Sequencing Effects and Loss Aversion in a Delay Discounting Task

by

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ABSTRACT

The attractiveness of a reward depends in part on the delay to its receipt, with more distant rewards generally being valued less than more proximate ones. The rate at which people discount the value of delayed rewards has been associated with a variety of clinically and socially relevant human behaviors. Thus, the accurate measurement of delay discounting rates is crucial to the study of mechanisms underlying behaviors such as risky sex, addiction, and gambling. In delay discounting tasks, participants make choices between two alternatives: one small amount of money delivered immediately versus a large amount of money delivered after a delay. After many choices, the experimental task will converge on an indifference point: the value of the delayed reward that approximates the value of the immediate one. It has been shown that these indifference points are systematically biased by the direction in which one of the alternatives adjusts. This bias is termed a sequencing effect.

The present research proposed a reference-dependent model of choice drawn from Prospect Theory to account for the presence of sequencing effects in a delay discounting task. Sensitivity to reference frames and sequencing effects were measured in two computer tasks. Bayesian and frequentist analyses indicated that the reference-dependent model of choice cannot account for sequencing effects. Thus, an alternative, perceptual account of sequencing effects that draws on a Bayesian framework of magnitude estimation is proposed and furnished with some preliminary evidence. Implications for future research in the measurement of delay discounting and sensitivity to reference frames are discussed.

DEDICATION

This thesis is dedicated to my parents.

ACKNOWLEDGMENTS

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CHAPTER 1

BACKGROUND

Humans make choices every day that promote satisfaction and well-being. These choices are the product of processes that integrate characteristics and experiences specific to the individual as well as features of the immediate environment. Efforts abound to identify and explain the effects of different traits and contexts on choice; the attractiveness of a consequence has been shown to depend on various properties, such as its magnitude, valence, and certainty of and delay to its receipt (Berry, Nickerson, & Odum, 2017; McKerchar, Pickford, & Robertson, 2013; Nishiyama, 2016; Odum, Baumann, & Rimington, 2006; Rachlin, Raineri, & Cross, 1991). For decades, researchers have devoted considerable attention to studying *delay discounting*—the inverse relationship between the value of an outcome and the time until its availability—to better understand humans' engagement in socially and clinically relevant behaviors.

There are individual differences in delay discounting *rates*: the degree to which delays imposed on outcomes influence choice (see Reynolds, 2006 for a review). A person who tends to defer immediate satisfaction in favor of greater long-term benefit can be called *self-controlled*; a person without such a disposition might be *impulsive*. While such labels may oversimplify a collection of behaviors by framing them as a prescriptive personality trait, discounting rate does appear to be robust throughout the lifespan (Audrain-McGovern et al., 2009; Kirby, 2009), and twin and genome studies indicate that these rates have a significant genetic component—heritability estimates hover around 40% (Anokhin, Golosheykin, Grant, & Heath, 2011; Gray & Mackillop, 2014; Isen, Sparks, & Iacono, 2014).

Moreover, these individual differences in discounting rate are correlated with the frequency and intensity of behaviors characterized by an alluring short-term gain and potential long-term loss, such as risky sex (Collado, Johnson, Loya, Johnson, & Yi, 2016; Johnson & Bruner, 2013), cigarette smoking (Audrain-McGovern et al., 2009; Odum, Madden, Bickel, 1999; Yi & Landes, 2012), substance abuse (Kirby, Petry, & Bickel, 1999; Yi, Mitchell, & Bickel, 2010), and pathological gambling (Petry & Casarella, 1999; Reynolds, 2006). Due to its relevance in human choice behavior, experimenters have developed an array of delay discounting procedures to measure sensitivity to delay.

A quintessential human delay discounting paradigm was introduced by Rachlin and colleagues (1991), who adapted a methodology used by Mazur (1987) with pigeons. In Rachlin et al., participants made a series of choices between two amounts of money: the first, between $1 and $1,000 and available immediately; the second, $1,000 available after a specified delay. Choices were made at seven delays that ranged from 6 hours to 25 years. Each delay block began with a choice between either the smallest or largest possible immediate amount (i.e. $1 or $1,000) and the delayed $1,000. Thereafter, the immediate alternative was adjusted after each choice to make the initially unattractive alternative more alluring, and eventually the participant's preference switched to the originally non-preferred option. For example, a participant may choose $1,000 available immediately over $1,000 available after 1 month. Then, the experimenter reduced the amount available immediately with each choice, and eventually the participant changed their choice and began preferring the delayed alternative. This switching point—the amount available immediately that approximated the value of the delayed $1,000—was referred to as the *indifference point* (IP), and served as an indicator of subjective value of

the delayed reward. Two IPs for each delay were estimated for each participant: one where the immediate amount started at the minimum $1 and increased (ascending sequence), and another where the immediate amount started at the maximum $1,000 and decreased (descending sequence). Then, these IPs were averaged to create one IP per delay, for a total of seven. Finally, a hyperbolic equation, found by Mazur (1987) to provide the best fit to pigeon IPs, was fit to aggregate and individual IPs along with an exponential function for comparison.

Quantitative models of delay discounting

Theoretically, an economically rational decision-maker should discount the value of an outcome at a constant rate over time (Samuelson, 1937). In such cases, value as a function of delay should decay exponentially,

$$V = Ae^{-kD} \ , \qquad (1)$$

where V is the discounted value of a reward A delivered after delay D, and k is a free parameter that represents the rate at which value decays. Larger values of k result in steeper discounting curves, which indicate a more rapid decay of value and stronger preference for immediate rewards. A critical assumption of the exponential model of discounting is time-consistent preferences: that the rate of discounting remains constant for given inter-reward intervals. In other words, preference between two rewards should not change if a constant delay is added to both rewards. However, this assumption contradicts choices in everyday life. People plan to exercise at the gym, only to change their mind as gym time draws nigh; one might decide over breakfast to cook a healthy dinner later, but decide to instead purchase fast food while on the drive home that evening. Such *preference reversals* have been shown to occur in experiments with

humans (Green, Fristoe, & Myerson, 1994; Rachlin et al., 1991), rats (Green & Estle, 2003), and pigeons (Rodriguez & Logue, 1988). The exponential equation does not predict preference reversals, and thus serves as an incomplete model of intertemporal choice.

In his 1987 experiment, Mazur determined that a hyperbolic equation served as the best-fitting quantitative model of discounting as a function of delay,

$$V = \frac{A}{1 + kD} \ , \qquad (2)$$

which has the same number of free parameters as the exponential equation (one: *k*), and often provides a superior fit to individual and aggregate IPs (Aparicio, 2015; McKerchar et al., 2013; Yi, Landes, & Bickel, 2009). Importantly, hyperbolic discounting models predict preference reversals.

Figure 1 illustrates a preference reversal. The height of the bars represents the absolute (undiscounted) value of two rewards (*A* in Eqs. 1 and 2), and the curves represent the subjective value of the two rewards per a hyperbolic model. When both

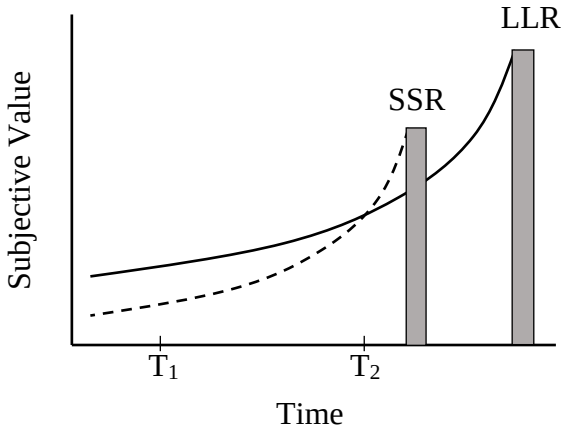


Figure 1. Preference reversals. Subjective value of a smaller-sooner reward (SSR) and a larger-later reward (LLR) as a function of delay to receipt. Bar height represents absolute (i.e., undiscounted) reward value, and curves show predicted subjective values per the hyperbolic model of discounting. The point at which the curves intersect is the point of preference reversal from LLR at T_1 to SSR at T_2

rewards are subject to lengthy delays (near the origin, at T_1), the subjective value of the larger, later reward (LLR) is greater than the smaller, sooner reward (SSR). This is demonstrated by the greater distance of the solid line (LLR) than the dashed line (SSR) from the X-axis at T_1. However, as the delays are reduced (moving towards T_2), the subjective value of the SSR overtakes that of the LLR at the intersection of the two hyperbolic functions. It is at this point where the allure of fast food overtakes the further-delayed prospect of a healthy homecooked meal. The ability of the hyperbolic to account for such preference reversals, coupled with superior model fits to empirical discounting curves compared to the exponential, leads it to serve as the benchmark quantitative model of delay discounting (Madden & Johnson, 2010; Reynolds, 2006).

A variety of delay discounting assessments have been employed in basic and translational research. Rachlin and colleagues' (1991) adjusting-immediate-amount (AIA) discounting procedure elicited individual and median IPs that were better described by a hyperbolic equation than an exponential. Other experimenters have estimated delay discounting rates with psychophysical assays that employ titration (Du, Green, & Myerson, 2002) or randomized presentation procedures (Robles & Vargas, 2007). Others still have estimated discounting rates with computer programs that resemble simple video games rather than conventional binary choice tasks (Dshemuchadse, Scherbaum, & Goschke, 2013; Scherbaum et al., 2016). Across paradigms, authors often use the parameter *k* from Eq. 2 as a primary dependent variable and find the hyperbolic function fits IP curves quite well. In many cases, the objective of these studies is to quantify and compare sensitivity to delay across populations or experimental conditions (e.g. smokers vs. non-smokers; Bickel et al, 1999). In other

cases, researchers instead focus on determining the shape of the discounting function and the mathematical formula that describes it. One avenue of research along these lines has suggested that a *hyperboloid* function is the best quantitative model of delay discounting (Green, Fry, & Myerson, 1994; Rachlin, 2006),

$$V = \frac{A}{1 + kD^s} \ , \qquad (3)$$

where *s* is another free parameter, and is supposed to represent nonlinear sensitivity to delay. When *s* equals one, Equation 3 reduces to Equation 2, and takes the form of a simple hyperbola. When *s* is less than one, as has been shown to be the case in children, sensitivity to differences between delays is increased.

However, Madden and Johnson (2010) advise experimenters to avoid using any of these mathematical models if they are interested primarily in quantifying and comparing sensitivity to delay between groups or conditions. In such cases, they advocate the calculation of area-under-the-curve (AUC) as an index of discounting rate, a technique originally suggested by Myerson, Green, and Warusawitharana (2001). To calculate AUC, a plot of indifference points is generated on a scale normalized to the maximum delay on the X-axis and maximum possible indifference point on the Y-axis (i.e., with a minimum of 0 and a maximum of 1). Then, the area under each two sequential IPs are calculated using the formula for a trapezoid,

$$AUC = \sum_{i=1}^{n} (D_{i+1} - D_i)\left(\frac{IP_i + IP_{i+1}}{2}\right) \ , \qquad (4)$$

where delays D_i and D_{i+1} are associated with indifference points IP_i and IP_{i+1}, respectively. The areas of all trapezoids are summed to compute AUC; see Figure 2 (left) for an illustration of AUC calculation.

One benefit of using AUC as a measure of discounting is that the frequency distribution of AUC values is often normal, whereas distributions of *k* are positively skewed (Myerson et al., 2001). Therefore, AUC is a measure better suited for parametric inferential statistics than untransformed *k* values. In addition, Myerson et al. argue that AUC is theoretically neutral, and that therefore its availability affords experimenters the option to not make any assumptions about the mathematical form of the discounting function with hyperbolas, hyperboloids, and exponentials. The widespread use of AUC is a testament to its convenience and utility as a point-estimate of individual discounting rates (Madden & Johnson, 2010), but it is not without its drawbacks.

Area-under-the-curve measures of discounting are disproportionally influenced by long delays relative to short delays (Borges, Kuang, Milhorn, & Yi, 2016). In most preference assessments the delayed alternative is held constant and the immediate amount

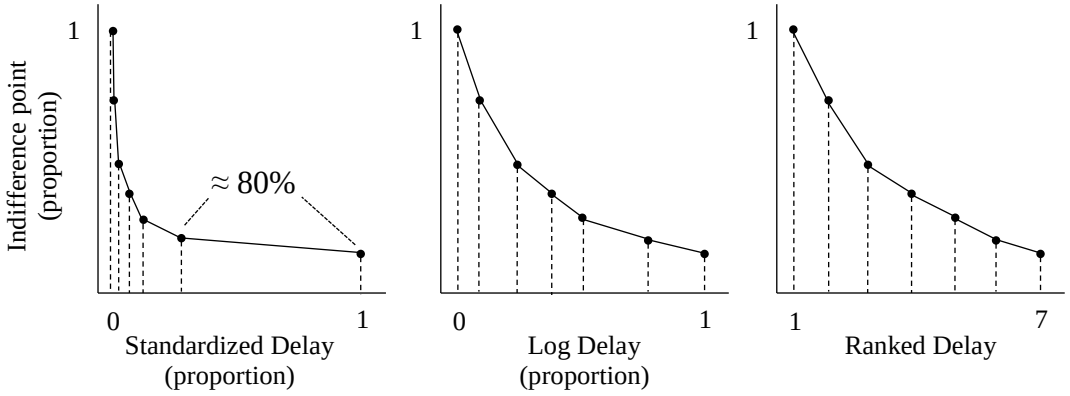


Figure 2. Area-under-the-curve. Vertical dashed lines separate 6 trapezoids whose areas are summed to compute AUC. *Left*: IPs plotted as a function of standardized delay (standard method of calculating AUC; see Green et al., 2001); by this formulation, the trapezoid formed by the final two IPs constitutes approximately 80% of the final AUC estimate. *Center*: IPs plotted as a function of *log*-transformed delay. *Right*: IPs plotted as a function of ordinal delays. Log and ordinal transformations of delays more evenly distribute the contribution of each trapezoid to AUC.

is adjusted until one IP is determined for each delay in a set of pseudo-exponentially scaled delays (e.g., in days: 1, 7, 30, 180, 365, 1825, 9125). Borges and colleagues (2016) show that when delays such as these are used to calculate AUC, the trapezoid comprised of the longest two delays (in our example, 1825 and 9125 days) constitutes approximately 80% of the total AUC. In contrast, the four shortest delays constitute less than 5% of the total AUC. Given that nonlinear regression techniques used to estimate *k* values equally weight each indifference point, it seems inconsistent to use AUC if it is so disproportionally influenced by the final two IPs. Thus, Borges et al. suggest *log*-transforming the delay to condense the delay scale and more closely equate the delay pairs in their contribution to the final measure of AUC_{logD}. Alternatively, one might instead transform the delays from a ratio scale to an ordinal scale, making the difference between each delay one, and forcing each trapezoid to have the same width. See Figure 2 (center) for an illustration of AUC_{logD} and Figure 2 (right) for an illustration of AUC_{ordD}.

Area-under-the-curve and *k* values estimated from Eq. 2 and 3 are regarded as valid estimates of the degree to which individuals discount the value of an outcome as a function of the delay to its availability. Indeed, all have seen use by experimenters investigating sensitivity to delay between groups or within individuals (Berry et al., 2017; Green, Fry, & Myerson, 1994; McKerchar et al., 2013; Odum, 2011). However, the new formulations of AUC proposed by Borges et al. (2016) have seen comparably less use due to them being proposed only recently. Therefore, further empirical exploration is necessary to determine the extent to which AUC_{logD} and AUC_{ordD} capture the same information as AUC.

Methodological effects in delay discounting paradigms

The degree to which people discount outcomes is moderated by a variety of task-specific factors (Berry et al., 2017; Dehart & Odum, 2015; Read, Frederick, Orsel, & Rahman, 2005). For example, one well-studied phenomenon in delay discounting research is the *magnitude effect*, where it is observed that hypothetical small delayed rewards are discounted more steeply than larger ones. McKerchar and colleagues (2013) found that group median *k* values from Eqs. 2 and 3 were smaller for participants who discounted $25,000 compared to those who discounted $1,000. Comparable results have been reported by other authors comparing a range of reward magnitudes (Estle, Green, Myerson, & Holt, 2006; Green, Myerson, & Mcfadden, 1997; Vanderveldt, Oliveira, & Green, 2016).

However, this magnitude effect is not reliably observed in experiments with animals (Green, Myerson, Holt, Slevin, & Estle, 2004, but c.f. Grace, Sargisson, & White, 2012), and a recent study showed that humans do not exhibit the magnitude effect when amounts are expressed as dots on a screen instead of numerically (Reyes-Huerta & dos Santos, 2016). Reyes-Huerta and dos Santos (2016) suggest that discounting rates do not vary as a function of magnitude when numerals are removed from the experimental context because participants must estimate the value of each alternative, rather than integrate a numerical value in the discounting process. Indeed, when amounts were presented as a collection of dots, participants underestimated the value of the immediate alternative in an AIA task when the value of the delayed reward was 16,000 Mexican pesos, but not when it was 2,000, suggesting non-linear scaling of amount estimation as a function of the magnitude of the delayed reward. Another noteworthy finding from their study is that effects of type of value representation (numeric vs. non-numeric) on

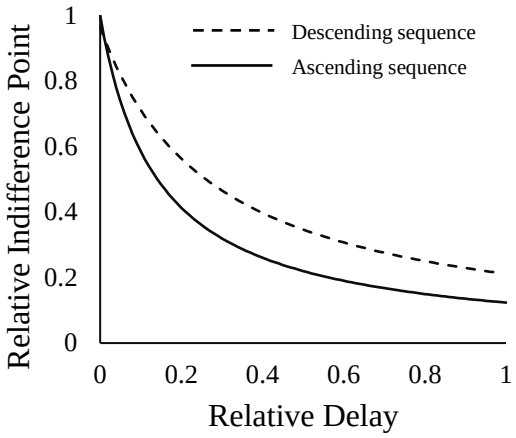


Figure 3. The sequencing effect. Hypothetical indifference curves illustrate steeper discounting as a function of delay when immediate values begin at the minimum $1 and are increased between each choice (solid line) compared to when they begin at the maximum $1,000 and are decreased (dashed line). Curves are hyperbolic (Eq. 2), where *k* for each curve is the median *k* in Robles et al., 2009 ($k_{Ascending}$ = .002; $k_{Descending}$ = .0004).

discounting rate were moderated by the starting point and direction of change of the immediate alternative, which is consistent with previous research demonstrating *sequencing effects* in delay discounting paradigms.

Sequencing effects are observed when IPs are systematically biased as a function of the direction in which the immediate alternative is adjusted after each choice in a series of decision problems. Results from Robles, Vargas, and Bejarano (2009) and Robles and Vargas (2008) demonstrate the sequencing effect; see Figure 3 for an illustration. Participants in Robles et al.'s studies made a series of choices between an SSR and an LLR, where the former ranged from $1 to $1,000 and the latter was held constant at $1,000. Indifference points were estimated in both an ascending and descending sequence. Estimates of participants' discounting rates—AUC and *k* values from a simple hyperbola (Eq. 2)—were higher in the ascending sequence, in which the SSR began at $1 and increased following each choice than in the descending sequence, in

Table 1
Choice varies as a function of decision frame

Frame	Response options	Choice %
Gain	a. If Program A is adopted, 200 people will be saved.	a. 72%
	b. If Program B is adopted, there is 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved.	b. 28%
Loss	c. If Program C is adopted, 400 people will die.	c. 22%
	d. If Program D is adopted, there is a 1/3 probability that nobody will die, and a 2/3 probability that 600 people will die.	d. 78%

Note. Response frequency values were taken from Tversky & Kahneman, 1981. $N = 152$

which the SSR began at $1,000 and decreased after each choice. At present, the mechanism underlying such sequencing effects is unclear.

A reference-dependent account of sequencing effects

A possible explanation for sequencing effects, suggested by Robles and his colleagues (2008; 2009), instantiates a reference-dependent model of choice (Levin & Gaeth, 1998; Tversky & Kahneman, 1991). This model proposes that people evaluate their options partly as a function of the way in which the decision problem is framed. Evidence for the effects of decision frame on human choice comes from both behavioral economics and experimental psychology (e.g. Dehart & Odum, 2015; Dshemuchadse et al., 2013; Tereyağoğlu, Fader, & Veeraraghavan, 2017; Tversky & Kahneman, 1981). A quintessential example of framing effects can be seen in Table 1, and is taken from Tversky and Kahneman's "Asian Disease Problem" (1981). Respondents ($N = 152$) were asked to imagine a scenario where the U.S. is preparing for an outbreak of a new Asian disease that is expected to kill 600 people. Half of the participants were assigned to the *Gain frame* condition, and the other half to the *Loss frame* condition; in each condition,

the respondent was presented two alternatives to combat the disease and asked to indicate which they preferred. These alternatives were mathematically equivalent across conditions (all outcomes had an expected value of 200 lives saved), and differed only in the language used to describe them. In the *Gain frame* condition choices were framed in terms of people being saved, whereas in the *Loss frame* condition choices were framed in terms of people dying. Participants' choice percentages are shown in Table 1, and the results are clear: the framing of the alternatives as either losses or gains had a systematic effect on participants' responses. Specifically, the loss frame elicited risk-seeking choice, and the gain frame elicited risk-averse choice.

This observed gain-loss framing effect in human decision making is a central tenet of Kahneman and Tversky's prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991; Tversky & Kahneman, 1981). Indeed, effects such as these are often attributed to *loss aversion* as it is described within this theoretical framework. Loss aversion is commonly conceptualized as the finding that, when it comes to humans making choices, "losses loom larger than gains" (Levin & Gaeth, 1998). Empirical evidence demonstrates that prospective losses often do carry greater weight than equivalent gains in human decision-making processes, especially in paradigms similar to the original Asian Disease Problem described above and others that establish a strong *reference point* (Kühberger, 1998). In his meta-analysis, Kühberger compiled 230 effect sizes from a diverse sample of paradigms and estimated that the average magnitude of framing effects was approximately Cohen's $d = 0.31$ (weighted by sample size), and that

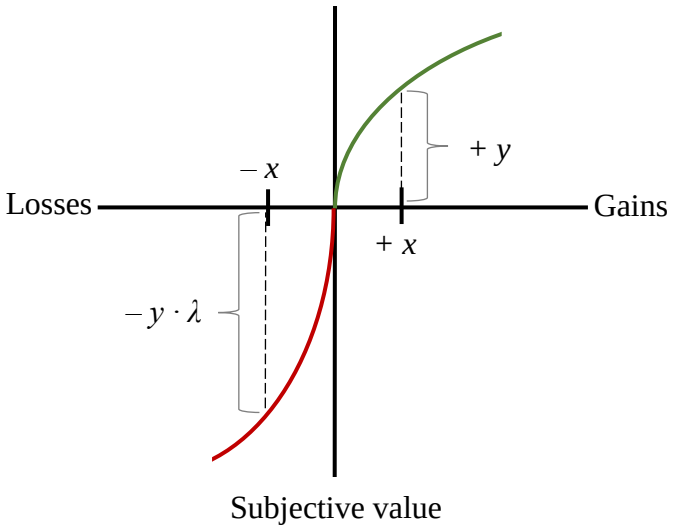


Figure 4. Hypothetical value functions as posited by a reference-dependent model of choice. Curves in the lower-left and upper-right quadrants represent the subjective value assigned to prospective losses and gains, respectively. Details in text.

this effect was notably greater for paradigms that established a strong reference point (mean weighted $d = 0.50$).

Figure 4 illustrates the effect of reference points and the gain-loss asymmetry in outcome evaluation processes. At the origin is a decision-maker's reference point, which describes one's current holdings—the status quo. Reference-dependent models of choice posit that all prospective gains and losses are evaluated in terms of deviations from this reference point. To the right and left of the origin along the x-axis is the nominal value of prospective gains and losses, respectively. The y-axis indicates the subjective value of gains and losses. The curves in the upper-right and lower-left quadrants represent the value functions for gains and losses, respectively. Imagine a decision-maker choosing to accept or reject an equivalent mixed gamble, where there is a 50% chance of winning some amount of money ($+x$) and a 50% chance of losing the same amount of money ($–x$). The value functions for gains and losses in Figure 4 predict that the pleasantness of the

prospective gain ($+y$) of the gamble is outweighed by the unpleasantness of the prospective loss ($-y \cdot \lambda$), where λ is a scaling factor characterizing the degree to which the decision-maker is loss averse. Thus, in contrast to classic "rational" economic theories of choice (e.g. expected value theory, see Edwards, 1954; Fishburn, 1970; Samuelson, 1937) reference-dependent models of choice predict that decision-makers will tend to reject equivalent mixed gambles due to the fact that $|(-y \cdot \lambda)| > (+y)$ when $\lambda > 1$; indeed, evidence shows that this is often the case (De Martino, Camerer, & Adolphs, 2010; Sokol-Hessner et al., 2009; Tom, Fox, Trepel, & Poldrack, 2007; but c.f. Walasek & Stewart, 2015).

Sequencing effects in the AIA discounting task may be the product of disproportionate weighting of losses relative to gains. In the descending sequence, immediate values are decreased between each choice trial. If a decision-maker were attentive to the direction in which value is changing—which reason predicts they would be, as it is the only changing parameter in the decision problem—then sequential changes in the negative direction may place them in a *loss* frame. The reference-dependent model of choice predicts that, because of framing effects, amount decrements (i.e. losses) experienced in the descending sequence should carry more subjective value relative to amount increments (i.e. gains) experienced in the ascending sequence. This gain-loss asymmetry could account for the systematic bias in discounting rates, as the subjective value of the SSR may not equal its nominal value (refer to Figure 4). Thus, the primary hypothesis of the present research is that differential sensitivity to gains and losses covaries with observed differences in estimated delay discounting rates between ascending and descending SSR sequences.

Estimating sensitivity to gain and loss frames with a mixed-gamble task

Authors have employed myriad strategies to estimate the degree to which individuals are loss averse (Abdellaoui, Bleichrodt, & L'Haridon, 2008; Abdellaoui, Bleichrodt, & Paraschiv, 2007; De Martino et al., 2010; Mukherjee, Sahay, Chandrasekhar, & Srinivasan, 2017; Sokol-Hessner et al., 2009; Tom et al., 2007). While methods differ, the result of these assays are all point estimates of loss aversion: a single value which characterizes the extent to which prospective losses outweigh gains in participants' decisions. For example, Tom et al. (2007), De Martino et al. (2010), and Walasek and Stewart (2015) asked participants to indicate whether they would accept or reject mixed gambles. Each participant's responses were submitted to a logistic regression that predicted the odds of accepting a gamble from the specified gain and loss amounts. The ratio of the estimated loss and gain model coefficients were used to compute a loss aversion coefficient λ, which served as a point-estimate of a participant's sensitivity to gain-loss framing effects.

In summary, a reference-dependent model of choice predicts that the magnitude of sequencing effects in an AIA delay discounting tasks should covary with decision-makers' differential sensitivity to gains and losses. The experiment presented herein tests this hypothesis with a within-subjects correlational design: participants provided indifference data from ascending and descending sequences that informed estimates of their delay discounting rates and the magnitude of the sequencing effect. The correlation between this effect and point-estimates of loss aversion was tested. A positive correlation between loss aversion and the magnitude of the sequencing effect would support the notion that discounting rates as estimated by AIA choice procedures are partly

confounded by an alternative, distinct process responsible for framing effects. Analyses also explored various quantitative models of delay discounting to assess the degree to which they captured the same information.

CHAPTER 2

METHODS

Participants

Participants were current undergraduate students recruited from Arizona State University's West Campus volunteer pool, and were compensated with course credit. An a priori power analysis conducted with the software G*Power suggested a sample size of $N = 43$ to detect a sequencing effect of size $d = 0.57$ with a Type I Error probability $\alpha = .05$ and power $(1 - \beta) = .95$ (Erdfelder, Faul, Buchner, & Lang, 2009). This effect size was estimated from descriptive statistics on AUC values given in Robles et al. (2009). Eighty-one (81) volunteers completed all experimental protocol by the end of the Fall 2017 semester. Data collection was continued beyond $N = 43$ to buffer against exclusion of participants based on a priori criteria described later in this section.

Procedure

All participants completed two computer assessments presented in counterbalanced order. One estimated delay discounting rates in ascending and descending SSR conditions, and the other estimated loss aversion. All experimental programs were written in Python 3.0. Computers were standard Dell desktop PCs, and all responses were recorded with the left button on a standard two-button mouse. The experiment took approximately 25 minutes to complete.

Abbreviated delay discounting task

Figure 5 (left) depicts the choice interface used in the *Abbreviated delay discounting task* (ADT). This task was identical to that used by Robles et al. (2009), which is an

abbreviated version of the original procedure used by Rachlin et al. (1991). After the experimenter started the program, the participant read the following instructions:

> "This program will show you a series of screens where you will be asked to choose between an amount of money available now and $1,000 available after some delay. The money in this program is hypothetical, "pretend money," but please make your selections as if you were really going to get the amounts you choose. We don't expect you to choose one in particular, so please don't select what you think we might want you to choose, but click on the alternative you really would prefer. After each choice, the program will go on to the next screen, and it will tell you when you are done. Now click on the START button when you are ready to begin."

In each trial, participants chose between two alternatives by clicking the left mouse button over a command button associated with their preferred outcome. After making their selection, a separate screen presented a new button labeled "CONTINUE" that, when pressed, began a new trial with the next pair of choices. One choice was always an amount of money available immediately (SSR), and the other always $1,000 available after a delay (LLR). Whether the SSR was presented on the left- or right-hand side of the screen was determined randomly for each trial. The 30 possible values of the SSR are the same as those used in previous studies (US $1000, $999, $995, $990, $960, $940, $920, $850, $800, $750, $700, $650, $600, $550, $500, $450, $400, $350, $300, $250, $200, $150, $100, $80, $60, $40, $20, $10, $5, $1), and IPs for the LLR were estimated in 8

Figure 5. Choice screens used in the ADT and MGT. *Left*. The choice screen presented in the ADT. Whether the SSR was presented on the left or right was randomly determined for each new trial. *Right*. The choice screen presented in the MGT. Whether the "accept" button was presented on the left or right was randomly determined for each new trial.

different delay blocks (6 hours, 1 day, 1 week, 2 months, 6 months, 1 year, 5 years, and 25 years). Participants completed the ascending and descending SSR conditions in a random order.

Conditions differed in the starting value and direction of change of the SSR. In the ascending condition, the value of the SSR began at $1 for each delay block and increased with each choice of the LLR. Once a participant chose the SSR, the value of the SSR in that trial was recorded as the IP and the next delay block began. In the descending condition, the SSR began at $1,000 and decreased with each choice of the SSR. Once a participant chose the LLR, the value of the SSR in that trial was recorded as the IP and the next delay block began. Delay blocks within each condition were presented in ascending order. Omitting choices beyond the IP reduces the amount of time the assessment takes, and has not been shown to systematically bias IPs (Robles & Vargas, 2008; Robles, Vargas, & Bejarano, 2009).

Mixed-gamble loss aversion task

Figure 5 (right) depicts the choice interface used in the *mixed-gamble loss aversion task* (MGT), which is similar to that used by other authors (De Martino et al., 2010; Tom et al., 2007; Walasek & Stewart, 2015). In the MGT, participants indicate whether they

would accept or reject each of 225 unique hypothetical mixed gambles, each of which features a 50% chance of gaining some amount of money and a 50% chance of losing some amount of money. The prospective gains and losses both ranged from $80 to $332 with increments of $18 between each value; participants responded to each possible combination of gain and loss amounts, which were presented in a pseudo-random order. Prior to the presentation of any gambles, participants read the following instructions:

> "This program will show you a series of screens where you will be asked to choose whether or not you would accept a hypothetical gamble. Please answer by pressing the 'accept' button if you would take the gamble, and the 'reject' button if you would not. All gambles are 50/50 shots; that is, there is a 50% chance of winning the green money and a 50% chance of losing the red money. We don't expect you to choose in any particular way, so please don't choose what you think we might want you to choose, but click on the choice you really would prefer given the option in real life. After each choice, the program will go on to the next screen, and it will tell you when you are done. Please click on the START button when you are ready to begin."

Participants were shown one gamble at a time and made their selection by clicking the left mouse button over a command button labeled either "accept gamble" or "reject gamble." After making their selection, a separate screen presented a new button labeled "CONTINUE" that, when pressed, began a new trial with the next gamble.

Data exclusion

Delay discounting exclusion criteria were chosen to maximize sample variability and minimize that contributed by non-monotonic discounters. Thus, participants were

excluded from all analyses if either of their sets of IPs had two or more instances where any single IP was greater than the preceding IP by more than $200. Four participants were excluded on the basis of this criterion (Johnson & Bickel, 2008). Johnson and Bickel (2008) also argued that participants may be excluded if the last IP (at 25 years) in a set of IPs was not less than the first (at 6 hours) by at least $100; this criterion was unused here to include those who are relatively insensitive to delay.

Data were also excluded from all analyses if the statistical software was unable to fit a logistic regression model to participants' MGT data. Thirteen participants responded so uniformly (i.e., rejected all gambles) that the software was unable to estimate model parameters. In other words, the logistic regression resulted in perfect predictions for these participants' responses to the hypothetical gambles, making parameter estimation mathematically impossible. Three more participants were excluded as their models were unable to converge after 25 iterations. In sum, 20 participants were excluded from all analyses, reducing the total sample size from $N = 81$ to $N = 61$ (75%).

CHAPTER 3

RESULTS

Data analysis

Except for hyperboloid (Eq. 3) model fits, all computations and statistical analyses were conducted in *R*, an open-source statistical computing software. Hyperboloid models were fit to indifference point data with the Microsoft Excel 2016 Solver add-in. Where appropriate, effect sizes are reported as Cohen's *d*.

Is there a sequencing effect in the ADT?

Hyperbolic (Eq. 2) and hyperboloid models (Eq. 3) were fit to each participant's set of indifference points from the ascending and descending conditions with nonlinear least-squares regression. AUC, AUC_{logD}, and AUC_{ordD} (Eq. 4) were computed for each participant in each condition. Table 2 shows descriptive statistics for $ln(k)_{\text{hyperbola}}$, $ln(k)_{\text{hyperboloid}}$, $ln(s)$, AUC, AUC_{logD}, and AUC_{ordD}, and Table 3 shows bivariate correlations between measures. Note that AUC_{logD} values can exceed one because the log of the shortest delay (0.25 days) is a negative number.

Included in Table 2 is the Standard Error of the Regression (SER) for the hyperbola and hyperboloid models:

$$SER = \sqrt{\frac{SS_{\text{Residual}}}{n - p}} \qquad (5)$$

Table 2

Descriptive statistics for the abbreviated delay discounting task

Sequence condition			$ln(k)$	$ln(s)$	*SER*	AUC	AUC_{logD}	AUC_{ordD}
Ascending	Hyperbola	mean (SD)	-6.39(4.55)	--	181.95(143.19)	.446(.305)	0.785(0.300)	.589(.232)
		median	-7.11	--	150.28	.458	0.864	.659
	Hyperboloid	mean (SD)	-6.15(6.03)	-0.49(1.29)	180.41(155.02)	--	--	--
		median	-5.32	-0.39	159.28	--	--	--
Descending	Hyperbola	mean (SD)	-8.89(2.61)	--	109.46(84.71)	.626(.280)	0.958(.0157)	.721(.126)
		median	-9.48	--	91.09	.705	0.999	.756
	Hyperboloid	mean (SD)	-5.54(3.97)	-1.01(1.38)	79.08(73.37)	--	--	--
		median	-4.41	-0.71	57.45	--	--	--

Note. SER = standard error of the regression; *AUC* = area under the curve; *SD* = standard deviation

where SS_{Residual} is the sum of squared residuals between the observed and predicted IPs, n is the number of IPs, and p is the number of free parameters in the model. The SER provides an index of goodness-of-fit that is better suited for non-linear models than the coefficient of determination R^2, because the former does not assume a linear relationship. Furthermore, the SER is exactly the size of the average residual, and thus features an intuitive interpretation: the mean number of dollars by which the predicted IP differs from the observed IP. Interestingly, mean SERs were significantly smaller in the descending condition for both hyperbolic fits, $t(120) = 3.40$, $p < .001$, and hyperboloid fits, $t(120) = 3.70$, $p < .001$.This finding suggests that these models of discounting were more predictive of IPs when SSRs decreased compared to when they increased.

Figure 6 (left) illustrates the sequencing effect at the participant-level across various measures of delay discounting rate in participant-pair plots. $Ln(k)_{\text{hyperboloid}}$ and $ln(s)$ values are not shown because hyperboloid model parameters cannot independently indicate a sequencing effect and are addressed later. Participants' $ln(k)_{\text{hyperbola}}$, AUC, AUC_{logD}, and AUC_{ordD} are plotted as colored circles and are separated by condition. Gray lines connect each participant's estimated delay discounting rate between ascending and descending conditions, and black targets are condition means. Note that larger $ln(k)$ values indicate greater discounting, whereas larger AUC values indicate less discounting.

Table 3

Bivariate correlation matrix of delay discounting measures

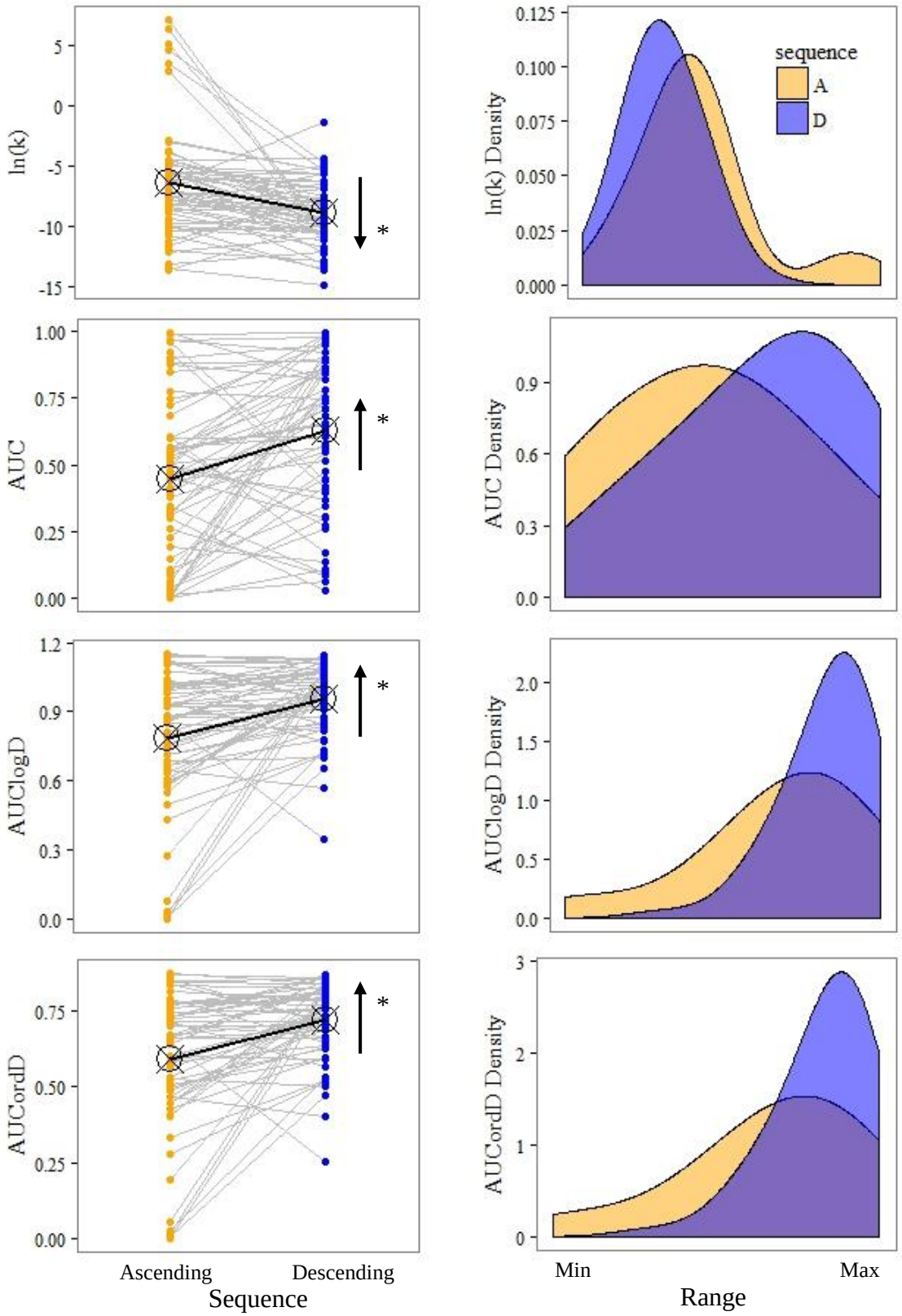
Measure	$ln(k)$	AUC	AUC_{logD}	AUC_{ordD}
$ln(k)$	--	-.78*	-.93*	-.93*
AUC	--	--	.79*	.80*
AUC_{logD}	--	--	--	.99*
AUC_{ordD}	--	--	--	--

Note. AUC = Area under the discounting curve. *$p < .001$

These plots demonstrate that—despite substantial variation between participants—an ascending sequence of immediate values usually engenders more impulsive choice.

This conclusion was corroborated by significance tests. As $k_{\text{hyperbola}}$ values were positively skewed, condition differences in discounting rate were assessed with a paired-sample Wilcoxon Signed Rank test. AUC values were more normally distributed, and thus simple linear regressions were used to compare delay discounting rates by sequence condition on these measures. Partial regression coefficients *b*s are reported. Each comparison indicated a statistically significant sequencing effect, with steeper observed discounting in the ascending condition: $k_{\text{hyperbola}}$, $W = 1552$, $p < .001$, median difference = 0.0004; AUC, $t(60) = 4.37$, $p < .001$, $b = 0.18$, $d = 0.62$; AUC_{logD}, $t(60) = 4.59$, $p < .001$, $b = 0.17$, $d = 0.72$; and AUC_{ordD}, $t(60) = 4.54$, $p < .001$, $b = 0.13$, $d = 0.70$. To examine potential methodological and demographical confounds, multiple linear regression analyses were conducted predicting discounting rate from sequence condition, task order (MGT or ADT first), condition order (ascending or descending sequence first), and participants' age and sex. All multiple regression models retained unique statistical

Figure 6 (Reverse). Sequence effects. *Left*. Participant-pair plots of estimated delay discounting rates across conditions as measured by $k_{\text{hyperbola}}$, AUC, AUC_{logD}, and AUC_{ordD}. Black arrows indicate the direction of a statistically significant difference. *Right*. Probability density functions of estimated delay discounting rates across conditions. *$p < .001$


ln(k)
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significance of the sequence condition parameter (all coefficient *p*s < .05) and suggested no unique influence of sex, task order, or ADT condition order on discounting rate (all *p*s > .05). In addition, all multiple regression models identified age as a unique predictor of discounting rate (all *p*s < .05), with older participants making more self-controlled choices than younger participants. Such a relationship is consistent with previous research (Green et al., 1994).

Figure 6 (right) shows probability density functions (*pdf*s) of the same measures of delay discounting rate. These *pdf*s afford additional confidence in the robustness of the sequencing effect to outliers. For example, six outliers in the ascending condition can be seen in the $ln(k)_{hyperbola}$ participant-pair plot (Fig. 6, top-left); those with a critical eye may wonder if these outliers are the driving force behind the difference between the means of the ascending and descending conditions. However, the *pdf*s of *ln*(*k*)s (Fig. 6, top-right) mitigate these concerns: the *pdf* of the ascending sequence is near-uniformly shifted to the right, indicating steeper discounting in this condition relative to the descending sequence, and features only a slight increase in density in its right tail. Clearly, the observed difference between these two distributions is not wholly due to outliers. Taken together, these data suggest that the ascending presentation of immediate values in the ADT engenders more impulsive choice than the descending presentation of the same amounts.

Does the hyperboloid model demonstrate a sequencing effect?

Figure 7 shows four condition median indifference curves: one curve is drawn for each condition per the hyperbola (solid lines) and hyperboloid (dashed lines). Visual inspection of the IPs, the simple hyperbola, and the hyperbola with the delay raised to a

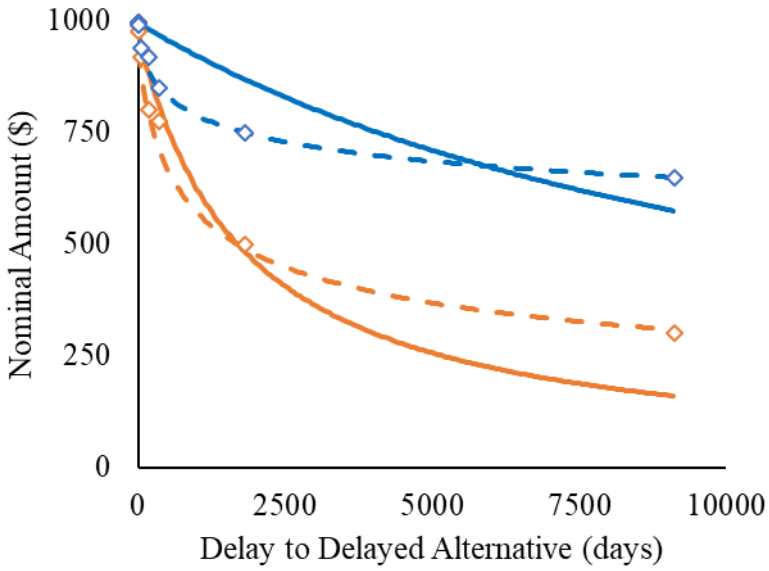

Figure 7. Best-fitting group-level discounting curves per hyperbolic (solid lines) and hyperboloid (dashed lines) models for the ascending (orange) and descending (blue) sequence conditions. Indifference points (diamonds) were condition median IPs for each delay.

power *s* indicates that participants discounted the value of the delayed alternative more in the ascending sequence than in the descending sequence (note the steepness of the orange [ascending] lines relative to the blue [descending] lines). The hyperboloid rate parameter $k_{\text{hyperboloid}}$ and scaling parameter *s* were both positively skewed and were thus natural-log transformed for statistical analyses. However, a statistical comparison of distributions of $ln(k)_{\text{hyperboloid}}$ between the ascending and descending conditions would not be analogous to between-condition comparisons of $ln(k)_{\text{hyperbola}}$ if the power *s* in the hyperboloid model differed from one. Note that $ln(1) = 0$. Thus, a one-sample *t*-test was conducted to compare the distribution of $ln(s)$ against the null hypothesis of $ln(s) = 0$, which revealed that the mean $ln(s)$ was significantly less than zero, $t(121) = -6.11$, $p < .001$, $d = -0.55$.

Different parameters within mathematical models of behavior are meant to model independent processes; thus, there should be no or minimal correlation between estimates of $ln(k)_{\text{hyperboloid}}$ and $ln(s)$. A significant correlation would imply that these parameters model the same or similar processes, and should not be interpreted independently. A test

of the Pearson's product-moment correlation coefficient *r* suggested that these parameters were inversely related, $r(120) = -0.62$, $p < .001$. A correlation coefficient of $r = -0.62$ indicates a strong relationship by conventional standards (Cohen, 1992), and such collinearity discourages the independent interpretation of estimates of *k* and *s* as "rate" and "scaling" parameters, respectively. Therefore, no attempt to do so will be made here, and the reader is directed to Figure 7 to conclude that the fit of Eq. 3 does not provide evidence against the presence of a sequencing effect.

Were participants loss averse?

Following Walasek & Stewart (2015) and Tom et al. (2007), MGT responses were analyzed by fitting a logistic regression to each participant's responses, which were dummy-coded as accept gamble = 1, reject gamble = 0:

$$Log\left[\frac{P(accept)}{1-P(accept)}\right] = \beta_{bias} + \beta_{gains} \cdot gain + \beta_{losses} \cdot loss \qquad (6)$$

The estimated partial regression weights β_{losses} and β_{gains} characterize a participant's sensitivity to prospective loss and gain, respectively. The absolute value of the ratio of each participant's estimated β_{losses} to β_{gains} were used to calculate loss aversion coefficients λ:

$$\lambda = \left|\frac{\beta_{losses}}{\beta_{gains}}\right| \qquad (7)$$

The intercept parameter β_{bias} is included to account for any tendency to respond "accept" holding constant the influence of the prospective gains and losses. Thus, the resulting λs are a more precise function of participants' differential sensitivities to losses and gains.

Note that loss aversion is observed when $\lambda > 1$; $\lambda = 1$ and $\lambda < 1$ suggest that participants are loss-neutral and loss-seeking, respectively.

Figure 8 (top) shows that the empirical cumulative distribution function (*ecdf*) for $|\beta_{losses}|$ is shifted to the right of the *ecdf* for β_{gains}; a nonparametric two-sample Kolmogorov-Smirnov test suggested that these parameters were likely not sampled from the same underlying population distribution, $D = 0.98$, $p < .001$. Figure 8 (middle) pairs each participant's estimated β_{gains} and $|\beta_{losses}|$; a simple linear regression showed that, on average, participants' $|\beta_{losses}|$ were greater than their β_{gains}, $t(60) = 3.91$, $p < .001$, $b = 0.03$, $d = 0.25$.

Figure 8 (bottom) transposes the *pdf* of observed loss aversion coefficients λ (purple) and the *pdf* of a hypothetical "null" distribution where the mean $\lambda = 1$ (gray). The dashed vertical line intersects with $\lambda = 1$. Coefficients are bounded within the range of $[0, +\infty]$ and more closely resemble a log-normal distribution than a gamma distribution; Akaike information criterions for these distributions were 176 and 189, respectively. Therefore, the hypothetical null distribution is comprised of 1,000 values randomly sampled from a hypothetical log-normal distribution with a mean of 1 and standard deviation of 1.57—the sample λ standard deviation. The distribution of observed λs is shifted slightly to the right and exhibits greater density in its right tail than the null; a one-sample *t*-test conducted on natural-log transformed λ values supported the conclusion that the mean λ ($\lambda_{mean} = 1.96$; $\lambda_{median} = 1.19$) was greater than 1, $t(60) = 5.28$, $p < .001$, $d = 0.68$. These data from the MGT task collectively show that loss aversion was observed: the decisions made by most participants to accept or reject the hypothetical gambles were driven more strongly by prospective losses than prospective gains.

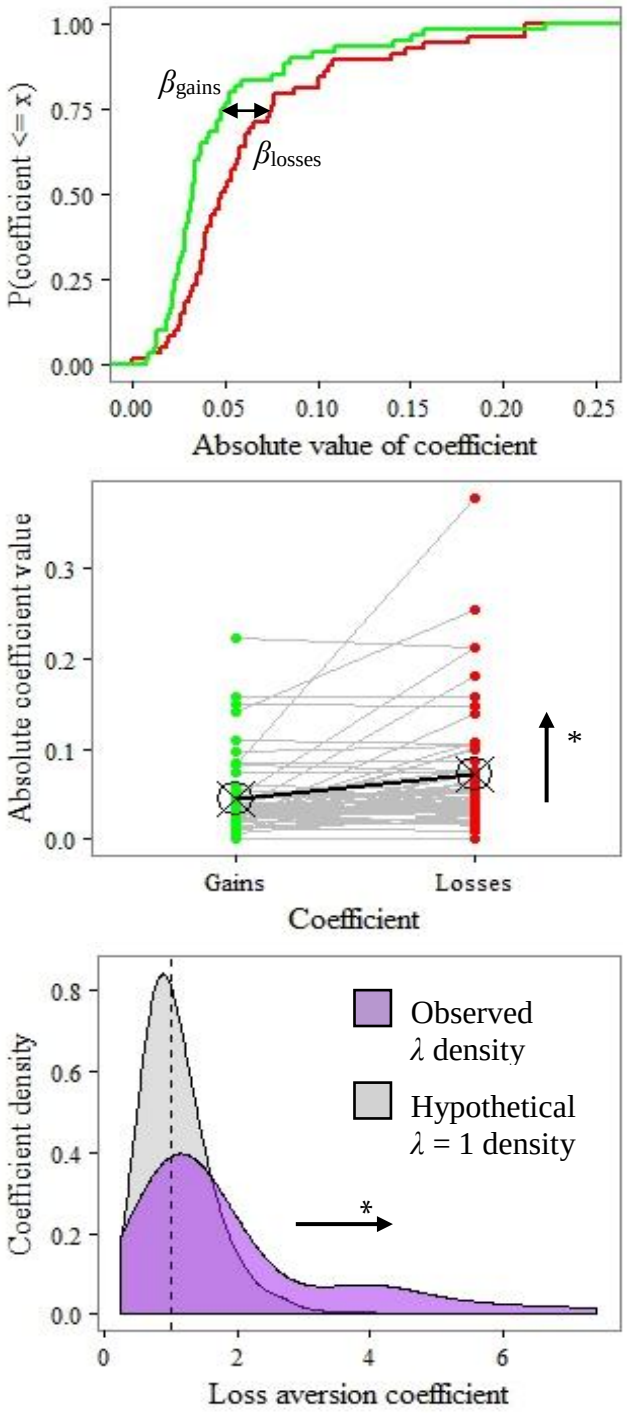

Figure 8. Top. Empirical cumulative distribution functions of $|\beta_{losses}|$ (red) and β_{gains} (green). The arrow illustrates the difference between the two functions. *Middle*. Participant-pair plot of β_{gains} and $|\beta_{losses}|$. Gray lines connect each participant's estimated coefficients, and the black line connects coefficient means (targets). *Bottom*. Probability density functions for observed λs (purple) and a hypothetical null distribution (gray) where the mean $\lambda = 1$. The hypothetical distribution is comprised of 1,000 random samples from a lognormal distribution with a mean of 1 and observed sample λ standard deviation of 1.57. The vertical dashed line is at $\lambda = 1$. *$p < .001$.

Can a reference-dependent model account for sequencing effects?

The magnitude of the sequencing effect for each measure of delay discounting rate was computed as the difference between the ascending and descending rates. Simple linear regressions were used to model the relationship between the magnitude of the sequencing effect and natural-log transformed λ values; standardized coefficients (β) are reported. For each delay discounting measure, significance tests failed to reject the null hypothesis that the sequencing effect and loss aversion coefficients were unrelated: $k_{\text{hyperbola}}$, $t(59) = -1.35$, $p = .18$, $\beta = -0.17$; AUC, $t(59) = 0.54$, $p = .59$, $\beta = 0.07$; AUC_{logD}, $t(59) = 0.53$, $p = .60$, $\beta = 0.07$; AUC_{ordD}, $t(59) = 0.41$, $p = .69$, $\beta = 0.05$. Figure 9 shows a scatterplot of magnitude of sequencing effect scores as measured by AUC and loss aversion coefficients along with the best-fitting linear model. It is important to note, however, that failure to reject the null hypothesis is not the same as evidence in its favor.

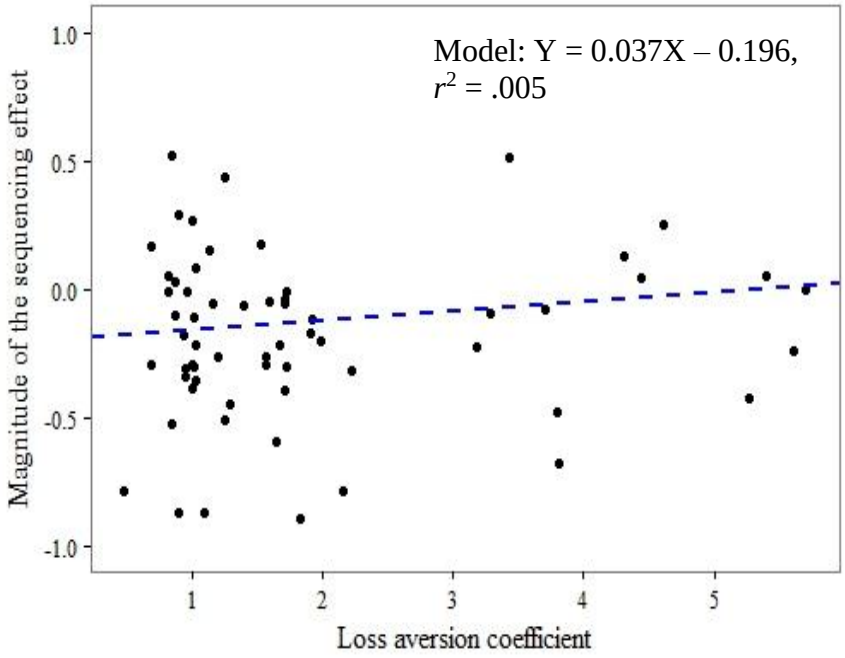

Figure 9. Predicting sequencing effect magnitudes (in terms of AUC) by loss aversion coefficients. The blue dashed line represents the best-fitting unstandardized linear relationship (equation inset) between these two variables.

Therefore, Bayesian estimation procedures were employed to examine the strength of evidence in favor of the null.

Bayesian methods can provide evidence in support of the null hypothesis, and they allow the analyst to incorporate information regarding the distribution of parameter estimates in the form of a prior distribution (Kruschke, 2014). The priors used to estimate correlations between the sequencing effect and loss aversion were normally distributed and *weakly informative*: they predicted effect sizes centered around a mean of zero—biasing parameter estimates towards a null effect—with a standard deviation of 0.5. This dispersion parameter is wide, and was chosen because there is no previous research on the correlation between these two variables. Thus, this prior reflects two reasonable assumptions: a relatively small correlation is more likely than a large one, but all are theoretically plausible. Bayesian estimation also allows the analyst to specify a non-normal population distribution for the predicted variable. Therefore, no variables were transformed to conform to a normal distribution. The prior distribution and data (also called a likelihood distribution) combine to estimate a posterior distribution of parameter estimates, which is used to make inferences about likely parameter values.

There is no threshold used to determine "statistical significance" in Bayesian estimation as in null hypothesis significance testing. However, multiple statistics can be used to drive inferences and are reported. Bayes Factors (BF_{01}) represent the ratio of the marginal likelihoods for the null hypothesis (H_0) relative to an alternative hypothesis (H_1) given the data:

$$BF_{01} = \frac{P(D \mid H_0)}{P(D \mid H_1)}, \qquad (8)$$

where *D* is the data. As Eq. 8 implies, marginal likelihoods may be interpreted as the probability of observing the data if the model in question is true. Thus, evidence mounts for H_0 as BF_{01} increases from 1, and mounts for H_1 as BF_{01} reduces from 1. Other statistics are the mean parameter estimate (b_B)—the mean of the posterior distribution—and 95% credibility intervals (CI 95: [*min*, *max*]), where *min* and *max* bound the central 95% of the posterior distribution. Note that credibility intervals differ from confidence intervals in that the former represent a characteristic of the posterior distribution, whereas the latter predict the range within which 95% of parameter estimates will fall after repeated samples.

A skewed normal distribution was specified as the population distribution from which sequencing effect magnitudes were drawn for $k_{hyperbola}$, as a D'Agostino test suggested that the sample distribution was positively skewed (skewness = 5.89), $D(61) = 8.47$, $p < .001$. A normal distribution was specfied for all AUC measures. For each measure, a Bayesian simple linear regression estimated a posterior distribution strongly in favor of the null hypothesis that loss aversion coefficients and the magnitude of the sequencing effect were unrelated: $k_{hyperbola}$, $b_B = -.01$, CI 95: [-.01, .01], $BF_{01} = 14979.87$; AUC, $b_B = .02$, CI 95: [-.04, .08], $BF_{01} = 352.92$; AUC_{logD}, $b_B = .02$, CI 95: [-.04, .07], $BF_{01} = 12107.36$; AUC_{ordD}, $b_B = .01$, CI 95: [-.03, .05], $BF_{01} = 576.92$. To interpret these results, consider statistics reported for AUC: the $BF_{01} = 352.92$ suggests that if one entered the hypothesis testing process with minimal information regarding the distribution of correlation coefficients, they should now be approximately 353 times more confident in H_0 than H_1. Said another way, the likelihood of observing these data under a null model is 353 times greater than the likelihood of observing them under an alternative

model. The CI 95: [-.04, .08] specifies that there is a .95 probability that the correlation between the magnitude of the sequencing effect and loss aversion lies between r = -.04 and r = .08.

Figure 10 superimposes the estimated posterior distribution of correlation coefficients between λ and the magnitude of the sequencing effect with the specified prior for AUC; plots of $k_{\text{hyperbola}}$, AUC_{logD}, and AUC_{ordD} effects are qualitatively similar. Vertical dashed lines bound the 95% credibility interval for the posterior distribution. Two important features of Figure 10 assist with inferences made on the basis of this analysis. First, the posterior distribution is narrower than the prior, which reflects the fact that the data are informative and can be used to update one's beliefs and exclude unlikely parameter estimates (e.g., those outside the CI). Second, the 95% credibility interval includes r = 0, which suggests that the null relationship is more probable than

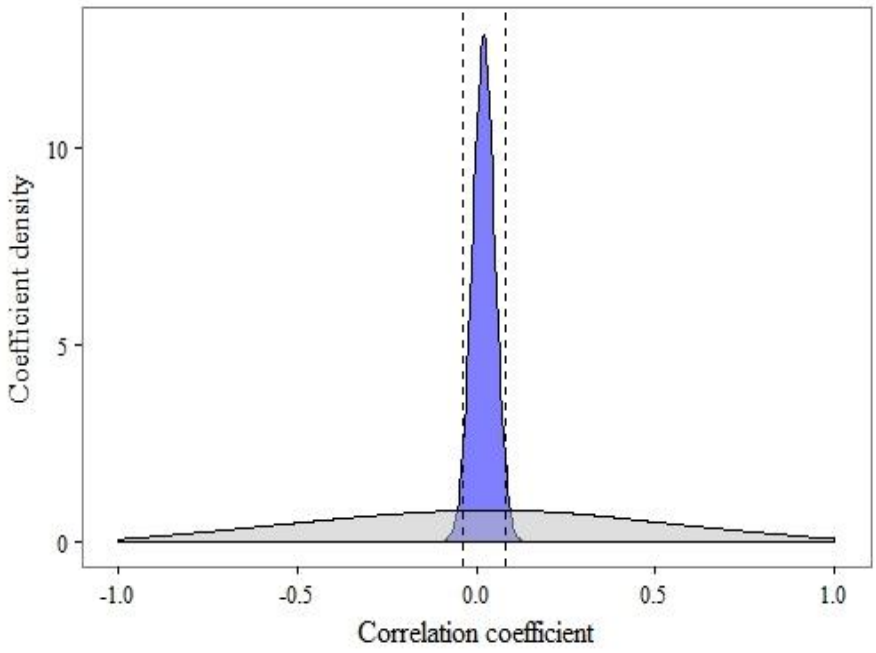

Figure 10. Superimposed prior (gray) and posterior (blue) distributions for the correlation coefficient between loss aversion and the magnitude of the sequencing effect as measured by AUC. The prior distribution is normal with mean = 0 and SD = 0.5, and the posterior is normal with mean = .02 and SD = .03; 95% of its density is within the range -.04 > r > .08, as shown by vertical dashed lines.

relationships of a magnitude outside the interval. Thus, the inference drawn from this analysis is clear: given the large BF_{01}, minute effect size ($r^2 = b_B^2 = .0004$), and 95% credibility interval that includes $r = 0$, loss aversion likely accounts for an inconsequential amount of the variance produced by sequence condition. Furthermore, this result generalizes to all measures of delay discounting rate given the high convergence between estimated posterior distributions.

CHAPTER 4

DISCUSSION

The present research predicted a positive correlation between the sequencing effect in the ADT with individual differences in loss aversion as measured by the MGT. The sequencing effect and loss aversion were observed (Figs. 6, 7 and 8), but both frequentist and Bayesian analyses suggested that these variables are likely unrelated (Figs. 9 and 10).

Researchers primarily use $ln(k)_{\text{hyperbola}}$ and/or AUC values to compare delay discounting rates between experimental groups or populations (Madden & Johnson, 2010), with AUC_{logD} and AUC_{ordD} seeing considerably less use. The present findings suggest that all of these measures are valid estimates of delay discounting rate, as evidenced by statistically significant correlation coefficients reported in Table 3. Moreover, *pdf*s of these variables (Fig. 6, right) suggest that log- and ordinally-transformed delays produce a distribution of AUCs that may be closer to normal than conventional AUC values, albeit with slight negative skewness. Therefore, the data presented here suggest that it may be preferable to apply inferential statistical tests to these transformed measures in order to more closely adhere to assumptions of normality, and to not overweight long delays relative to short ones in the calculation of discounting rates.

Hyperbola and hyperboloid goodness-of-fit were not assessed with measures of R^2 despite its conventional use in the delay discounting literature. In a simulation study, Spiess and Neumeyer (2010) demonstrated the inadequacy of R^2 as a descriptor of model fit in non-linear models. They instead advocate the use of Akaike and Bayesian

Information Criteria for researchers interested in model selection, as these measures had higher rates of correct rejections and acceptances compared to R^2. Interestingly, these authors also assessed the quality of residual variance as a model selection tool and found that it performed no better than R^2. Residual variance and SER are similar indices: SER is simply the square root of the residual variance. However, SERs were not used here for model selection, but rather for model description as they afford a highly intuitive interpretation in the context of indifference points. Researchers fitting equations to indifference points might consider replacing R^2 as a goodness-of-fit index with a more appropriate, intuitive statistic—SER should be considered an attractive candidate due to its interpretability and simplicity.

Results from the MGT indicate that the majority of participants' choices were consistent with the notion of loss aversion. A loss aversion coefficient $\lambda > 1$ suggests that a participant was more heavily influenced by prospective losses than prospective gains in the MGT, whereas a $\lambda < 1$ indicates the opposite. As can be seen in Figure 8 (bottom), participants generally exhibited at least mild loss aversion ($\lambda_{mean} = 1.96$; $\lambda_{median} = 1.19$); Equation 6 estimated 45 λs > 1, 15 λs < 1, and one $\lambda = 1$, and a test of $ln(\lambda)$s against the null hypothesis of $ln(\lambda)_{mean} = 0$ estimated a Cohen's *d* of 0.68—an effect size consistent with those reported by Kühberger (1998). Such convergence suggests that the MGT accurately captures sensitivty to framing effects, despite recent reports of potential methodological shortcomings relating to task stimuli (Walasek & Stewart, 2015). Nonetheless, numerous features of the MGT have yet to be fully explored. Task parameters such as the magnitude and ease of divisibility of dollar amounts in the MGT may have effects on estimates of loss aversion (Harinck, Van Dijk, Van Beest, &

Mersmann, 2007; Sokol-Hessner et al., 2009); thus, future research in this area is warranted.

A perceptual account of sequencing effects in the ADT

The primary hypothesis tested here was that sequencing effect magnitudes would be correlated with estimates of sensitivity to framing effects. Frequentist statistical tests failed to reject the null hypothesis, and Bayesian statistical procedures supported the null hypothesis that these variables are unrelated. These results call into question the influence of reference points on choice in tasks such as the ADT. Importantly, reference-dependent models include two decision-making stages: an initial framing stage followed by an evaluation stage (Kahneman & Tversky, 1979). The data shown here suggest that participants may not consciously frame changes in the SSR as losses or gains; rather, they might evaluate each decision without paying much attention to the direction of change in the SSR between trials. Thus, a perceptual account of the sequencing effect may be more tenable, as it does not rely on participants' framing of improvements and decrements in SSRs as gains and losses from a reference point.

Research in psychophysics has demonstrated that people's estimates of stimulus magnitude are often biased towards the values assigned to previously-judged stimuli. As a result, people overestimate the magnitude of a stimulus when stimuli are presented in a

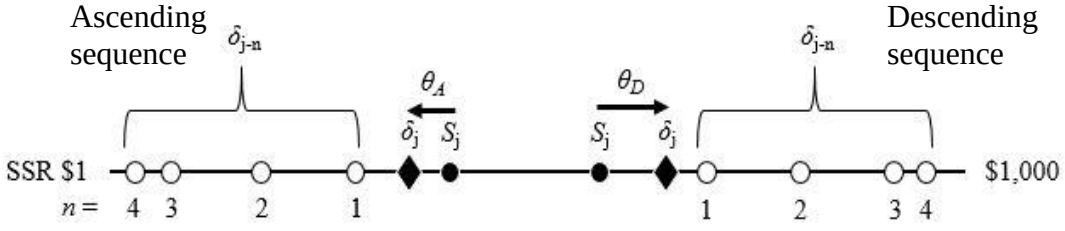

Figure 11. A perceptual account of sequencing effects.

descending sequence, and underestimate it when stimuli are presented in an ascending sequence (Cross, 1973; Jesteadt, Luce, & Green, 1977; Petzschner, Glasauer, & Stephan, 2015). It may be the case that participants make choices in the ADT by evaluating the initially non-preferred option (i.e., the LLR in the descending condition and the SSR in the ascending condition); importantly, this perceptual model of choice rests on this assumption. Figure 11 illustrates the hypothesis in the context of the ADT in the ascending and descending sequences. The number line represents relative values of the non-preferred alternative, from $1 to $1,000, and the filled circles represent to-be judged values of the initially non-preferred alternative of magnitude S_j within ascending (*A*) and descending (*D*) conditions. S_j is preceded by *n* previously-evaluated options (open circles) $\delta_{j\text{-}n}$. The estimated value of S_j within a trial is δ_j, which is subject to bias (θ) introduced by all or some of these preceding judgments. When the previous judgments were larger than S_j (as in *D*), $\delta_j > S_j$; when they were smaller (as in *A*), $\delta_j < S_j$.

The logic of this perceptual hypothesis draws on a Bayesian framework of magnitude estimation recently discussed in Petzchner et al. (2015). In Bayesian inference, wider likelihood distributions (i.e., more variable observations) exert a weaker effect on the posterior distribution than narrower, more precise observations. This perceptual account proposes that the width of the likelihood distribution is determined by the certainty of the value of the present non-preferred alternative S_j. The posterior distribution of estimates δ_j is a product of the likelihood and prior distributions—the latter of which is some function of $\delta_{j\text{-}n}$. Thus, less certain estimates of S_j exhibit a weaker influence on δ_j, which is biased towards the prior. It is important to note that, although S_j is a given numerical stimulus (e.g., $1,000), participants must estimate how much S_j is

actually worth to them, a process that introduces error. The greater the error about S_j, the stronger the relative influence of the prior $\delta_{j\text{-}n}$, and the larger the bias θ of δ_j towards it. Therefore, if the width of the distribution of estimates S_j is greater in the ascending sequence than the descending sequence, then $\theta_D > \theta_A$, and choice is more biased towards the LLR in the descending sequence than in the ascending sequence.

The present data and this Bayesian framework allow for an initial exploration of this perceptual hypothesis, albeit only at the group level. Coefficients of variation (CV = SD/Mean) provide a measure of variability of S_j that is relative to the mean estimate. As such, CVs should index the uncertainty of estimates of S_j between participants and hence, the width of the likelihood distribution. Therefore, CVs of indifference points (the closest possible approximation of S_js available here) were calculated for each delay within the ascending and descending conditions at the group level.

Figure 12 shows CVs of S_js across the range of delays for the two conditions. There is a clear effect of sequence condition on CVs: there was more within-condition variability in S_js in the ascending sequence relative to the descending sequence. This finding is consistent with the proposed perceptual account of the sequencing effect, as the CV of the likelihood distribution for S_j is inversely related to its influence on the posterior. Indeed, assuming priors of equal width and relative location across conditions, $\theta_D > \theta_A$. However, inferences drawn from this analysis should be qualified because they are based on group-level data, and may be unrepresentative of single participants' repeated judgments. Furthermore, this hypothesis assumes that participants specifically attend to and evaluate the non-preferred alternative in each trial. Thus, whether or not the sequencing effect is due to the perceptual bias proposed here is a question that may be

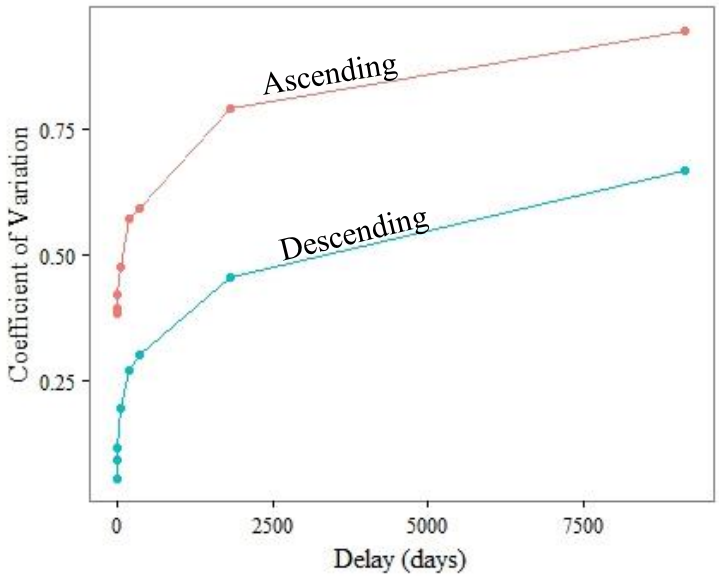

Figure 12. Group-level coefficients of variation (CV) of indifference points as a function of delay for the ascending (orange) and descending (blue) sequence conditions. The CV of a likelihood distribution is inversely related to its influence on the posterior.

better answered by a within-subjects design wherein the width of the likelihood distribution S_j is estimated for each participant with repeated sequences of each delay. Additional insights may also be provided by eye-tracking data to determine which stimulus participants allocate more attention towards in each trial.

Methodological considerations

Alternatively, the null relationship between people's loss aversion coefficients and sequencing effect magnitudes may be attributable to modality-specific processes in the MGT and ADT. For instance, the loss averse behavior elicited in the MGT may be specific to probabilistic outcomes, and sequencing effects in the ADT specific to delayed outcomes. That said, there are some similarities between delay and probability discounting processes; for example, Lawyer and colleagues (2010) found that IPs for sexual and monetary rewards elicited in both types of discounting tasks were well-described by a hyperbolic function. Such findings are consistent with a single-process

view in which a shared mechanism underlies both probability and delay discounting (Rachlin et al., 1991). However, to the author's knowledge, sequencing effects have not been explored in the context of probability discounting. Thus, it is unclear whether differences in discounting rate between ascending or descending sequences are caused by a shared delay–probability mechanism or some third variable; this awaits experimental psychologists as a line of future research.

The sample size used in the present experiment was determined to be sufficient to detect a sequencing effect of size $d = 0.57$, and the present data suggest a comparable effect size (range of *d*s: .62–.72). However, a substantially greater sample size may be necessary to detect a statistically significant correlation between loss aversion coefficients and sequencing effect magnitude. A power analysis in G*Power suggested that 779 participants would be necessary to detect a significant correlation of $r = .1$ with power $(1 - \beta) = .80$ and $\alpha = .05$ (Erdfelder et al., 2009). This sample size is reduced to 82 if $r = .3$; however, both of these estimates are likely too large given the posterior distribution of correlation coefficients (see Fig. 10). Nonetheless, replication of the null effect reported here with a larger sample size would increase the confidence that the present results are not a Type II error (i.e. a false negative).

Thirteen of 81 participants responded so uniformly in the MGT that a logistic regression was unable to estimate model parameters—such response patterns may be due to two task-specific parameters: the attractiveness of the gambles and the number of response options. First, the most attractive gamble in the MGT featured a potential gain of $332 and loss of $80—a gain/loss ratio of 4.15. Participants who are particularly loss averse might reject even these gambles; to encourage them to accept at least some

gambles, it might be necessary to make an offer they cannot refuse. Thus, future instantiations of the MGT might consider extending the sampling origin of losses and gains to include more alluring gain/loss ratios, or even some gambles that include prospective losses of $0. Second, forcing participants to either "accept" or "reject" gambles reduces the fine-grainedness of the assessment (Krosnick & Presser, 2010; Preston & Colman, 2000). That is, participants may possess some degree of uncertainty regarding their choice, and may be biased towards rejecting a gamble when they are unsure of their preference. To avoid this issue, MGT responses could be instead expressed on an ordinal scale with options such as "definitely accept," "maybe accept," "maybe reject," and "definitely reject." Such response scales have been used before in MGTs (e.g., Tom et al., 2007), but their merits and limitations have not yet been compared to those of binary scales.

Conclusion

In summary, the present experiment sought to relate sequencing effects in a delay discounting task to loss aversion via a reference-dependent model of choice, and the data did not support this relationship. In fact, Bayesian procedures provided very strong support for the null hypothesis for each quantitative measure of delay discounting rate. As such, an attentive, motivational account of sequencing effects in the ADT is unsatisfactory. A low-level, perceptual hypothesis built within a Bayesian framework was proposed and furnished with some preliminary supporting evidence. Future research should explore methodological parameters that influence choice in the ADT and MGT, the covariance and applicability of various quantitative models of delay discounting rate, and the application of Bayesian analytical procedures to test the perceptual account of

sequencing effects. Importantly, the proposed perceptual hypothesis does not explain why indifference points are more variable in the ascending sequence than in the descending sequence. Thus, this observation is worthy of further study *per se*.

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