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Attentional processing: Replication and extension of selection bias as a predictor of intertemporal choice behavior

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Attentional Processes:

Replication and Extension of Selection Bias as a Predictor of Intertemporal Choice Behavior

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Abstract

Basic underlying mechanisms of discounting delayed rewards remain unclear (Green & Myerson, 2013). There has been evidence that attentional mechanisms (e.g., fixation and fixation duration) could be further investigate processes related to the discounting of delayed rewards (Franco-Watkins, Matteson, & Jackson, 2016). Franco-Watkins et al. (2016) was the first to propose a measure of attentional mechanisms in a discounting paradigm, known as selection bias. The authors found selection bias was positively correlated with choice behavior. The present study replicated selection bias using a titration procedure and Area Under the Curve scores. This study also analyzed selection bias across choice presentations at the individual level. Our findings reveal that there are potential artifacts with discounting procedures. When choices were presented in a logical sequence, selection bias predicted choice behavior. When choices were randomized in a way that a participant could not predict the next choice, attention did not predict choice behavior. Overall, our findings suggest further research is needed to for a better understanding of eye-tracking within discounting paradigms.

Key words: discounting, attention, eye-tracking, choice behavior

Attentional Processing: Replication and Extension of Selection Bias as a Predictor of Intertemporal Choice Behavior

Impulsivity is a multifactorial construct with varying definitions. The disagreement among researchers is in part due to theoretical approaches (Evenden, 1999). Impulsivity is commonly used to refer to problematic behavior characterized by failures to attend, inhibit a response, and/or consider probable negative long-term outcomes of a behavior. For example, a child may be considered impulsive when they yell out comments or interrupt in class. A college student would be described as impulsive when they go out the night before an exam instead of studying. An adult may also be considered impulsive when they go on a shopping spree without considering the interest payments at the end of the month.

One approach to investigate impulsivity has been to study preferences between smaller-sooner and larger-later rewards. Choices may be considered impulsive when an animal has a tendency to choose a smaller reward over a larger reward. For example, an animal may be considered impulsive when choosing to forage at a patch with a smaller number of berries that is closer to them over a batch with more berries that is farther away, because of the potential detrimental outcome of less food. However, choices are not always this simple. Choices often involve delay to receiving a reward or have some probability associated with receiving said reward.

Two areas of particular interest in behavioral economics are temporal and probabilistic discounting. Temporal, or delay, discounting refers to the decrease in subjective value as the delay to receiving a reward increase. Probabilistic discounting refers to the decrease in subjective value of a reward as the odds against receiving it increases. These two types of discounting represent intertemporal and risky choice phenomena.

The discounting framework provides a systematic methodology for studying impulsivity that involves choices with outcomes varying at different points in time and/or outcomes that are more or less likely to occur. The field of behavioral economics has also come to influence the ways in which researchers' study decision-making. Specifically, behavioral economists have provided evidence that contradicts standard economic theory, which assumes humans are rational decision makers (Thaler, 1981).

Procedures

Discounting procedures involve choices between a smaller, sooner reward and a larger, later reward. For example, participants are presented with choices between $500 now or $1,000 in 1 year. Most commonly, the smaller, sooner reward is adjusted until there is an equal likelihood of choosing both the smaller, sooner and larger, later reward, also known as the indifference point. The amount of the smaller, sooner reward at indifference points are determined to be the subjective value of the reward. This same logic is used for both delay and probability discounting procedures. In probability choices between smaller, certain rewards are crossed with larger, less certain rewards. For example, participants are presented with choices between $500 for sure or $1,000 with a 5% chance.

Rachlin, Raineri, and Cross (1991) pioneered a common procedure to evaluate the exponential and hyperbolic discounting models for delay and probability discounting with human participants. To determine the subjective value of a reward, participants were asked to state their preference for a reward between hypothetical amounts of $1,000 now or $1,000 with delays ranging from 1 month to 50 years. Similar choices were presented with probabilities ranging from 5% to 95%. For each delay and probability, an adjusting-amount procedure was used that decreased the amount of money available immediately. A prescribed list of 30 different amounts were presented in a fixed sequence. Half of the participants were exposed to immediate-amounts presented up then down, and the other half were exposed to immediate-amounts presented down then up. For example, in the "up then down" 1-month condition, participants selected a preference for $1 Now or $1,000 in 1 month. The second choice was then $5 Now or $1,000 in 1 month. In the similar "down the up", participants first selected a preference for $1,000 Now or $1,000 in 1 Month. The second choice was then $990 Now or $1,000 in 1 month. This process was repeated for every prescribed amount across each delay and probability condition. Indifference points were derived by averaging the amounts before and after participants switched their preference to the immediate or delayed outcome.

Another common procedure for measuring discounting is the titration procedure (Du, Green, & Myerson, 2002; Johnson & Bickel, 2002; Richards, Zhang, Mitchell, & Wit, 1999). As with the fixed-sequence procedure, participants make choices between smaller-sooner amounts and larger-later amounts. The participants' previous choice then brackets their subsequent choices, excluding any values that fall outside of that range for which their indifference might fall. When participants choose smaller-sooner amounts, the next smaller-amount is decreased by half of the upper bound and lower bound. For example, say a participant choose $500 now over $1,000 in 1 month. The participant is now bracketed between $0 now (lower bound) and $500 now (upper bound), so the next choice presented is $250 now or $1,000 in 1 month. If the participants choose the larger-later amount, the next choice reward in increased by half the amount between the upper bound ($500) and lower bound ($250). For example, the next choice presented is $375 now and $1,000 in 1 month. This procedure then rapidly converges on an indifference point using an iterative process over 6 to 7 choices. It is assumed that there is no utility in asking participants more than once about a particular choice. Indifference points are derived by estimating the value between the last choice and the next potential choice.

Regardless of the procedures used, the research generally concludes that any differences in observed discounting values are non-systematic (Odum & Baunamann. 2010). Rozden, Berry, and Odum (2011) used a within-subjects design to compare fixed-sequence and titration procedures. The authors reported no statistical differences between the degree of discounting for the fixed-sequence and titration procedures. AUC values also produced no statistical differences and were strongly correlated (Rozden et al., 2011). Thus, researchers may select a discounting procedure due to convenience of implementation without the threat to internal validity.

Typically, hypothetical rewards are used in discounting research with human participants. For example, in Rachlin et al. (1999), participants were asked questions about money but never received compensation for their choices. The use of hypothetical rewards is concerning because hypothetical rewards have the chance of theoretically increasing the probability that participants would make all choices as if they were not real. However, research supports the use of hypothetical rewards as substitutes for real rewards. Hypothetical rewards reveal no differences across rates of discounting as compared to real rewards (Johnson & Bickel, 2002; Lagario & Madden, 2005; Madden, Begotka, Raiff, & Kastern, 2003; Madden et al., 2004). Thus, the use of hypothetical rewards acts as a quick and cost-efficient method of assessing discounting functions with human participants.

Analyses

Discounting models. One way in which indifference points are analyzed is by fitting observed values to the nonlinear regression models. A decrease in subjective value is a result of each additional unit of delay, decreasing the ratio of amount to delay. One formula proposed to describe delay discounting was based on the standard utility model in economics. The model assumed that the value of future a reward should decrease due to the risk involved in waiting for that reward. This model also assumed that this risk occurs at a constant rate. For example, when an animal is foraging for food, there may a constant probability that a predator would prevent that animal from obtaining food. If this constant rate does exists, then such discounting could be explained using an exponential value function:

$$\mathrm{V_d} = \mathrm{A}e^{-kd} \quad (1)$$

where V_d is the discounted value of a future reward, A is the amount of the reward, d is the delay to its receipt, k is the rate of discounting, and e is a base of the natural logarithm (2.718).

Behavior economists have proposed alternatives to exponential discounting to counter the argument that humans are rational decision makers. Systematic deviations from the exponential discounting function have been well documented in both human and non-human animals (see Vanderveldt, Olivera, & Green, 2016). Mazur (1987) proposed the discounting function is a hyperbola:

$$V = A/(1+kD) \quad (2)$$

where the variables share the same relation as exponential discounting model but takes a hyperbolic form where the values decrease more rapidly at smaller delays and decrease more slowly at longer delays. When the exponential and hyperbola functions are fit to observed values, the exponential function tends over-predict observed values at smaller delays and under-predict at larger delays. Research supports that temporal discounting is described better by this hyperbolic function by correcting for the over-predictions and under-predictions of the exponential model (Green & Myerson, 2004). However, the Equation 2 also tends to over-predict observed values at smaller delays and under-predict larger delays. This equation is also used more often when a single-index of discounting is needed to make comparisons across or within-groups (Green & Myerson, 2004).

Green, Fry, and Myerson (1994) were the first to propose a hyperbola-like function where the denominator is raised to the power of *s*:

$$V = A/(1+kD)^s \quad (3)$$

This *s* parameter represents a nonlinear scaling parameter for amount and/or time. When $s = 1$, the hyperbola-like function is reduced to Equation 2. When $s < 1$, the discounting curve decreases less sharply at larger delay values than it does when described by the hyperbola formula. Green and Myerson (2004) argued that the hyperbola-like model accurately describes the relations between subjective value and delay as well as the amount of variance accounted for over the exponential and hyperbola discounting models. By adding the *s* parameter, the proportion of variance accounted for is statistically significant and has been replicated through numerous studies (Green & Myerson, 2004). The significant increase in the variance explained by Equation 3 is greater than what would be expected by having two free parameters rather than one free parameter like Equation 1 and 2 (Green & Myerson, 2004). Also, the second free parameter not only provides a better fit at the group level but provides a better fit of the data at the individual level (Green & Myerson, 2004). A better fit of the data is particularly important when describing the shape of the discounting function or quantifying the rate of discounting at the individual or group levels.

The discounting of delayed and probabilistic rewards can also be described by the hyperbola-like model (Green, Myerson, & Ostaszewski, 1999):

$$V = A/(1+bX)^s \quad (4)$$

V represents the subjective value of a delayed or probabilistic reward, *A* represents amount, *b* is rate of discounting, *X* represents the independent variable (e.g. delay or odds against), and *s* represents the nonlinear scaling parameter. Green et. al (1999) found evidence that the hyperbola-like model describes the discounting of both delayed and probabilistic rewards, where the exponent was significantly less than 1, and the additional free parameter significantly improved the fit of the data. Further evidence that the hyperbola-like model describes both delay and probability discounting was found by Estle, Green, Myerson, and Holt (2006). This evidence suggested support of the hypothesis that similar processes were involved in the discounting of delayed and probabilistic rewards. However, this interpretation would be later challenged (see Discounting Processes).

The research on discounting has implications for a variety of socially important issues, such as substance abuse (Yi, Mitchell, & Bickel, 2010), financial risk (Loewenstein & Thaler, 1989), and obesity (Price, Higgs, Maw, & Lee, 2016).

Discounting has been established in a variety of nonhuman species as well (Vanderveldt, Oliveira, & Green, 2016).

Area under the curve. Myerson, Green, and Warusawitharana (2001) discussed issues that arise when using mathematical models and inferential statistics to analyze discounting functions. The authors mention that confidence intervals surrounding individual estimates of individual participants' data are large. There is also a large degree of variability between subjects, and the distribution of k-values are skewed (Myerson, Green, & Warusawitharana, 2001). The hyperbola-like model (Equation 3) also has two free parameters of *k* and *s*, which makes quantifying discounting curves difficult to simply quantify individual differences. The use of inferential statistics is particularly useful when single-subject designs (e.g., ABAB) are not possible with discounting data sets; however, skewed distributions make inferential analysis difficult. In such cases, nonparametric analyses can be used, but these analyses are usually less powerful and assume linear relations between estimates (Myerson et al., 2001). These issues are especially true when making comparisons across amounts, within-subjects, or groups. Thus, Myerson et al. (2001) developed a theoretically neutral measure of discounting known as Area-Under-the-Curve (AUC).

AUC is calculated by normalizing delay and subjective values. Here delays are expressed as a proportion of the maximum delay or probability, and subjective values are expressed as proportion of the nominal amount. Trapezoids between data points are drawn, and then area is calculated using the formula:

$$(x_2 - x_1)[(y_1+y_2)/2] \quad (5)$$

where x_1 and x_2 represent the successive delays and y_1 and y_2 represent the subjective values associated with those delays. Finally, the sum of all the trapezoids are taken to gather the area under the discounting function. The area under the discounting function can vary from 0.0 (steepest discounting possible) to 1.0 (no discounting).

Myerson et al. (2001) discussed several limitations with AUC as a measure of discounting. First, due to values being expressed as proportions of normalized values with values scaled from 0.0 to 1.0, making comparisons across studies cannot be obtained unless adjustments of the independent variables are made. Another concern is that area under two curves may be the same but have different shapes. Regardless of these limitations, AUC measures are based on observed values and provide a theoretically neutral measure of discounting. AUC is useful when a single index of discounting is desired, such as making comparisons across individuals or groups. However, it is not a substitute for a theoretically based discounting functions.

Discounting Processes

Researchers are interested in understanding the underlying processes that are involved in discounting and its relation to impulsivity. Given that delay and probability discounting are well described by a hyperbola-like equation, questions arise about whether both are represented by the same psychological process or different psychological processes. Myerson, Green, Hanson, Holt, & Estle (2003) noted several explanations from previous research for the similarities among delay and probability discounting in support the same process. For one, choices involving delay or probability entail risk (Myerson et al., 2003). Delay increases the likelihood that something will prevent receiving the reward. Environmental events that could prevent receiving the reward could occur during the delay period. Another reason is that probability also entails delay. When the odds against receiving a reward is higher, repeated gambles must be made in order to receive the reward. Those repeated gambles therefore necessarily delay time to receiving the reward. Both delay and probability also reflect properties of attribute weighting: decreasing absolute sensitivity and increasing proportional sensitivity (Myerson et al., 2003). Increasing the attributes of two choice alternatives by a constant decreases the preference for one over the other (decreasing absolute sensitivity). For example, when you compare your preference for receiving $10 to $1 and $1,000 to $991. Most people would have a stronger preference for the larger amount in the first alternative and would have a weaker preference for the larger amount in the second alternative; even though difference between the two choices is nine dollars in both alternatives. Also, by multiplying the attributes of two alternatives increases the preference for one over the other (increasing proportional sensitivity). For example, compare your preferences to receiving $10 to $1 and $1000 to $100. People are more likely to have a stronger preference for larger amount in the $1,000 choice alternative than in the $10 choice alternative; even though both alternatives are multiplied by 10.

If the same psychological processes were involved in decisions regarding delayed and probabilistic outcomes, then experimental manipulations should have the same effect(s) on both types of discounting. If different processes were involved, manipulations should have differential effects. Indeed, the literature provides more evidence that demonstrates different processes might be involved in delay and probability discounting (Green & Myerson, 2010; Green & Myerson, 2013).

First, magnitude effects are a robust finding in the literature that demonstrate larger delayed rewards are discounted less steeply than smaller delayed rewards. (Green & Myerson, 2010). These effects have been observed in medical treatments, vacation time, and directly consumable rewards (Green & Myerson, 2010). In terms of probabilistic discounting, magnitude effects occur in the opposite direction. That is, large probabilistic rewards are discounted more steeply than smaller probabilistic rewards. Green and Myerson (2010) suggest that this opposite effect of amount supports that different processes are involved in delay and probability discounting.

When the outcome of the reward is manipulated (e.g., gains vs. losses), mixed results are observed. Experimental literature of preference reversals among delayed rewards has been well established when outcomes involve gains (Green & Myerson, 2010). That is, those who prefer larger-later gains switch their preferences for smaller-sooner gains when considering both rewards in the future. Holt, Green, Myerson, and Estle (2008) demonstrated preference reversals in delayed losses. Here, a choice is considered to be impulsive when a person prefers to make larger-later payments over smaller-sooner payments. Holt et al. (2008) found that, people preferred to make smaller-sooner payments at shorter delays and switched to making larger-later payments at longer delays. The authors also found an absence of the magnitude effect. The amount of rewards had no differential effects on choices involving the loss of a reward. Estle et al. (2006) also found little to no magnitude effects for delay losses, opposite direction of magnitude effects for probabilistic gains, and no effects for probabilistic losses. Green and Myerson (2010) argue that these findings make impulsive choices situation specific, clear similarities and differences exist for outcomes of gains vs. losses, and the processes involved in magnitude effects for losses appear to be non-existent, or minimally so, for both delay and probabilistic discounting.

Green & Myerson (2010) also mention that correlational analyses should be indicative of the process or processes involved in discounting. If delay and probability discounting share the same process, then a negative correlation should exist. People who cannot wait for a reward would show steep delay discounting. Those who cannot wait would also not consider risks involved and should show shallow probability discounting. However, the literature does not support this negative correlation between delay and probability discounting (Green & Myerson, 2010). The authors argue that this strongly suggests different processes are involved, and that delay-and probability discounting represent different traits of impulsivity.

There is other evidence to support the different processes are involved. For example, there differential effects of the *b* and *s* parameters in Equation 4 (Green & Myerson, 2013). The literature shows that increasing the amounts of probabilistic rewards increases the degree of discounting. Here, the *s* parameter increases, whereas *s* remains constant in delay discounting (Green & Myerson, 2013). Increasing the amounts of rewards, decreases the degree of delay discounting. Here the *b* parameter decreases, whereas *b* remains constant (Green & Myerson, 2013). Yet again, this evidence demonstrates different processes must be involved in delay and probability discounting. This begs the question: what else should be considered to discover different processes behind delay and probability discounting?

Attentional Processes

Although there is a vast amount of research supporting the discounting phenomenon, the understanding of the basic underlying processes still remains unclear (Carter, Meyer, & Huettel, 2010; Green & Myerson, 2013; Franco-Watkin, Mattson, & Jackson 2016). Understanding the discounting processes impacts our understanding of the outcomes associated with choosing smaller, sooner rewards over larger, later rewards. Understanding the outcomes then leads to the development of interventions to target individuals who fail to consider the disadvantageous outcomes of choosing a smaller, sooner reward. To shed light on the fundamental differences in the processes involved in discounting, understanding the attentional mechanisms involved might be important.

In decision making, people have to attend to the variables in order to gather information. Decision-making theories (e.g., Prospect Theory: Kahneman & Tversky, 1979) assume that value in choices is connected to the extent to which respondents attend to the variables within the decision. Given the technological limitations, researchers were unable to directly measure attention. Prior research has addressed attention without specifying the type or its role in decision making (Franco-Watkins et al., 2016). Recently, researchers have focused on overt attention (Franco-Watkins & Johnson, 2011a; Franco-Watkins & Johnson, 2011b, Franco-Watkins et al. 2016). With technological advances (e.g., eye-tracking devices), researchers can now measure attentional processes in decision making. Eye-tracking devices have allowed researchers to use attentional measures to extend models that include binary and multi-attribute choices, such as the Drift Diffusion Model (DDM; Krajbich, Armel, & Rangel. 2010). DDM has shown that a critical role in decision making, is the amount of time spent attending to competing options. Generally, information about comparative values is gathered by allocating attention across different variables. Over time, individuals will fixate on the option with greater subjective value until revisiting the alternative yields no further value, leading to a choice.

Franco-Watkins et al. (2016) was one of the first studies to measure attentional processes within an intertemporal choice paradigm (e.g., discounting). Using a Tobii eye-tracking monitor paired with a fixed sequence discounting task, the authors sought to address the discounting of gains and loss, as well as the correspondence of selection bias and choice behavior. Participants completed two monetary gains tasks and two monetary loss tasks. Delayed amounts of $100 and $1,000 were used for both gains and loss tasks. Five preset amounts were crossed with the delayed amounts across five delay conditions (1 month, 6 months, 1 year, 5 years, and 10 years). For example, in the $100 gain amount task, choice of $20, $40, $60, $80, and $100 Now were paired with $100 at each delay. Choices were randomized, but it was unclear how the randomization occurred. Participants pressed keys to indicate choice preference. Pressing 1 selected the immediate choice. Pressing 2 selected the delayed choice. Of note here, is that the immediate choice was always presented on the left.

To measure choice behavior, Franco-Watkins and colleagues used the mean proportion of choosing the immediate option. Strong correlations were found between the discounting parameter *k* and proportion of choosing the immediate option, leading the authors to argue both measures yield similar interpretations of the data. In terms of overall discounting, the authors replicated previous findings that people discount later gains and prefer larger, later losses. Magnitude effects were found for the gains task, where higher k-values were reported for \$100 gains than \$1000 gains. However, no magnitude effects were observed for monetary losses, supporting the general findings in the discounting literature (Green & Myerson, 2013).

To capture attentional processes, Franco-Watkins and colleagues created four Areas of Interest (AOIs) around the amount and delay variables in the task. The number of fixations and fixation duration for each variable for each participant were measured. In terms of eye-tracking variables, Franco-Watkins et al. (2016) found that participants allocated more attention to monetary amounts over delays and more attention to larger, delayed costs than larger, delayed gains. Selection bias (SB) scores were also used to measure attentional processes. Selection bias scores range from -1 to + 1 and were calculated using the formula:

SB = (AOI now time + AOI now money) - (AOI delay time + AOI delay money)/Total AOIs (6)

SB scores of -1 indicated the participant was biased towards the delayed choice. SB scores of +1 indicated the participant was biased towards the immediate choice. SB scores of 0 indicated that there was no specific bias to either choice. These scores were calculated for each choice trial. Only fixation count was used in the SB formula, because strong correlations were reported between fixation and fixation durations. The authors also reported that they were concerned with the deployment of attention and not the amount of time spent. Using binary logistic regressions, SB scores were found to be a significant predictor of immediate and delayed choices. Averaged SB scores across trials for each participant were also created for a single metric. Averaged SB scores also predicted overall proportions of choosing the immediate option. Franco-Watkins and colleagues reported that these results support that differential allocation is predictive of choice in an intertemporal decision task. The authors mention that selection bias could possibly be used to capture attentional processing throughout the trial as opposed to only the last fixation, which is more informative of the processes involved in the choice.

Present Study

The purpose of this study was to replicate the findings, by Franco-Watkins et al. (2016), that selection bias scores predict choice behavior and extend selection bias scores to a titration procedure. Using similar independent and dependent variables as Franco-Watkins et al. (2016), the current study measured discounting of $1,000 gains via a titration procedure. If there are no known systematic differences between fixed sequence and titration procedures, selection bias should predict choice behavior in a titration procedure. We predicted that a positive correlation would exist between proportion of choosing the immediate option and selection bias scores, and similar relationships would exist with other choice measures (e.g., AUC).

As noted above, selection bias scores can be used to capture attentional processes throughout choice trials. Yet, this information is not yet known. Selection bias scores in a titration procedure can be used to capture the process of how participants arrive at indifference points. Arriving at indifference between two choices should also be psychologically more difficult, which should be reflected through attentional mechanisms (e.g., fixation and duration). In other words, the participants should allocate equal amounts of attention to the immediate and delayed choices if they are truly indifferent between the two choices. We predicted that across the iterative choice trials, those who chose the immediate choice should have a positive selection bias score, and those who chose the delayed choice should have a negative selection bias score.

Method

Participants

A total of 28 college age students (21 female) attending James Madison University were recruited through the Department of Psychology's Participant Pool and used for the final analysis. Participants received course credit for participation upon completion of the study. The entire session lasted approximately 15 minutes. Participants who wore glasses were screened out through the recruitment process.

Apparatus

Tobii Pro Glasses 2 was used to video record the eye tracking information during the decision-making tasks. These glasses used a binocular eye tracking system with corneal reflection and dark pupil techniques. Sampling rates for the eye tracking was 50 Hz. The camera system used to capture scene used four eye-tracking sensors and contained 1920 x 1080 video resolution with a refresh rate of 25 frames per second. The scene camera field view captured approximately 82 degrees horizontal and 52 degrees vertical (160 degree horizontally, 70 degrees vertically due to frame obstruction).

Task

A within–subjects experimental design was used, where all participants completed all tasks and all conditions. The decision-making task used in the study was the same used by Holt, Green, & Myerson (2012). The task consisted of two conditions each consisting of a $100 and $1,000 amount across five delayed values (1 month, 6 months, 1 year, 5 years, 10 years). Each choice condition consisted of six iterative choice trials. The first choice presented was between a smaller reward, available immediately and a larger reward, available at a delay. The smaller reward was half the amount of larger reward (e.g., $500 now versus $1,000 in 1 week). In the 5 subsequent choices, the immediate reward was adjusted based on the previous choice. If the participant chose the immediate reward, the amount of the next immediate reward was decreased. If the participant chose the delayed reward, the amount of the next immediate reward was increased.

The size of the adjustment itself decreased or increased by half the amount of the difference between the immediate and delayed rewards of the previous choice. For example, if the participant chose $500 now over $1,000 in 1 week, the next immediate choice was between $250 now over $1,000 in 1 week. If in subsequent choice the participant chose $1,000 in 1 week over $250 now, the next immediate choice was between $375 now over $1,000 in 1 week. This procedure was repeated until the participant made 6 choices for each delay and was designed to converge on the subjective value of the delayed reward.

A potential artifact of the fixed-sequence and titration procedure is that the only smaller, amount variable changes during each condition. Thus, control measures were implemented throughout the study. To control for the immediate choice always being presented on the left, the discounting application randomly assigns which choice is presented on the left; however, this presentation is held constant throughout the task. In the standard task 18 participants experienced the delayed choice presented on the left and 10 participants experienced the immediate choice presented on the left. Likewise, for the random task, 18 and 10 participants experienced the delayed and immediate choices on the right and left, respectively.

To further control for any artifacts, participants completed two decision-making tasks: standard and randomized. In the standard task, the choice trials were presented in a linear fashion where the participant made six choices about one delay at a time, but the order of the delays presented was randomized. For example, participants completed six choice trials at the one-week delay and then six choice trials at the five-years delay. The procedure for the random task was the same as that for the standard task, except that the choices were presented in a way that the participant could not predict next choice. For example, the participants would make a choice between $50 now and $1,000 in 1 year, and the next choice would be between $25 now and $100 in 5 years. The two tasks were pseudo-randomized so that the tasks were not presented in the same order for each participant. Altogether participants completed 60 choice trials per task (120 choice trials in total).

Procedure

Participants first consented to participating in the study. Afterwards, each participant fit the glasses to their face using adjustable nose pieces to ensure comfort and accurate recordings during the experiment. Then a one-dot calibration check was implemented via the Tobii Glasses Pro 2 software. Participants completed both decision-making tasks while using a chin rest to stabilize their head. The screen was presented about 12 inches away from the participant. A 5-minute break was provided in between decision-making tasks. If the participant chose to take a break, the calibration check procedure was repeated before the start of the next task. In the beginning of the decision-making task, participants read general instructions below:

> You will be asked to make a group of choices between hypothetical monetary alternatives. These choices will be displayed on the screen. For each choice, you will specify the option you would prefer with a mouse click. There are no correct or incorrect choices. We are interested in the option you would prefer.
>
> On these trials, one amount of money is to be paid right now and one amount is to be paid after a specified delay. The screen will show you how long the delay will be. You will complete a practice trial to become familiar with the task. If you have any questions at this point, please do not hesitate to ask the experimenter. Please evaluate each choice carefully before selecting the alternative you prefer.

Six practice choices were used to orient the participants to the decision-making task at the beginning of each task. Choice responses were recorded via the discounting application, and eye-movements were recorded during the decision-making task via Tobii Pro Glasses 2 software.

Results

Data Preparations

A total of 40 participants were originally recruited. Twelve participants were removed from the final analysis for the following reasons: (a) calibration issues (i.e., the software failed to calibrate or the participant moved their head which disrupted the calibration), (b) no fixation data via Tobii Pro Lab was obtained for a choice trial, and/or (d) issues with fixation and fixation durations via Tobii Pro Lab (i.e., the output results did not match the video results).

Tobii Pro lab was used to draw four areas of interests (AOI). AOIs contained monetary values and delay amounts presented in the decision-making task but were not visible to the participants. AOIs were mapped onto a photograph of the scene viewed by the participants and were identical in size (830 x 310 pixel height). Tobii Pro Lab was used to calculate AOI fixation and fixation durations. AOI Fixations were calculated by using the velocity-threshold identification (I-VT) Attention Filter. A fixation was classified as any directional shift in the eye less than 100 degrees per second. A fixation duration was classified as any fixation greater than 60 ms.

To calculate the proportion of choosing the immediate choice (PSI), experimenters watched recordings via Tobii Pro Lab across each choice trial for all participants for both standard and random tasks. A “1” designated that the participant chose the immediate reward. A “2” designated that the participant chose the delayed reward. The count of 1's and 2's were summed and divided by 6 (iterative choice trials) to create the proportion of choosing the immediate choice or delayed choice, respectively.

Choice Behavior

Figure 1 presents the group mean subjective value plotted as a function of delay. In order to compare the discounting of monetary amounts, subjective value was calculated as a proportion of the actual delayed amount. The curves represent Equation 2 fit to the group average data using a nonlinear, least squares algorithm. The results for the standard and random tasks are shown in the upper and lower graphs, respectively. The R^2s for the standard task were 0.66 and 0.81 for the $100 and $1,000 conditions, respectively. The R^2s for the random task were 0.85 and 0.95 for the $100 and $1,000 conditions respectively. At the group level, the $100 was discounted more steeply than the $1,000 and was well described by Equation 2 (hyperbola). Thus, we replicated magnitude effects from previous literature (Green & Myerson, 2013; Franco-Watkins et al., 2016). Also, the rate of discounting between the standard and random titration procedures were qualitatively similar. See Table 1 for a summary of discounting variables.

The fact that the rates of discounting were well described by Equation 2 does not resolve the statistical errors that might result due to that the fact that thee *k* parameter is often highly skewed (Green, Myerson, & Warusawitharana, 2001). Therefore, AUC values for each participant (see Table 1) were generated based on the obtained $1,000 subjective values to provide a single, approximately distributed, atheoretical measure of the degree of discounting (Green, Myerson, & Warusawitharana, 2001). The subjective value was expressed as a proportion of $1,000, and the delays were expressed as a proportion of 10 years. AUC scores can range from 0, indicating the steepest rate of discounting, to 1.0, indicating the shallowest rate of discounting.

We also replicated strong correlations between choice behavior measures of AUC and PSI ($r = -.85$, $p < .00$ for standard $1,000 gains; $r = -.81$, $p < .00$ for random $1,000 gains). Thus, we were able to support claims by Franco-Watkins et al. (2016) that both techniques yield similar patterns of intertemporal choices. See Table 2 for a summary of PSI and AUC values.

Eye-Tracking Variables

To examine differential allocation of attention to different choice elements of the two tasks we examined the mean number of fixations per AOI for each task (see Figure 2). Table 2 collapses these findings across time periods per task to simplify the presentation of the general eye-tracking variables. A 2 (task type: standard and random) x 2 (choice: small and large) x 2 (choice elements: amount and delay) repeated measures ANOVA was used. A main effect for task type (F (1,27) = 6.996, p = .013, $\eta^2_p = .206$) and choice (F (1,27) = 11.256, p = .002, $\eta^2_p = .294$) were found, but not for the choice elements (F (1,27) = .046, p = .832). People looked more at each AOI in the random task and looked more at the delayed choice more than the immediate choice. Only a two-way interaction between amount and choice elements approached significance (F (1,27) =

4.150, p = .052, η^2_p = .113). People looked more at the smaller amount variable and larger delay variable (see figure 3) A three-way interaction did not emerge (F (1,27) = .098, p = .757).

Attention and Choice Behavior

To replicate selection bias (SB) scores based on fixations, we used Formula 6. A SB score of +1 indicates extreme bias to the immediate choice parameter, SB score of -1 indicates extreme bias to the delayed choice parameter, and SB score of 0 indicates no specific bias. These values were also calculated at a trial by trial level per participant. Strong correlations were found between fixation and fixation durations (r = .76, p = .000 for standard $1,000 gains; r = .75, p = .000 for random $1,000 gains). Thus, we were able to support that both measures of yield similar interpretations of overt attention to AOIs for the basis of SB scores (Franco-Watkins et al., 2016). The subsequent data report fixations as the basis for SB scores.

As in Franco-Watkins et al. (2016), we averaged SB scores across trials to make comparisons comparable to AUC and PSI. The left panel of Figure 4 presents the scatter plot representing the relationship between the averaged SB score per participant and PSI. The right panel of Figure 3 presents the same relationship with AUC values. Averaged SB scores ranged from .16 to -.34 for standard $1,000 and .29 to -.46 for random $1,000. We ran a simple linear-regression with both averaged PSCI and AUC scores. Although there was a positive relationship between SB and PSI in the standard titration procedure (r = .323, p = .047), we found that SB scores were not a significant predictor of PSI for $1,000 gains across both tasks: standard (b = .343, t(26) = 1.738, p = .094, R^2 = .104, F(1,26) = 3.019, p = .094); and random (b = -.106, t(26) = -.521, p = .607, R^2 = .010,

$F(1,26) = .272$, $p = .607$). However, we found that SB scores were a significant predictor of AUC for the standard task ($b = -.838$, $t(26) = -2.930$, $p = .007$, $R^2 = .248$, $F(1,26) = 8.586$, $p = .007$), but not the random task (b = ..035, $t(26) = 136$, $p = .893$, $R^2 = .027$, $F(1,27) = .018$, $p = .893$).

Figure 5 presents the average SB scores for those who chose the immediate or delayed choice across the 6 iterative choice trials. The top panel of Figure 4 represents the standard titration procedure, while the bottom panel represents the random titration procedure. In the standard titration procedure, those who selected the immediate choice tend to look at the immediate choice (at least during the last three iterative choice trials). Across both standard and random titration procedures, those who chose the delayed choice looked at the delay choice.

Discussion

The present study sought to replicate the findings from previous literature that support selection bias predicts intertemporal choice behavior (Franco-Watkins et al., 2016). Given literature to support that no systematic differences arise between a fixed-sequence design and titration procedure discounting procedures (Odum & Baumann, 2010; Rodzon et al., 2011), a titration procedure was used to measure the rates of delay discounting. The methods were also designed to control for potential artifacts in the previous literature. Further, the study also examined selection bias scores across iterative choice trials as participants arrived at indifference.

Overall, in terms of choice behavior, subjective value decreased as the delay to the larger, later choice increased; indicating that, at-least at the group level, discounting occurred. Although this was not a primary goal of the current study, participants displayed magnitude effects. The study also replicated similar results between other measures of choice behavior. Strong correlations existed between PSI and AUC.

In general, we found support for that task type and amount resulted in different allocation of attention. Participants fixated more in the random task and fixated more on the delayed choices than the immediate choices in both tasks. In other words, when participants could not predict the next logical choice, they searched for more information and looked more at the delayed choice. Contrary to Franco-Watkins et al. (2016), participants looked at both amount and delay variables equally. This could be due to the limited distance between the variables. It should be noted that the distance had no impact on the overall selection bias scores, because the formula collapses both variables. Although not significant, participants looked more at the amount variables for the immediate choice and delay variables for the immediate choice regardless of the task. This would make sense, given that the smaller, delay (e.g., now) and larger, amount (e.g., $1,000) variables are held constant throughout the tasks.

When examining selection bias and choice behavior, we found partial evidence to support claims by Franco-Watkins et al. (2016). Selection bias was a significant predictor of AUC values only in the standard titration procedure, but selection bias was not a significant predictor of the proportion of choosing the immediate option. In the random titration procedure, selection bias was not a significant predictor of either choice behavior measure. Also, when examining selection bias and choice behavior across the six iterative choice trials, the effects hold true. In other words, when choices are presented in a logic sequence, where the next choice is in the same delay condition, participants that chose the immediate choice, looked at the immediate choice. However, when the choices are presented in a random sequence, what participants looked at did not predict what they choose.

The current findings suggest there is a potential artifact of the fixed-sequence and titration procedures. Firstly, Franco-Watkins et al. (2016) always presented the immediate choice on the left. The authors also found a consistent pattern of participants first look to the immediate option, which they concluded was consistent with reading left to right. The current findings could also suggest similar results with more people experiencing the delay choice of the left and a general selection bias towards the delay choice. However, across both tasks only 18 (64%) of participants experienced the delay choice on the left, and 10 (36%) of participants experienced the immediate choice on the left. Of the 28 participants, 13 (46%) experienced the delayed choice on the left for both tasks. The remaining 15 participants experienced a mix of either choice option of the left or the immediate presented on the left across both tasks. The discounting task application also controlled the random presentation. Although any bias that might have occurred, could be due to the 12 participants that were excluded from the final analysis. It is unlikely that the results are due to the discounting task.

It is also the case that any findings could be a result of group level analyses. When selection bias scores and choice behavior measures are collapsed across delays, significant results are found. However, at a more individual level (e.g., across choice trials), the expected results did not hold true. In the standard titration procedure, those who chose the immediate choice did not always look at the immediate choice. Also, in the random procedure, even those who chose the immediate choice looked at the delayed choice more often.

There is a potential limitation with attention and choice behavior in general. Researchers in the eye-tracking and reading field rely on cognitive interpretations of behavior and what is known as the "eye-mind assumption" (Just & Carpenter, 1980). This assumption states that when the eye moves to a target (e.g., $1,000), the mind begins to process the information immediately. While this assumption is generally accepted in the field (Orquin & Loose, 2013), this assumption does not account for covert shifts in attention without moving one's eye (Franco-Watkins & Johnson, 2011b). In other words, a participant could fixate on the immediate amount but be attending to the delayed choice. Our findings suggest that covert mechanisms might be at play in terms of decision-making with intertemporal choices.

Two limitations in the current study exist. First, the screen was positioned about 12 inches away from the participants. Therefore, it was possible for the participants to view both immediate and delayed choices at the same time. Our effects could be driven by the fact that participants did not have to revisit options as often in order to make a decision. However, this factor was held constant across both tasks and yet clear differences emerged and this is normally case in typical discounting procedures. Selection bias predicted choice behavior when choices were presented in a logical sequence but did not when the choice patterns were randomized. Anecdotally, when viewing the video recordings, it is clear that participants looked at each choice option and variables. Second, the distance between immediate and delayed choices and the amount and delay variables was small (about 3 inches and 1 inch, respectively). This was due to an artifact of discounting application that was not controlled for due to resource constraints. Yet again, the data show clear differences between the tasks.

Future research should control for these limitations by decreasing the distance between the monitor and the participant or by increasing the distance between each AOI variable in order to force the participants' eye movements to specific AOIs. Future research should also focus on investigating other ways of studying attention and how that impacts intertemporal choice behavior. Attention is a way that people gather information. We then use this information to behave. Stated another way, attention is an input of data and our behavior is the output of that data. We gather data through all of our senses. Studying only the eye-movements is a narrow definition of attention. How might other sensation modalities inform researchers of the processes involved in decision-making?

The current study was the first attempt to replicate and extend findings that showed attention predicts intertemporal choice behavior. Eye-tracking is a well-established method for studying attentional processing and decision-making. However, within intertemporal choice procedures results are suspect. Continued research is still needed to better understand the processes underlying discounting.

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Table 1

Mean values when Eq. 2 was fit to the data from each participant by task type

	Mean	
Task	Small	Large
Standard	.66	.81
Randomized	.85	.95

Table 2
Mean Summary of Choice Behavior Measures by Task

	Standard		Randomized	
Participant	PSI	AUC	PSI	AUC
P1	0.21	0.44	0.47	0.38
P2	0.34	0.26	0.53	0.18
P3	0.27	0.52	0.30	0.54
P4	0.21	0.49	0.57	0.37
P5	0.28	0.35	0.33	0.39
P6	0.07	0.82	0.40	0.31
P7	0.36	0.45	0.43	0.39
P8	0.00	0.99	0.13	0.83
P9	0.42	0.34	0.47	0.31
P10	0.32	0.37	0.43	0.31
P11	0.20	0.52	0.47	0.51
P12	0.25	0.49	0.40	0.38
P13	0.14	0.45	0.40	0.21
P14	0.56	0.10	0.77	0.05
P15	0.39	0.11	0.77	0.13
P16	0.27	0.29	0.67	0.13
P17	0.39	0.26	0.57	0.28
P18	0.31	0.48	0.63	0.07
P19	0.11	0.53	0.40	0.60
P20	0.41	0.24	0.53	0.33
P20	0.52	0.12	0.87	0.03
P21	0.17	0.42	0.23	0.52
P22	0.32	0.39	0.43	0.31
P23	0.32	0.48	0.33	0.34
P24	0.55	0.07	0.47	0.09
P25	0.20	0.79	0.23	0.88
P26	0.28	0.50	0.37	0.46
P27	0.27	0.28	0.47	0.21
P28	0.21	0.44	0.47	0.38

Note: PSI = proportion of choosing the immediate choice averaged across all delay conditions; AUC = area under the curve

Table 3

Summary Eye-Tracking Variables for$1,000 Amounts by Task

	Standard	Randomized
AOI Variable	*M (SD)*	*M (SD)*
Small Amount	1.88 (1.29)	1.97 (1.17)
Small Delay	1.53 (1.34)	1.96 (1.44)
Large Amount	1.91 (1.46)	2.22 (1.46)
Large Delay	2.00 (1.29)	2.78 (1.76)

Note: AOI = area of interest

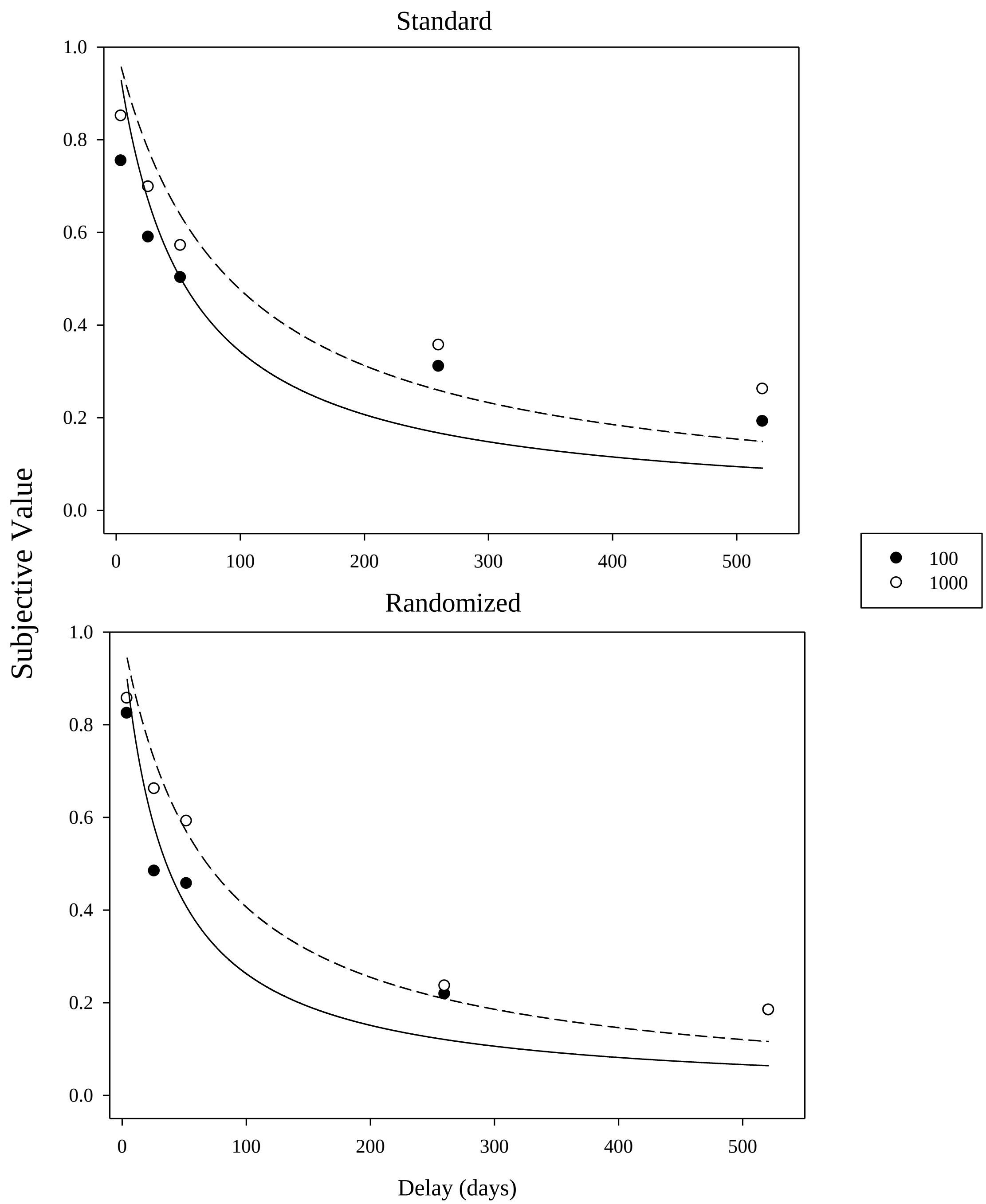

Figure 1. Mean subjective values plotted as function of delay at the group level for the standard and randomized titration procedure. Predicted values are displayed as a solid line.

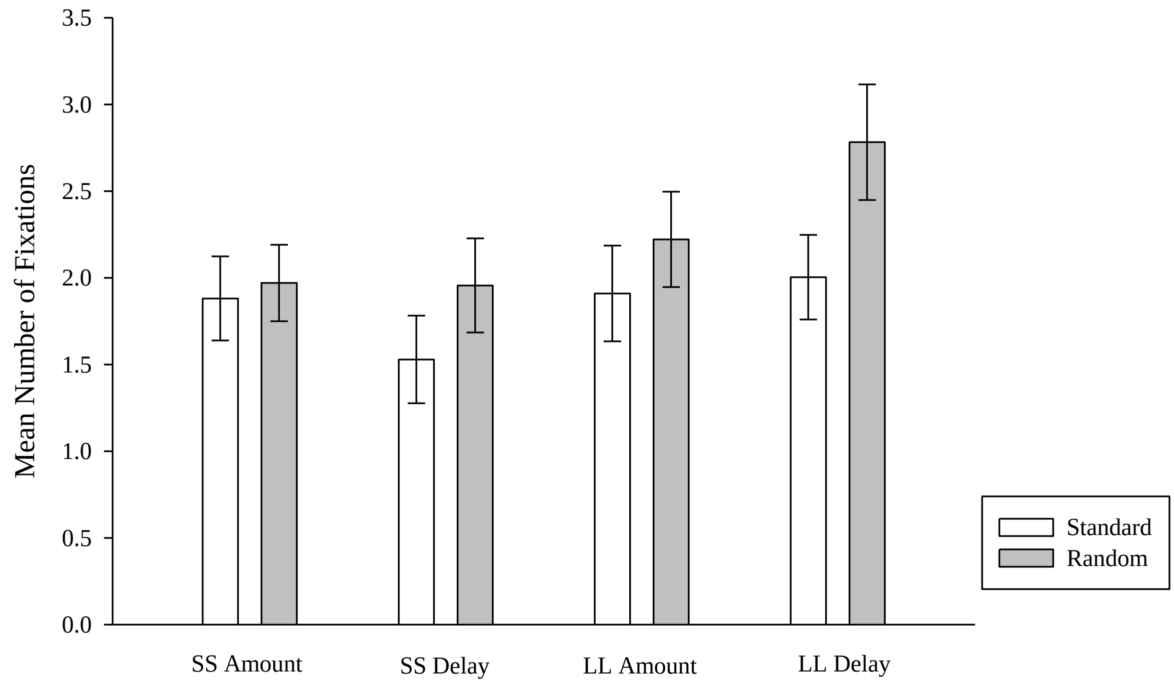

Figure 2. Mean number of fixations for each AOI of the standard and random titration procedure. Error bars are represented by the standard error of the mean (SEM).

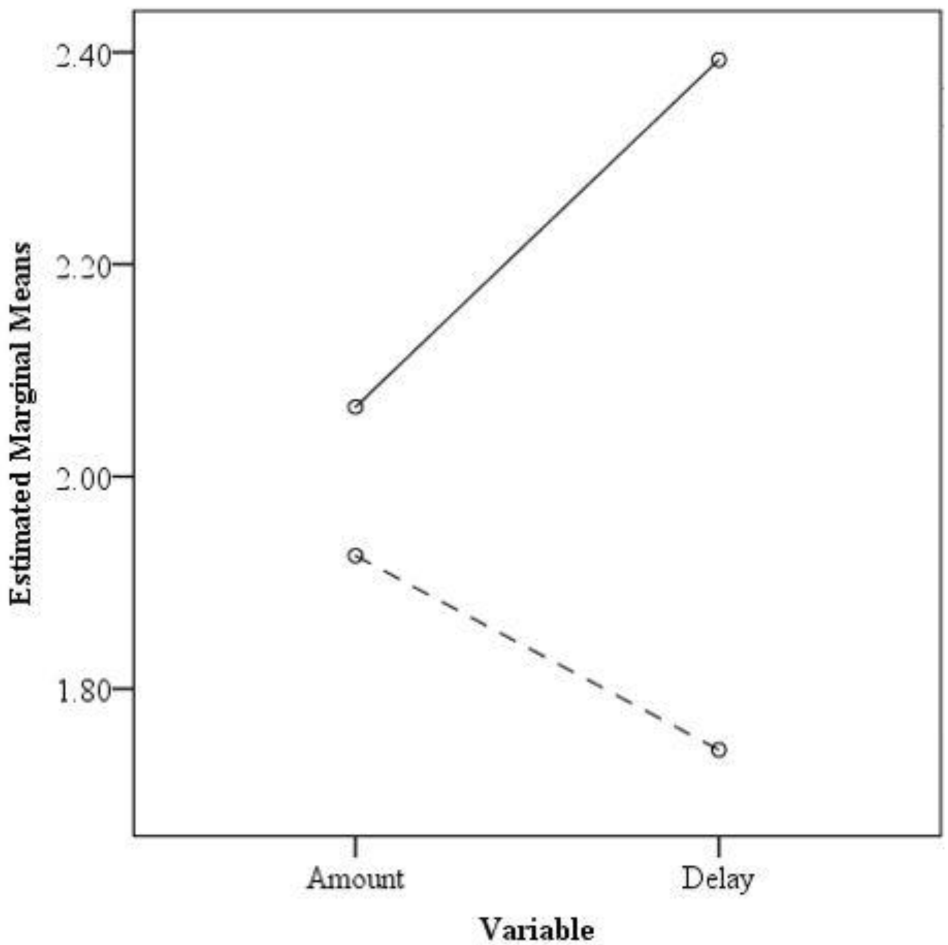

Figure 3. Two-way interaction of choice and variables from the repeated-measures ANOVA (p = .052).

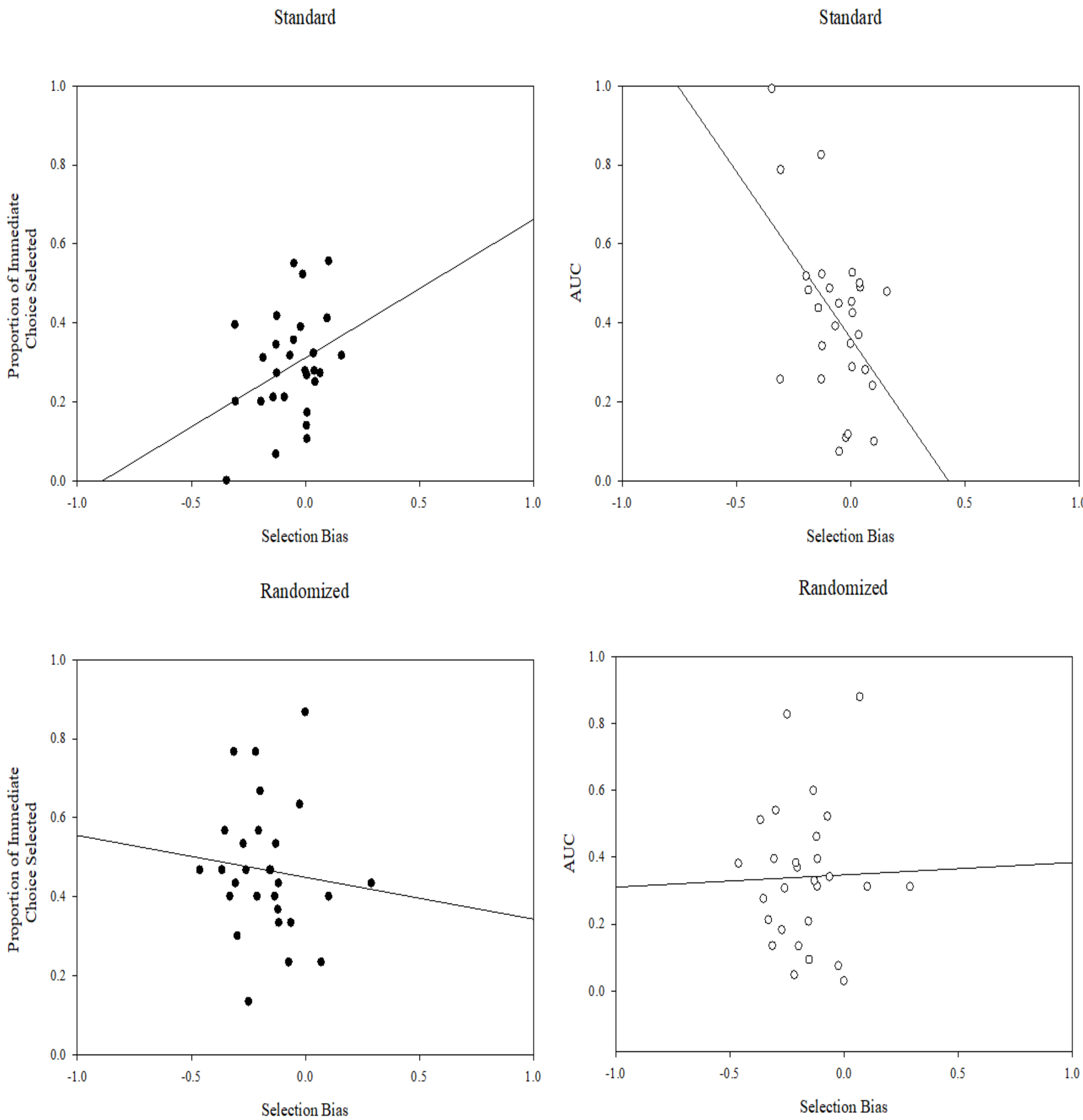

Figure 4. Scatter plots representing the relationship between selection bias scores and proportion of immediate choices selected (left panel), and proportion of immediate choice and AUC (right panel) for $1,000 gains.

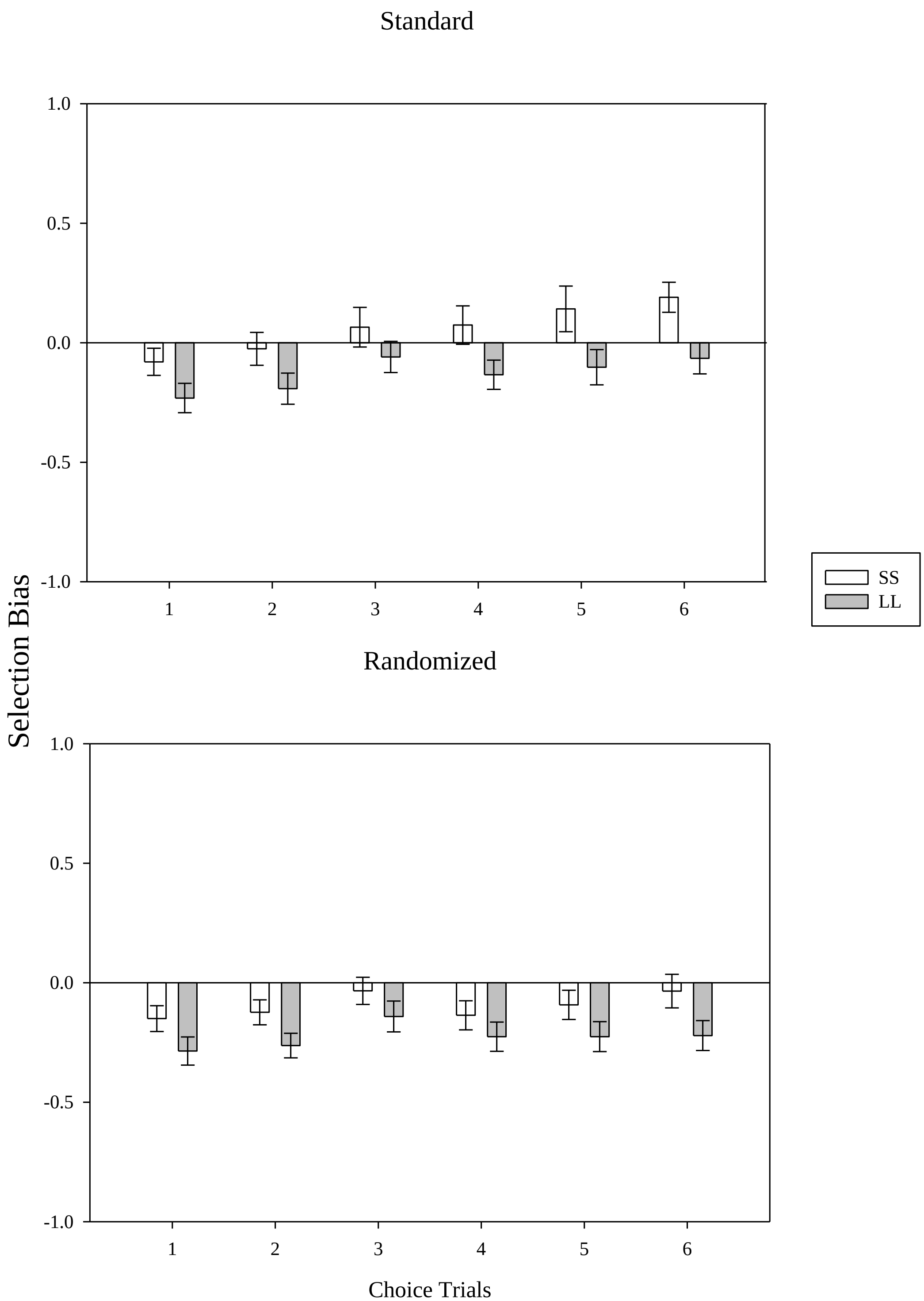

Figure 5. Mean selection bias across the iterative choice trials of the standard (top panel) and random (bottom panel) titration procedure. Error bars represent the standard error of the mean (SEM).