

Toward a Mechanistic Account of Gender Differences in Reward-Based Decision-Making

Kaileigh A. Byrne and Darrell A. Worthy
Texas A&M University

Gender differences in reward-based decision-making have been extensively researched, yet the mechanisms underlying these differences remain poorly understood. We sought to develop a mechanistic account of how men and women differ in their decision-making strategies. We examined gender differences in performance on the Iowa Gambling Task (IGT; Experiment 1) as well as the Soochow Gambling Task (SGT; Experiment 2). Expectancy valence and prospect valence learning computational models were fit to the data for both tasks to assess specific strategies that men and women utilized during the decision-making process. Our results replicated the behavioral gender difference finding on the IGT. Women selected the disadvantageous Deck B more than did men. We extended these findings to the SGT. Modeling results revealed that women's data were best fit by higher recency, or learning rate, parameter values than were men's data in the IGT and SGT. This suggests that women gave greater weight to recent events than did men and that they tended to ignore large, infrequent losses in both experiments. Overall, our results suggest that the mechanism accounting for how men and women differ in reward-based decision-making is that women tend to focus on the relative frequency of gains and losses and attend to recent reward outcomes, whereas men focus more on the extreme gains and losses associated with each alternative and attend to long-term decision outcomes. Implications for these gender differences in reward-based decision-making strategies are discussed.

Keywords: decision-making, gender, Iowa Gambling Task, computational modeling

The complex process of reward-based decision-making involves the selection of an outcome among several possible alternatives and the evaluation of rewards and losses associated with each option (Edwards, 1954). There are many factors that affect reward-based decision-making, and much recent work has focused on performance differences in decision-making between men and women using the Iowa Gambling Task (IGT; e.g., De Visser et al., 2010; Evans & Hampson, 2015; Overman et al., 2004; Reavis & Overman, 2001; van den Bos, Homberg, & de Visser, 2013).

Although much recent work has been aimed at investigating gender differences in reward-based decision-making, the conclusions have been mixed, and there have been few conclusions regarding *how* men and women differ in their decision-making preferences and strategies. For example, in studies of risk preferences, women have been shown to be more risk *seeking* on the cups task, a task of risk assessment that includes both sure and risky options of varying probabilities, compared to men (Weller, Levin, & Bechara, 2010) but more risk *averse* in other probabilistic gambling situations (Eckel & Grossman, 2008). Other work has shown that gender differences in reward sensitivity influence decision-making such that men have a tendency to maximize future rewards, whereas women are biased toward optimizing immediate rewards (Byrne & Worthy, 2015). Perhaps, the most extensively studied task that has been used to study gender differences in decision-making is the IGT (Bechara, 2005; Bechara & Damasio, 2005). One of the more consistent findings is

This article was published Online First September 26, 2016.

Kaileigh A. Byrne and Darrell A. Worthy, Department of Psychology, Institute for Neuroscience, Texas A&M University.

Correspondence concerning this article should be addressed to Darrell A. Worthy, Department of Psychology, Institute for Neuroscience, Texas A&M University, 4235 TAMU, College Station, TX 77845. E-mail: worthyda@tamu.edu

that men typically outperform women on the IGT, yet the mechanisms underlying this male advantage remain unclear (Overman, 2004; Overman, Boettcher, Watterson, & Walsh, 2011; Reavis & Overman, 2001; van den Bos et al., 2013). The data appear to show a male advantage, yet both behavioral and modeling analyses have failed to provide mechanistic accounts for the specific decision strategy that explains *how* men perform better than women on the IGT.

One noted shortcoming of the IGT is that poorer performance on the task can result from reliance on either the frequency of gains and losses or the expected value of each option (Chiu et al., 2008). Thus, although men seem to consistently select the more advantageous options on this task, few conclusions that can inform a mechanistic account of how men and women differ in decision-making can be drawn. A variant of the IGT, the Soochow Gambling Task (SGT), addresses this limitation of the IGT and may be useful in identifying gender differences in how men and women approach decision-making situations (Chiu et al., 2008). Consequently, the purpose of the present investigation was to examine gender differences in decision-making strategies on both the IGT (Experiment 1) and the SGT (Experiment 2). Additionally, we applied a more comprehensive set of computational models, including expectancy valence (EV) and prospect valence learning (PVL) models with a delta rule, to participants' data than has been used in prior work, which has primarily focused on the application of a single model to examine gender differences on the IGT. These models allow for further inference regarding the specific mechanism that accounts for how individuals can behave differently during decision-making (Yechiam, Busemeyer, Stout, & Bechara, 2005).

We predicted that, consistent with previous research, men would choose the advantageous decks more frequently than would women on the IGT. Research on gender differences on the SGT has been limited. However, we predicted that because men choose more options with higher expected values on the IGT than do women, they would choose more advantageous (higher expected value) options on the SGT. If this is the case, then it would provide evidence that men attend more to each option's expected

value, whereas women are guided more by the relative frequency of gains and losses.

Experiment 1

Method

Participants. A total of 116 undergraduate participants (58 men; $M_{\text{age}} = 18.57$ years) completed the experiment for partial course credit through their psychology course.

Materials and procedure. Participants completed the IGT (Bechara, Damasio, Damasio, & Anderson, 1994) on personal computers using MATLAB software with Psychtoolbox (Version 2.5; MATLAB and PsychToolbox Release 2009b). The decision-making instructions and task design of the IGT were the same as those used in the original version (see the Appendix). Participants were informed that the purpose of the task was to assess how people use information to make decisions. They were asked to repeatedly select from one of four decks of cards were and told that they could either gain or lose points on each draw. Each deck corresponded to a key on the keyboard (*W*, *P*, *Z*, and *?*). Each time participants selected a deck, the card was turned over and the number of points they gained or lost was displayed. Participants were told that they would be given 2,000 points at the start of the task, and their goal was to finish the task with at least 2,500 points. They were asked to do their best to maximize their gains and minimize their losses so they could finish with at least 2,500 points. The task was self-paced, and participants were not informed about the number of trials in the task.

The task included 100 trials of selections from one of the four decks of cards. Deck A offered high-magnitude reward and high-frequency losses (five loss trials equivalent to 250 points each), with a net loss of 250 points over every 10 trials. Deck B yielded the same net loss as did Deck A for every 10 trials but offered high-magnitude, low-frequency losses (one loss trial valued at 1,250 points), with a net loss of 250 points over every 10 trials. In contrast, Decks C and D both offered a net gain of 250 points across every 10 trials. Like Deck A, Deck C gave frequent losses of low magnitude but yielded more gains than losses overall. Similar to Deck B, Deck D provided infrequent

losses of high magnitude but offered more gains compared to losses over every 10 trials. Thus, Decks A and B were the disadvantageous decks because they resulted in overall net losses, whereas Decks C and D represented the advantageous decks because they yielded overall net gains. The schedule of rewards and penalties was identical to that in the original IGT (Bechara et al., 1994; see Table 1). IGT performance was determined by computing the difference in proportion of advantageous deck selections from disadvantageous deck selections [(C + D) - (A + B)] across all trials during the task.

Experiment 2

Participants

Eighty-four undergraduate participants (42 men; $M_{\text{age}} = 19.17$) completed the experiment for partial course credit through their psychology course.

Materials and procedure. Participants completed the SGT on personal computers, using, as in Experiment 1, MATLAB software with Psychtoolbox (Version 2.5).

Soochow Gambling Task. The decision-making instructions and task design for the SGT were identical to those in Experiment 1—except that the reward structure of each deck differed (Chiu et al., 2008; see the Appendix). The primary difference between the IGT and SGT is

the frequency of gain and loss outcomes. On the IGT, infrequent losses are evident in both advantageous and disadvantageous options. In contrast, on the SGT, only the disadvantageous options provide infrequent losses. Specifically, for the SGT the advantageous options provide small losses on 80% of trials and large gains on 20% of trials, whereas the disadvantageous options provide small gains on 80% of trials and large losses on 20% of trials. Thus, whereas attention to the frequency of gains and losses should have little influence on IGT performance, attention to loss frequency should negatively impact SGT performance. Participants were informed that they could gain or lose points on each selection and that they should press the corresponding key on the keyboard (W, P, Z, and ?) for the deck they wanted to select on each draw. Upon selection, participants were shown the amount of points that they gained or lost. The expected value for each card in this task is twice the expected value of cards in the IGT (± 500 points over 10 trials in the SGT compared to ± 250 points over 10 trials in the IGT). Therefore, the goal and starting amount were also increased. Participants were informed that they would start the task with 4,000 points, and their goal was to have at least 5,000 points by the end of the task. Participants were informed that they should try to gain as many points as possible and avoid losing points, so that they could

Table 1
Reward Schedule (in Points) for the Iowa Gambling Task

Variable	Deck A	Deck B	Deck C	Deck D
Draw from deck				
1	100	100	50	50
2	100	100	50	50
3	100, -150	100	50, -50	50
4	100	100	50	50
5	100, -300	100	50, -50	50
6	100	100	50	50
7	100, -200	100	50, -50	50
8	100	100	50	50
9	100, -250	100, -1,250	50, -50	50
10	100, -350	100	50, -50	50, -250
Cumulative payoff	-250	-250	250	250

Note. See Bechara, Damasio, Damasio, and Anderson (1994) for the full table, which lists payoffs for the first 40 cards drawn from each deck. In the present task the sequence was repeated for Cards 41–80 and 81–100 so that a participant could potentially select the same deck on all 100 draws.

reach the goal amount. No information regarding the number of trials in the task was provided.

Like the IGT, the SGT entails 100 trials of selections from one of four decks of cards. On the basis of expected values, both Decks A and B are the disadvantageous decks in this task because they offer a net loss of 500 points over every 10 trials, whereas Decks C and D are advantageous because they offer a net gain of 500 points over every 10 trials. Decks A and C provided high-magnitude gains and losses, whereas Decks B and D offered low-magnitude gains and losses. The gains and losses for each deck over every 10 trials are shown in Table 2 (Chiu et al., 2008). Performance on the SGT was computed by subtracting the proportion of disadvantageous deck selections from the proportion of advantageous deck selections [(C + D) - (A + B)] across all trials.

Model descriptions. Among computational models that have been used to evaluate IGT strategies, the expectancy valence (EV) and prospect valence learning (PVL) models are considered the most frequently used and best fit models for IGT data (Dai, Kerestes, Upton, Busemeyer, & Stout, 2015; Steingroever, Wetzels, & Wagenmakers, 2013a, 2013b). Both models share three fundamental assumptions: choice payoffs are evaluated on the basis of a utility function, expectations about each option are updated using learning rules, and expected utilities of each option probabilistically deter-

mine option selections (Dai et al., 2015). In the present study, we fit an EV and a PVL model using a delta rule that assumes that expected values are updated via a recency-weighted exponential function on each trial. Crucially, the EV and PVL models we fit included an auto-correlation, or perseveration parameter, to account for participants' tendency to persevere or switch during the IGT (Worthy, Pang, & Byrne, 2013). The addition of this autocorrelation parameter substantially improved the model fit. The EV model assumes that gains and losses are integrated on each trial to determine the expected values for each option (Busemeyer & Stout, 2002). The PVL model (Ahn, Busemeyer, Wagenmakers, & Stout, 2008; Ahn, Krawitz, Kim, Busemeyer, & Brown, 2011) assumes that the weight given to gains and losses follows the assumptions of prospect theory (Kahneman & Tversky, 1979). Both the PVL delta and EV delta models include an exploitation parameter based on a trial-independent action-selection rule and a recency parameter that depends on a value-updating rule.

For the EV model, the utility function assumes that gains and losses are weighted differently. After a choice has been made and feedback—points gained, $\text{win}(t)$, and points lost, $\text{loss}(t)$ —is presented, the utility $u(t)$ for the choice made on trial t is denoted by

$$u(t) = w \cdot \text{win}(t) - (1 - w) \cdot \text{loss}(t), \quad (1)$$

where w ($0 \leq w \leq 1$) indicates the degree to which participants weigh gains compared to losses.

In contrast to the utility function in the EV model, that in the PVL model is derived from prospect theory (Ahn et al., 2008; Kahneman & Tversky, 1979), in which the evaluation of the outcome on each trial has diminishing sensitivity to increases in magnitude and different sensitivity to gains than to losses. The utility, $u(t)$, on trial t , of each net outcome $x(t)$ for the PVL model is

$$u(t) = \begin{cases} x(t)^\alpha & \text{if } x(t) \geq 0 \\ -\lambda |x(t)|^\alpha & \text{if } x(t) < 0 \end{cases} \quad (2)$$

The shape parameter α ($0 < \alpha < 1$) determines the shape of the utility function, and λ represents the loss aversion parameter ($0 < \lambda < 5$)

Table 2
Reward Schedule (in Points) for the Soochow Gambling Task

Variable	Deck A	Deck B	Deck C	Deck D
Draw from deck				
1	200	100	-200	-100
2	200	100	-200	-100
3	200	100	-200	-100
4	200	100	-200	-100
5	-1,050	-650	1,050	650
6	200	100	-200	-100
7	200	100	-200	-100
8	200	100	-200	-100
9	200	100	-200	-100
10	-1,050	-650	1,050	650
Cumulative payoff	-500	-500	500	500

Note. See Chiu et al. (2008) for the full table, which lists payoffs for the first 40 cards drawn from each deck. The above sequence of 10 was repeated for all subsequent trials.

that governs loss sensitivity compared to gain sensitivity. A value of λ greater than 1 indicates that an individual is more sensitive to losses than gains. Similarly, a λ value less than 1 signifies enhanced sensitivity to gains compared to losses.

Both the EV delta and PVL delta models include the value-updating rule, which determines how the utility, $u(t)$, is used to update expected values or expectancies, $E_i(t)$, for the selected option, i , on trial t . The delta rule assumes that expected values are recency-weighted averages of the rewards received for each option, as shown in the following:

$$E_i(t) = E_i(t - 1) + \phi \cdot [u(t) - E_i(t - 1)]. \quad (3)$$

The recency parameter ϕ ($0 \leq \phi \leq 1$) defines the weight given to recent outcomes in updating expected values. Higher values of ϕ denote a greater weight to recent outcomes, whereas lower values of ϕ indicate a greater weight to past outcomes.

Both the EV and PVL models also include an action-selection rule that controls the predicted probability that deck j will be chosen on trial t , $\Pr[G_j(t)]$, and is calculated using a Softmax rule (Sutton & Barto, 1998). The models also include a parameter p in Equation 4 that controls for individual differences in tendencies toward perseveration ($p > 0$) or switching ($p < 0$) on each trial (Daw, Gershman, Seymour, Dayan, & Dolan, 2011; Lau & Glimcher, 2005):

$$\Pr(G_i(t)) = \frac{e^{\theta(t)[E_i(t) + p \cdot \text{rep}(i)]}}{\sum_{j=1}^4 e^{\theta(t)[E_j(t) + p \cdot \text{rep}(j)]}} \quad (4)$$

Here $\text{rep}(i)$ is equal to 1 if the same action was chosen on the previous trial and zero otherwise. We allowed p to vary from -100 to 100 , effectively adding or subtracting 100 points from the net value of the action that was selected on the previous trial. The addition of the p parameter follows from previous results where we showed that perseveration is a critical component to account for in IGT models (Worthy et al., 2013). The trial-independent action-selection rule governs expected values and is represented as

$$\theta(t) = 3^c - 1, \quad (5)$$

where c ($0 \leq c \leq 5$) is the choice consistency or

exploitation parameter. Larger values of c indicate that an individual has a greater tendency to choose options with higher expected values. Similarly, smaller c values indicate a greater tendency to explore options with lower expected values.

Finally, the baseline model assumes equal fixed-choice probabilities for each option (Gur-eckis & Love, 2009; Worthy & Maddox, 2011; Yechiam et al., 2005). The baseline model has three free parameters that signify the probability of selecting Deck A, B, or C. The probability of choosing Deck D is the sum of the probability of Decks A, B, and C subtracted from 1.

Overall Results

Behavioral Analyses for Gender Differences in Performance

Figure 1 shows the proportion of advantageous minus disadvantageous deck selections by gender for each trial block in both the IGT and SGT. A 2 (gender: male vs. female) \times 2 (task: IGT vs. SGT) \times 5 (20-trial block) mixed analysis of variance (ANOVA) was conducted for decision-making performance [(C + D) – (A + B)]. A significant three-way Gender \times Task \times Trial Block interaction was observed, $F(4, 784) = 3.42, p < .01, \eta_p^2 = .02$. Results also revealed a significant main effect of gender, $F(1, 196) = 15.18, p < .001, \eta_p^2 = .07$. Across both the IGT and SGT, men ($M = -.02, SD = .34$) selected the advantageous decks significantly more than did women ($M = -.18, SD = .29$). Furthermore, a significant main effect of task showed that individuals selected the advantageous options more in the IGT ($M = -.01, SD = .28$) compared to the SGT ($M = -.22, SD = .35$) overall, $F(1, 196) = 25.26, p < .001, \eta_p^2 = .11$. To determine the locus of the three-way interaction, we conducted 2 (gender: male vs. female) \times 2 (task: IGT vs. SGT) ANOVAs within each trial block. A significant Gender \times Task interaction was observed for Block 4 (Trials 61–80) only, $F(1, 196) = 4.07, p < .05, \eta_p^2 = .02$. Follow-up t tests within the IGT and SGT revealed that men ($M = .15, SD = .61$) chose the advantageous options significantly more than did women ($M = -.22, SD = .49$) in the SGT, $t(82) = -3.07, p < .05, d = -.67$, but not the IGT ($p = .12$). Thus, men sharply improved their performance on the SGT

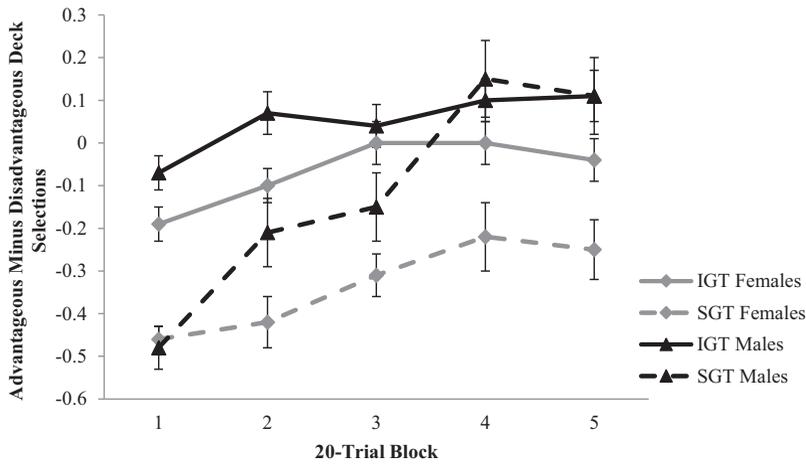


Figure 1. Proportion of IGT and SGT advantageous minus disadvantageous deck selections ((C + D) + [A + B]) over each of the five 20-trial blocks by gender in Experiment 1. Error bars represent standard errors of the mean for the proportion of advantageous deck selections. IGT = Iowa Gambling Task; SGT = Soochow Gambling Task.

beginning in Block 4 of the task, whereas women did not demonstrate as substantial an increase in improvement as the task progressed. Finally, a significant main effect of trial block indicated that individuals learned to select the advantageous options more in both the IGT and SGT, $F(4, 784) = 32.56, p < .001, \eta_p^2 = .14$. The Gender \times Task interaction was not significant, however ($p = .24$).

Additional 2 (gender: male vs. female) \times 5 (trial block) ANOVAs were conducted to examine gender differences in selections from each individual deck within the IGT and SGT (see Figure 2). In the IGT, a 2 (gender: male vs. female) \times 5 (trial block) ANOVA for Deck B revealed a significant main effect of gender such that women ($M = .33, SD = .13$) selected disadvantageous Deck B more than did men ($M = .27, SD = .11$), $F(1, 114) = 7.55, p < .01, \eta_p^2 = .06$. The Gender \times Trial Block interaction ($p = .86$) and main effect of trial block ($p = .13$) were not significant, however. Similarly, the Gender \times Trial Block ANOVA for Deck C also showed a significant main effect of gender, $F(1, 114) = 4.05, p = .047, \eta_p^2 = .03$. Men ($M = .25, SD = .13$) selected advantageous Deck C significantly more in the IGT than did women ($M = .20, SD = .09$). The Gender \times Trial Block interaction and main effect of trial block were nonsignificant for Deck C ($ps > .90$). ANOVA results for Decks

A and D revealed main effects of trial block ($ps < .001$), indicating learning over time, but there were no Gender \times Trial Block interactions or main effects of gender for either deck on the IGT ($ps > .40$).

In the SGT, a Gender \times Trial Block ANOVA for Deck A revealed a significant Gender \times Trial Block interaction, $F(4, 328) = 3.22, p = .01, \eta_p^2 = .04$, and main effect of trial block, which indicated that individuals tended to select Deck A less frequently as the task progressed, $F(4, 328) = 15.64, p < .001, \eta_p^2 = .16$. Follow-up t tests for gender within each 20-trial block showed a significant effect in the final block in which women ($M = .38, SD = .18$) selected Deck A more than did men ($M = .26, SD = .22$). The main effect of gender was not significant, however ($p = .26$). Similarly, for Deck B a significant Gender \times Trial Block interaction was observed, $F(4, 328) = 3.74, p < .01, \eta_p^2 = .04$. Follow-up t tests revealed that women selected Deck B significantly more than did men in Blocks 2–5 ($p < .05$). Additionally, main effects of gender, $F(1, 82) = 13.90, p < .001, \eta_p^2 = .15$, and trial block $F(4, 328) = 6.14, p < .001, \eta_p^2 = .07$, were observed. Women ($M = .28, SD = .08$) selected Deck B more overall compared to men ($M = .21, SD = .09$), and overall individuals selected Deck B less frequently across the course of the SGT. As with Decks A and B, there was a significant

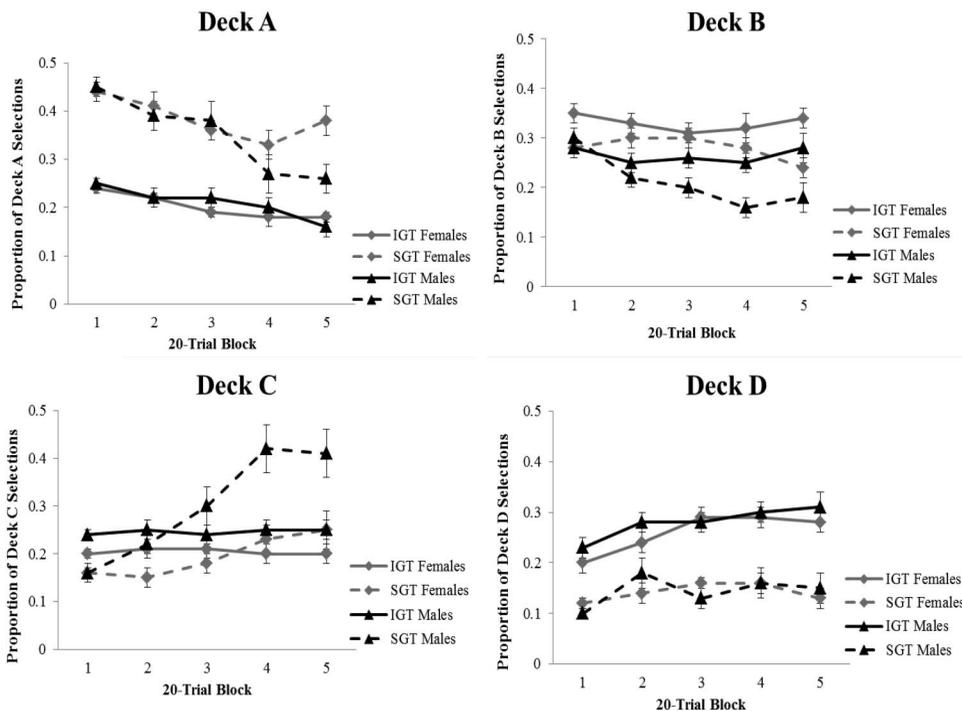


Figure 2. Proportion of IGT and SGT deck selections for each of the four decks (A–D) by gender for each 20-trial block. Error bars represent standard errors of the mean for each deck. IGT = Iowa Gambling Task; SGT = Soochow Gambling Task.

Gender \times Trial Block interaction for Deck C, $F(4, 328) = 3.88, p < .01, \eta_p^2 = .05$. Post hoc t tests within each block revealed that men selected Deck C significantly more than did women in Blocks 3–5 ($p < .01$). Moreover, a significant main effect of gender indicates that men ($M = .30, SD = .18$) selected Deck C more overall in the SGT compared to women ($M = .19, SD = .11$), $F(1, 82) = 11.51, p < .001, \eta_p^2 = .12$. Finally, the significant main effect of trial block indicated that participants selected Deck C progressively more across trials, $F(4, 328) = 17.01, p < .001, \eta_p^2 = .17$. The ANOVA for Deck D did not reveal a significant Gender \times Trial Block interaction ($p = .39$) or main effect of gender ($p = .96$), although a significant main effect of trial block showed that participants selected Deck D more often as the SGT progressed, $F(4, 328) = 2.48, p = .04, \eta_p^2 = .03$.

Modeling Analyses

Versions of the EV delta and PVL delta models with a perseveration term and the baseline

were individually fit to each participant’s data by maximizing the log likelihood for each model’s prediction on each trial. Akaike’s information criterion (AIC) and Bayesian information criterion (BIC) were computed to compare the fits of each model. AIC penalizes models that contain more free parameters. For each model, i , AIC is defined as

$$AIC_i = -2\log L_i + 2V_i. \tag{6}$$

L_i represents the maximum likelihood for model i , and V_i denotes the number of free parameters in the model. BIC is expressed as

$$BIC_i = -2\log L_i + V_i \log(n). \tag{7}$$

Here n indicates the number of trials.

Smaller values for AIC and BIC indicate a better fit to the data. On the basis of both AIC and BIC values, the PVL model provided the best fit to the IGT and SGT data for women. The PVL model was also the best fit to the IGT and SGT data for men on the basis of AIC

values. However, the EV and PVL model fit the men's IGT data equally well on the basis of BIC values, and the EV model fit men's SGT data better according to BIC values. The average AIC and BIC values for each model are shown by task and gender in Table 3.

The parameter estimates for each of the models are shown in Table 4. Because the PVL model most consistently fit the data best for both men and women, we examined differences in best fitting parameter values for this model by gender. For each PVL delta model parameter, a 2 (gender: male vs. female) \times (task: IGT vs. SGT) ANOVA was conducted. Results revealed a significant main effect of gender, $F(1, 196) = 5.54, p < .05, \eta_p^2 = .03$, for the recency parameter, ϕ , such that data from women ($M = .55, SD = .41$) were best fit by higher recency parameter values than were data from men ($M = .33, SD = .39$). Thus, women placed greater weight on recent outcomes when making selections compared to men. We observed significant gender differences for the best fitting shape (α) and perseveration term (p) parameters. For the shape parameter, a significant Gender \times Task interaction was observed, $F(1, 196) = 9.13, p < .01, \eta_p^2 = .04$. Follow-up t tests showed that men's SGT data ($M = .70, SD = .38$) had higher shape parameter values than did women's SGT data ($M = .44, SD = .38$), $t(82) = -3.22, p < .01$. This suggests that men tended to discount large-magnitude gains and losses less than did women. Despite a marginally significant main effect of gender ($p = .06$), no significant gender differences in shape parameter estimates were evident on the IGT ($p = .39$). There was also a main effect of gender for the perseveration term parameter in

which men's data ($M = 11.50, SD = 44.22$) had higher parameter values than did women's data ($M = 0.61, SD = 39.90$), $F(1, 196) = 4.65, p < .05, \eta_p^2 = .02$, which suggests that men tended to persevere, or consistently select the same option, more than did women.

General Discussion

The purpose of this study was to characterize gender differences in reward-based decision-making strategies using the IGT and SGT and apply computational models to the data for both tasks. Although several studies have observed behavioral gender differences on the IGT, none have shown consistent results regarding why men perform better on the task. Our results were consistent with those in previous research demonstrating that men select the advantageous options more than do women on the IGT; however, we also extend these findings to the SGT. Thus, our study not only is the first to show a gender difference on the SGT but also reveals that this behavioral gender difference is consistent with the difference observed on the IGT.

On the IGT, women chose the high-magnitude gains option with large, infrequent losses (Deck B) more than did men. Additionally, men selected the low-magnitude gains options with frequent low-magnitude losses (Deck C) more than did women. The results of the SGT replicate the IGT findings in which men selected the high expected value, advantageous options more than did women. This finding provides further evidence that men tend to rely more on expected values of options relative to women, whose decisions are guided more by the frequency of gains and losses. In contrast to the

Table 3
Average AIC and BIC Values (and Standard Deviations) for Each Model by Gender

Task and gender	EV delta		PVL delta		Baseline	
	AIC	BIC	AIC	BIC	AIC	BIC
IGT						
Women	250.30 (36.33)	258.72 (36.33)	242.27 (38.63)	255.30 (38.63)	265.07 (22.48)	277.49 (22.48)
Men	253.65 (34.20)	262.07 (34.20)	249.41 (35.50)	262.44 (35.50)	263.41 (30.19)	275.83 (30.19)
SGT						
Women	240.32 (35.97)	248.74 (35.97)	232.57 (35.69)	245.59 (35.69)	254.28 (26.86)	266.70 (26.86)
Men	214.07 (52.99)	222.49 (52.99)	211.42 (51.44)	224.45 (51.44)	244.65 (36.70)	257.07 (36.70)

Note. AIC = Akaike's information criterion; BIC = Bayesian information criterion; EV = expectancy valence; PVL = prospect valence learning; IGT = Iowa Gambling Task; SGT = Soochow Gambling Task.

Table 4
Average Parameter Estimates (and Standard Deviations) From Maximum Likelihood Fits for the IGT and SGT

Task and variable	Women	Men
Iowa Gambling Task		
PVL		
α	.63 (.37)	.57 (.39)
λ	1.08 (1.82)	1.32 (1.92)
Φ	.65* (.39)	.41* (.41)
c	.24 (.35)	.36 (.40)
p	-3.52 (44.66)	-1.56 (38.13)
EV		
w	.67 (.23)	.61 (.35)
Φ	.32 (.43)	.21 (.35)
c	.25 (.37)	.38 (.46)
p	5.83 (53.48)	13.04 (52.19)
Soochow Gambling Task		
PVL		
α	.44** (.38)	.70** (.38)
λ	1.90 (2.12)	1.09 (1.85)
Φ	.40* (.40)	.21* (.33)
c	.30 (.33)	.27 (.37)
p	6.32** (31.83)	29.54** (46.10)
EV		
w	.72 (.34)	.75 (.33)
Φ	.34** (.42)	.13** (.28)
c	.17 (.33)	.29 (.40)
p	20.98 (61.95)	27.93 (49.17)

Note. IGT = Iowa Gambling Task; SGT = Soochow Gambling Task; PVL = prospect valence learning; EV = expectancy valence.

* $p < .05$. ** $p < .01$.

pattern on the IGT, however, men began to show substantial improvements in learning the advantageous options after 60 trials, whereas women's performance was more consistent through the SGT. Thus, although men selected the advantageous options more than did women in both tasks, men showed more evidence of learning over the course of the SGT than did women. When we evaluated gender differences in individual SGT deck selections, women showed a preference for the low-magnitude frequent gain, moderate-magnitude infrequent loss option (Deck B) over the option that gave large frequent gains and large infrequent losses (Deck A). This suggests that women were aware that Deck A offered the largest loss magnitude but were also sensitive to the frequency of gains relative to losses so they tended to prefer the deck that gave small, frequent gains but also the

smaller magnitude of infrequent losses. In contrast, men chose the option with the large, frequent loss of 200 points (Deck C) for the sake of occasionally earning the largest possible reward (1,050 points). Thus, overall women seemed to prefer the option with frequent gains and the smallest variability between gains and losses, whereas men seemed perfectly willing to withstand moderately large consistent losses when it meant also earning the biggest payoffs possible on some trials. Furthermore, minimizing variability between gains and losses may represent a specific mechanism to account for women's enhanced risk aversion in uncertain situations that has been observed in previous research (Eckel & Grossman, 2008). In other words, rather than loss magnitude representing risk aversion in these tasks, loss frequency (infrequent losses, frequent gains) drove women's risk-averse behavior.

Several important gender differences in the pattern of option selections, in addition to overall deck selections, were observed between the IGT and SGT. Specifically, on the IGT women consistently chose the option with high magnitude; frequent gains; and large, infrequent losses, whereas men reliably based decisions on the long-term expected values of each option. On the SGT, however, the reward magnitude became less critical for women's decisions, and they progressively chose options with high-frequency small gains and infrequent moderate losses across the task. Men progressively chose Deck C, the option with a net positive expected value and high-magnitude, though infrequent, gains, despite encountering frequent large losses on the SGT. Thus, it appears that initially reward and loss magnitude was heavily factored into women's decision-making strategies, but over time optimizing the frequency of gains and minimizing loss frequency became more important. In contrast, when the expected value of options was salient, men consistently used these values to make decisions. When loss frequency is initially more salient than expected values, men were slower to select high expected value options with frequent losses and large gains but progressively decreased the weight given to frequent losses and increased the weight given to expected values.

Moreover, we sought to further explore the specific strategies that men and women used on each task using computational models. Across

both tasks, men's decision-making behavior was guided by options with higher long-term expected values, whereas women's decisions were characterized more by attention to recent outcomes. The computational modeling results show not only that men's and women's decision-making strategies differ under uncertainty but also that these effects can be observed on two different decision-making tasks. Our findings provide a possible mechanistic account of the effect of reward or punishment sensitivity on gender differences in decision-making. Specifically, men and women differ in the emphasis they place on recent outcomes, frequency of gains and losses, and expected values. These distinctions suggest that female decision-makers may be cautious in making decisions under uncertainty—attending more to recent events and the frequency of rewards. In contrast, male decision-makers are more driven by expected values and attending to past outcomes, which in these tasks is necessary in order to keep track of options with net losses. The frequency of rewards and punishments seems to be of less importance to men compared to women on these tasks—men selected options with frequent losses in order to achieve a net or high-value reward, which led to successful decision-making performance on both the IGT and SGT, although in many real-world situations, this may not always be the case.

These findings have important implications for decision-making under uncertainty. Our results demonstrate that gender differences in decision-making depend on the weight given to expected values, reward frequency and variability, and past reward experiences. Women's characteristic risk-averse behavior observed in previous research may result not only from avoidance of high-magnitude losses but also from high-frequency losses. Moreover, individuals' past history with rewarding and punishing outcomes of decisions and differences in the weight they give to these events significantly influences their future pattern of decisions. Furthermore, whether individuals place more importance on reward frequency or on the long-term expected value of each option is an important distinction that can affect decision-making performance. Our findings suggest that the attributes of each choice alternative and the weight given to those attributes, particularly the

weight given to recent versus distant outcomes and gain or loss frequency, may be different for men and women.

References

- Ahn, W.-Y., Busemeyer, J. R., Wagenmakers, E. J., & Stout, J. C. (2008). Comparison of decision learning models using the generalization criterion method. *Cognitive Science*, *32*, 1376–1402. <http://dx.doi.org/10.1080/03640210802352992>
- Ahn, W.-Y., Krawitz, A., Kim, W., Busemeyer, J. R., & Brown, J. W. (2011). A model-based fMRI analysis with hierarchical Bayesian parameter estimation. *Journal of Neuroscience, Psychology, and Economics*, *4*, 95–110. <http://dx.doi.org/10.1037/a0020684>
- Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist drugs: A neurocognitive perspective. *Nature Neuroscience*, *8*, 1458–1463. <http://dx.doi.org/10.1038/nn1584>
- Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis: A neural theory of economic decision. *Games and Economic Behavior*, *52*, 336–372. <http://dx.doi.org/10.1016/j.geb.2004.06.010>
- Bechara, A., Damasio, A. R., Damasio, H., & Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition*, *50*, 7–15. [http://dx.doi.org/10.1016/0010-0277\(94\)90018-3](http://dx.doi.org/10.1016/0010-0277(94)90018-3)
- Busemeyer, J. R., & Stout, J. C. (2002). A contribution of cognitive decision models to clinical assessment: Decomposing performance on the Bechara gambling task. *Psychological Assessment*, *14*, 253–262. <http://dx.doi.org/10.1037/1040-3590.14.3.253>
- Byrne, K. A., & Worthy, D. A. (2015). Gender differences in reward sensitivity and information processing during decision-making. *Journal of Risk and Uncertainty*, *50*, 55–71. <http://dx.doi.org/10.1007/s11166-015-9206-7>
- Chiu, Y.-C., Lin, C.-H., Huang, J.-T., Lin, S., Lee, P.-L., & Hsieh, J.-C. (2008). Immediate gain is long-term loss: Are there foresighted decision makers in the Iowa Gambling Task? *Behavioral and Brain Functions*, *4*: 13. <http://dx.doi.org/10.1186/1744-9081-4-13>
- Dai, J., Kerestes, R., Upton, D. J., Busemeyer, J. R., & Stout, J. C. (2015). An improved cognitive model of the Iowa and Soochow Gambling Tasks with regard to model fitting performance and tests of parameter consistency. *Frontiers in Psychology*, *6*: 229. <http://dx.doi.org/10.3389/fpsyg.2015.00229>
- Daw, N. D., Gershman, S. J., Seymour, B., Dayan, P., & Dolan, R. J. (2011). Model-based influences on

- humans' choices and striatal prediction errors. *Neuron*, 69, 1204–1215. <http://dx.doi.org/10.1016/j.neuron.2011.02.027>
- de Visser, L., van der Knaap, L. J., van de Loo, A. J. A. E., van der Weerd, C. M. M., Ohl, F., & van den Bos, R. (2010). Trait anxiety affects decision-making differently in healthy men and women: Towards gender-specific endophenotypes of anxiety. *Neuropsychologia*, 48, 1598–1606. <http://dx.doi.org/10.1016/j.neuropsychologia.2010.01.027>
- Eckel, C. C., & Grossman, P. J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior & Organization*, 68, 1–17. <http://dx.doi.org/10.1016/j.jebo.2008.04.006>
- Edwards, W. (1954). The theory of decision making. *Psychological Bulletin*, 51, 380–417. <http://dx.doi.org/10.1037/h0053870>
- Evans, K. L., & Hampson, E. (2015). Sex differences on prefrontally-dependent cognitive tasks. *Brain and Cognition*, 93, 42–53. <http://dx.doi.org/10.1016/j.bandc.2014.11.006>
- Gureckis, T. M., & Love, B. C. (2009). Short-term gains, long-term pains: How cues about state aid learning in dynamic environments. *Cognition*, 113, 293–313. <http://dx.doi.org/10.1016/j.cognition.2009.03.013>
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47, 263–291. <http://dx.doi.org/10.2307/1914185>
- Lau, B., & Glimcher, P. W. (2005). Dynamic response-by-response models of matching behavior in rhesus monkeys. *Journal of the Experimental Analysis of Behavior*, 84, 555–579. <http://dx.doi.org/10.1901/jeab.2005.110-04>
- MATLAB and PsychToolbox Release 2009b (Version 2.5) [Computer software]. Natick, MA: The MathWorks, Inc.
- Overman, W. H. (2004). Sex differences in early childhood, adolescence, and adulthood on cognitive tasks that rely on orbital prefrontal cortex. *Brain and Cognition*, 55, 134–147. [http://dx.doi.org/10.1016/S0278-2626\(03\)00279-3](http://dx.doi.org/10.1016/S0278-2626(03)00279-3)
- Overman, W. H., Boettcher, L., Watterson, L., & Walsh, K. (2011). Effects of dilemmas and aromas on performance of the Iowa Gambling Task. *Behavioural Brain Research*, 218, 64–72. <http://dx.doi.org/10.1016/j.bbr.2010.11.015>
- Overman, W. H., Frassrand, K., Ansel, S., Trawalter, S., Bies, B., & Redmond, A. (2004). Performance on the IOWA card task by adolescents and adults. *Neuropsychologia*, 42, 1838–1851. <http://dx.doi.org/10.1016/j.neuropsychologia.2004.03.014>
- Reavis, R., & Overman, W. H. (2001). Adult sex differences on a decision-making task previously shown to depend on the orbital prefrontal cortex. *Behavioral Neuroscience*, 115, 196–206. <http://dx.doi.org/10.1037/0735-7044.115.1.196>
- Steingroever, H., Wetzels, R., & Wagenmakers, E. J. (2013a). A comparison of reinforcement learning models for the Iowa Gambling Task using parameter space partitioning. *Journal of Problem Solving*, 5(2): 2. <http://dx.doi.org/10.7771/1932-6246.1150>
- Steingroever, H., Wetzels, R., & Wagenmakers, E. J. (2013b). Validating the PVL-delta model for the Iowa Gambling Task. *Frontiers in Psychology*, 4: 898. <http://dx.doi.org/10.3389/fpsyg.2013.00898>
- Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction* (Vol. 1). Cambridge, MA: Cambridge University Press.
- van den Bos, R., Homberg, J., & de Visser, L. (2013). A critical review of sex differences in decision-making tasks: Focus on the Iowa Gambling Task. *Behavioural Brain Research*, 238, 95–108. <http://dx.doi.org/10.1016/j.bbr.2012.10.002>
- Weller, J. A., Levin, I. P., & Bechara, A. (2010). Do individual differences in Iowa Gambling Task performance predict adaptive decision making for risky gains and losses? *Journal of Clinical and Experimental Neuropsychology*, 32, 141–150. <http://dx.doi.org/10.1080/13803390902881926>
- Worthy, D. A., & Maddox, W. T. (2011). Age-based differences in strategy use in choice tasks. *Frontiers in Neuroscience*, 5: 145. <http://dx.doi.org/10.3389/fnins.2011.00145>
- Worthy, D. A., Pang, B., & Byrne, K. A. (2013). Decomposing the roles of perseveration and expected value representation in models of the Iowa Gambling Task. *Frontiers in Psychology*, 4: 640. <http://dx.doi.org/10.3389/fpsyg.2013.00640>
- Yechiam, E., Busemeyer, J. R., Stout, J. C., & Bechara, A. (2005). Using cognitive models to map relations between neuropsychological disorders and human decision-making deficits. *Psychological Science*, 16, 973–978. <http://dx.doi.org/10.1111/j.1467-9280.2005.01646.x>

(Appendix follows)

Appendix

IGT/SGT Instructions

In this study we are interested in how people use information to make decisions.¹ You will repeatedly select from one of four decks of cards, and you could gain or lose points on each draw. You will be given 2,000 points to start and your goal is to try to finish with at least 2,500 points.

Each time you draw, the card you picked will be turned over and the number of points you gained and lost will be displayed.

You will press the 'Z,' 'W,' 'P,' and '?' keys to draw from each deck.

Just do your best to maximize your gains and minimize your losses so you can finish with at least 2,500 points.

¹ In the Soochow Gambling Task (SGT), participants began with 4,000 points, and were given a goal of reaching 5,000 points. All other instructions were identical to those in the Iowa Gambling Task (IGT).

Received February 23, 2016
Revision received June 22, 2016
Accepted June 26, 2016 ■