Gmax	29.79	38.30
	G2	65	−10	−85	−10.00	—[a]	38.30	29.79
	G3	65	−30	−65	−10.00	Lmin	31.91	31.91
6	prob.	0.33	0.33	0.33				
	G1	60	10	−75	−1.67	Gmax	20.00	24.44
	G2	50	20	−75	−1.67	—[a]	40.00	31.11
	G3	50	10	−65	−1.67	Lmin	40.00	44.44
7	Prob.	0.25	0.25	0.50				
	G1	95	−10	−65	−11.25	Gmax	8.51	31.91
	G2	75	10	−65	−11.25	Pwin	61.70	53.19
	G3	85	−10	−55	−8.75	Lmin, EV	29.79	14.89
8	Prob.	0.33	0.33	0.33				
	G1	95	−20	−90	−4.95	Gmax	12.77	23.40
	G2	70	5	−90	−4.95	Pwin	65.96	51.06
	G3	85	−20	−75	−3.30	Lmin, EV	21.28	25.53
9	Prob.	0.33	0.33	0.33				
	G1	60	−5	−65	−3.30	Gmax	17.02	27.66
	G2	45	10	−65	−3.30	Pwin	42.55	40.43
	G3	55	−5	−50	0.00	Lmin, EV	40.43	31.91
10	Prob.	0.44	0.28	0.28				
	G1	80	−5	−50	19.80	Gmax, EV	21.28	40.43
	G2	75	10	−60	19.00	Pmax	68.09	36.17
	G3	75	−5	−45	19.00	Lmin	10.64	23.40
11	Prob.	0.33	0.33	0.33				
	G1	90	−15	−75	0.00	Gmax, EV	27.66	38.30
	G2	75	5	−90	−3.30	Pmax	61.70	42.55
	G3	75	−15	−70	−3.30	Lmin	10.64	19.15
12	Prob.	0.33	0.33	0.33				
	G1	55	−5	−55	−1.65	Gmax, EV	27.66	34.04
	G2	45	10	−65	−3.30	Pwin	53.19	36.17
	G3	45	−5	−50	−3.30	Lmin	19.15	29.79
13	Prob.	0.25	0.50	0.25				
	G1	85	5	−65	7.50	Gmax	21.28	36.17
	G2	70	15	−60	10.00	EV	48.94	44.68
	G3	65	5	−45	7.50	Lmin	29.79	19.15
14	Prob.	0.33	0.33	0.33				
	G1	60	−15	−70	−8.25	Gmax	10.64	25.53
	G2	55	−5	−65	−4.95	EV	68.09	38.30
	G3	50	−15	−60	−8.25	Lmin	21.28	36.17

Trials 1 and 2 were practice trials.
[a]G2 in Trials 5 and 6 are the same as the intermediate alternative in the Pwin unavailable trials in Study 1.

showed that the effect of EV in the experience format was stronger than that of Pwin. Yet there was no corresponding preference for alternatives associated with increased EV in the description format. These results suggest that the natural mean heuristic and EV maximization play an important role in DFE for complex gambles, similar to prior findings with binary gambles (Hau et al., 2008). Critically, the differences in choice preferences across description and experience formats may be explained by the use of systematically different decision strategies across these formats.

Our findings extend our understanding of the use of decision strategies in risky choice across presentation formats.

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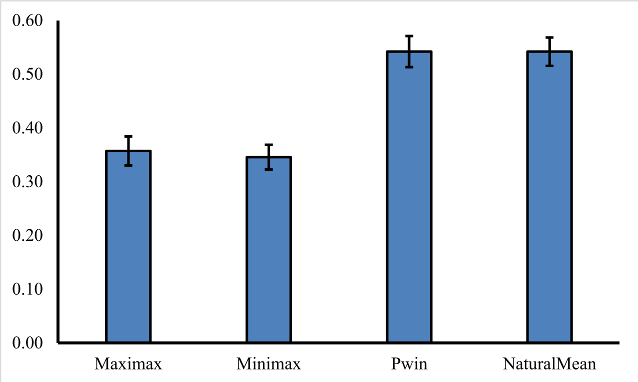

Figure 3. The prediction accuracies for the experience format from maximax, minimax, Pwin, and natural mean strategies in Study 2. [Colour figure can be viewed at wileyonlinelibrary.com]

First, this study investigated the description-based and experience-based decision making outside of canonical binary gambles, which have been extensively used in previous studies (Rakow & Newell, 2010). Even though there are numerous studies investigating experience-based decisions using multiple alternative–multiple outcome tasks, they were either heavily focused on binary outcome gambles with multiple alternatives or binary alternative gambles with multiple outcomes, or they did not directly compare preferences between experience-based and description-based formats (Hills et al., 2013; Newell, Rakow, Yechiam, & Sambur, 2015; Noguchi & Hills, 2015; Teodorescu & Erev, 2014; Wulff, Hills, & Hertwig, 2015; Yechiam, Rakow, & Newell, 2015). Here, we examined risk preferences in description-based and experience-based decision making using a three-outcome mixed gamble task and using a within-subject design to directly compare different decision strategies across the two presentation formats. Second, unlike the commonly used framework for D-E gap that involves alternatives with rare outcomes, we demonstrate preference reversals across the two formats using three-outcome mixed gamble task with equal probability and with slight variations from the equal probability. Some recent studies have demonstrated similar D-E gap in equal probability binary gamble tasks (Ludvig et al., 2014; Ludvig & Spetch, 2011), but in this study, we examined how the valence of outcomes in a choice set influences decisions in the description format and in the experience format without involving any rare event. Last, we try to relate any differences across the formats to differences in the underlying decision strategies across the two formats.

We found that both the natural mean and Pwin heuristics were significant predictors of choice across both studies in DFE. Participants essentially treated the gambles across the Pwin available and Pwin unavailable types as homogenous in the experience condition, but not description condition where they switched away from the Pwin heuristic when a Pwin alternative was not available. This is also evident from the fact that participants took longer for Pwin unavailable trials relative to Pwin available trials in the description condition, but there were no differences in the number of samples across problem types in the experience condition. Critically, the ExpEV was the strongest predictor of choice in DFE. However, EV did not significantly predict choice in decisions from description when it was explicitly modulated in Study 2, arguing again in favor of explicit differences in decision strategies across the two formats using very similar tasks.

In summary, our findings suggest that presentation format plays a crucial role in shaping decision strategies. However, the current study has several limitations that need to be explored further in subsequent studies. First, we could not systematically dissociate the role of EV and Pwin in predicting choices in the experience condition, as these variables were highly correlated in both studies. For example, the correlations between experienced Pwin and ExpEV were really high ($r(67) = .75$ in Study 1, $r(64) = .91$ in the follow-up study of Study 1, and $r(45) = .77$ in Study 2). Even though we tried to dissociate the effect of Pwin and EV in Study 2 by employing diverse sets of stimuli, they were still highly correlated. Therefore, although the current studies used more complex gambles than the binary gambles in previous studies, we might need to extend it further to include five-outcome mixed gambles in future studies to successfully dissociate the roles of experienced EV and probability of winning in the experience condition. These gambles may also make it easier to explicitly separate EV choices from Gmax, Lmin, and Pwin alternatives in the description condition (e.g., Venkatraman et al., 2014), allowing us to evaluate differences in the decision strategies between experience and description conditions more robustly.

Table 6. Conditional logistic regression results for the experience format in Study 2

	(1)	(2)	(3)	(4)	(5)
MaxGain	0.307***				0.020
	(0.077)				(0.117)
MinLoss		0.242**			−0.070
		(0.076)			(0.103)
ExpOP			0.643***		0.325**
			(0.065)		(0.092)
ExpEV				0.923***	0.748***
				(0.084)	(0.120)
N	1647	1647	1647	1647	1647
Pseudo-R^2	.015	.009	.094	.137	.152

Standard errors in parentheses.
$^{**}p < .01$.
$^{***}p < .001$.

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APPENDIX A:

Mean overall probabilities of winning and expected values of each alternative across the problems used in Study 1, based on predefined probability distribution (Set columns) and the experienced samples (Experienced columns)

			Predefined			Experienced		
Trial	Pwin		Gmax	Intermediate	Lmin	Gmax	Intermediate	Lmin
3	Available	OP	0.33	0.66	0.33	0.36	0.64	0.39
		EV	−1.65	−1.65	−1.65	2.90	−6.00	4.31
4	Available	OP	0.33	0.66	0.33	0.33	0.68	0.28
		EV	0.00	0.00	0.00	−0.24	0.48	−5.20
5	Available	OP	0.33	0.66	0.33	0.34	0.72	0.27
		EV	0.00	0.00	0.00	2.45	8.29	−9.16
6	Available	OP	0.33	0.66	0.33	0.34	0.67	0.34
		EV	−6.60	−6.60	−6.60	−7.02	−5.57	−6.40
7	Unavailable	OP	0.33	0.33	0.33	0.35	0.36	0.38
		EV	−9.90	−9.90	−9.90	−8.12	−5.73	−4.80
8	Unavailable	OP	0.33	0.33	0.33	0.72	0.71	0.65
		EV	−1.65	−1.65	−1.65	3.46	1.81	−3.27
9	Unavailable	OP	0.33	0.33	0.33	0.31	0.30	0.36
		EV	0.00	0.00	0.00	−3.82	−4.82	3.05
10	Unavailable	OP	0.33	0.33	0.33	0.63	0.65	0.67
		EV	0.00	0.00	0.00	−2.01	−2.11	0.02

OP: overall probability of winning, EV: expected value

APPENDIX B:

Stimuli and an example of original format and matched format used in the follow−up study of Study 1

	Base Gamble				
Trial	O1	O2	O3	Constant	EV
1	55	−15	−65	20	−8.25
2	40	−10	−65	15	−11.55
3	70	−5	−85	20	−6.6
4	65	−10	−75	20	−6.6
5	60	−20	−60	25	−6.6
6	50	−5	−40	20	1.65
7	65	−20	−80	15	−11.55
8	50	10	−75	10	−4.95
9	80	−25	−70	15	−4.95
10	60	5	−70	5	−1.65
11	40	5	−40	15	1.65
12	65	−20	−50	10	−1.65

APPENDIX C:

G1	90 (0.33)	-5 (0.33)	-85 (0.33)
G2	70 (0.33)	15 (0.33)	-85 (0.33)
G3	70 (0.33)	-5 (0.33)	-65 (0.33)

a. Original Format

G1	90 (0.30)	-5 (0.35)	-85 (0.35)
G2	70 (0.41)	15 (0.12)	-85 (0.47)
G3	70 (0.21)	-5 (0.43)	-65 (0.36)

b. Matched Format

An example (Trial 3 of Appendix B) of presentation formants for the original condition and matched condition for one representative subject. Probabilities for each outcome can now vary across alternatives, and hence are presented in the parentheses. The probabilities in the matched format condition are based on the participant's sampling history for the same trial in their experience format condition.

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Authors' biographies:

Sangsuk Yoon is a graduate student in Marketing at Fox School of Business, Temple University.

Khoi Vo is a graduate student in the Cognitive Neuroscience Admitting Program (CNAP) at Duke University.

Vinod Venkatraman is an Assistant Professor of Marketing and Associate Director of the Center for Neural Decision Making at the Fox School of Business, Temple University.

Authors' addresses:

Sangsuk Yoon, Center for Neural Decision Making, Fox School of Business, Temple University, Philadelphia, PA USA.

Khoi Vo, Center for Cognitive Neuroscience, Duke University, Durham, NC USA.

Vinod Venkatraman, Center for Neural Decision Making, Fox School of Business, Temple University, Philadelphia, PA USA.

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