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The role of experience in decisions from description

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We extend research on the distinction between decisions from experience *or* description to situations in which people are given perfect information about outcome probabilities *and* have experience in an environment which matches the described information. Participants read a description of a die with more sides of one color than another (e.g., 4 black and 2 white sides) and were then asked either to predict the outcomes of rolls of the die or to select the best strategy for betting on the most likely outcome for each roll in a hypothetical game. Experience in the environment (trials), contingency (probability of the more likely alternative), and outcome feedback all had significant effects on the adoption of the optimal strategy (always predicting the most likely outcome), despite their normative irrelevance. Comparisons of experience with description-only conditions suggested that experience exerted an influence on performance if it was active—making predictions—but not if it was passive—observing outcomes. Experience had a *negative* initial impact on optimal responding: participants in description-only conditions selected the optimal strategy more often than those with 60 trials of prediction experience, a finding that reflects the seduction of "representative" responding.

This article unites research into one phenomenon that has intrigued scientists for many years with research into another that has only begun to attract interest recently. The "old" phenomenon is probability learning (Myers, 1976; Tversky & Edwards, 1966); the "new" one is the contrast between decisions made on the basis of described versus experienced information (Erev & Barron, 2005; Hertwig, Barron, Weber, & Erev, 2004).

Decisions From Experience and Description

In decisions from description, outcomes and their respective probabilities are clearly and unequivocally specified to the decision maker. For example, participants are asked to choose between (A) an 80% chance of winning \$4 and a 20% chance of winning nothing or (B) \$3 for sure. Such gambles represent the standard way for economists and psychologists to infer the utility of different outcomes presented to participants, and have provided abundant data requiring explanation (see, e.g., Kahneman & Tversky, 2000).

In decisions from experience the decision maker must learn the probabilities and outcomes associated with each option by observation. For example, Hertwig et al. (2004) gave participants a "computerized money machine" in which they selected one of two options (A or B) by clicking on unmarked buttons and then received immediate feedback of the outcome associated with that button (on that occasion). The task was analogous to a "two-armed bandit" with a different payoff associated with each lever. Participants sampled the environment for as long as they wanted, and then stated their preferred option.

A striking contrast was observed when the options were experienced versus described. In the description version, only 36% of participants chose Option A in the example above, whereas in the experience version, 88% chose A (Hertwig et al., 2004). Explanations of this difference focus on the idea that rare events (i.e., the 20% chance of winning nothing) are over-weighted in the description case, leading to the majority choice of Option B, but under-weighted in the experience case, leading to the majority choice of Option A (Erev & Barron, 2005; Hertwig et al., 2004; Weber, Shafir, & Blais, 2004).

Probability Learning

The standard procedure in probability learning tasks is to predict which of two mutually exclusive outcomes will occur on each trial of a multiple trial experiment (e.g., which of two lights will be turned on). A typical contingency used in such experiments is 70:30, in which one light comes on 70% of the time and the other 30% of the time (e.g., Shanks, Tunney, & McCarthy, 2002). The optimal strategy given this contingency is to predict the $p = .7$

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option on every trial (i.e., *maximize*), since this will yield 70% correct predictions. Despite the existence of a clear optimal strategy, participants in such experiments often deviate from maximization and show responding closer to *probability matching*—allocating responses to the two options in proportion to their relative probabilities of occurrence. This strategy is suboptimal, since it only yields 58% correct predictions ($.7 \times .7 + .3 \times .3$).

The failure to maximize has been explained in terms of deficiencies in the structure of learning environments (e.g., lack of financial incentives and feedback; Shanks et al., 2002), of participants searching for nonexistent patterns in the sequences of events (Kahneman & Tversky, 1972; Peterson & Ulehla, 1965), and of individual differences in computational ability (West & Stanovich, 2003).

Relating the Two Phenomena

Erev and Barron (2005) presented an extensive review and integration of studies involving binary choice and immediate feedback which brought together research from the "older" probability learning tasks and the more recent "experience" tasks. However, their review was restricted to situations in which people had no prior information about possible outcomes and outcome probabilities.

The present study extends this integrative approach by using problems in which the possible outcomes and outcome probabilities can be straightforwardly inferred from information provided at the outset. This is not an entirely novel way to examine the tendency to match or maximize (see, e.g., Gal & Baron, 1996; West & Stanovich, 2003), but it is a less commonly used procedure. This "information-given" arrangement also allows us to investigate an issue that is rarely addressed: how does experience in an environment that matches the description of a problem affect choice propensities? Despite differences in choice behavior when problems are described *or* experienced, it is not yet clear how people *combine* these two types of information if both are present. It seems important to consider this situation as it is arguably characteristic of many real-world decisions (e.g., doctors prescribing on the basis of experience with patients *and* summary statistics about the probabilities of side-effect or cure for specific conditions).

The Die Problem

We used a task adapted from Gal and Baron (1996; see also West & Stanovich, 2003) in which participants are told that a die with four sides of one color and two sides of another is going to be rolled 60 times. In the description-only version participants are asked to choose from a selection of five possible response strategies the best one for betting on the most likely outcome for each roll in a hypothetical game. In the "combined" conditions, participants read the description and predict the outcome of each roll in an actual game. In both versions, the optimal strategy is to predict the most likely outcome on *every* trial; furthermore, the "experience" afforded by playing an actual game provides no extra information about the structure of the problem, because the description that participants receive before they experience the task provides sufficient information for them to know, with certainty, the optimal strategy. Thus, normatively, because we are not employing any form of deception, experience should not affect the tendency to adopt a maximizing strategy.

Predictions

Previous research has suggested that in description-only versions of the die problem, approximately one third to one half of participants choose a maximizing strategy (Gal & Baron, 1996; West & Stanovich, 2003), with the remainder endorsing a probability matching strategy or one that alternates between alternatives, in keeping with the *gambler's fallacy*. Research on probability learning has indicated that maximizing behavior in situations in which the structure must be learned from observation only manifests itself after many hundreds of trials (e.g., Erev & Barron, 2005; Shanks et al., 2002). It is therefore possible that despite the fact that the experience our participants gain is normatively irrelevant, it may act to push them toward the optimal strategy. Thus, we might see more maximizers than the third to a half typically found in the description-only version.

An alternative prediction is that *non*maximizing strategies are more appealing in a trial-by-trial version of the die problem because they offer the *possibility* of predicting the correct outcome on more than the 66.66% of trials dictated by a strict maximizing strategy (i.e., an average of 4 out of every 6 rolls correct; see Tversky & Kahneman, 1972; West & Stanovich, 2003). The notion here is that participants attempt to produce patterns of responses that are representative of what they know to be the source of the sequence (Kahneman & Tversky, 1972). Although participants may realize that black is the most likely outcome on any specific role of the die, across all trials a mix of black and white outcomes is virtually certain to occur—with a mixture in proportion to the contingency on the die being the most *representative* long-run outcome (see Gal & Baron, 1996; West & Stanovich, 2003). If this is the case, we might expect to see fewer maximizers in the combined conditions than are typically found in the description-only versions.

One final possibility is that the appeal of responding in a 'representative' manner is restricted to the early stages of the experiment and it is gradually eroded by continuing experience. Thus we may see fewer maximizers early in the experiment but similar numbers once more trials have been experienced.

The experiment examined performance in description-only versions of the problem and in situations in which experience and description were combined. We examined three factors that normatively should have no impact on choice propensities. The first was contingency: whether the die had 5 faces of one color and 1 of another or 4 and 2 (hereafter, the 5:1 and 4:2 conditions). The second, in the combined conditions was feedback: feedback has no normative influence on learning about the problem but it may be crucial in illuminating the rewards associated with different prediction strategies. The third, within subjects, was exposure or number of trials: Some participants were asked to make judgments several times after they had seen more trials.

Finally, it is important to note that for all groups in the combined conditions, the optimal, and easily inferrable, strategy is to choose the most likely outcome (i.e., black) on every trial, and for those in the description-only conditions, the best strategy is clearly the maximizing one.

METHOD

Participants

One hundred seventy-five undergraduate students from the University of New South Wales participated in the experiment in return for course credit. The average age was 19.0 (*SD* = 2.81). In each of the seven conditions reported, 25 individuals took part, with an approximately equal distribution of males and females in each condition.[1]

Design, Materials, and Procedure

The core design was 2 × 2, with contingency (5:1 or 4:2) and information type (description only or combined description and experience). Three additional conditions—observation, combined no feedback, and generate—were run in order to examine alternative hypotheses (as described below). Thus, in total the experiment included the seven conditions shown in Table 1.

Description-only conditions. Participants read either a description of the 5:1 or the 4:2 version of the die problem and then five options describing different strategies. Participants then selected the strategy that they thought was the best one for maximizing hypothetical earnings. The 4:2 version read as follows:

> Imagine that a die with 4 black faces and 2 white faces will be rolled 60 times. Before each roll you will be asked to predict which color (black or white) will show up once the die is rolled. You will be given one dollar for each correct prediction. Assume that you want to make as much money as possible. What strategy would you use in order to make as much money as possible by making the most correct predictions?

> Strategy A. Go by intuition, switching when there has been too many of one color or the other.
>
> Strategy B. Predict the more likely color (black) on most of the rolls but occasionally, after a long run of blacks, predict white.
>
> Strategy C. Make predictions according to the frequency of occurrence (4 of 6 for black and 2 of 6 for white). That is, predict twice as many blacks as whites.
>
> Strategy D. Predict the more likely color (black) on all of the 60 rolls.
>
> Strategy E. Predict more black than white, but switching back and forth depending on "runs" of one color or the other.

Observation condition. Participants read a description of the 4:2 problem and then observed 60 trials of the die being "rolled" by the computer. At the end of 60 trials they were asked to choose the strategy from the questionnaire that they *would have adopted* in order to earn the most money in the game that they had just observed. This procedure was repeated for five games of 60 trials each. This condition maintains strategy selection as the dependent variable but adds trial experience via observation, thus comparing performance with the 4:2 description-only condition enables a direct examination of the effect of experienced outcomes on strategy choice in the questionnaire.

Combined conditions. In each of these three conditions (5:1 F, 4:2 F, and 4:2 NF), participants read a description of the relevant die problem; in the 4:2 condition, the problem read as follows:

> In this computerized dice game you will be playing with a die with 4 black faces and 2 white faces. The computer will roll the die 60 times. Before each roll you will be asked to predict which color (black or white) will show up once the die is rolled.

Hypothetical payment for correct predictions was the same as in the description-only conditions.[2] The description was present on the screen for every prediction trial, along with a message telling participants that the die was fair and unbiased. On each trial participants made a prediction by clicking a button marked BLACK or WHITE; a screen then told them that the computer was now rolling the die and then in the two feedback conditions (5:1 F and 4:2 F) the side showing face up on the die was revealed. In the no-feedback (4:2 NF) condition, participants were simply told the die had been rolled and were asked for their next prediction. Each game comprised 60 trials and at the start of each new game participants were told that the same die was being used and that their task remained the same. The computer generated outcomes according to the programmed contingencies in each condition. All five games took approximately 20 min to complete.

Generate condition. Participants read a description of the 4:2 problem and then generated predictions for a 60 trial game on a piece of paper. Participants only completed one game. Comparing this condition with the 4:2 F combined condition enables a direct examination of the effect of experienced outcomes on prediction responses. The comparison with the 4:2 NF combined condition is also informative, since although the two conditions were similar—predictions were made without feedback—the generate condition differed in that participants created an entire stream of predictions in front of them, whereas the 4:2 NF participants only saw one prediction at any given time.

RESULTS

Majority Responding in Combined Conditions

Figure 1 plots the mean proportion of majority responses (predicting black) for each of the three combined conditions. A simple summary of the results is that three factors—

Table 1
Details of the Seven Conditions of the Experiment

Condition Name	What to Do on Trials	Feedback?	Questionnaire?
Description Only			
5:1	X	X	Select strategy (×1)
4:2	X	X	Select strategy (×1)
Observation			
4:2	Observe (60×5)	X	Select strategy (×5)
Combined			
5:1 F	Predictions (60×5)	yes	X
4:2 F	Predictions (60×5)	yes	X
4:2 NF	Predictions (60×5)	no	X
Generate			
4:2	Generate 60 outcomes	X	X

Note—X, not applicable to that condition; F, feedback; NF, no feedback.

contingency, feedback, and number of trials (games)—that normatively *should* have no effect on predicting the majority response all had highly significant effects. The effect of number of trials is shown by the steady increase in the lines for all three groups [main effect of game, $F(4,288) = 22.75$, $p < .001$]. The effect of contingency is shown by the higher majority responding in the 5:1 F than in the 4:2 F conditions [main effect of contingency, $F(1,48) = 8.63, p < .005$]. The difference between the conditions was greater in the earlier games than in the later ones [significant contingency by game interaction, $F(4,192) = 4.77, p < .001$]. The effect of feedback is shown by the higher level of majority responding in the 4:2 F than in the 4:2 NF condition [main effect of feedback, $F(1,48) = 10.86$, $p < .005$]. The difference between these conditions was *smaller* in the earlier games than the later ones [significant feedback $\times$ game interaction, $F(4,192) = 4.24$, $p < .005$]. Together the results emphasize the influence of experience even in environments with perfect descriptive information.

Strategy Classification

To explore the effects of experience and description we classified participants on the basis of either prediction responses or strategy choices. Figure 2 (top panel) displays the number of participants who were classified as maximizing or matching on the basis of their prediction responses. Maximizing is defined as predicting the majority outcome (black) on more than 95% of trials in a game; matching is defined as allocating choices within 3% of those predicted by a matching strategy (i.e., for 4:2, 66.6% $\pm$ 3%).[3] Figure 2 (bottom panel) displays the number of participants who were classified as maximizing or matching on the basis of their strategy choices on the questionnaire. (Note that participants not shown on this figure chose one of the three "other" strategies, A, B, or E—all variants of the gambler's fallacy.)

To examine the effect of experiencing outcomes we compared strategy allocation/choice across information type and dependent variable. Inspection of Figure 2 suggest that in the early stages of the combined conditions (Game 1) nonmaximizing strategies appear to be *more* appealing than in the description-only conditions where no experience is provided. Comparing the leftmost bars of the top and bottom panels of Figure 2 reveals that more participants chose a maximizing strategy on the basis of the description-only in the 5:1 condition (bottom panel) than were classified as maximizers in Game 1 of the 5:1 F combined condition (top panel) [$\chi^2(1) = 3.92$, $p < .05$]. This pattern is also true for the 4:2 conditions (3rd bar from left in top panel vs. 2nd bar from left in bottom panel), though the difference is not statistically significant.[4]

To gain more direct evidence of the effect of information type alone, we then compared strategy allocation/choice in conditions with the *same* dependent variable (prediction or questionnaire). This analysis revealed a slightly different picture. The top panel of Figure 2 shows very similar distributions of maximizers and matchers in the 4:2 F combined condition (Game 1) and the 4:2 generate conditions, suggesting that when response type is equated (both made predictions on each trial) and only the experience of outcomes differs (present in combined, absent in generate), strategies are equally appealing. (Indeed, as shown in Figure 1, the mean number of majority responses in the 4:2 generate condition was .77—identical to that in Game 1 of the 4:2 F combined condition.) Comparing generate with the 4:2 NF combined condition was also revealing: Here, neither group experienced outcomes, but generate participants made more majority responses than did 4:2 NF participants (.77 vs. .71; see Figure 1), though the difference was not significant [$F(1,49) = 2.35$, $p > .10$]. Consistent with this higher level of majority responding, Figure 2 (top panel) shows that

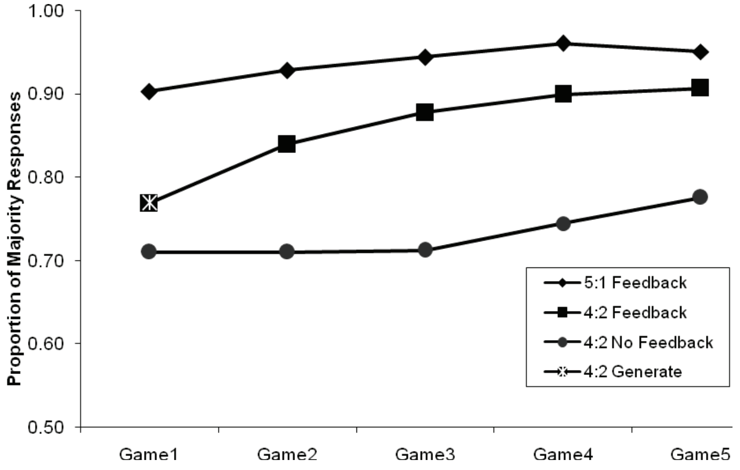

Figure 1. Proportion of majority responses (predicting black) across games in the three combined conditions and the generate condition. "4:2" refers to the die problem featuring a six-sided die with 4 black sides and 2 white sides; "5:1" refers to 5 black sides and 1 white. NF (no-feedback) participants did not see which side of the die appeared after the roll (participants in all other groups did). "4:2 Generate" refers to the condition in which participants read a description and then generated predictions on a piece of a paper. Each game was 60 trials; generate participants only completed one game.

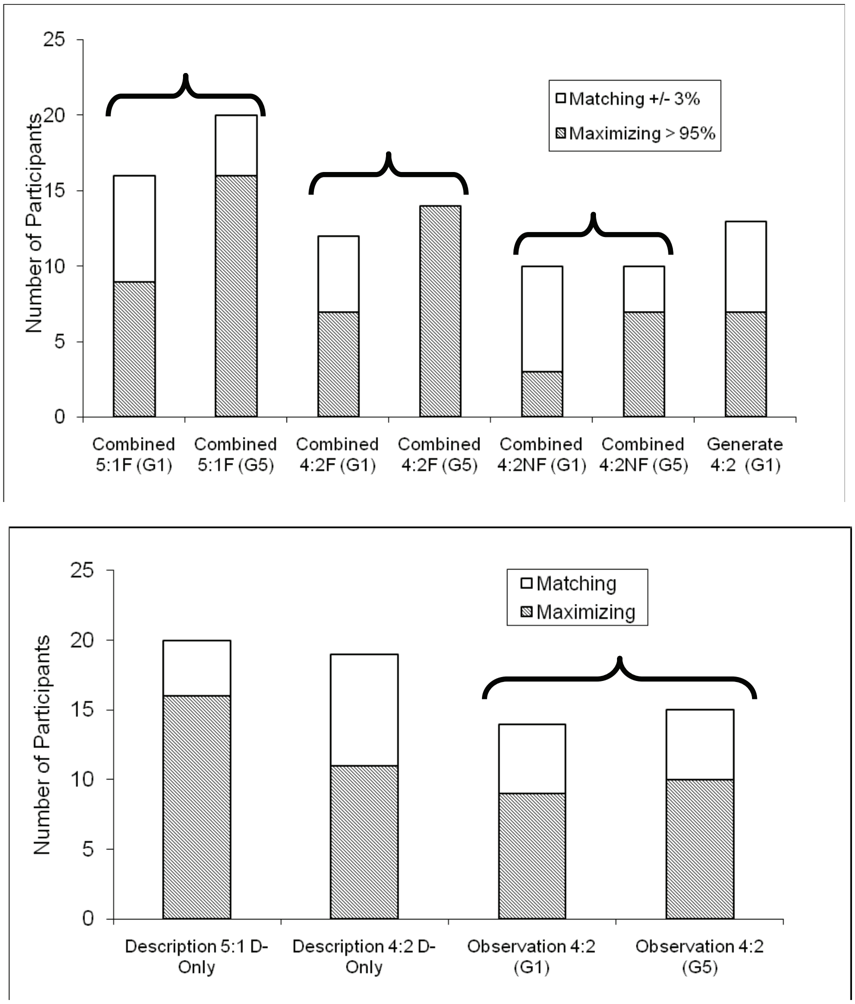

Figure 2. Top panel: Number of participants (out of 25) adopting a maximizing or matching strategy as classified by prediction responses in the three combined conditions and the generate condition. Bottom panel: Number of participants (out of 25) adopting a maximizing or matching strategy as classified by choices on the dice game questionnaire in the two description-only conditions and the observation condition. In both panels, the bracketed bars indicate data from the same participants over time. In combined and generate conditions, *maximizing* is defined as predicting the majority outcome (black) on more than 95% of trials in a game; *matching* is defined as allocating choices within 3% of those predicted by a matching strategy (i.e., for 4:2, 66.6% ± 3%). "4:2" refers to the die problem featuring a six-sided die with 4 black sides and 2 white sides; "5:1" refers to 5 black sides and 1 white. (See Table 1 for a description of the conditions.) F, feedback; NF, no feedback; G1, Game 1; G5, Game 5.

there are more maximizers in the 4:2 generate condition than in the 4:2 NF condition, although again the distributions did not differ significantly [$\chi^2(1) = 2.00, p > .05$].

The data from conditions in which responses were made by selecting a strategy from the questionnaire (Figure 2, bottom panel) suggest that the opportunity to observe outcomes has very little overall effect on strategy choice. The number of maximizers in the observation condition did not increase significantly between Games 1 and 5, and although there were slightly *more* maximizers in the 4:2 description-only condition than in the observation condition, the distributions did not differ significantly when compared with either Game 1 or Game 5 (χ^2s < 1). Analysis of the individual data in the observation condition revealed an absence of any systematic effects of observation: 5 participants selected the optimal strategy after every 60 trial game; 5 changed from a suboptimal strategy in Game 1 to the optimal strategy by Game 5; 4 changed in the opposite direction (optimal→suboptimal), and the remainder either stuck to a matching strategy throughout (2 participants) or fluctuated across the games but failed to hit upon the optimal strategy by Game 5.

DISCUSSION

It is clear from looking at Figure 1 and the top panel of Figure 2 that the experience of making *predictions* has a positive effect on optimal responding, even in an environment in which probabilities are explicitly stated at the outset, and experience is normatively irrelevant. In contrast, the data in the bottom panel of Figure 2 suggest that experience of *observing* outcomes has little systematic impact on strategy choice: Observing no trials, 60 trials, or 300 trials of outcomes led to similar patterns of strategy selection.

Thus, it appears that the nature of an experience—*prediction* or *observation*—is crucial for its effective utilization. Participants who are engaged actively in the task by making predictions, receiving feedback and presumably reflecting on that feedback are gradually pushed toward optimal responding. The superior performance of the 4:2 generate group over the 4:2 NF group suggests that this engagement is also promoted by simply generating a list of predictions. Although feedback was not provided to either group, participants in the generate condition could reflect on the stream of predictions they had made which gave them an advantage over 4:2 NF participants with no feedback, and no record of predictions. In contrast, when no engagement is promoted and participants are mere passive observers of outcomes, reflection does not appear to occur and there is no increase in the choice of the optimal strategy.

Perhaps the most intriguing and paradoxical result from this study is that when compared across dependent variables there is clear evidence that experience has a *negative* initial effect on the tendency to maximize. More participants were classified as maximizers when they only received a description of the problem than after 60 trials of prediction experience. We suggest this is due to the initial appeal of "representative" nonoptimal strategies in the trial-by-trial version. At first this type of responding is seductive because participants are tempted by the possibility of predicting more than the proportion of correct outcomes dictated by the contingency (West & Stanovich, 2003). If one applies the "weighting" terminology of risky choice, these findings could be interpreted as a tendency to *over-weight* the importance of trying to predict the rarer alternative in the experience task. This pattern contrasts with the *under-weighting* of rare events found in experienced gambles (Hertwig et al., 2004) but is consistent with the case-based reasoning account of probability matching (Erev & Barron, 2005).

Participants appear to make predictions, initially, that are representative of what they know to be the source of the outcomes (Kahneman & Tversky, 1972). The gentle slopes of the learning curves shown in Figure 1 suggest that these beliefs are only gradually eroded by experience in the environment. Moreover, this experience must include outcome feedback. As noted above, this presumably engages participants by making apparent the rewards of optimal responding, as well as the costs of suboptimal responding.

This observation on the role of feedback is important as it distinguishes two contributors of the effect of experience: the experience of making predictions and the effect of experiencing feedback. Previous research has ignored the first effect. The present results demonstrate that this aspect of experience can lead to a bias toward suboptimal responding.

Limitations and Future Directions

We have stated throughout that the experience participants derived in the combined conditions was normatively irrelevant; however, one might argue that our invocation of normativity is overly restrictive. Although we did not deceive participants in the experiments, given psychologists' propensity for deception (Hertwig & Ortmann, 2001) participants may have been suspicious about the nature of the task ("e.g., is it really an unbiased die?"). However, for a nonmajority response to be favored, participants would have to believe that they were being grossly deceived (e.g., that the stated contingencies were the *opposite* of the real ones). We suggest that the significant learning effects we observed are more consistent with the idea that in the early stages of experience nonmaximizing strategies are appealing not because participants believe they are being deceived but because they are seduced to respond in a representative manner.

An interesting future direction for this research is to explore how people deal with experienced and described information when they have different beliefs about the source of the outcomes. People know that dice are supposed to be random, however, if a nonrandom source is generating the outcomes how might responding be affected? Recent research shows that the tendency to predict that runs of one event in binary prediction tasks will continue (a "hot hand" prediction) or switch (a "gambler's fallacy" prediction) is influenced by beliefs about the source of the events (Ayton & Fischer, 2004). It seems likely that the weight people place on described and experienced information in many real world situations will be influenced by what they perceive to be the source of that information. Experiments which manipulate description, experience and beliefs about cause would appear to be a fruitful avenue for future research.

AUTHOR NOTE

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NOTES

1. Some studies report higher levels of maximizing in males than females (West & Stanovich, 2003). We ensured equal male/female proportions in all groups; however, no evidence of a gender effect on maximizing was present in the data.

2. In a follow-up study, we examined the effect of actual payment in combined conditions (offering 1 cent [AU$1 = approx US$0.75] for every correct prediction). Results did not differ significantly from the hypothetical payment conditions.

3. One could use a strict (100%) rule for classifying maximizers because all information is provided at the outset, but given potential boredom or distraction effects, a 95% criterion is perhaps more reasonable. A similar justification can be made for the ±3% criterion for matching.

4. If a 100% criterion is used for classification of maximizers, the comparison is significant [$\chi^2(1) = 4.66$, $p < .05$].

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