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Working Memory Affects Attention to Loss Value and Loss Frequency in Decision-Making under Uncertainty

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Abstract

Decision-making under uncertainty is pervasive. This work sought to understand the role of working memory (WM) in loss sensitivity by utilizing two widely used tasks, the Iowa Gambling Task (IGT) and the Soochow Gambling Task (SGT), and manipulating WM with a dual-task paradigm. We hypothesized that WM load would reduce attention to both loss value and frequency in the decision-making tasks. To better delineate the psychological processes underpinning choice behavior, we developed an Expectancy-Frequency-Perseveration (EFP) model which parsimoniously captures three critical factors driving choices: expected value, frequency of gains and losses, and perseveration. Behavioral and computational modeling results indicate that WM load compromised performance in the IGT due to reduced attention to loss value but enhanced performance in the SGT because of diminished attention to loss frequency. Our findings suggest that WM heightens attention to losses, but that greater attention is given to loss frequency than loss value.

Keywords: decision-making under uncertainty, working memory, loss, frequency, Iowa Gambling Task

Introduction

Many decisions in everyday life involve some degree of uncertainty, either small decisions, such as whether to pick a new restaurant for dinner or eat at one you frequently visit, or major ones, such as whether to invest in a risky hedge fund for a foreign oil company or invest in safer alternatives such as bonds. The Iowa Gambling Task (IGT; Bechara, Damasio, Damasio, & Anderson, 1994) and the Soochow Gambling Task (SGT; Chiu et al., 2008) mimic real-life decision-making situations involving uncertainty. In the present work we utilize these two tasks to examine how working memory load affects sensitivity to losses versus gains, a critical factor in many decision-making situations.

The IGT is widely used to examine choice behavior in various clinical populations (e.g., brain damage, substance abuse), developmental samples, and in healthy adults (Buelow & Suhr, 2009). The IGT manipulates the uncertainty of premises and outcomes, as well as gains and losses provided by each deck. In this task, players choose between four decks of cards, which yield both gains and losses. Unbeknownst to players, Decks A and B are disadvantageous because they have a negative net expected value, while Decks C and D are advantageous because they have a positive net expected value. The task is initially challenging because the disadvantageous decks consistently yield larger gains (100 versus 50 points), yet they also give larger losses.

Although it is assumed that players make choices by comparing expected values for options in the IGT, some authors present critiques that gain-loss frequency plays an important role in choice behavior in the IGT (Chiu et al., 2008; Steingroever, Wetzels, & Horstmann, 2013). In the IGT, Decks A and C give frequent losses (on 50% of trials), while Decks B and D give less frequent losses (on 10% of trials). A tendency to avoid decks with frequent losses will not have an effect on the net amount of points gained since the high-frequency loss decks are split across the advantageous and disadvantageous decks. The SGT was recently developed to further distinguish the influence of expected value and gain-loss frequency (Chiu et al., 2008). In this task the two advantageous decks (C and D) also give the most frequent losses – on 80% of trials compared to only 20% of trials for the disadvantageous decks (A and B). Thus, a tendency to avoid decks that give frequent losses will lead to poor performance, but a tendency to focus on the net expected value will lead to good performance. Comparing performance in both tasks allows for better inference about the mechanisms that contribute to decision-making performance. Attention to the net expected values provided by each deck should lead to good performance in both tasks, while attention to the frequency of losses should have little effect on performance in the IGT, but a negative effect on performance in the SGT.

Working memory (WM), a central component of cognitive executive function, is crucial to a variety of higher-order cognitive tasks. It might contribute to the decision-making processes in the IGT and the SGT. Recently, a number of studies have examined the role of WM on choice behavior in the IGT or its variants, but the findings have been somewhat mixed (e.g., Hinson, Jameson, & Whitney, 2002; Turnbull, Evans, Bunce, Carzolio, & O'Connor, 2005). Thus, the first goal of the current research was to examine whether completing the IGT requires WM by utilizing the original IGT and a dual-task paradigm. We also evaluated the contribution of WM on choice behavior in the SGT, which is the first attempt to do so. As such, results from these two tasks would provide convergent evidence for the role of WM in decision-making.

Perhaps of greater importance, we sought to pinpoint the specific mechanisms through which choice behavior in the IGT and SGT are reliant on WM. Sensitivity to potential losses is crucial to make reasonable choices in the IGT and other decision scenarios. With impaired attention to losses, decision makers might base their choices mainly on the gains that they expect to receive. In the context of the IGT, such a strategy leads to preference for the disadvantageous decks because these options consistently yield larger gains than the advantageous decks (e.g., Cella, Dymond, Cooper, & Turnbull, 2012). WM might be important to maintain attention to losses, especially in such a complicated task. For example, in a study demonstrating that WM load interferes with performance in a three-deck variant of the IGT (Hinson et al., 2002), participants under low WM load produced different anticipatory emotional reactions to different decks as the task progressed. These prospective emotional reactions are theorized as somatic markers and assumed to facilitate decision-making under uncertainty (Bechara & Damasio, 2005; Damasio, 1994). Participants under high WM load, however, did not exhibit distinguishable emotional reactions, which might be due to inadequate sensitivity to losses when WM resources were taxed by a WM-demanding concurrent task. We speculated that intact WM resources may enable decision makers to adequately attend to gains and losses and maintain them across trials, making it possible that participants represent appropriate expected values for each option. However, insufficient WM resources may impair players' attention to losses and bias them towards gains, causing inaccurate expected values and poor performance in both tasks.

Besides expected value, attention to the frequency of losses versus gains might also be an important component of decision-making that is mediated by WM. Tracking the frequency and choosing the option with infrequent losses and frequent gains is a heuristic-based strategy, which appears simple but might be WM-sensitive. Indeed, previous studies have shown that participants with intact WM resources prefer heuristic-based strategies, such as win-stay, lose-shift, by remembering the outcomes from past trials more than participants under WM load (Worthy, Otto, & Maddox, 2012). In contrast, Worthy et al. (2012) found that participants under WM load preferred a strategy that implicitly track expected values of options. One possibility is that the frequency of losses is more salient than the net value of each option. WM load may attenuate participants' ability to attend to both the value and the frequency of losses, but because the frequency of losses is more salient than the value of losses, participants with intact WM resources will attend more to the frequency of losses than to the value of losses. This would lead to a pattern of behavior where participants performing the task under no-load conditions would perform better than participants under WM-load on the IGT due to superior attention to the loss value of each deck, but worse on the SGT due to enhanced attention to the frequency of losses.

Computational Modeling

In addition to our behavioral approach of utilizing tasks where attention to loss frequency differentially affects performance, we also utilize computational modeling to isolate and identify these specific psychological mechanisms underpinning choice behavior. A range of computational models have been applied to IGT and SGT data. Prospect valence learning (PVL) models, including PVL-Delta and PVL-Decay, and value-plus-perseveration (VPP) models have been most popular in recent work (Ahn et al., 2008; Worthy, Pang, & Byrne, 2013). As with most reinforcement learning (RL) models (Sutton & Barto, 1998), the basic assumptions behind the PVL models are that outcomes of past decisions are integrated to determine expected values for each option and that decision makers tend to choose options with larger expected value (Ahn et al., 2008). The VPP model further accounts for both the tendency to choose the option with the highest expected value and to perseverate or stay with the same option that was selected on the past trial (Worthy et al., 2013). However, as discussed above, attention to gain-loss frequency is another central source of choice behavior, which may also be affected by WM load. As such, in this work, we developed a new model which accounts for attention to expected value, to the frequency of gains versus losses, and perseveration, which we believe are three critical mechanisms in gambling tasks. We call this the Expectancy-Frequency-Perseveration (EFP) model.

The PVL models and the VPP model have been extensively discussed in many recent articles (e.g., Ahn et al., 2008; Worthy et al., 2013). Readers are referred to these articles for the models' details. In what follows, we first introduce the EFP model and evaluate it against other models by applying all the models to a large data set of IGT data. We then use the EFP model to simulate choice behavior in the IGT and SGT. This model explicitly accounts for the attention people give to the frequency of net gains versus losses so that we could make predictions as to how attention to gain-loss frequency would affect decision-making performance in the tasks.

EFP Model In contrast to the PVL models with a single expected value term and the VPP model with expected value and perseveration terms, the EFP model includes three terms to account for three critical components of choice behavior: expected value, gain-loss frequency, and perseveration. Increasing the number of terms may ostensibly improve the fit of the model or lead to overfitting simply because the model has too many parameters. Considering this, we sought to design a model to capture these three important psychological components while keeping it as parsimonious as possible.

This model first assumes that after making a choice and receiving feedback ($gain(t)$ and $loss(t)$), the utility $u(t)$ for the choice made on trial *t* is given by:

$$u(t) = gain(t) - \rho \cdot |loss(t)| \quad (1)$$

Here ρ represents a loss aversion parameter ($0 \leq \rho \leq 5$) that governs the sensitivity of losses compared to gains. A value of ρ greater than 1 indicates that an individual is more sensitive to losses than gains, and a value less than 1 indicates greater sensitivity to gains than to losses. Note that the EFP model assumes that the subjective utility is linearly proportional to the actual payoff amount, in contrast to the PVL models that use a nonlinear function (see Ahn et al., 2008). One major reason for the nonlinear function is to implicitly account for the gain-loss frequency. The EFP model, however, explicitly captures the gain-loss frequency (see below) and thus a shape parameter is not necessary. Additionally, using a linear function improves the parsimony.

The EFP model then assumes that the utility $u(t)$ is used to update expectancies $E_j(t)$ for the chosen option, *i,* on trial *t*. It utilizes the Delta rule (Sutton & Barto, 1998) which assumes that expectancies are recency-weighted averages of the rewards received for each option:

$$E_i(t) = E_i(t-1) + \phi \cdot [u(t) - E_i(t-1)] \quad (2)$$

Here ϕ represents the recency parameter ($0 \leq \phi \leq 1$) that describes the weight given to recent outcomes in updating expectancies. As ϕ approaches 1, greater weight is given to the most recent outcomes in updating expectancies, indicating more active updating of expectancies.

The perseveration term in the VPP model was designed to model the tendency to perseverate following gains and to switch following losses. Thus, it also implicitly captures the frequency of gains and losses. In the EFP model we decompose the tendency to select the option with infrequent losses and frequent gains and the tendency to perseverate. The frequency term for chosen option *i*, on trial *t*, differed based on whether the net outcome, *x(t)*, was positive or negative:

$$F_i(t) = \begin{cases} (1-\phi)\cdot F_i(t-1)+1 & \text{if } x(t)\geq 0 \\ (1-\phi)\cdot F_i(t-1)-1 & \text{if } x(t)<0 \end{cases} \quad (3)$$

The frequency value increases by 1 following a net gain or decreases by 1 following a net loss. Instead of using a separate parameter to capture the weight to previous information as in the VPP model, the EFP model utilizes $1 - \phi$. Here ϕ has the same meaning as in Equation 2, accounting for weight given to recent information. Thus, utilizing the same recency parameter for both the value updating function and the gain-loss frequency function increases the parsimony of the EFP model.

The perseveration term for chosen option *i*, on trial *t*, is determined by:

$$P_i(t) = \gamma \quad (4)$$

The tendency to perseverate or switch is denoted by γ which varies between -100 and 100. This perseveration term simply gives a bonus or a reduction to the value of the option that was selected on the last trial, and thus indicates a general tendency to stay or switch to a different option on each trial.

The overall value of each option was determined by taking a weighted average of the expected value and the frequency plus the perseveration strength of each *j* option:

$$V_j(t) = \omega \cdot E_j(t) + (1-\omega) \cdot F_j(t) + P_i(t) \quad (5)$$

where ω ($0 \leq \omega \leq 1$) quantifies the weight given to the expected value for each option versus the weight given to the frequency of losses versus gains provided by each option.

Finally, these overall values $V_j(t)$ were entered into a Softmax rule function to determine the probability of selecting each option, *j*, on each trial, *t*:

$$Pr\left(G_j(t)\right) = \frac{e^{\theta(t)\cdot V_j(t)]}}{\sum_{j=1}^{4} e^{[\theta(t)\cdot V_j(t)]}} \quad (6)$$

$$\theta(t) = 3^c - 1 \quad (7)$$

Here c ($0 \leq c \leq 5$) represents the response consistency or exploitation parameter. Lower values indicate more random responding over the course of the task.

Model Evaluation We then compared the fit of the EFP, VPP, PVL-Delta, and PVL-Decay models by employing a large IGT dataset (*N*=504) of healthy participants. We fit each participant's data by maximizing the log-likelihood for each model's prediction on each trial. We used Bayesian Information Criterion (BIC; Schwarz, 1978) to assess the relative fit of the model. BIC penalizes models with more free parameters. For each model, *i*, BIC_i is defined as:

$$BIC_i = -2\log L_i + V_i \log(n)$$

where L_i is the maximum likelihood for model *i*, V_i is the number of free parameters, and *n* is the number of trials. Smaller BIC values indicate a better fit to the data. The EFP model exhibited the smallest median BIC value (see Table 1), indicating that it provides a better fit to the data than other models. Also, note that the VPP model fits were close to those of the EFP model, followed by the PVL-Decay model. The PVL-Delta model had a poorer fit compared to these models.

Table 1: Median BIC values for each model

Model	EFP	VPP	PVL-Delta	PVL-Decay
	242.58	242.85	256.76	246.05

Simulations and Predictions To predict the effects of WM load on participants' performance, the proportion of trials when the good decks are selected minus the proportion of trials that the bad decks are selected, we next utilized the EFP model, to simulate choice behavior in the IGT and SGT. Specifically, we focused on how WM load would affect performance by biasing attention to either the value or frequency of losses versus gains. We conducted 2,000 simulations for the EFP model for each of the two tasks by systematically varying either the loss aversion parameter or the weight parameter for value versus gain-loss frequency, while fixing other parameters at reasonable values. In the loss aversion simulations, the loss aversion parameter varied from 0 to 5 in increments of .5, other parameters used were .5 for recency, 1 for exploitation, .5 for weight (indicating equal attention to the expected value and gain-loss frequency), and 0 for perseveration. Figure 1 (left panel) displays the results for the loss aversion parameter. As attention to losses increased, performance improved. This relationship held for both the IGT and SGT, although the slope for the SGT was slightly steeper. In the weight parameter simulation, the weight parameter varied from 0 to 1 with an increment of .1, other parameters were .5 for recency, 1 for exploitation, 1 for loss aversion (indicating equal weighting of the value of gains and losses), and 0 for perseveration. Figure 1 (right panel) depicts the simulation results. Clearly, increased weight to expected value enhanced performance in the SGT. A similar tendency was present for the IGT but was considerably weaker. It appears that weight to expected value versus gain-loss frequency does not strongly impact performance in the IGT. This notion is consistent with the payoff structure of the IGT. Both advantageous and disadvantageous IGT decks include one option with high-frequency losses and another option with low-frequency losses. As such, reliance on the frequency of gains versus losses does not have a strong impact on performance in the IGT.

As discussed earlier, we predict that WM load would compromise attention to losses, or reduce the loss aversion parameter value in the EFP model, and drive participants away from the frequency heuristic, or increase the weight parameter value in the EFP model. According to the simulations, in the IGT decreased loss aversion is associated with poorer performance, while greater weight to expected value does not strongly impact performance. Thus, we predicted that WM load would impair performance in the IGT. In the SGT, reduced loss aversion is also associated poorer performance, but increased weight to expected value versus gain-loss frequency leads to better performance. As such, WM load should either improve or compromise performance in the SGT, depending on whether participants performing the task without WM load attend more to the value or to the frequency of losses.

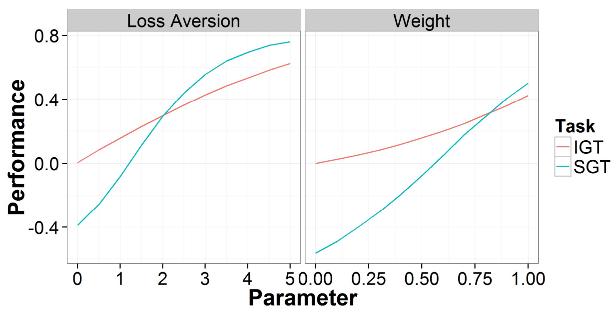

Figure 1. Performance in the IGT and SGT from the EFP model's simulations with varying loss aversion parameter (left panel) and weight parameter (right panel) values.

Experiment In this work, we aimed to examine whether WM contributes to decision-making under uncertainty by utilizing the IGT (Experiment 1A) and SGT (Experiment 1B), and to investigate what specific decision-making mechanisms WM load affects. To manipulate WM, we used a numerical Stroop task which has been used in previous experiments (e.g., Worthy, Otto, & Maddox, 2012). Specifically, in the single task (ST) condition participants only performed the decision-making task, the IGT (Experiment 1A) or the SGT (Experiment 1B), while in the dual task (DT) condition participants concurrently performed the decision-making task and the numerical Stroop task. Two potential mechanisms were tested that might drive the effects of WM load on the decision performance: attention to losses and gain-loss frequency. We combined behavioral analysis and computational modeling to evaluate these possible mechanisms. The computational models described above were fit to the data, and best-fitting parameter estimates, indicative of specific psychological components involved in decision-making processes, from the best-fitting model were compared between the ST and DT conditions. This procedure enabled us to infer the mechanisms whereby WM load affected decision-making behavior.

Experiments 1A 1B

Method

Participants 169 participants (101 females) recruited from an introductory psychology course at Texas A&M University participated in the experiment for course credit. Participants were randomly assigned to either the ST or DT condition in Experiments 1A and 1B.

Materials and Procedures Participants performed the experiment on PCs using Psychtoolbox for Matlab (version 2.5). In Experiment 1A, participants in the ST condition performed the computerized IGT (Bechara et al., 1997). On each of 100 trials four decks of cards appeared on the screen and participants were prompted to select one deck. Upon each selection the computer screen displayed the gain and loss, if applicable, and net value beneath the card decks. The task was self-paced, and participants were unaware of how many card draws they would receive. The schedule of gains and losses was identical to those used in the original IGT (Bechara et al., 1994).

In the DT conditions, in addition to the IGT participants performed a numerical Stroop task concurrently. The memory task required participants to remember which of two numbers was physically larger and which was larger in numerical value while performing the IGT. At the beginning of each trial, two numbers for the concurrent memory task were presented on each side of the screen, one number on each side, for 300 ms. Participants were then allowed to make a selection from among four decks of cards, followed by feedback as mentioned above. A new screen then appeared that queried participants with either *VALUE* or *SIZE*, and they selected either *Left* or *Right* to indicate which side had the number largest in either numerical value or physical size. Upon making a selection, they were told whether they were correct or not, and then the next trial began. Participants were told that they should focus on achieving good performance on the numerical Stroop task and "use what you have left over" for the decision-making task. To allow them to become familiar with the procedure, participants were given 10 practice trials. The practice trials were the same as the formal ones except that each selection on the IGT resulted in zero points regardless of which deck they selected.

The materials and procedures in Experiment 1B were identical to those in Experiment 1A except that participants performed the SGT (see Chiu et al., 2008) instead of the IGT.

Results and Discussion

Experiment 1A We examined performance by 20-trial blocks in the IGT (see the right panel of Figure 2). A mixed ANOVA with WM load (ST versus DT) as a between-subjects factor and Block (five 20-trial blocks) as a within-subject factor revealed a significant main effect of WM load, $F(1, 84) = 12.35$, $p = .001$, $\eta_p^2 = .13$, but not of block, $F < 1$. Moreover, there was a significant interaction, $F(4, 336) = 6.74$, $p < .001$, $\eta_p^2 = .07$. To examine this interaction, we looked at the simple effect of block within each WM load condition using trend analysis. For ST participants, performance improved linearly as the task progressed, $F(1, 42) = 12.27$, $p = .001$, $\eta_p^2 = .23$. In contrast, participants in the DT condition showed a linear downwards trend in performance across blocks, $F(1, 42) = 5.25$, $p = .03$, $\eta_p^2 = .11$. That is, participants learned to perform better over time, whereas WM load impaired normal progress and led to worse performance across blocks.

Experiment 1B The same ANOVA for SGT performance revealed a significant main effect of WM load, $F(1, 81) = 6.50$, $p = .01$, $\eta_p^2 = .07$, and for block, $F(4, 324) = 14.76$, $p = .00$, $\eta_p^2 = .15$. The WM load X Block interaction was also significant, $F(4, 324) = 2.95$, $p = .02$, $\eta_p^2 = .04$. To examine this interaction, we looked at the simple effect of WM load within each block using *t*-tests. As can be seen in Figure 2 (right panel), although participants in both the ST and DT conditions appeared to learn to perform better across the task, DT participants performed better compared to ST participants in the first three blocks (*ps* < .01), but ST participants reached a similar performance level as DT participants in the last two blocks (*ps* > .72). This result suggests that WM load affected decision-making early in the SGT such that WM load improved performance.

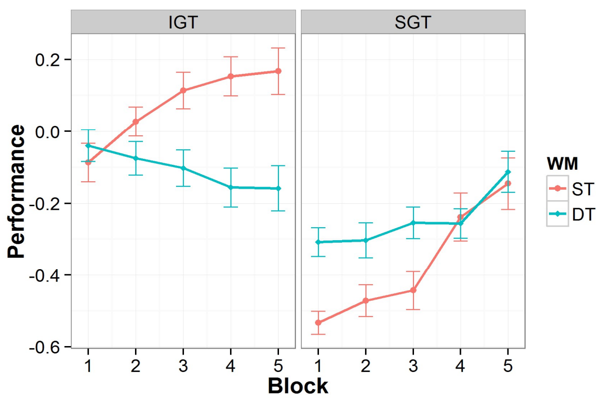

Figure 2. The performance in the IGT (right panel) and in the SGT (left panel) by 20-trial block for each WM condition (ST versus DT).

Computational Modeling

Table 2: Median BIC values for each model as a function of the task and WM condition

	Model	IGT	SGT
ST	EFP	**261.71**	257.96
	VPP	262.68	258.76
	Delta	277.96	264.07
	Decay	271.16	**252.85**
DT	EFP	**273.90**	**269.86**
	VPP	286.20	277.73
	Delta	284.18	274.67
	Decay	285.47	275.60

Model Selection

Four models, the EFP model, the two PVL models, and the VPP model, were evaluated with the method as above. Median BIC values are listed in Table 2. In the both WM conditions for the IGT and the WM load condition for the SGT, the EFP model had the smallest median BIC values, suggesting that this model fit the data best in these conditions. In the ST condition for the SGT, the EFP model exhibited larger median BIC value than the PVL-Decay model. Considering the model fitting results here and those from the aforementioned large IGT dataset, it seems clear that the EFP, PVL-Decay, and VPP models provide a better fit than the PVL-Delta model.

Modeling Results

We next compared the parameter estimates of the EFP model between the ST and DT conditions for each task to examine the effects of WM load on specific psychological processes related to decision-making. Table 3 lists the average best fitting parameter values of the EFP model for each task under each WM condition. Nonparametric Mann-Whitney *U* tests were used because the best-fitting model parameters were not normally distributed. In the IGT, ST participants' data were best fit by higher loss aversion parameter values than DT participants' data, $U = 569$, $p = .002$. This suggests that ST participants were more attentive to losses than DT participants, thus providing direct evidence to support the impaired loss sensitivity hypothesis. Furthermore, participants under WM load showed marginally significantly higher weight to RL expected value, $U = 708$, $p = .057$, providing some evidence to support our prediction that WM load would cause less reliance on a frequency-based strategy.

In the SGT, ST participants exhibited lower values for the weight parameter than did DT participants, $U = 645$, $p = .04$. This suggests that participants with compromised cognitive resources were less likely to utilize the frequency heuristic in the SGT, which is consistent our predictions the IGT results. Although we observed a trend that ST participants showed a higher loss aversion parameter estimates than did DT participants, this difference did not reach significance, $U = 697$, $p = .13$. Moreover, data from ST participants were best fit by higher recency parameter values than data from DT participants, $U = 643$, $p < .05$. This results suggests that ST participants were more attentive to recent outcomes, which might allow participants with intact WM resources to more actively update expectancies compared to participants under WM load.

Table 3: Average parameter estimates as a function of the task and WM condition

Parameters	IGT		SGT	
	ST	DT	ST	DT
ϕ	0.40 (0.39)	0.32 (0.39)	0.40 (0.39)	0.19 (0.27)
ρ	2.11 (2.28)	0.61 (1.43)	1.56 (1.96)	0.97 (1.69)
γ	−0.41 (28.56)	−10.77 (26.92)	20.74 (37.56)	−0.96 (25.69)
ω	0.26 (0.39)	0.37 (0.43)	0.31 (0.41)	0.42 (0.46)
c	0.70 (0.96)	0.57 (0.94)	0.47 (0.48)	0.53 (0.71)

Standard deviations are listed in parentheses.

General Discussion

Our results provide clear evidence that WM contributes to choice behavior in decision-making under uncertainty. Results from Experiment 1A indicated that intact WM is necessary to do well on the IGT. These results were at odds with Turnbull et al. (2005), possibly because random number generation and articulatory suppression tasks used in Turnbull et al. did not tax enough WM resources to interfere with decision making processes, and/or their experiment lacked statistical power due to relatively small sample sizes (n = 25 for each group). On the other hand, our findings confirm implications from previous behavioral studies using variants of the IGT (instead of the original IGT; Hinson et al., 2002) and from brain lesion studies with DLPFC damage patients (Fellows & Farah, 2005). As such, this work contributes to the IGT literature by lending direct support to the idea that choice behavior in the IGT is dependent on WM. Moreover, results from Experiment 1B showed that WM load influenced performance in the SGT. This is the first work demonstrating that WM contributes to choice behavior in this frequently used decision-making task. Therefore, this work provides convergent evidence to support the notion that WM plays a role in decision-making under uncertainty.

Further, our results provide considerable insight into the mechanisms through which WM contributes to decision-making under uncertainty. First, we found that participants with compromised WM resources performed worse in the IGT and had data better fit by smaller loss aversion parameter values, suggesting that WM enables decision-makers to adequately attend to losses in decision-making under uncertainty. In contrast, we found that participants with impaired WM resources performed better overall in the SGT and exhibited greater weight to expected value versus gain/loss frequency, indicating that another role of WM in decision-making under uncertainty is to attend to the frequency of gains versus losses, rather than just the net expected value of each alternative. Much evidence suggests that a prediction error, the difference between the outcome received and the expected value for a given option, is tracked by the ventral striatum, a subcortical region implicated in implicit, procedural learning (e.g., Hare, O'Doherty, Camerer, Schultz, & Rangel, 2008). In many RL models, including models used in this article, these prediction errors are used to update the expected value for the option that was chosen on each trial. Given the ability of subcortical regions to track expected value, people may be able to implicitly learn which option provides the largest expected value across the task. However, with intact WM resources decision makers prefer heuristics such as the frequency heuristic which can be efficient in many situations, but counterproductive in situations like the SGT where gain-loss frequency is directly opposed with expected value.

Collectively, this work demonstrates that WM strongly contributes to choices involving uncertainty. Intact WM resources mainly enable decision makers to maintain adequate attention to loss value and loss frequency, with loss frequency receiving greater attention than loss value.

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