

Delay and probability discounting in the context of gambling function and expectancies

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Abstract

The current study investigated the relationship between two forms of discounting (delay and probability) and two measures of factors that may maintain gambling behavior (behavioral contingencies and expectancies). Participants (272 undergraduates) completed discounting questions for scenarios of gaining or losing \$1,000 or \$100,000 with uncertain or delayed outcomes. They also filled out the South Oaks Gambling Screen, the Gambling Functional Assessment – Revised, and the Gambling Expectancies Questionnaire. Results showed that gambling for positive reinforcement was consistently the best predictor of discounting, suggesting that the function of gambling behavior may be a better predictor of discounting than are the emotional expectancies of gambling. However, the direction of the relationship was inconsistent, with function negatively predicting discounting of both uncertain gains and losses. No consistent relationship was found between discounting and gambling for negative reinforcement or emotional expectancies. Results were generally the same when non-gamblers were excluded from the analyses. The results suggest that studying gambling function may be an informative pursuit.

Résumé

Cette étude s'est penchée sur le lien entre deux formes de rejet du délai (retard et probabilité) et deux mesures de facteurs pouvant maintenir un comportement de jeu compulsif (possibilités et attentes comportementales). Les participants (272 étudiants de premier cycle) ont répondu à des questions portant sur le rejet du délai pour des scénarios de gain ou de perte de 1 000 \$ ou 100 000 \$ menant à des résultats incertains ou tardifs. Ils ont également rempli les questionnaires South Oaks Gambling Screen, Gambling Functional Assessment – Revised (GFA-R) et Gambling Expectancies Questionnaire (GEQ). Les résultats ont démontré que le recours au jeu compulsif pour obtenir un renforcement positif était, de façon constante, le meilleur indicateur de rejet du délai. Ceci suggère que la fonction du comportement de jeu compulsif s'avérait un meilleur indicateur de rejet du délai que ne l'étaient les attentes émotionnelles liées au jeu compulsif. Toutefois, la direction

que prenait la relation n'était pas cohérente, la fonction prédisant, de façon négative, le rejet du délai quant aux pertes et aux gains incertains. Aucun lien cohérent n'a été établi entre le rejet du délai et les activités de jeu compulsif pour un renforcement négatif ou des attentes émotionnelles. Les résultats étaient généralement les mêmes lorsque les analyses excluaient les personnes qui ne s'adonnaient pas au jeu compulsif. Ceux-ci suggèrent que l'étude de la fonction du jeu compulsif peut s'avérer une voie riche en connaissances.

Introduction

Researchers interested in pathological gambling have paid particular attention to the phenomenon of delay discounting, which occurs when the subjective value of an outcome is changed because of a delay in its delivery (see Madden & Bickel, 2010). An example of delay discounting would be choosing \$100 that was available now versus waiting 2 weeks to receive \$200. Such a choice would indicate that the value of the \$200 had been decreased by 50% by being delayed for 2 weeks (Madden & Bickel, 2010). Steep rates of discounting would indicate that the value of the delayed outcome decreases rapidly as the delay to the outcome increases.

Numerous researchers (e.g., Alessi & Petry, 2003; Petry & Madden, 2010) have associated pathological gambling, as measured by scores on the South Oaks Gambling Screen (SOGS; Lesieur & Blume, 1987), with steep rates of delay discounting. For instance, Stea, Hodgins, and Lambert (2011) found that gambling severity accounted for discounting rates beyond other addictive behavioral problems.

However, the relationship between gambling and delay discounting is not entirely consistent. Dixon, Jacobs, and Sanders, (2006) found that discounting by pathological gamblers was not as steep in a non-gambling context (such as coffee shops, restaurants, and business locations) as it was in a gambling context (an off-track betting service). Similarly, Weatherly and Derenne (2010) found that discounting varied with SOGS scores for delayed monetary, but not non-monetary, outcomes. Self-reported frequency of gambling has also been shown to be unrelated to discounting of a variety of different outcomes (Weatherly, Terrell, & Derenne, 2009). Furthermore, Petry (2011) found no association between gambling treatment outcomes and rates of delay discounting.

Delay discounting may also be related to other factors that are often seen in problem gamblers, and researchers have investigated this possibility. One factor is impulsivity, which is thought to be influential in the delay discounting decision (Madden & Bickel, 2010). The results of one study indicated that problem gamblers are more impulsive and have more trouble planning than do non-problem gamblers (Ledgerwood, Alessi, Phoenix, & Petry, 2009). The same study also reported that

problem gamblers delayed discounting at steeper rates than did non-problem gamblers (Ledgerwood et al., 2009). A meta-analysis by MacKillop et al. (2011) found that individuals with gambling or substance use addiction tended to delay discount at greater rates than did non-clinical samples. The authors posited that delay discounting rates most likely are unchanged by addiction themselves and may even be predictive of addiction potential and recovery (MacKillop et al., 2011).

Another relationship that has been examined is that between pathological gambling and probability discounting. Probability discounting occurs when the subjective value of an outcome is changed because of the uncertainty of its delivery (see Madden & Bickel, 2010). For instance, someone who chooses a 50% chance of winning \$1,000 is thought to be making a riskier decision than when choosing to get \$500 with 100% certainty (Madden & Bickel, 2010). Studies indicate that pathological and non-pathological college gamblers place greater value on probabilistic gains than do non-gamblers. In other words, they are more likely to accept the uncertain outcome than the smaller but certain outcome (Holt, Green, & Myerson, 2003; Madden, Petry, & Johnson, 2009). These findings suggest that gamblers are less affected by risk than are non-gamblers (Holt et al., 2003; Madden et al., 2009). However, this relationship has also not been consistently shown across studies. For instance, Shead, Callan, and Hodgins (2008) found that gambling severity did not relate to rates of probability discounting, suggesting that this relationship may not be entirely reliable.

In order to further understand the relationship between gambling and discounting of both probabilistic and delayed outcomes, some researchers have begun to examine the purpose that gambling behavior serves and how it may relate to the process of discounting. One measure that has been used is the Gambling Functional Assessment (GFA; Dixon & Johnson, 2007). This self-report measure was originally designed to measure four contingencies that may maintain gambling behavior: Tangible, Sensory Experience, Social Attention, and Escape (Dixon & Johnson, 2007). Tangible refers to monetary gain, Sensory to sensory stimulation, Social Attention to the social components or attention received from gambling, and Escape to gambling as an escape (Dixon & Johnson, 2007). However, Miller, Meier, Muehlenkamp, and Weatherly (2009) factor analyzed data from the GFA and found that it actually measured two contingencies, which they labeled positive reinforcement (i.e., gain) and negative reinforcement (i.e., escape).

The Gambling Functional Assessment – Revised (GFA-R; Weatherly, Miller, & Terrell, 2011) differs from the original in that it has 16 items as opposed to 20 and has only two subscales, Positive reinforcement and Negative reinforcement (Miller et al., 2009). Research indicates that the GFA-R subscales have high internal consistency, with $\alpha = 0.94$ for Positive reinforcement and $\alpha = .91$ for Negative reinforcement (Weatherly, Miller, Montes, & Rost, 2012). The measure demonstrates adequate test-retest reliability at 4 weeks ($r = .74$ for positive reinforcement scores, and $r = .87$ for negative reinforcement; Weatherly et al., 2012). The GFA-R

has also been shown to have good construct validity in university students in the United States and the United Kingdom (Weatherly, Dymond, Samuels, Austin, & Terrell, 2014).

Further research on the GFA has found that pathological gamblers scored higher than non-gamblers on gambling as an escape (Miller, Dixon, Parker, Kulland, & Weatherly, 2010). Weatherly, Montes, and Christopher (2010) found that higher escape scores on the GFA were predictive of betting more credits in a laboratory gambling situation. Research on the revised GFA (GFA-R) has also demonstrated a strong association between GFA-R escape scores and SOGS scores (Weatherly et al., 2012).

Weatherly and Derenne (2012) examined the relationship between GFA-R escape scores and probability discounting. Their study replicated previous results in that SOGS scores were more closely related to gambling as an escape than to gambling for positive reinforcement. They also found that rates of probability discounting were sometimes predicted by gambling as an escape, but were not predicted by gambling for positive reinforcement. However, the results indicated that this relationship was not consistent, suggesting that the relationship between gambling for negative reinforcement and probability discounting may not be reliable (Weatherly & Derenne, 2012).

Another instrument that has been used to examine the function of gambling behavior is the Gambling Expectancy Questionnaire (GEQ; Stewart & Wall, 2005). The GEQ measures what the individual expects to obtain as a result of gambling. It is similar to the GFA and GFA-R in that the expectancies are related to either increasing positive emotion or decreasing negative emotion. The measure has 18 items and was modeled after questionnaires designed to measure alcohol expectancies (Stewart & Wall, 2005). Relief measures the expected reductions in negative emotions as a result of gambling, and Reward measures the expected increases in positive emotions as a result of gambling (Shead et al., 2008; Stewart & Wall, 2005). The developers of the scale, Stewart and Wall (2005), originally structured it by using nine items for each of the two scales. A later study conducted by Shead and Hodgins (2009) found via factor analysis that 12 items loaded onto the Relief factor and six items loaded onto the Reward factor. Using this scoring method, Shead and colleagues (2008) studied how scores on the GEQ subscales related to probability discounting and found that positive emotion expectancies were predictive of riskier choices. This result is inconsistent with that obtained by Weatherly and Derenne (2012), who found that gambling for positive reinforcement was not predictive of rates of probability discounting.

The purpose of the current study was to answer whether (a) scores on the GFA-R and GEQ are reliably related to discounting rates, (b) discounting rates are better predicted by positive reinforcement function or expectancies versus negative reinforcement function or expectancies, and (c) in the case that a consistent

relationship is found, whether expectancies predict rates of discounting after accounting for the contributions of gambling function. Unlike the studies by Shead et al. (2008) and Weatherly and Derenne (2012), the current study included measures of both delay and probability discounting. Delay discounting was included because of previous research that has found a relationship between problem gambling and delay discounting rates (e.g., Ledgerwood et al., 2009; Madden & Bickel, 2010). We hypothesized that, because rates of discounting are related to pathological gambling (e.g., Holt et al., 2003) and pathological gambling is related to gambling for negative reinforcement (Miller et al., 2010), the measures pertaining to negative reinforcement would be more predictive of delay and probability discounting than would the measures pertaining to positive reinforcement.

Method

Participants

Data were collected from 300 undergraduate students enrolled in psychology courses at the University of North Dakota, who received course credit for participating. Data from 28 participants were removed because the participants did not fully complete the discounting tasks, resulting in a final sample size of 272 participants. Of the participants, 65 identified themselves as male and 207 as female. Mean reported age was 20.0 years ($SD = 3.1$ years) and mean self-reported grade point average was 3.4 out of 4.0 ($SD = 1.8$). The majority of the sample (91.5%) was Caucasian.

Regarding gambling behavior, 23.5% denied and 76.1% endorsed having engaged in any gambling behavior throughout their lifetime. The majority of participants (39.3%) reported that the largest sum of money they had ever gambled with during one day ranged from \$10 to \$100. Four percent of the sample endorsed having gambled with \$100 up to \$1,000 during one day, and 0.2% endorsed having gambled with \$1,000 up to \$10,000 in one day. Finally, 4% endorsed having gambled less than \$1 in one day, and 23.9% endorsed having gambled between \$1 and \$10 in one day. Twenty-seven percent denied having ever gambled, and 0.4% declined to answer the question. Participants endorsed having engaged in a variety of gambling behaviors, including betting on races, betting on sports, playing dice games for money, betting on lotteries, going to a casino, playing bingo, playing the stock market, playing slot machines or other gambling machines, and playing games for money. Non-gamblers were included in the study to determine whether results were different between non-gamblers and gamblers. For instance, if discounting rates are unrelated to gambling, we would expect that discounting rates would be unchanged after excluding the non-gamblers.

Procedure and Materials

The study took place entirely online through an online experiment-management system (SONA Systems, Ltd; Version 2.72; Tallinn, Estonia). After giving their

informed consent to participate in this study, which was approved by the Institutional Review Board, participants completed several different measures. The first was a demographic questionnaire, which asked about the information provided in the Participants subsection.

Afterwards, participants filled out the SOGS, a diagnostic screen for pathological gambling (Lesieur & Blume, 1987). The SOGS was included to determine whether problem gambling explained any variance in discounting beyond the GEQ and the GFA-R. The SOGS consists of 20 self-report items (Lesieur & Blume, 1987). Scores of 3 or 4 are indicative of potential problem gambling, and scores of 5 or more are indicative of potential pathological gambling. The SOGS has been shown to have sound psychometric properties (Lesieur & Blume, 1987; Stinchfield, 2002, 2003).

Participants next completed the GFA-R (Weatherly et al., 2012). The GFA-R consists of 16 items, half corresponding to negative reinforcement function (e.g., “I gamble when I feel stressed or anxious”) and the other half corresponding to positive reinforcement function (e.g., “After I gamble, I like to go out and celebrate my winnings with others”). Participants endorse the measure on a Likert-like scale of 0 (*never*) to 6 (*always*). As mentioned earlier, the GFA-R has been shown to demonstrate suitable test-retest reliability and construct validity (Weatherly et al., 2011, 2012). Higher scores on the Negative reinforcement scale indicate higher endorsement of gambling as an escape, and higher scores on the Positive reinforcement subscale indicate higher endorsement of gambling to get something desirable. If a participant had never gambled in his or her lifetime, he or she would score a “0” on both GFA-R subscales.

The next measure that participants completed was the GEQ (Stewart & Wall, 2005). The GEQ consists of 18 items. Of these items, 12 measure the individual’s expectancies for decreased negative emotion (relief) and six measure expectancies for increased positive emotion (reward). Participants endorse their agreement of the items on a Likert scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Four items are reverse scored prior to scoring. For the current study, the GEQ was scored according to the method used by Shead and Hodgins (2009). The GEQ has been shown to have adequate factor loadings when scored according to this method (Shead et al., 2008; Shead & Hodgins, 2009). Higher scores on the Reward subscale indicate higher endorsement of beliefs that gambling increases positive emotions, and higher scores on the Relief subscale indicate higher endorsement of beliefs that gambling reduces negative emotions. Participants who have not gambled can still complete the GEQ because it measures beliefs about gambling and not actual gambling behavior.

The final two items that participants completed were the delay discounting and the probability discounting tasks. The delay discounting questions had four different outcomes: winning \$1,000, losing \$1,000, winning \$100,000, and losing \$100,000. A wide range of monetary values was used to demonstrate that discounting rates varied as expected, because rates of discounting typically vary as a function of the magnitude of the outcome. Participants answered five questions related to each outcome, which had

different delays of the hypothetical outcome (6 months, 1 year, 3 years, 5 years, and 10 years). The “gain” delay discounting questions featured the following scenario:

You own a number of bonds. Your financial advisor tells you that if you wait X time, the bonds will be worth \$1,000 (\$100,000). However, you can cash them in now, although you will not get the full amount. What is the smallest amount of money you would accept today rather than waiting X time to get \$1,000 (\$100,000)?

The “loss” delay discounting questions featured the following scenario:

You recently lost money on a bad investment, and in X time you will have to pay your broker \$1,000 (\$100,000). Your broker, however, is willing to make a deal with you to allow you to pay part of what you owe immediately instead of the full amount in X time. What is the most money you would be willing to pay immediately rather than waiting to pay the full \$1,000 (\$100,000)?

The probability discounting task also had four different outcomes: gaining \$1,000, losing \$1,000, gaining \$100,000, and losing \$100,000. Participants answered five questions related to each outcome, which had different probabilities of the hypothetical outcome (1, 10, 50, 90, or 99%). The “gain” probability discounting questions featured the following scenario:

You have inherited stock in a company that may succeed or fail. Your financial advisor tells you that there is an $X\%$ chance that the company will succeed and, if so, your stock will be worth \$1,000 (\$100,000). If the company does not succeed, however, your stock will be worthless. What is the smallest amount of money would you be willing to accept rather than having an $X\%$ chance of gaining \$1,000 (\$100,000)?

The “loss” probability discounting questions featured the following scenario:

You have a \$1,000 (\$100,000) stake in a company that may succeed or fail. Your financial advisor tells you that there is an $X\%$ chance that the company will fail and your stake will become worthless. However, if you do not want to take this risk, you can sell your stake now for a fraction of its value. What is the smallest amount of your original stake that you would accept rather than having an $X\%$ chance of losing your \$1,000 (\$100,000) investment?

The order of all the outcomes (i.e., delayed/probabilistic gains/losses) and the five delays or probabilities for each outcome were randomly determined for each participant so as to control for order effects.

The multiple-choice (MC) method was used to collect participants’ responses (Beck & Triplett, 2009). The participants could choose their answer from 51 possible response

options, ranging from \$0 to \$1,000 (or \$100,000) in \$20 (or \$2,000) increments. This method was used because it involves fewer questions than the binary-choice method (see Madden & Bickel, 2010). The MC method has been demonstrated to be temporally reliable, at least for measuring delay discounting (Beck & Triplett, 2009). It also typically produces rates of discounting that are statistically similar to those of other brief-response measures of delay discounting (Weatherly & Derenne, 2011).

Data Preparation

The discounting data were analyzed by calculating the area under the discounting curve (AUC; Myerson, Green & Warusawitharana, 2001), using the following equation:

$$\sum_{i=1} (x_{i+1} - x_i) \times (y_i + y_{i+1})/2 \quad (1)$$

With Equation 1, AUC is calculated by adding the areas of the trapezoids formed by the indifference points across the five delays or probabilities. For the delay discounting data, x was calculated in terms of months. For the probability discounting data, x was calculated in terms of the odds against the outcome. For both types of discounting, AUC values can vary between 0.0 and 1.0, with the values differing inversely with the level of discounting. Low AUC values suggest steep decreases in the subjective value of the outcome as it becomes increasingly delayed or improbable. High AUC values suggest little decrease in the subjective value of the outcome as it becomes increasingly delayed or improbable. The AUC method of data analysis was chosen because AUC values are typically normally distributed and therefore do not require transformation before statistical tests are used. Perhaps more important, AUC does not assume what pattern the discounting data will take (e.g., a hyperbola), which is not the case with other analysis methods (see Madden & Bickel, 2010).

Results

Relationship Between the GFA-R and GEQ

A Pearson's correlational analysis was conducted to examine the relationship between the GFA-R and GEQ subscales, the SOGS, and discounting outcomes. Results indicate that the positive reinforcement subscale of the GFA-R and the reward subscale of the GEQ, which both measure gambling to gain something, had a moderate relationship with each other ($r = .338, p < .01$). The negative reinforcement (escape) of the GFA-R subscale demonstrated a strong relationship with the relief subscale of the GEQ ($r = .695, p < .01$), suggesting that both measure gambling to escape aversive stimuli or experiences. The positive and negative reinforcement subscales of the GFA-R demonstrated a moderate relationship with each other ($r = .386, p < .01$). The reward and relief subscales of the GEQ correlated strongly ($r = .602, p < .01$). Regarding discounting, the GFA-R scores

were more consistently related than were the GEQ scores, with GEQ reward unrelated to any of the discounting outcomes ($p > .05$). The SOGS was positively correlated with the probability discounting variables ($p < .05$), but not significantly correlated with the delay discounting outcomes. Finally, the GFA-R negative reinforcement subscale and the GEQ relief subscale were both positively correlated with discounting AUC values, whereas the GFA-R positive reinforcement subscale was positively correlated. A correlation matrix for all variables can be seen in Table 1.

Relationship Between the GFA-R, GEQ, and SOGS

The GFA-R subscale means were 15.19 ($SD = 13.00$) for positive reinforcement and 3.58 ($SD = 7.43$) for negative reinforcement. This outcome indicates that participants were generally endorsing higher agreement of gambling for positive reinforcement as opposed to negative reinforcement. The item level mean scores of the GEQ subscale were 2.75 for reward ($SD = 1.41$) and 1.71 for relief ($SD = 1.09$), indicating that participants generally endorsed stronger beliefs that gambling increases positive emotions than that gambling decreases negative emotions. However, both scores were low, indicating general disagreement with both expectancies. The mean for the SOGS was 1.03 ($SD = 1.97$). The maximum SOGS score in the sample was 13. In the sample, 34 participants (12.5% of the total sample) had SOGS scores of 3 or higher, which suggests problematic gambling behavior.

To determine how the GFA-R and the GEQ were related to the SOGS, we performed a simultaneous linear regression analysis with participants' SOGS scores serving as the dependent measure and their GFA-R and GEQ subscales scores as the potential predictors. Results indicated that the model was significant, $F(4, 256) = 33.732$, $p < .001$. It also accounted for a significant proportion of the variance in SOGS scores ($R^2 = .345$). Within the model, GFA-R negative reinforcement ($\beta = .265$) and GEQ relief subscales ($\beta = .311$) appeared to be the strongest predictors, with GEQ relief being a slightly stronger predictor than GFA-R negative reinforcement, although both reached significance at $p < .001$. GFA-R positive reinforcement also appeared to be a better predictor than GEQ reward, as GFA-R positive reinforcement was a significant predictor of SOGS scores ($\beta = .137$, $p = .015$), and GEQ reward was not ($\beta = -.011$, $p = .871$). However, GFA-R positive reinforcement was not as strong a predictor as GEQ relief or GFA-R negative reinforcement. In summary, gambling to get away from something undesirable was more closely related to gambling problems than was gambling to get something desirable.

Relationship Between the Gambling Measures and Discounting

Eight hierarchical linear regressions were conducted on each possible gain or loss outcome for delay and probability discounting. The first step included GFA-R

Table 1.
Variable Intercorrelations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. GFA-R Pos	-												
2. GFA-R Neg	.386**	-											
3. GEQ Reward	.338**	.435**	-										
4. GEQ Relief	.295**	.695**	.602**	-									
5. SOGS	.330**	.531**	.341**	.532**	-								
6. Uncertain gain \$1,000	-.083	.111	.030	.112	.175**	-							
7. Uncertain gain \$100,000	-.165**	.133*	.087	.146*	.141*	.761**	-						
8. Uncertain loss \$1,000	-.224**	.038	.028	.068	.051	.551**	.580**	-					
9. Uncertain loss \$100,000	-.088	.119	-.081	.157**	.123*	.575**	.618**	.682**	-				
10. Delayed gain \$1,000	-.123*	.000	-.004	-.019	-.014	.279**	.233**	.234**	.259**	-			
11. Delayed gain \$100,000	-.031	-.009	-.037	-.036	-.004	.158**	.111	.069	.012	.550**	-		
12. Delayed loss \$1,000	-.082	.149*	.095	.180**	.083	.309**	.339**	.324**	.257**	.276**	-.082	-	
13. Delayed loss \$100,000	-.082	.149*	.095	.180**	.083	.309**	.339**	.324**	.257**	.276**	.262**	.599**	-

Note. GFA-R = Gambling Functional Assessment – Revised; Pos = Positive Reinforcement; Neg = Negative Reinforcement; GEQ = Gambling Expectancy Questionnaire; SOGS = South Oaks Gambling Screen.
** $p < .001$. * $p < .05$.

Table 2
Final Step of Regression Models for Variables Predicting Discounting of Delayed Gains and Losses

Predictors	<i>B</i>	<i>SE B</i>	β	<i>p</i>
Gains of \$1,000				
GFA-R Positive Reinforcement	-.002	.001	-.154*	.028
GFA-R Negative Reinforcement	.002	.002	.074	.421
GEQ Reward	.001	.002	.054	.497
GEQ Relief	.000	.001	-.064	.525
SOGS	.002	.008	.023	.760
Gains of \$100,000				
GFA-R Positive Reinforcement	.000	.001	-.027	.699
GFA-R Negative Reinforcement	.001	.002	.029	.755
GEQ Reward	.000	.002	-.029	.718
GEQ Relief	.000	.001	-.039	.696
SOGS	.002	.007	.025	.750
Losses of \$1,000				
GFA-R Positive Reinforcement	-.005	.001	-.259*	<.001
GFA-R Negative Reinforcement	.006	.003	.187*	.037
GEQ Reward	.000	.002	.015	.843
GEQ Relief	-.002	.002	-.085	.384
SOGS	.015	.009	.124	.099
Losses of \$100,000				
GFA-R Positive Reinforcement	-.003	.001	-.173*	.012
GFA-R Negative Reinforcement	.003	.003	.109	.224
GEQ Reward	.001	.002	.022	.776
GEQ Relief	.003	.002	.145	.139
SOGS	.000	.009	-.004	.955

Note. GFA-R = Gambling Functional Assessment – Revised; GEQ = Gambling Expectancy Questionnaire; SOGS = South Oaks Gambling Screen.

**p* < .05.

positive reinforcement and negative reinforcement scores, the second step included GEQ reward scores and GEQ relief scores, and the third step included SOGS scores. Although only reward and negative reinforcement have been linked to pathological gambling, all subscales were included in order to determine whether these two relationships would be replicated. Regression results are summarized in Tables 2 and 3.

Discounting of delayed outcomes. The regression analysis of the AUC values indicated that the model did not reach significance for a delayed outcome of gaining \$1,000 (mean AUC = 0.72, *SD* = 0.20) or \$100,000 (mean AUC = 0.74, *SD* = 0.19). Although the models were not significant overall, the pattern of results is similar to those found for the other dependent variables and is therefore displayed in Table 2 for ready comparison.

The model predicting AUC values for a delayed outcome of losing \$1,000 (mean AUC = 0.62, *SD* = 0.25) was significant at the first step, $F(2, 258) = 8.166, p < .001,$

Table 3
Final Step of Regression Models for Variables Predicting Discounting of Uncertain Gains and Losses

Predictors	<i>B</i>	<i>SE B</i>	β	<i>p</i>
Gains of \$1,000				
GFA-R Positive Reinforcement	-.004	.002	-.182*	.008
GFA-R Negative Reinforcement	.003	.004	.759	.449
GEQ Reward	.000	.003	-.011	.137
GEQ Relief	.001	.002	.024	.807
SOGS	.028	.011	.187*	.013
Gains of \$100,000				
GFA-R Positive Reinforcement	-.007	.002	-.294*	<.001
GFA-R Negative Reinforcement	.005	.004	.120	.172
GEQ Reward	.003	.003	.075	.324
GEQ Relief	.001	.002	.039	.684
SOGS	.020	.012	.128	.083
Losses of \$1,000				
GFA-R Positive Reinforcement	-.007	.002	-.297*	<.001
GFA-R Negative Reinforcement	.003	.004	.070	.432
GEQ Reward	.002	.003	.059	.442
GEQ Relief	.001	.002	.031	.752
SOGS	.012	.011	.077	.303
Losses of \$100,000				
GFA-R Positive Reinforcement	-.005	.002	-.181*	.009
GFA-R Negative Reinforcement	.003	.004	.058	.517
GEQ Reward	.001	.003	.032	.681
GEQ Relief	.003	.002	.107	.275
SOGS	.015	.012	.086	.256

Note. GFA-R = Gambling Functional Assessment – Revised; GEQ = Gambling Expectancy Questionnaire; SOGS = South Oaks Gambling Screen.

**p* < .05.

$R^2 = .060$. Adding GEQ subscale scores did not significantly improve the model ($\Delta F = .122, p = .885$) and neither did adding SOGS scores ($\Delta F = 2.274, p = .099$). GFA-R negative reinforcement scores remained a significant negative predictor, and positive reinforcement scores remained a significant positive predictor at all steps of the equation ($p < .05$).

The same pattern emerged with the delayed outcome of losing \$100,000 (mean AUC = 0.56, $SD = 0.24$). Specifically, the first step of the model achieved significance, $F(2, 258) = 6.208, p = .002, R^2 = .039$. The model was not significantly improved by adding the GEQ Reward and Relief subscale scores ($\Delta F = 1.767, p = .173$) or the SOGS scores ($\Delta F = .003, p = .955$). The GFA-R Positive reinforcement subscale remained a significant negative predictor at all steps of the regression ($p = .012$), but the GFA-R Negative reinforcement lost significance as a positive predictor once the SOGS was added in the final step ($p = .224$).

Discounting of probabilistic outcomes. The regression analysis of the AUC values for an uncertain outcome of gaining \$1,000 (mean AUC = 0.66, $SD = 0.16$) suggested that the first step of the model was significant, $F(2, 258) = 4.365, p = .014, R^2 = .033$. Adding the GEQ subscales did not significantly improve the model ($\Delta F = .398, p = .672$). However, adding SOGS scores as a positive predictor in the third step did significantly improve the model ($\Delta F = 6.205, p = .013$). It also increased the amount of variance explained by the model ($R^2 = .059$). GFA-R Positive reinforcement was a significant negative predictor throughout each step of the model ($p < .05$). GFA-R Negative reinforcement was significant as a positive predictor in the first step, but lost significance during the second and third steps. SOGS scores were a significant positive predictor in the final step of the model ($p = .013$). The analysis conducted on AUC values for an uncertain outcome of gaining \$100,000 (mean AUC = 0.64, $SD = 0.16$) suggested that the model was significant at the first step, $F(2, 258) = 10.524, p < .001, R^2 = .075$. Adding the GEQ Reward and Relief subscale scores did not significantly improve the model ($\Delta F = 1.522, p = .220$). The same was also found to be true for adding SOGS scores ($\Delta F = 3.031, p = .083$). The GFA-R Positive reinforcement remained significant as a negative predictor at all steps ($p > .05$), but the GFA-R Negative reinforcement subscale lost significance as a positive predictor in the second and third steps ($p > .05$).

The analysis performed on AUC values for an uncertain outcome of losing \$1,000 (mean AUC = 0.648, $SD = 0.166$) suggested that the first step of the model was significant, $F(2, 258) = 9.027, p < .01, R^2 = .065$. Adding the GEQ subscales did not significantly improve the model ($\Delta F = .835, p = .672$). Adding SOGS scores in the third step did not significantly improve the model ($\Delta F = 1.064, p = .303$). GFA-R Positive reinforcement was a significant negative predictor throughout each step of the model ($p < .05$). GFA-R Negative reinforcement was significant as a positive predictor in the first step, but lost significance during the second and third steps ($p > .05$). The model predicting AUC values for an uncertain outcome of losing \$100,000 (mean AUC = 0.626, $SD = 0.173$) was also significant during the first step, $F(2, 258) = 4.890, p = .008, R^2 = .037$. The model was not significantly improved by adding GEQ subscale scores ($\Delta F = 1.682, p = .188$) or SOGS scores ($\Delta F = 1.298, p = .256$). As with the previous analysis, GFA-R Positive reinforcement remained a significant negative predictor at all steps of the regression ($p < .05$), but GFA-R Negative reinforcement lost significance as a positive predictor during the second and third steps ($p > .05$).

Likely Non-Gamblers Excluded

To determine the effect that non-gamblers were having on results, the regression analyses were also replicated, this time excluding participants who had denied any history of gambling. The exclusion criteria used were the participants' response to SOGS Item 1a through 1j, which asks about history of gambling in a number of different contexts (e.g., going to a casino, playing cards, betting on sports).

Participants who denied having engaged in any of these gambling behaviors were excluded from the analyses, resulting in a sample size of 200 participants.

Once again, results were generally the same as in the original analyses, with a few exceptions. First, GFA-R Negative reinforcement scores lost significance as a positive predictor in the final step of the analysis performed on AUC values for a delayed outcome of losing \$1,000 ($p > .05$). Second, SOGS scores were a significant positive predictor in the final step of the regression analysis performed on AUC values for an uncertain outcome of gaining \$100,000 ($p = 0.016$). Third, there were no significant predictors in the final step of the analysis performed on AUC values for an uncertain outcome of losing \$100,000 ($p > .05$).

Discussion

Results from the current study suggest that the function of gambling was the best predictor of delay and probability discounting. The emotional expectancies associated with gambling did not significantly contribute to any of the variance in discounting rates after the contributions of gambling functions were accounted for. This finding is consistent with Cooper's motivational model of addictive behavior, which posits that the functions of addictive behavior are the primary predictors of addictive behavior and that expectancies act through these functions (Cooper, 1994).

Results also indicated that the best consistent predictor of discounting rates was gambling for positive reinforcement. The relationship between discounting and gambling for negative reinforcement was inconsistent. One possibility for this inconsistency is that the gambling for negative reinforcement scores share variance with problem gambling and gambling expectancy scores, as gambling for negative reinforcement lost significance when scores for the other two variables were added. This likelihood would explain the current study's failure to find consistent significance with gambling for negative reinforcement as a predictor of discounting rates, a finding that is consistent with those of Weatherly and Derenne (2012).

One interesting finding is that the relationship found between gambling for positive reinforcement and discounting rates for uncertain gains and losses was not in the expected direction, as results indicated that gambling for positive reinforcement was inversely related to steeper discounting rates for both probability and delay discounting. These results were unexpected but not unheard of, as other research has found that gambling was associated with less discounting (e.g., Weatherly, 2011).

Furthermore, gambling for negative reinforcement predicted higher delay discounting rates when it was a significant predictor. Therefore, the results on gambling function appear to be inconsistent for both the significance of the prediction and the direction of the relationship. The results also suggest that individuals who gamble to escape something aversive may be more likely to discount small losses, whereas

individuals who gamble to gain something desirable are less likely to discount gains or losses than are other gamblers. One potential explanation for this possibility is that individuals who gamble for negative reinforcement might have characteristics that make them more likely to discount, such as an impulsivity or emotion regulation deficits, than do individuals who gamble for positive reinforcement.

The current study also examined gambling function and expectancies as predictors of gambling severity as measured by the SOGS. The results were consistent with previous research that had suggested gambling severity is associated with gambling maintained by negative reinforcement (Miller et al., 2009). Whether or not relief expectancies and positive reinforcement function will be reliable predictors of gambling severity will need to be established by future research.

Results were generally the same when non-gamblers were excluded from analyses. GFA-R positive reinforcement was once again consistently the strongest predictor of discounting rates, with GFA-R negative reinforcement occasionally reaching significance as well (again, any lack of significance was possibly due to shared variance).

This study was the first to examine the relationship between gambling function or expectancies and discounting of delay or probabilistic gains and losses. In terms of discounting of delayed gains, the results did not find a predictive relationship between discounting and measures of either gambling function or expectancies. The failure to find such relationships adds to a growing literature that suggests that discounting of delayed gains may not be reliably associated with measures of gambling (e.g., Weatherly & Derenne, 2010; Weatherly et al., 2009).

In terms of discounting of delayed losses, both gambling for positive reinforcement and gambling for negative reinforcement were significant predictors of at least one of the tested outcomes. Interestingly, gambling for positive reinforcement was a better predictor of discounting of delayed losses than was gambling as an escape. One might intuitively predict the opposite. Some researchers (e.g., Mitchell & Wilson, 2010) have argued that discounting of gains and losses are distinct processes. Thus, finding that measures of gambling may be related to discounting of delayed losses, but not delayed gains, may not be unexpected. With that said, however, previous and the present results suggest that gambling severity is more strongly related to gambling for negative, rather than positive, reinforcement. Thus, the finding that gambling for positive reinforcement is more strongly related to discounting of delayed losses than is gambling for negative reinforcement may also serve to question the relationship between discounting and pathological gambling.

The current findings also suggest that gambling for positive reinforcement may be more closely related to rates of probability discounting than to gambling as an escape. Shead et al. (2008) reported a similar finding, but their predictors were gambling expectancies and not function. However, the current study also found that

the relationship was the inverse, indicating that gambling for positive reinforcement may be related to less discounting (or that the direction of the relationship is not wholly reliable). Gambling expectancies were not significant predictors of discounting in the present study for any outcome after accounting for the impact of gambling functions. Furthermore, the current study also failed to find a relationship between GEQ relief or reward subscales and discounting, which is inconsistent with results obtained by Shead et al. (2008). One reason for this inconsistency may be the fact that Shead et al. (2008) used a laboratory discounting task, whereas the current study used a hypothetical scenario. In addition, Shead et al. (2008) excluded non-gamblers, whereas the current study included them.

Weatherly and Derenne (2012) reported that gambling for negative reinforcement was a better predictor of probability discounting than was gambling for positive reinforcement. However, they also reported that neither were reliable predictors of probability discounting. Taken together, the results from Shead et al. (2008), Weatherly and Derenne (2012), and the present study would seem to question the reliability of the relationship between measures of gambling and probability discounting. Given that one could also potentially question the reliability between measures of gambling and delay discounting, one begins to question the reliability of the relationship between gambling and discounting altogether.

In support of this last statement, it should also be noted that participants' SOGS scores were also entered into the regression models as potential predictors of discounting. The SOGS was a significant predictor for discounting uncertain gains of \$1,000, which is consistent with past research indicating that gambling severity may be related to discounting. However, this relationship was inconsistent, as the other uncertain outcomes did not demonstrate a significant relationship to SOGS scores, nor did any of the delayed outcomes. The SOGS was generally not a significant predictor of gambling after accounting for both gambling function and expectancies. In addition, SOGS scores were significantly correlated with discounting uncertain outcomes but not with discounting delayed outcomes. These findings provide further support that SOGS scores are related to probability discounting but not to delay discounting.

Both negative and positive reinforcement gambling function, as well as relief and reward expectancies, predicted SOGS scores. However, negative reinforcement and relief expectancies were stronger predictors than positive reinforcement and reward expectancies. This finding is consistent with previous research that has found pathological gambling may be more associated with gambling to escape or to reduce negative experiences or emotions than with gambling to obtain positive experiences or emotions (Miller et al., 2010). Similar results have been obtained in alcohol research, which has found that relief expectancies and negative reinforcement functions are the best predictors of problematic alcohol use (Cooper, 1994; Farber, Khavari, & Douglass, 1980). These findings are consistent with Cooper's model of addictive

behavior, which posits that engaging in addictive behavior in order to escape or reduce negative experiences results in more negative consequences (Cooper, 1994).

In terms of the gambling measures used in the present study, future research should examine the role of positive versus negative reinforcement and expectancies. The present comparison found that function, as measured by the GFA-R, was consistently a better predictor of discounting than were expectancies, as measured by the GEQ. It would seem important to determine whether this result is reliable. If it is, then perhaps gambling for positive reinforcement captures both increases in positive mood and other rewards obtained through gambling, such as monetary and social gains, instead of just capturing increases in positive emotion. This potential explanation is supported by the strong correlation between the GFA-R positive reinforcement and GEQ reward scores. As previous research has not examined these two measures together, it has yet to be established how closely these two subscales are related. Another potential reason for this finding may lie with the GEQ itself in that there was a strong correlation between its two subscales. This strong correlation suggests that the GEQ reward and relief subscales (i.e., positive and negative emotional expectancies, respectively) may be measuring the same construct. Furthermore, unlike the GFA-R, the GEQ subscales have an unequal number of items associated with each subscale, with twice as many items intended to measure negative expectancies than positive expectancies, which might explain the failure of positive expectancies to significantly predict discounting. Finally, the authors scored the GEQ using the scoring method devised by Shead and Hodgins (2009) instead of the original theoretical scoring intended by its developers (Stewart & Wall, 2005). It is possible that the current study's results would have been different had the theoretical scoring method been used. Researchers may want to conduct further confirmatory factor analyses on the scale to determine whether the theoretical structure derived by Stewart and Wall (2005) or that observed by Shead and Hodgins (2009) is the better factor structure.

Pursuing research on whether function or expectancies are the best predictors of behavior would seem to be a worthy endeavor. The present results favor function. However, research from other areas of psychology suggests that expectancies have predictive value. For instance, studies on alcohol abuse, a behavior pattern that, like pathological gambling, has been associated with impulse control, have found that positive expectancies play a large role in drinking behavior and treatment outcome (see Jones, Corbin, & Fromme, 2001, for a review). Studies have also examined the motivating antecedents and consequences of problematic drinking behavior (e.g. Cooper, Russell, & George, 1988). Future research may also want to examine the same variables that have been examined in alcohol research, such as how motives may account for the relationship between expectancies and drinking behavior (e.g., Kuntsche, Knibbe, Gmel, & Engels, 2005). Furthermore, gambling researchers may also want to examine the relation of gambling function and expectancies regarding heavier gambling behaviors as opposed to gambling problems.

Before drawing broad conclusions from the present study, it should be noted that it had several potential limitations. First, the research was conducted by using the MC method of collecting discounting data. Although previous research (e.g., Weatherly & Derenne, 2011) has shown that this method typically produces rates of delay discounting that are similar to those of other methods, that research has also shown that this outcome is not always the case. Thus, it is possible that other or different predictive relationships may have been found had another method of collecting the discounting data been used. Next, the sample consisted of undergraduate students, most of whom were female and/or Caucasian. Thus, the results may not generalize to the overall population. The sample also did not contain a large number of individuals with gambling problems, at least as measured by the SOGS, and so one cannot assume that the present results would be replicated in the population of pathological gamblers. Finally, the discounting questions were hypothetical and asked about stock decisions with which college students may not be entirely familiar, and this possibility could have also influenced the results.

Despite these potential limitations, the current study's failure to consistently relate discounting to constructs that are associated with gambling is an important finding. Negative reinforcement or escape has been found to be highly associated with pathological gambling (Miller et al., 2009), yet the current study found no reliable relationship between escape and rates of discounting, although a strong relationship between gambling as an escape and gambling severity was observed. The results showed that gambling for positive reinforcement was sometimes, but not always, related to discounting. Furthermore, when it was related, the relationship was not in the expected direction. These results could be due to other reasons, but they are consistent with the idea that there is not a strong and reliable relationship between measures of gambling and rates of discounting. Beyond the phenomenon of discounting, the present results suggest that measuring expectancies may not provide much additional information beyond what can be learned from measuring function.

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