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Identifying the Underlying Components of Delay Discounting Using Latent Factor Modeling

W. Brady DeHart
Utah State University

IDENTIFYING THE UNDERLYING COMPONENTS OF DELAY

DISCOUNTING USING LATENT FACTOR MODELING

by

W. Brady DeHart

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Approved:

Amy L. Odum Major Professor	Gregory J. Madden Committee Member
Christian Geiser Committee Member	Michael Twohig Committee Member
Timothy A. Slocum Committee Member	Mark R. McLellan, Ph.D. Vice President for Research and Dean of the School of Graduate Studies

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Logan, Utah

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ABSTRACT

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W. Brady DeHart

Major Professor: Amy L. Odum, Ph.D.
Department: Psychology

Delay-discounting procedures measure the decrease in the value of an outcome as the delay to the receipt of that outcome increases. The degree to which individuals discount delayed outcomes is said to be an underlying mechanism of many problematic behaviors including drug abuse, gambling, and risky sexual behaviors. Greater discounting is positively correlated with engagement in these behaviors. From this perspective, delay discounting is a general process that leads to maladaptive behaviors and has been suggested to have trait-like qualities. However, evidence suggests that delay discounting is also the aggregate product of separate psychological processes. Common quantitative models do not describe these processes. Latent factor modeling may allow for the identification of the individual components that sum to delay discounting. Chapters 2 and 3 present findings that demonstrate that framing of the delay or outcome unit can change delay discounting and encourage a further understanding of the underlying components of delay discounting. Chapter 4 describes the results of an experiment that seeks to identify the psychological processes of delay discounting to better understand how it can be changed. The results of Chapter 4 do not demonstrate that the previously proposed components of marginal utility and cardinal utility account for how delayed outcomes are discounted. Nonlinear time perception; however, does appear to account for a portion of how delayed outcomes are discounted. The results of Chapter 4 also provide further evidence for delay discounting as a trait. Chapter 5 provides a general discussion of the three papers.

(197 pages)

PUBLIC ABSTRACT

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Many problematic behaviors can be conceptualized as choosing a smaller, immediate outcome over a larger, delayed outcome. For example, drug abuse involves choosing between the immediate euphoric effects of the drug and the delayed health and legal consequences of drug abuse. Individuals that consistently choose the smaller outcome are said to behavior "impulsively." The goal of this dissertation was to understand how to change impulsive choice. Chapters 2 and 3 successfully demonstrate that impulsive choice can be altered by reframing how the choice is presented. For example, framing a delayed outcome using a specific date instead of a duration of time (e.g., 1 year) reduced impulsive choice. However, these findings do not explain why impulsive choice changed. The goal of Chapter 4 was to identify the underlying processes that result in impulsive choice with the hopes that by understanding these processes, impulsive choice can be reduced. Latent factor modeling was used to understand the role if three proposed processes in impulsive choice: marginal utility, cardinal utility, and nonlinear time perception. The results of the latent factor model indicated that nonlinear time perception does relate to how delayed outcomes are valued but not marginal utility and cardinal utility.

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CHAPTER 1

INTRODUCTION

Delay discounting is the process by which an outcome loses value as the delay to its receipt increases. Organisms are frequently faced with inter-temporal choices in which they must choose between a small but immediate outcome and a large but delayed outcome. Individuals that consistently choose the smaller, immediate outcome are said to choose “impulsively” (Ainslie, 1974). Delay-discounting tasks are one measure of impulsive choice and aim to identify a point of subjective indifference between a small, immediate outcome and a larger, delayed outcome. Importantly, impulsive choice, as measured by delay discounting, is strongly related to a variety of maladaptive behaviors including cigarette smoking (Bickel, Odum, & Madden, 1999; Mitchell, 1999), cocaine (Coffey, Gudleski, Saladin, & Brady, 2003; Heil, Johnson, Higgins, & Bickel, 2006), and heroin (Madden, Petry, Badger, & Bickel, 1997) abuse; gambling (Petry, 2001; Reynolds, 2006), risky sexual activity (Herrmann, Johnson, & Johnson, 2015; Reimers, Maylor, Stewart, & Chater, 2009), obesity (Fields, Sabet, Peal, & Reynolds, 2011; Fields, Sabet, & Reynolds, 2013), and even seatbelt use (Daugherty & Brase, 2010).

Delay discounting has strong trait-like tendencies (Odum, 2011) and is consistent across time without intervention (Kirby, 2009). How an individual discounts one outcome is strongly related to how they discount other outcomes (Friedel, DeHart, Madden, & Odum, 2014). These within-individual consistencies, as well as the strong correlation of delay discounting with maladaptive behaviors, have led some to posit that delay discounting is a general process that underlies impulsive choice (Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012; Bickel, Koffarnus, Moody, & Wilson, 2014).

However, there is also a growing body of evidence that indicates that despite its consistencies, delay discounting can be changed (Koffarnus, Jarmolowicz, Mueller, & Bickel, 2013). One such manipulation is differentially framing the delay or unit of the outcome. DeHart and Odum (2015) found that framing the delay to the larger outcome in specific dates (compared to calendar units of weeks and months) reduced delay discounting and that framing the delay in units of days (e.g., 9,000 days; compared to calendar units of weeks and months) increased discounting. Additionally, DeHart, Friedel, Frye, Galizio, and Odum (2017) found that framing the outcomes in fuzzy (e.g., less concrete) units increased delay discounting (e.g., 10 servings of peanuts compared to 50 peanuts). What remains unclear is why these manipulations alter delay discounting. Current models of delay discounting do not provide a clear explanation for understanding these findings.

Evidence exists to suggest that delay discounting is the aggregate result of various psychological processes. For example, time perception (Baumann & Odum, 2012; Zauberman, Kim, Malkoc, & Bettman, 2008), working memory capacity (Wesley & Bickel, 2014), general intelligence (Shamosh et al., 2008), and number fluency (e.g., numeracy; Peters et al., 2006) have all been found to relate to delay discounting and provide an explanation as to why delayed outcomes lose value hyperbolically. However, most theoretical models only weakly incorporate reductive psychological processes, if at all (e.g., Killeen, 2015; Mazur, 1987; Rachlin, 2006). These psychological processes may explain why certain interventions such as framing alter delay discounting.

The purpose of this dissertation is to better understand delay discounting by changing it through intervention and identifying its underlying components through statistical modeling. Chapter 2 presents the results of DeHart and Odum (2015) in which delayed outcomes were framed in specific dates, days, and calendar units. Chapter 3 presents the results of DeHart et al. (2017) in which the unit of the outcome was framed in clear and "fuzzy" units. Chapter 4 presents the results of a structural equation model analysis that explores three possible underlying processes of delay discounting: marginal utility, cardinal utility, and nonlinear time perception. Finally, Chapter 5 integrates the results of Chapters 2-4 and suggests future directions for investigating the underlying processes of delay discounting.

References

Ainslie, G. (1974). Impulse control in pigeons. *Journal of the Experimental Analysis of Behavior, 21*, 485-489.

Baumann, A. A., & Odum. A. L. (2012). Impulsivity, risk taking and timing. *Behavioural Processes, 90*, 408-414. doi: 10.1016/j.beproc.2012.04.005

Bickel, W. K., Jarmolowicz, D. P., Mueller, E. T., Koffarnus, M. N., & Gatchalian, K. M. (2012). Excessive discounting of delayed reinforcers as a trans-disease process contributing to addiction and other disease-related vulnerabilities: Emerging evidence. *Pharmacology and Therapeutics*, *134,* 287-297. doi: 10.1016/ j.pharmthera.2012.02.004

Bickel, W. K., Koffarnus, M. N., Moody, L., & Wilson, A. G. (2014). The behavioral- and neuro-economic process of temporal discounting: A candidate behavioral marker of addiction. *Neuropharmacolgy, 76*, 518-527. doi: 10.1016/ j.neuropharm.2013.06.013

Bickel, W. K., Odum, A. L., & Madden, G. J. (1999). Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. *Psychopharmacology, 146*, 447-545. doi: 10.1007/PL00005490

Coffey, S. F., Gudleski, G. D., Saladin, M. E., & Brady, K. T. (2003). Impulsivity and rapid discounting of delayed hypothetical rewards in cocaine-dependent individuals. *Experimental and Clinical Psychopharmacology, 11*, 18-25. doi: 10.1037/1064-1297.11.1.18

Daugherty, J. R., & Brase, G. L. (2010). Taking time to be healthy: Predicting health behaviors with delay discounting and time perspective. *Personality and Individual Differences, 48*, 202-207. doi: 10.1016/j.paid.2009.10.007

DeHart, W. B., Friedel, J. E., Frye, C. C. J., Galizio, A., & Odum, A. L. (2017). *A fistful of quarters: The effects of outcome unit framing on delay discounting.* Manuscript submitted for publication.

DeHart, W. B., & Odum, A. L. (2015). The effects of the framing of time on delay discounting. *Journal of the Experimental Analysis of Behavior, 103*, 10-21. doi: 10.1002/jeab.125

Fields, S., Sabet, M., Peal, A., & Reynolds, B. (2011). Relationship between weight status and delay discounting in a sample of adolescent cigarette smokers. *Behavioural Pharmacology*, *22*, 266-268. doi: 10.1097/FBP.0b013e328345c855

Fields, S., Sabet, M., & Reynolds, B. (2013). Dimensions of impulsive behavior in obese, overweight, and healthy-weight adolescents. *Appetite, 70*, 60-66. doi: 10.1016/j.appet.2013.06.089

Friedel, J. E., DeHart, W. B., Madden, G. J., & Odum, A. L. (2014). Impulsivity and cigarette smoking: Discounting of monetary and consumable outcomes in current and non-smokers. *Psychopharmacology, 231*(23), 4517-4526. doi: 10.1007/s00213-014-3597-z

Heil, S. H., Johnson, M. W., Higgins, S. T., & Bickel, W. K. (2006). Delay discounting in currently using and currently abstinent cocaine-dependent outpatients and non-drug-using matched controls. *Addictive Behaviors, 31*, 1290-1294. doi: 10.1016/j.addbeh.2005.09.005

Herrmann, E. S., Johnson, P. S., & Johnson, M. W. (2015). Examining delay discounting of condom-protected sex among men who have sex with men using crowdsourcing technology. *Aids and Behavior, 19*, 1655-1665. doi: 10.1007/s10461-015-1107-x

Koffarnus, M. N., Jarmolowicz, D. P., Mueller, E. T., & Bickel, W. K. (2013). Changing delay discounting in the light of the competing neurobehavioral decision systems theory: A review. *Journal of the Experimental Analysis of Behavior, 99*, 32-57. doi: 10.1002/jeab.2

Killeen, P. R. (2015). The arithmetic of discounting. *Journal of the Experimental Analysis of Behavior, 103*, 249-259. doi: 10.1002/jeab.130

Kirby, K. (2009). One-year temporal stability of delay-discount rates. *Psychonomic Bulletin & Review, 16*, 457-462. doi: 10.3758/PBR.16.3.457

Madden, G. J., Petry, N. M., Badger, G. J., & Bickel, W. K. (1997). Impulsive and self-control choices in opioid- dependent patients and non-drug-using control participants: Drug and monetary rewards. *Experimental and Clinical Psychopharmacology, 5*(3), 256-262.

Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. In M. L. Commons, J. E. Mazur, J. A. Nevin, & H. Rachlin (Eds.), *Quantitative analysis of behavior: Vol. 5 The effect of delay and intervening events on reinforcement value* (pp. 53-73). Hillsdale, NJ: Erlbaum.

Mitchell, S. H. (1999). Measures of impulsivity in cigarette smokers and non-smokers. *Psychopharmacology, 146*, 455-464. doi: 10.1007/PL00005491

Odum, A. L. (2011). Delay discounting: Trait variable? *Behavioural Processes, 87*(1), 1-9. doi: 10.1016/j.beproc.2011.02.007

Peters, E., Västjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science, 17*, 407-413. doi: 10.1111/j.1467-9280.2006.01720.x

Petry, N. M. (2001). Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology, 154*, 243- 250. doi: 10.1007/s002130000638

Rachlin, H. (2006). Notes on discounting. *Journal of the Experimental Analysis of Behavior, 85*, 425-435. doi: 10.1901/jeab.2006.85-05

Reimers, S., Maylor, E. A., Stewart, N., & Chater, N. (2009). Associations between a one-shot delay discounting measure and age, income, education and real-world impulsive behavior. *Personality and Individual Differences, 47*, 973-978. doi: 10.1016/j.paid.2009.07.026

Reynolds, B. (2006). A review of delay-discounting research with humans: Relations to drug use and gambling. *Behavioural Pharmacology, 17*(6), 651-667. doi: 10.1097/FBP.0b013e3280115f99

Shamosh, N. A., DeYoung, C. G., Green, A. E., Reis, D. L., Johnson, M. R., … Gray, J. R. (2008). Individual differences in delay discounting: Relation to intelligence, working memory, and anterior prefrontal cortex. *Psychological Science, 19*, 904-911. doi: 10.1111/j.1467-9280.2008.02175.x

Wesley, M. J., & Bickel, W. K. (2014). Remember the future II: Meta-analyses and functional overlap of working memory and delay discounting. *Biological Psychiatry, 75*, 435-448. doi: 10.1016/j.biopsych.2013.08.008

Zauberman, G., Kim, B. K., Malkoc, S. A., & Bettman, J. R. (2009). Discounting time and time discounting: Subjective time perception and intertemporal preferences. *Journal of Marketing Research, 46*, 543-556. doi: 10.1509/jmkr.46.4.543

CHAPTER 2

THE EFFECTS OF THE FRAMING OF TIME ON DELAY DISCOUNTING[1]

Introduction

Impulsivity is a multifaceted construct denoting several forms of potentially maladaptive behavior (Green & Myerson, 2013; Stahl et al., 2013). Commonly studied forms include the inability to refrain from a prepotent response (behavioral inhibition), lapses of attention, and the diminished ability of delayed consequences to influence behavior (de Wit, 2008). Insensitivity to delayed consequences is encompassed by delay discounting, which is the decrease in the present value of temporally remote outcomes (Mazur, 1987). If someone chooses a smaller sooner reward over a larger but more delayed reward, this behavior is termed impulsive; whereas, if someone forgoes a smaller sooner reward to receive a larger later reward, this behavior is termed self-controlled (Logue, 1988). For example, someone may forgo a dessert with tonight's dinner to achieve better health in the long term.

The degree to which delayed rewards are discounted is associated with the acquisition and maintenance of maladaptive behaviors. For example, substance abuse is consistently linked to steep delay discounting (de Wit, 2008). Better understanding the mechanisms of substance abuse is important because of its high economic and societal costs. In the U.S., the total annual economic cost of tobacco use alone is over $190 billion

[1] Chapter 2 of this dissertation was adapted from DeHart, W. B., & Odum, A. L. (2015). The effects of the framing of time on delay discounting. *Journal of the Experimental Analysis of Behavior, 103*, 10-21. (See Appendix A for permission letter.)

(Centers for Disease Control and Prevention [CDC], 2005). Problematic users of alcohol (e.g., Petry, 2001), cigarettes (e.g., Bickel, Odum, & Madden, 1999; Mitchell, 1999), cocaine (e.g., Heil, Johnson, Higgins, & Bickel, 2006), heroin (e.g., Madden, Petry, Badger, & Bickel, 1997), and methamphetamine (e.g., Hoffman et al., 2006) discount delayed outcomes more steeply than control participants who do not use these substances. In addition to substance abuse, steep delay discounting is also related to problematic gambling behaviors (e.g., Petry, 2001; Reynolds, 2006), obesity (e.g., Fields, Sabet, & Reynolds, 2013; Hendrickson & Rasmussen, 2013), and a variety of unhealthy behaviors, such as sedentary activity patterns and lack of safety belt use in automobiles (e.g., Daugherty & Brase, 2010).

Because steep delay discounting is related to socially significant behaviors, the development of techniques to reduce the degree of discounting could be helpful. For example, Bickel, Yi, Landes, Hill, and Baxter (2011) provided working memory training to people with stimulant abuse because working memory capacity is related to how steeply delayed rewards are discounted (Wesley & Bickel, 2014). Although the Bickel et al. intervention did not increase working memory capacity, the participants discounted delayed money less steeply at the end of training compared to a group that received sham training. In contrast, Renda, Stein, and Madden (2015) provided training intended to increase working memory ability in rats, but this training had no effect on delay discounting.

An alternative approach was taken by Morrison, Madden, Odum, Friedel, and Twohig (2014) who provided brief training in Acceptance and Commitment Therapy

(ACT) to college undergraduates who presented at baseline with steeper than average delay discounting. During the brief ACT exposure, the therapist worked to increase the student's tolerance for distressing and uncomfortable events and psychological experiences. Relative to a waitlist control group, the ACT group demonstrated more shallow delay discounting. These and other recent examples (e.g., Black & Rosen, 2011; Hendrickson & Rasmussen, 2013) provide promising evidence that delay discounting, despite being generally consistent within an individual (i.e., across commodities and time; Odum, 2011a), can be decreased by therapeutic means. These methods, however, are time and resource intensive, making their implementation limited.

Another means by which to influence delay discounting, the one investigated here, is the manner in which delay-discounting decisions are framed. Framing refers to the context in which a decision is presented (Tversky & Kahneman, 1981). This technique is of particular interest because it can be readily and immediately implemented. In a large meta-analysis, Kühberger (1998) demonstrated that framing has moderate influences on decision-making (mean $d = 0.33$). Specifically, Kühberger identified several aspects such as reference points, outcome salience, and response mode that affect choice. For example, in studies that change the reference point of a decision, participants are often confronted with identical outcomes that are framed as gains or losses. When the outcome is framed as a gain, participants are more likely to choose that outcome than when the outcome is framed as a loss, despite the outcomes being otherwise identical.

Tversky and Kahneman's (1981) disease outbreak scenario provides a well-known example of the effects of changing the reference point of a decision. Participants are assigned to either a gain or a loss scenario in which they must choose between two outcomes: one certain and one probabilistic. In the gain scenario, the certain outcome is to save 200 out of 600 lives; in the loss scenario, the certain outcome is to lose 400 out of 600 lives (the uncertain outcome is held constant across these scenarios). Despite the fact that the certain outcomes are functionally equivalent (200 people will live and 400 will die) the certain outcome is more frequently selected in the gain than in the loss scenario.

In delay discounting, framing outcomes as gains or losses affects decision making as well. For example, in a phenomenon known as *gain-loss asymmetry* or the *sign effect*, delayed gains are generally discounted more steeply than delayed losses (e.g., Baker, Johnson, & Bickel, 2003; Ohmura, Takahashi, & Kitamura, 2005; Tanaka, Yamada, Yoneda, & Ohtake, 2014). Another framing manipulation, Read, Frederick, Orsel, and Rahman (2005) found that framing the delay to the larger-later reward as a specific date (e.g., January 28, 2018) resulted in less steep discounting than framing the delay in calendar unit form (e.g., 3 years). This finding held true for a variety of delay durations, outcome amounts, and with hypothetical and real rewards. Similar results have been found in other studies (Klapproth, 2012; LeBoeuf, 2006).

One surprising finding from the Read et al. (2005) study was that when delayed rewards were framed as specific dates, point estimates of the rate of discounting appeared linear, indicative of exponential discounting. In exponential discounting (Samuelson, 1937), the present value of an outcome decreases by the same proportion per unit time. This finding was unexpected, because many studies examining delay discounting have found instead that discounting is hyperbolic: the present value of an outcome decreases proportional to the delay (Ainslie, 1992). Specifically, reward value decreases by an increasingly smaller proportion as delay increases (e.g., Bickel et al., 1999; Myerson & Green, 1995; Rachlin, Raineri, & Cross, 1991). Due to the nature of the procedure they used and the range of the indifference points obtained, Read et al. were not able to fit a theoretical model to their data to ascertain whether the present value of the delayed rewards was best described by an exponential or hyperbolic function.

Therefore, one of the main goals of the present study was to determine the best-fitting model for discounting when delays are described as specific dates. The theoretical model that best describes the discounting process is important, because different models can make different predictions about behavior (see Mazur, 2006; Odum, 2011a). For example, due to the deeply bowed shape of the hyperbolic curve relating present value to delay, hyperbolic discounting readily predicts the phenomenon of preference reversal. In this difficult behavior pattern, people may initially prefer a larger later reward, but as the time to obtaining the rewards draws nearer, switch their preference (“defect”) to the smaller sooner outcome. This phenomenon is familiar to people with addiction problems, for example, in which someone may quit taking a drug in hopes of achieving better health, only to relapse to drug use to gain a short-term high.

In this paper, we will evaluate three models to determine which provides the best description of the discounting process when delays are framed as specific dates. Equation 2-1 is an exponential model (Samuelson, 1937):

$$V = Ae^{-kD} \tag{2-1}$$

In this model, V is the present (discounted) value of a delayed outcome, A is the amount of that future outcome, D is the delay to the outcome, and k quantifies the degree to which the delayed outcome loses value as a function of delay. The mathematical constant e is approximately equal to 2.718 and is the base of the natural logarithm. Equation 2-2 is a hyperbolic model (Mazur, 1987):

$$V = \frac{A}{(1+k\mathrm{D})} \tag{2-2}$$

where the parameters are as in Equation 2-1. Equation 2-2 has been found to provide a better fit to data from nonhuman as well as human participants in delay discounting experiments (e.g., Bickel et al., 1999; Madden, Begotka, Raiff, & Kastern, 2003; Mazur, 1987; see also Odum, 2011a). We evaluated the fit of a third model as well, which for data from human participants often provides a better account than Equation 2-2 (e.g., McKerchar et al., 2009; Myerson & Green, 1995). Equation 2-3 is a hyperboloid model represented as

$$V = \frac{A}{(1+k\mathrm{D})^{s}} \tag{2-3}$$

with the addition of s as a scalar of delay and/or amount. If s is 1.0, Equation 2-3 reduces to Equation 2-2.

In addition to determining which theoretical model provided the best fit for discounting data when delays were framed as specific dates, we also sought to explore the generality of the framing effect. Framing time as a specific date, as opposed to calendar units, has been shown to reduce delay discounting. Could framing time differently than calendar units also increase the degree of delay discounting? To investigate the generalizability of the delay framing effect, we also compared the degree of discounting when delays were framed as a single short-duration calendar unit (days) vs. when they were framed in the typical way, as different calendar units (days, weeks, months, and years) depending on the delay duration. Thus, this study had two novel goals: (1) determine the effect of a new method of framing delays and (2) determine the best fit theoretical model when delays to rewards are framed in three different ways: in calendar units, as specific dates, and in days. Based on prior results obtained with a different procedure (Read et al., 2005), we predicted that when time was framed as a specific date, participants would discount less than when time was framed in calendar units (days, weeks, months, and years). Because of the novelty of the manipulation, we did not have a specific prediction for the degree of discounting obtained when the delay was framed in units of days as opposed to calendar units (days, weeks, months, and years). Finally, based on prior results (e.g., Myerson & Green, 1995; Rachlin et al., 1991), we predicted that the hyperbolic-type models (Equations 2-2 and 2-3) would provide a superior fit to the indifference points than the exponential model (Equation 2-1).

Method

Participants

Seventy-six undergraduate students (31 males, 45 females; mean age 21 years) took part in this experiment. Participants were recruited from a variety of introductory courses at Utah State University (USU) through classroom announcements and an online registration system. All students received course/laboratory credit or extra credit for participation. Of the 76 participants, 41 students (17 males, 24 females) were randomly assigned to the *specific date* condition and 35 students (14 males, 21 females) were randomly assigned to the *days* condition.

Procedure

Participants completed the experiment at a desk with a touch-screen computer in a private office. Each task in the experiment was programed using E-Prime computing software. All participants completed an informed consent document that was approved by the USU Institutional Review Board. Each session lasted approximately 1 hour. During the experimental session, participants also completed two unrelated delay-discounting tasks for food (data not presented here).

Participants completed two titrating delay-discounting tasks for hypothetical money. In one task, delays were described using calendar units (days, weeks, months, and years) and in the other task delays were framed as either specific dates or days, depending on the condition to which the participant was assigned. The order of the two tasks (calendar and dates/days) was random. Participants were not assigned to both the specific dates and days tasks to avoid the possibility of carryover effects. Each task began with instructions adapted from to those found in Odum, Baumann, and Rimington (2006), which read:

> The following choices are hypothetical, and you will not receive the actual outcomes. There are no "right" or "wrong" answers. Please just pick the choice that you prefer. Please note that the choices will switch sides randomly across questions. Please give special attention to the units of time as well as the amount that you are being asked about.

The delay discounting tasks determined the present value of the delayed outcome ($100) at a variety of delays. The procedure for all three delays was the same; only the manner in which time was framed differed. Each delay began with the following question: “Would you prefer $50 now or $100 in (delay)?” The position (left and right sides of the screen) of the immediate and delayed options was assigned randomly for each trial. The participant chose between the immediate and the delayed amounts using the touchscreen monitor. After each choice, the immediate amount was adjusted per Du, Green, and Myerson (2002). On the first question, the immediate amount was increased (if the delayed amount was chosen) or decreased (if the immediate amount was chosen) by $25. On the subsequent questions, the immediate amount was adjusted by 50% of the proceeding adjustment. The tenth question completed each delay presentation and the amount of the small immediate option on that trial was used as the indifference point for analysis. The indifference point represents the present value of the delayed amount at that delay.

In the calendar unit delay-discounting task, each participant made choices between smaller-sooner and larger-later rewards at six delays completed in the following order: 1 week, 2 weeks, 1 month, 6 months, 5 years, and 25 years (cf., Rachlin et al., 1991). In the specific date delay-discounting task, participants experienced the same delays framed as specific dates. For example, if the participant completed the task on January 1, 2014, they would see the following six delays: January 8, 2014; January 15, 2014; January 31, 2014; June 30, 2014; December 31, 2018; December 26, 2038, in that order. For the day’s delay-discounting task, each participant experienced the same delays, but described in terms of days: 1 day, 7 days, 14 days, 30 days, 180 days, 1.825 days and 9,125 days, in that order. The 1-day delay was added because a preliminary study of discounting in the calendar-unit and days tasks revealed substantial differences at the shortest delay (1 week). Therefore, to allow us to more fully characterize the discounting curves, we added the 1-day delay to the calendar-unit and days tasks in the *days'* condition.

Data Analysis

The three models of delay discounting (Equations 2-1, 2-2, and 2-3) were fit to the median group indifference points for each tasks using nonlinear regression (Graphpad Prism®). To compare these models of delay discounting we used the Akaike Information Criterion (AIC), which determines the relative quality of two models by comparing goodness of fit in light of parsimony (i.e., complexity). Models are compared in pairs, and a positive score indicates that the second of the two equations is preferred. Inferential statistical analyses were not conducted with the *k* parameter from Equation 2-3 because in the Myerson and Green (1995) model, the value of the *k* parameter interacts with the *s* parameter. Therefore, an independent interpretation of *k* is not appropriate.

Prior to fitting the models to the median indifference points, we applied the Johnson and Bickel (2008) criteria for identifying nonsystematic discounting. The first criterion is if an indifference point increases by more than 20% of the first indifference point. The second criterion is if the final indifference point is not less than 90% of the first indifference point. Data sets meeting either or both criteria were excluded. We only applied the criteria to data from the calendar unit task. If a participant's data met the exclusion criteria for the calendar unit task, all data from that participant were excluded from analysis. We did not exclude data from the specific dates and days tasks for nonsystematic discounting because we did not want to limit our ability to detect different patterns of discounting for these experimental tasks. In practice, however, removing all data from participants with nonsystematic data for the calendar unit task removed nonsystematic data for the experimental tasks as well, because participants with nonsystematic data for one task had nonsystematic data for the other task. Data from 4 and 9 participants were removed from the final analysis for *specific date* and *days* conditions, respectively. Comparisons of age and gender variables did not identify differences between participants whose data were removed for non-systematic discounting and those whose data remained.

To quantify the degree of delay discounting we calculated Area Under the Curve (AUC; Myerson, Green, & Warusawitharana, 2001). AUC is the sum of the area between each indifference point: $x_2 - x_1[(y_1+y_2)/2]$. The values x_1 and x_2 are the delays and y_1 and y_2 are the indifference points for those delays. AUC can range between 0 and 1, with lower AUC indicating greater delay discounting. Differences in AUC between tasks in each condition were analyzed using the Wilcoxon Matched-Pairs Signed Rank Test, which is a non-parametric statistic to analyze within-subject differences with two data points (essentially a non-parametric paired *t* test). For across condition comparisons (e.g., comparison of the AUC from the specific date and days condition), the Mann Whitney U (essentially a nonparametric independent samples *t* test) was used. These tests were chosen because AUC was not normally distributed for time framed as days ($W = 0.87$, $p < .01$) and time framed in the calendar unit form in the *days'* condition ($W = 0.92$, $p < 0.05$) or time framed in the calendar unit form in the *specific date* condition ($W = 0.92$, p

< .05). AUC was normally distributed for time framed as specific dates ($W = 0.99$, $p = 0.92$).

Results

Model Fits

The three models of delay discounting were fit to the median indifference points for each task using nonlinear regression. We used a two-stage analysis to determine the best fitting model overall. First, the fit of the exponential model (Equation 2-1) was compared to the fit of the hyperbolic model (Equation 2-2). The Akaike Information Criteria (AIC) and R^2 both favored the hyperbolic model (Table 2-1). Across the tasks, the median R^2 for the exponential model was 0.86, whereas for the hyperbolic model the median R^2 across the tasks was 0.94. Next, the hyperbolic (Equation 2-2) and hyperboloid (Equation 2-3) model fits were compared using AIC and R^2 values. Both measures favored the hyperboloid model (Table 2-1). The hyperboloid model provided an excellent fit to the median indifference points (median R^2 across tasks = 0.99) and the improvement in fit exceeded the loss of parsimony of the extra free parameter in the hyperboloid model as compared to the hyperbolic model as assessed by the AIC.

To further evaluate the appropriateness of the hyperboloid model, the three equations were fit to the indifference points for individual participants for each task. Table 2-2 displays the median values of the individual fits for the *k* and *s* parameters as well as the median R^2 values for each task. Equation 2-3 provided the best description of

Table 2-1

Equation 2-1 (Exponential) vs. Equation 2-2 (Hyperbolic) vs. Equation 2-3 (Hyperboloid) Model Fits to Group Median Indifference Points

		R^2				
Condition	Task	Exponential	Mazur (1987)	Myerson and Green (1995)	AIC Difference equation 1 vs. 2	AIC difference equation 2 vs. 3
Specific date						
	Specific date	0.81	0.93	0.99	5.99	7.74
	Calendar	0.91	0.97	0.99	6.57	9.43
Days						
	Days	0.85	0.92	0.98	4.14	2.03
	Calendar	0.86	0.95	0.99	7.03	17.66

Note. Comparison of Equation 2-1 (exponential), Equation 2-2 (hyperbolic) and Equation 2-3 (hyperboloid) model fits to group median indifference points. R^2 and AIC values favor Equation 3.

Table 2-2

Median of Equation 2-1 (Exponential), Equation 2-2 (Hyperbolic), and Equation 2-3 (Hyperboloid) Model Fits to Individual Indifference Points

		Free parameters				
Equation	Condition	k	s	R^2	AIC difference	Wilcoxon signed rank test
Exponential						
	Specific date	0.01		0.87		
	Calendar	0.02		0.86		
	Days	0.04		0.74		
	Calendar	0.01		0.79		
Mazur (1987)						
	Specific date	0.01		0.89	1.79	
	Calendar	0.03		0.91	2.54	
	Days	0.16		0.79	1.87	
	Calendar	0.02		0.83	2.82	
Myerson and Green (1995)						
	Specific date	0.01	0.73	0.95	4.38	-424.0*
	Calendar	0.03	0.76	0.96	5.27	-432.0**
	Days	0.13	0.66	0.97	1.93	-224.0*
	Calendar	0.007	0.59	0.97	0.25	-256.0*

Note. Equation 2-1 (exponential), Equation 2-2 (hyperbolic), and Equation 2-3 (hyperboloid) were fit to the indifference points for each participant. Median values of the individual fits are reported. All three equations have a k parameter. Only the Myerson and Green model includes the additional s parameter. AIC was used to compare Equation 2-1 to Equation 2-2 and Equation 2-2 to Equation 2-3. The Wilcoxon Signed Rank Test values report the comparison of the s parameter of the Myerson and Green (1995) model to the specific value of 1.

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

the individual participant data. The median R^2 for Equation 2-3 ranged from 0.95 to 0.97. We also determined whether the value of the exponent, *s*, was different from 1.0 using Wilcoxon Signed Ranks tests. For each task, the *s* parameter was significantly different from 1.0, indicating that this parameter is important in accounting for the variance in indifference points from individual participants (Table 2-2). Therefore, multiple forms of evidence indicate that the hyperboloid model (Equation 2-3) provided the best fit to the data for each task.

Specific Date Condition

For both the specific date and calendar unit discounting tasks, the present value of money decreased as the delay increased (Figure 2-1, top panel). The median indifference points decreased less when the delays were framed as specific dates than when the delays were framed in calendar unit of time. The hyperboloid model (Equation 2-3) provided a good fit to the individual and group median indifference points (see Tables 2-1 and 2-2).

To provide a summary measure of the steepness of discounting, Figure 2-1 (bottom panel) also presents the AUC obtained in the specific date task and the AUC obtained in the calendar unit task. The AUC was significantly greater in the specific date task (median = 0.51) as compared to the AUC in the calendar unit task (median = 0.34; $W = -351.00$, $p < .05$). This finding shows that framing time as a specific date, rather than in calendar units of time (days, weeks, etc.), resulted in less delay discounting. Finally, AUC for the specific-date and calendar-unit tasks were significantly and moderately positively correlated (Spearman Rho $r = 0.54$, $p < .001$).

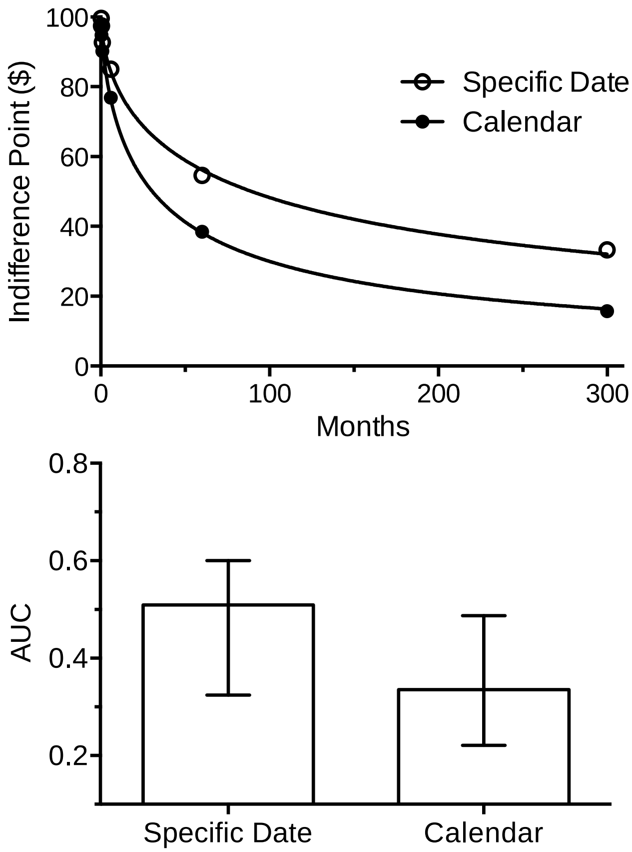

Figure 2-1. Discounting functions and AUC comparison for specific dates and calendar unit framing. Top panel: Temporal discounting functions when delays were expressed as specific dates (open circles) and calendar units (filled circles). Points show median indifference points for $100 as a function of delay. Lines show the best-fitting discounting functions generated by the hyperboloid model (Equation 2-3). Bottom panel: Median and interquartile ranges for the AUC of individual participants for the specific date and calendar units' delay discounting.

Days Condition

Figure 2-2 (top panel) shows that for both the calendar units and days units discounting tasks, the present value of the money decreased as the delay increased, with median indifference points decreasing more steeply when the delays were framed as days. The hyperboloid model (Equation 2-3) provided a good fit to the individual and group

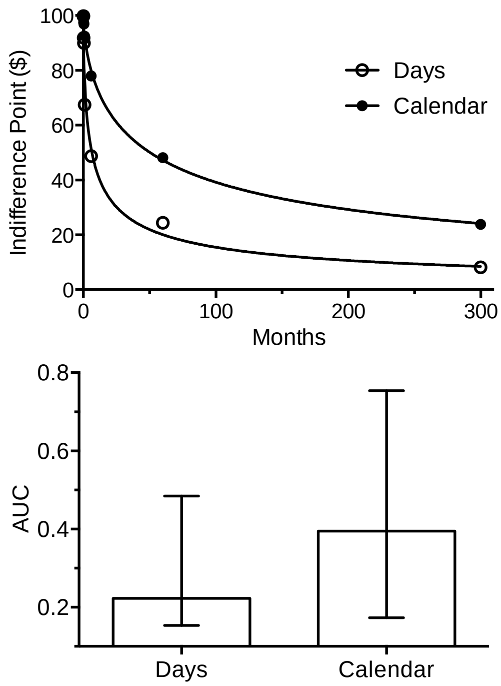

Figure 2-2. Discounting functions and AUC comparison for days and calendar unit framing. Top panel: Temporal discounting functions when delays were expressed as days (open circles) and calendar units (filled circles). Points show median indifference points for $100 as a function of delay. Lines show the best-fitting discounting functions generated by the hyperboloid model (Equation 2-3). Bottom panel: Median and interquartile ranges for the AUC of individual participants for the days and calendar units' delay discounting.

median indifference points (see Tables 2-1 and 2-2). Figure 2-2 (bottom panel) compares the median AUC values (and interquartile ranges) obtained in the days and calendar-units' tasks. The AUC was significantly less in the days' task (median = 0.22) as compared to the AUC in the calendar units' task (median = 0.40; $W = 171.00$, $p < .001$). Thus, delays degraded present value more when delays were framed as days than when delays were framed in calendar units. The AUC values obtained in the days and calendar-units tasks were significantly and strongly positively correlated within individuals (Spearman Rho $r = 0.75$, $p < .001$).

Comparisons Across Conditions

We also compared AUC value obtained in the calendar-units task across the specific-date and days conditions. These results should be interpreted with caution because the number of indifference points differed across conditions (six for the specific date condition and seven for the days' condition). Despite these procedural differences, AUC did not significantly differ between groups (*U* = 412.00, p = 0.66). Also, we compared AUC values obtained in the specific date and days tasks (an across-participants comparison). AUC was significantly different between groups (*U* = 237.00, p < .01) with participants discounting less when time was framed as specific dates than when time was framed as days.

Discussion

There were three main findings in the present experiment. First, how time is framed had clear effects on the degree of delay discounting. When time was framed as a specific date, participants discounted less steeply than they did when time was framed in calendar units (weeks, months, years). Conversely, when time was framed in days, participants discounted more steeply than they did when time was framed in calendar units. Second, the form of the discounting function when delays were framed as specific dates was not exponential, as had been suggested by (Read et al., 2005). Instead, the discounting functions were more hyperbolic than exponential, and more hyperboloid model than the hyperbolic. Finally, the degree of discounting in the calendar task was significantly positively correlated with the degree of discounting for both the specific date and days tasks. Below we discuss each of these findings in turn.

Results of the specific dates condition replicates previous findings that framing delays as specific dates results in less discounting than when time is framed in the calendar units (LeBoeuf, 2006; Read et al., 2005). This finding was demonstrated using both hyperboloid model fits and AUC. Additionally, this finding held when we examined discounting using an adjusting procedure that obtained indifference points at a wide range of delays (Du et al., 2002), expanding the generality of this effect to a different delay discounting procedure than has been used previously.

The hyperboloid model (Equation 2-3) provided a better fit to the indifference point data from all of the tasks than either the exponential (Samuelson, 1937; Equation 2-1) or hyperbolic (Equation 2-2) models. This finding is in contrast to that of Read et al. (2005), who found that point estimates of the rate of discounting showed a linear, rather than hyperbolic, decrease with increases in delay when delays were framed as specific dates. They suggested it was possible that the manner in which specific dates were framed could change not only the degree of delay discounting but also the form of the discount function (hyperbolic vs. exponential). Read and colleagues did not use the same procedure for generating indifference points, nor did they use as wide of a range of delays, as we did in the present study. Specifically, we used shorter delays, which comprise a range over which the functions may differ substantially. These procedural differences may have allowed us to more fully characterize the discount function. Thus, changing the delay frame, while changing how steeply delayed outcomes are discounted, does not appear to change the discounting process *per se*. Changes in discounting produced by delay framing would seem to be changes in the *degree* of discounting, not the *kind* of discounting.

We also found that not only did the hyperbolic (Equation 2-2) provide a better fit to the indifference points than the exponential model (Equation 2-1), a newer hyperboloid model (Equation 2-3) provided a superior fit than the hyperbolic model did. The data from discounting with different delay frames support those from a variety of studies (see McKerchar et al., 2009) showing that at least for human data, the hyperboloid provides a better description of the indifference points from delay discounting procedures. The superiority of the fit of the hyperboloid model exceeded that obtained by just adding an additional free parameter, because the AIC penalizes models for the added complexity inherent with more parameters. Instead, the hyperboloid model appears to capture meaningful variability in the form of the discount function generated by nonlinear effects of amount and/or time. At shorter delays, the indifference points decrease more steeply than predicted by the simple hyperbola, and at longer delays, the indifference points decrease less steeply than the simple hyperbola (see Odum et al., 2006). In conclusion, while the framing of time did alter the degree to which delayed outcomes were discounted, the manner in which delays were framed did not change which model provided the best description of the form of the discount function.

Importantly, we have generalized the effect of altering how delays are framed to include framing delays in solely units of days (e.g., 1,825). Framing time in units of days was found to have the opposite effect of framing time as specific dates. The time framed as days' task resulted in greater discounting compared to the calendar method of framing time in units of days, weeks, months and years.

A number of explanations exist for why framing time differently affects delay discounting. First, participants may have discounted delays framed in units of days more steeply because the high number of days may have been so large that the participants simply stopped attending to the delayed option. The opposite may be true for the specific date condition: framing time as a specific date may have increased how intently the participant attended to the delayed outcome.

There is evidence that changing attending to delayed outcomes changes the degree of discounting. For example, in the "explicit zero" effect (Radu, Yi, Bickel, Gross, & McClure, 2011) the default or null outcomes are stated directly. Rather than "a little now vs. a lot later," for example, choices are described as "a little now and nothing later vs. nothing now and a lot later." This form of framing reduces the degree of delay discounting, an outcome that Radu et al. attributed to enhanced attending to future outcomes.

An alternative, and not necessarily mutually exclusive possibility, is that when a delay is presented as a larger number (e.g., 1,825 days), the delay is perceived to be longer than when it is framed as a smaller number (e.g., 5 years). That is to say, despite the two methods describing the same objective time, they may not represent the same subjective time. People who perceive time as passing more quickly (i.e., overestimate the passage of time) show steeper discounting of money than people who perceive time as passing more slowly (Baumann & Odum, 2012). Therefore, in the present experiment, if framing delays in terms of days makes the delays appear longer, that could result in steeper discounting.

An additional explanation is that how time is framed may affect the valuation of delayed rewards. Specific neural structures such as the orbitofrontal cortex that allow an organism to experience the value of delayed rewards (Bar, 2009) have been shown to be involved in delay discounting processes (Torregrossa, Quinn, & Taylor, 2008). The orbitofrontal cortex is thought to be involved in the encoding of the quality, quantity, probability, and timing of a delayed reward (Windmann et al., 2006). Windmann et al. found that how outcomes are framed affects the extent to which this neural mechanism is engaged in the decision-making task. Using the Iowa gambling task, they found that different areas of the orbitofrontal cortex were activated depending on the perceived risk of the task. When greater risk was involved, the medial orbitofrontal cortex showed greater activation. When less risk was involved, the lateral orbitofrontal cortex showed greater activation. Patak and Reynolds (2007) found that delay discounting might also involve an assessment of risk. They asked participants about the likelihood that they would actually receive the delayed outcome. The longer the delay, the less was the perceived chance of actually receiving the delayed outcome. When delays are framed as specific dates, the outcome may be perceived as more certain and when time is framed in days, the outcome may be perceived as less certain. Therefore, how time is framed may differentially activate the neuroanatomical areas involved in valuation, resulting in different perceived levels of outcome risk.

Future research should focus on expanding the generality of the effects of framing time on delay discounting. For example, how does delay framing affect discounting of larger amounts (e.g., $10,000)? Would delay-framing effects generalize to nonmonetary outcomes (e.g., food), or to smaller units of time (e.g., 1 week vs. 0.019 years)? Delay framing may prove useful in applied and clinical settings. For example, when setting goals for abstinence, giving a specific date as a goal instead of a period of time may be a more effective strategy. Therefore, a goal for abstinence framed as “through January 31, 2014” may be more effective than a goal of “at least 30 days.” Framing the outcome more effectively may increase the present value of the delayed reward, therefore increasing the likelihood of obtaining that goal. Finally, future research should investigate the mechanism of the delay framing effect.

There are at least two potential limitations of the present study. First, we used hypothetical outcomes instead of real rewards. Perhaps the results would differ if people actually received the consequences of their choices. Studies that have explicitly compared the degree of discounting and the shape of discounting curves obtained using hypothetical and real outcomes generally find good concordance between the two methods though (see Odum, 2011a, for a complete discussion).

Second, the sample size used in the present study was not as large as in Read et al. (2005), who found that when delays were framed as specific dates, the pattern of discounting across delays appeared to suggest an exponential decay process rather than a hyperbolic one. In the present study, we replicated the main effect from Read and colleagues, that the degree of discounting was reduced when delays were framed as specific dates. Our adjusting procedure that obtained indifference points at a variety of delays allowed us to fit a theoretical model to the data, which Read et al. were not able to do. Thus, while the limited data of Read et al. suggested discounting might be exponential with delays framed as specific dates, our more extensive investigation of that element of their findings does not support that suggestion. Our sample size was sufficient to allow detection of the main result, that discounting is shallower with delays framed as specific dates, and therefore we do not believe that sample size was a factor in our finding that the shape of the discounting curve was hyperboloid in nature.

Regardless of the mechanism of the effect of framing of time on delay discounting and possible limitations of our procedure, the present study replicated the relation between the degree of discounting as measured in one task and the degree of discounting as measured in another task (see Odum, 2011b; Johnson & Bickel, 2002; Rodzon, Berry, & Odum, 2011). Participants who tended to show steep discounting as measured in the calendar units' task showed steep discounting as measured in the other task. Similarly, people who show steep discounting of one type of outcome tend to show steep discounting for another type of outcome (Charlton & Fatino, 2008; Odum, 2011b), and people who show steep discounting at one time point tend to show steep discounting when assessed at other time points (up to a year later; Kirby, 2009; Simpson & Vuchinich, 2000). These types of findings and others have led us to suggest in that delay discounting may have enduring trait-like aspects (Odum, 2011a, 2011b).

Fortunately, in addition to trait influences, delay discounting also shows strong state influences and is also potentially modifiable. Some promising interventions to reduce the degree to which people discount delayed outcomes include neurocognitive rehabilitation through working memory enhancement (Bickel et al., 2011), financial education and training (Black & Rosen, 2011), and acceptance and mindfulness interventions (Hendrickson & Rasmussen, 2013; Morrison et al., 2014). These interventions, though providing encouraging results, are in some cases time- and resource-intensive. Framing manipulations, however, are potentially immediate and relatively easily accomplished (Radu et al., 2011), and thus provide a promising additional avenue for research into effective ways to modify maladaptive steep delay discounting.

References

Ainslie, G. (1992). *Picoeconomics: The strategic interaction of successive motivational states within the person.* Cambridge: UK, Cambridge University Press.

Baker, F. Johnson, M. W., & Bickel, W. K. (2003). Delay discounting in current and never-before cigarette smokers: Similarities and differences across commodity, sign, and magnitude. *Journal of Abnormal Psychology, 112*(3), 382-392. doi: 10.1037/0021-843X.112.3.382

Bar, M. (2009). The proactive brain: Memory for predictions. *Philosophical Transactions of the Royal Society B: Biological Sciences, 364*(1521), 1235-1243. doi: 10.1098/rstb.2 008.0310

Baumann, A. A., & Odum, A. L. (2012). Impulsivity, risk taking, and timing. *Behavioral Processes, 90*(3), 408-414. doi: 10.1016/j.beproc.2012.04.005

Bickel, W. K., Odum, A. L., & Madden, G. J. (1999). Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. *Psychopharmacology, 146,* 447-545. doi: 10.1007/PL00005490

Bickel, W. K., Yi, R., Landes, R. D., Hill, P. F., & Baxter, C. (2011). Remember the future: Working memory training decreases delay discounting among stimulant addicts. *Journal of Biological Psychiatry, 69*(3), 260-265. doi: 10.1016/j.biopsych.2010.08.017

Black, A. C., & Rosen, M. I. (2011). A money management-based substance use treatment increases valuation of future rewards. *Addictive Behaviors, 36*, 125-128. doi: 10.1016/j.addbeh.2010.08.014

Centers for Disease Control and Prevention. (2005). Smoking: Attributable mortality, years of potential life lost, and productivity losses—United States, 2000-2004. *Journal of the American Medical Association, 301*(6). doi: 10.1001/jama.301.6.593

Charlton, S. R., & Fantino, E. (2008). Commodity specific rates of temporal discounting: Does metabolic function underlie differences in rates of discounting? *Behavioural Processes, 77*(3), 334-342. doi: 10.1016/j.beproc.2007.08.002

Daugherty, J. R., & Brase, G. L. (2010). Taking time to be healthy: Predicting health behaviors with delay discounting and time perspective. *Personality and Individual Differences, 48,* 202-207. doi: 10.1016/j.paid.2009.10.007

de Wit, H. (2008). Impulsivity as a determinant and consequence of drug use: A review of underlying processes. *Addiction Biology, 14*, 22-31. doi: 10.1111/j.1369-1600.2008.00129.x

Du, W., Green, L., & Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *The Psychological Record, 52,* 479-492. doi: 10.1037/e527342012-639

Fields, S. A., Sabet, M., & Reynolds, B. (2013). Dimensions of impulsive behavior in obese, overweight, and healthy-weight adolescents. *Appetite, 70*, 60-66. doi: 10.1016/j.appet.2013.06.089

Green, L., & Myerson, J. (2013). How many impulsivities? A discounting perspective. *Journal of the Experimental Analysis of Behavior, 99*(1), 3-13. doi: 10. 1002/jeab.1

Heil, S. H., Johnson, M. W., Higgins, S. T., & Bickel, W. K. (2006). Delay discounting in currently using and currently abstinent cocaine-dependent outpatients and non-drug-using matched controls. *Addictive Behaviors, 31,* 1290-1294. doi: 10.1016/j.addbeh.2005.09.005

Hendrickson, K. L., & Rasmussen, E. B. (2013). Effects of mindful eating training on delay and probability discounting for food and money in obese and healthy-weight individuals. *Behaviour Research and Therapy, 51*, 399-409. doi: 10.1016/j.brat.2013.04.002

Hoffman, W. F., Moore, M., Templin, R., McFarland, B., Hitzemann, R. J., & Mitchell, S. H. (2006). Neuropsychological function and delay discounting in methamphetamine-dependent individuals. *Psychopharmacology, 188*(2), 162-170. doi: 10.1007/s00213-006-0494-0

Johnson, M. W., & Bickel, W. K. (2002). Within-subject comparison of real and hypothetical money rewards in delay discounting. *Journal of the Experimental*

Analysis of Behavior, 77(2), 129-146. doi: 10.1901/jeab.2002.77-129

Johnson, M.W., & Bickel, W.K. (2008). An algorithm for identifying nonsystematic delay-discounting data. *Experimental and Clinical Psychopharmacology, 16*(3), 264-274. doi: 10.1037/1064-1297.16.4.321

Kirby, K. N. (2009). One-year temporal stability of delay-discounting rates. *Psychonomic Bulletin & Review, 16*(3), 457-462. doi: 10.3758/PBR.16.457

Klapproth, F. (2012). The date-delay framing effect in temporal discounting depends on substance abuse. *Behavioural Processes, 90*, 420-423. doi: 10.1016/j.beproc.2012.03.013

Kühberger, A. (1998). The influence of framing on risky decisions: A meta-analysis. *Organizational behavior and Human Decision Processes, 75*(1), 23-55. doi: 10.1006/obhd.1998.2781

LeBoeuf, R. A. (2006). Discount rates for time versus dates: The sensitivity of discounting to time-interval description. *Journal of Marketing Research, 43,* 59-72. doi: 10.1509/jmkr.43.1.59

Logue, A. W. (1988). Research on self-control: An integrating framework. *Behavioral and Brain Sciences, 11*(4), 665-679. doi: 10.1017/S0140525X00053978

Madden, G. J., Begotka, A. M., Raiff, B. R., & Kastern, L. L. (2003). Delay discounting of real and hypothetical rewards. *Experimental and Clinical Psychopharmacology, 11*(2), 139-145. doi: 10.1037/1064-1297.11.2.139

Madden, G. J., Petry, N. M., Badger, G. J., & Bickel, W. K. (1997). Impulsive and self-control choices in opioid-dependent patients and non-drug-using control participants: Drug and monetary rewards. *Experimental and Clinical Psychopharmacology, 5*(3), 256-262. doi: 10.1037/1064-1297.5.3.256

Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. In: Commons ML, Mazur JE, Nevin JA, Rachlin, H (Eds), *Quantitative analysis of behavior: Vol. 5. The effect of delay and intervening events on reinforcement value* (pp. 55-73). Erlbaum, Hillsdale, NJ.

Mazur, J. E. (2006). Mathematical models and the experimental analysis of behavior. *Journal of the Experimental Analysis of Behavior, 85*, 275-291. doi: 10.1901/jeab.2006.65-05

McKerchar, T. L., Green, L., Myerson, J., Pickford, T. S., Hill, J. C., & Stout, S. C. (2009). A comparison of four models of delay discounting in humans. *Behavioural Processes, 81,* 256-259. doi: 10.1016/j.beproc.2008.12.017

Mitchell, S. H. (1999). Measures of impulsivity in cigarette smokers and non-smokers. *Psychopharmacology, 146*(4), 455-464. doi: 10.1007/pl00005491

Morrison, K. L., Madden, G. J., Odum, A. L., Friedel, J. E., & Twohig, M. P. (2014). Altering impulsive decision making with an acceptance-based procedure. *Behavior Therapy, 45*(5), 630-639. doi: 10.1016/j.beth.2014.01.001

Myerson, J., & Green, L. (1995). Discounting of delayed rewards: Models of individual choice. *Journal of the Experimental Analysis of Behavior, 64,* 263-276. doi: 10.1901/jeab.1995.64-263

Myerson, J., Green, L., & Warusawitharana, M. (2001). Area under the curve as a measure of discounting. *Journal of the Experimental Analysis of Behavior, 76*, 235-243. doi: 10.1901/jeab.2001.76-235.

Odum, A. L. (2011a). Delay discounting: I'm a *k*, you're a *k*. *Journal of the Experimental Analysis of Behavior, 96*, 427-439. doi: 10.1901/jeab.2011.96-423.

Odum, A. L. (2011b). Delay discounting: Trait variable? *Behavioural Processes, 87,* 1-9. doi: 10.1016/j.beproc.2011.02.007

Odum, A. L., Baumann, A. A. L., & Rimington, D. D. (2006). Discounting of delayed hypothetical money and food: Effects of amount. *Behavioral Processes, 73,* 278-284. doi: 10.1016/j.beproc.2006.06.008

Ohmura, Y., Takahashi, T., & Kitamura, N. (2005). Discounting delayed and probabilistic monetary gains and losses by smokers of cigarettes. *Psychopharmacology, 182,* 508-515. doi: 10.1007/s00213-005-0110-8

Patak, M., & Reynolds, B. (2007). Question-based assessments of delay discounting: Do respondents spontaneously incorporate uncertainty into their valuations for delayed rewards? *Addictive Behaviors, 32,* 351-357. doi: 10.1016/j.addbeh.2006.03.034

Petry, N. M. (2001). Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology, 154*, 243-250. doi: 10.1007/s002130000638

Rachlin, H., Raineri, A., & Cross, D. (1991). Subjective probability and delay. *Journal of the Experimental Analysis of Behavior, 55*(2), 233-244. doi: 10.1901/jeab.1991.55-233

Radu, P. T., Yi, R., Bickel, W. K., Gross, J. J., & McClure, S. M. (2011). A mechanism for reducing delay discounting by altering temporal attention. *Journal of the Experimental Analysis of Behavior, 96*(3), 363-385. doi: 10.1901/jeab. 2011.96.363

Read, D. Frederick, S., Orsel, B., & Rahman, J. (2005). Four score and seven years from now: The date/delay effect in temporal discounting. *Management Science, 51*(9), 1326-1335. doi: 10.1287/mnsc.1050.0412

Renda, C. R., Stein, J. S., & Madden, G. J. (2015). Working-memory training: Effects on delay discounting in male Long Evans rats. *Journal of the Experimental Analysis of Behavior, 103*, 50-61. doi: 10.1002/jeab.115

Reynolds, B. (2006). A review of delay-discounting research with humans: Relations to drug use and gambling. *Behavioural Pharmacology, 17*(6), 651-667. doi: 10.1097/fbp.0b013e3280115f99

Rodzon, K., Berry, M. S., & Odum, A. L. (2011). Within-subject comparison of degree of delay discounting using titrating and fixed sequence procedures. *Behavioural Processes, 86*(1), 164-167. doi: 10.1016/j.beproc.2010.09.007

Samuelson, P. A. (1937). A note on the measurement of utility. *Review of Economic Studies, 4*, 155-161. doi: 10.2307/2967612

Simpson, C. A., & Vuchinich, R. E. (2000). Reliability of a measure of temporal discounting. *The Psychological Record, 50*, 3-16.

Stahl, C., Voss, A., Schmitz, F., Nuszbaum, M., Tüscher, O., Lieb, K., & Klauer, K. C. (2013). Behavioral components of impulsivity. *Journal of Experimental Psychology: General, 143*(2), 850-886. doi: 10.1037/a0033981

Tanaka, S. C., Yamada, K., Yoneda, H., & Ohtake, F. (2014). Neural mechanisms of gain-loss asymmetry in temporal discounting. *Journal of Neuroscience, 34*(16), 5595-5602. doi: 10. 1523/JNEUROSCI.5169-12.2014

Torregrossa, M. M., Quinn, J. J., & Taylor, J. R. (2008). Impulsivity, compulsivity, and habit: The role of the orbitofrontal cortex revisited. *Biological Psychiatry, 63*(3), 253-255. doi: 10.1016/j.biopsych.2007.11.014

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211*(4481), 453-458. doi: 10.1126/science.7455683

Wesley, M. J., & Bickel, W. K. (2014). Remember the future II: Meta-analysis and functional overlap of working memory and delay discounting. *Biological Psychiatry, 75*(6), 435-448. doi: 10.1016/j.biopsych.2013.08.008

Windmann, S., Kirsch, P., Mier, D., Stark, R., Walter, B., Güntürkün, O., … Vaitl, D. (2006). On framing effects in decision making: Linking lateral versus medial orbitofrontal cortex activation to choice outcome processing. *Journal of Cognitive Neuroscience, 18*(7), 1198-1211. doi: 10.1162/jocn.2006.18.7.1198

CHAPTER 3

A FISTFUL OF QUARTERS: THE EFFECTS OF OUTCOME UNIT FRAMING ON DELAY DISCOUNTING[2]

Introduction

People are frequently faced with choosing between a small but immediate outcome and a comparatively larger but delayed outcome. An individual that more consistently prefers the smaller, immediate outcome to the larger, delayed outcome is said to behave in a relatively "impulsive" manner (Ainslie, 1974). An example of an impulsive decision is eating a poor diet now (choosing the small, immediate outcome) at the expense of long-term health (the large, delayed outcome).

Delay discounting encompasses this insensitivity to delayed outcomes. Delay discounting is the process by which delayed outcomes lose value (Mazur, 1987; see also Odum, 2011). The degree to which delayed outcomes lose value is an important predictor of the acquisition and maintenance of many maladaptive behaviors (Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012; de Wit, 2008). Delayed outcomes are more steeply discounted in users of cocaine (e.g., Heil, Johnson, Higgins, & Bickel, 2006), cigarettes (e.g., Bickel, Odum, & Madden, 1999; Mitchell, 1999; Reynolds, Richards, Horn, & Karraker, 2004), alcohol (e.g., Petry, 2001), heroin (e.g., Odum, Madden, Badger, & Bickel, 2000), and methamphetamine (e.g., Hoffman et al., 2006) compared to

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[2] Chapter 3 of this dissertation was adapted from "A fistful of quarters: The effects of outcome unit framing on delay discounting," DeHart, W. B., Friedel, J. E., Frye, C. C. J., Galizio, A., & Odum, A. L. (n.d.). This manuscript is currently being revised for the *Journal of the Experimental Analysis of Behavior*. (See Appendix B for permission letters.)

discounting by individuals who do not use these substances. In addition to substance abuse, steep delay discounting is also related to problematic gambling behaviors (e.g., Petry, 2001; Reynolds, 2006), obesity (e.g., Fields, Sabet, & Reynolds, 2013; Hendrickson & Rasmussen, 2013), and safety belt use in automobiles (e.g., Daugherty & Brase, 2010).

Because steep delay discounting is related to a variety of maladaptive behaviors, interest has grown in the development of techniques to reduce delay discounting. Acceptance and Commitment Therapy (ACT) and mindfulness training have been productive avenues in regards to decreasing delay discounting. For example, Morrison, Madden, Odum, Friedel, and Twohig (2014) administered a brief ACT intervention to college students who met a criterion for steep discounting. The ACT intervention sought to increase the participant's tolerance of negative emotional experiences such as distress. Delay discounting was reduced for the students receiving the ACT intervention compared to a waitlist control group. Hendrickson and Rasmussen (2013) found that a mindful-eating intervention was also an effective intervention to decrease delay discounting. Participants were given the option of several foods to sample and instructed to attend to the various sensations of eating including the texture and taste of the food choice. Participants that engaged in mindful eating experienced a decrease in delay discounting for food compared to baseline. Working-memory training has also been shown to effectively reduce delay discounting. Bickel, Yi, Landes, Hill, and Baxter (2011) administered working-memory training to participants that abused stimulants. After several training sessions, participants in the working-memory-training condition demonstrated a decrease in delay discounting compared to participants in the sham training condition. However, a more recent attempt to replicate the finding that working memory training reduces delay discounting was unsuccessful (Rass et al., 2015).

Although various interventions have proven effective for reducing delay discounting (Koffarnus, Jarmolowicz, Mueller, & Bickel, 2013), several disadvantages hinder their administration. One disadvantage of the interventions described so far is that they can require a large time investment. Another disadvantage is that an expert is often needed to effectively administer the intervention. For example, a trained clinician may be needed to administer ACT or to train others to administer the treatment. Both of these disadvantages may be required to effect a lasting change in behavior that generalizes across context, but less-intensive methods of influencing choice are also valuable. An alternative approach that is not hindered by these same restrictions is differential framing of the decision. Framing refers to the specific context of how a decision is presented (Tversky & Kahneman, 1981), such as the probability or unit of an outcome, while maintaining the objective components of the decision. One advantage of framing over more time-intensive interventions is that it can be employed to influence many decision-makers at once. For example, menu items can be framed to encourage patrons to choose a healthier food item. While this framing intervention may not produce a lasting change in an individual's behavior, it has the possibility of influencing many individual's immediate choice.

Framing has been shown to affect decision making in a variety of contexts (Kühberger, 1998). In Tversky and Kahneman's (1981) original example, individuals were presented with a choice scenario and asked to choose between a certain and probabilistic outcome. In one group, the certain outcome was framed as a gain whereas in the second group the certain outcome was framed as a loss, even though the objective amount of both certain outcomes was identical. Participants in the gain group were more likely to choose a certain outcome compared to the loss group despite the outcomes being equivalent. In a more recent example, Gurm and Litaker (2000) informed a group of patients about the risks of undergoing a medical procedure. Half of the patients were shown a video that described the procedure as 99% safe whereas the video for the second group of patients described the likelihood of complications as 1 in 100. When told that the procedure would improve quality of life but not increase life expectancy, patients that viewed the "99% safe" video were more likely to consent to the surgery than patients that viewed the "complications of 1 in 100" video.

Framing has specifically been shown to reduce impulsive choice. Magen, Dweck, and Gross (2008) found that including an explicit zero in the intertemporal choice scenario increased choices for delayed outcomes. In other words, participants who chose between $10 today and $0 in 1 week or $0 now and $100 in 1 week (explicit zero condition) more often selected the delayed outcome than participants that chose between $10 today or $100 in 1 week (implicit zero condition). Radu, Yi, Bickel, Gross and McClure (2011) replicated this finding using delay-discounting tasks over the course of several experiments.

Other researchers have demonstrated that framing time for the delayed outcome can affect delay discounting. Read, Frederick, Orsel, and Rahman (2005) demonstrated that when the occurrence of the delayed outcome was framed as a specific date (e.g., July 10, 2021), the degree of discounting for participants was less steep compared to the degree of discounting of participants who answered choice scenarios with occurrence of the delayed outcome framed in units of weeks or months (e.g., in 60 months). Other researchers have replicated this finding between groups (Klapproth, 2012; LeBoeuf, 2006) and within subjects (DeHart & Odum, 2015). Additionally, DeHart and Odum found that participants discounted more when the delay was framed in units of days (e.g., 9,125 days) than when time was framed in units of weeks, months, and years (e.g., 25 years).

One unexplored manipulation within this paradigm is how the framing of the unit of the outcome affects delay discounting. For example, food is consistently discounted by delay more steeply than money (Friedel, DeHart, Madden, & Odum, 2014; Holt, Newquist, Smits, & Tiry, 2014; Odum, Baumann, & Rimington, 2006; Odum & Rainaud, 2003), even when the objective value of the food and the money is equated. Food is often framed in “fuzzy” units such as servings (Friedel et al., 2014) or bites (Rasmussen, Lawyer, & Reilly, 2010). Servings of food are “fuzzy” because the perception of the amount represented can vary between individuals. This fuzzy unit framing results in a less precise description of the actual amount of food that is represented in the delay-discounting task. Money, however, is always framed in the “clear” unit of dollars. A quantity of clear outcomes is more likely to be interpreted in the same manner across participants, whereas participants are more likely to differently interpret the quantity of fuzzy outcomes. Clear outcomes also do not require additional computation for comparison between amounts. Fuzzy framed outcomes may increase delay discounting by increasing the computational load required to make the decision, or by requiring the participant to rely more heavily on decision-making heuristics (e.g., larger amounts are discounted less than smaller amounts regardless of the outcome unit). The exact mechanism, however, is unknown.

In this study, we examined the effects of framing the outcomes in clear and fuzzy units on delay and probability discounting. Probability discounting tasks were included to investigate whether the effects of outcome unit framing were similar between delay and probability discounting. Comparing the results with delay discounting tasks to the results obtained with probability tasks is important as research suggests that delay and probability disocunting are separate processes, so it is unknown if fuzzy unit framing will affect both processes similarly (Myerson, Green, Hanson, Holt, & Estle, 2003). In Experiment 1, participants completed delay-discounting tasks that included both clear and fuzzy units of money and food. A subset of participants also completed two probability-discounting tasks for clear and fuzzy units of money. In Experiment 2, participants completed delay-discounting tasks that included clear units of dollars and clear units of quarters to determine if differences in handling costs between dollars and quarters account for the results of Experiment 1. Our prediction was that outcomes framed in clear units (e.g., dollars, 100 candy pieces) would be discounted less steeply than outcomes framed in fuzzy units (e.g., handfuls of quarters, servings). We were unsure, however, whether these results would generalize to probability discounting, given that probabilistic food rewards are not discounted differently than probabilistic money

(Estle, Green, Myerson, & Holt, 2007).

Experiment 1

Method

Participants. Sixty participants (29 males, 31 females, mean age of 35 years) were recruited from the community through online advertisements via Craigslist. Prior to any experimental tasks we obtained informed consent from each participant and answered any questions they had about the study. Participants were paid $25 for participating.

Procedure. All portions of this experiment were conducted in a private office. All experimental tasks were controlled with custom-written E-Prime (Psychology Software Tools, Inc.) experimental programs. Sessions were completed within approximately 40 minutes. The Institutional Review Board at Utah State University approved all procedures.

All participants completed four delay-discounting tasks presented in a random order. The delay-discounting tasks were identical except for the choice outcomes across tasks. Those outcomes were money in dollars (clear money), handfuls of quarters (fuzzy money), number of food items (e.g., 250 grapes; clear food), and servings of food (fuzzy food). Twenty participants also completed two probability-discounting tasks. The probability-discounting tasks were always experienced last to ensure that those participants' choices in the delay-discounting tasks were not affected by experiencing the probability-discounting task. These tasks were added to investigate whether the effects of framing generalized to probability discounting. The order of presentation of the two probability-discounting tasks was random. The choice alternative outcomes for the probability-discounting task were money in dollars (clear money) and handfuls of quarters (fuzzy money).

Seven indifference points were obtained for each task. The indifference point, or immediate amount of the outcome that is subjectively equivalent to the larger delayed or probabilistic outcome, was determined for each delay or probability using a titrating (e.g., adjusting) procedure (Du, Green, Myerson, 2002; Frye, Galizio, Friedel, DeHart, & Odum, 2016). Participants completed seven trials per delay or probability. On the first trial, participants were asked to choose between the immediate amount (1/2 of the delayed amount) and the larger delayed amount. Both choices were presented simultaneously to the participants and participants could make their choice either by touching the screen or by using the mouse to click a box that contained the choice text. If the participant chose the immediate amount, the immediate amount on the subsequent trial decreased by 50%. If the participant chose the delayed amount, the immediate amount on the subsequent trial increased by 50%. For the remaining questions, the immediate amount was increased or decreased by 50% of the previous titration. After the participant made the choice, a feedback screen displayed the text “You chose” followed by the text displayed on their desired choice alternative. All of the outcomes were hypothetical; the participants did not receive any of the outcomes associated with their choices. The delays for the delay-discounting tasks were: no delay (i.e., the choice alternatives were smaller and immediate vs. larger and immediate), 1 day, 1 week, 2 weeks, 1 month, 6 months, and 1 year. The probabilities for the probability discounting-tasks were: 100% likely, 95% likely, 75% likely, 50% likely, 33% likely, 10% likely, and 5% likely. No-delay and 100% probability conditions were included in the delay- and probability- discounting tasks to test the proportion of choice of the larger outcome when the only difference in the choices was amount. The now and 100% indifference points were not included in the model fits or AUC analyses.

All of the discounting outcomes were equated to \$50. The clear amount of money was displayed to participants as "\$50." For the clear amount of food, participants selected their favorite food item from a list of items. All of the items were small, easily quantifiable and cost approximately \$0.05 per unit. The amounts of food that participants were asked about were determined by the amount of that food item that could be obtained, based on local prices, for \$50. For example, the local unit price for a grape was \$0.05, so the larger amount of grapes was 1000 for all participants. The list of food items was M&M's®, grapes, Goldfish®, Skittles®, raisins, and peanuts.

The amounts for the participant-determined outcomes (i.e., fuzzy money and fuzzy food) were established by asking participants several questions. For the fuzzy money, all amounts of money were put in terms of "handfuls of quarters". Participants were asked how many quarters they could retrieve if they reached into a bucket of quarters and grabbed as many as possible at one time. The participant then typed into the computer the number of quarters. The number of quarters the participant reported as the amount they thought they could retrieve from the bucket was then divided into \$50 to give the number of handfuls used as the larger amount (for example, 20 quarters per handful would mean asking about a larger amount of "10 handfuls of quarters"). For the servings of food condition, participants were first asked their favorite food. Participants were then asked how much a serving of their favorite food cost. The cost was then divided into $50 to give the number of servings used as the larger amount (for example, $5 for a serving of hamburger would mean asking about a larger amount of "10 servings of hamburgers").

Data analysis. Results of the delay-discounting tasks were analyzed in two ways. First, two models of delay discounting were fit to indifference points via curvilinear regression. Indifference points were calculated as a proportion of the larger, delayed or probabilistic outcome. Indifference points for the probability discounting tasks were expressed as normalized indifference (indifference point amount / larger amount) as a function of probability (odds against; O = [1/p] - 1, where O represents odds against and p represents probability of obtaining the outcome), for clear money and fuzzy money. The no-delay and 100% probability indifference points were not included in the model fits. Equation 3-1 (Mazur 1987) is a one free-parameter hyperbolic model:

$$V = \frac{A}{1 + kD} \tag{3-1}$$

where *V* is the present (discounted) value of the delayed outcome, *A* is the amount of the delayed outcome, *D* is the delay to the outcome, and *k* is the degree to which the delayed outcome loses value as a function of delay. *k* is a free parameter that varies to produce a line of best fit through the data; the value of *k* determines the steepness of the delay discounting curve. We also evaluated a two free-parameter hyperbolic-like model, Equation 3-2 (Rachlin, 2006), which is similar to Equation 3-1 but with the addition of an *s* parameter for the nonlinear scaling of time:

$$V = \frac{A}{1 + kD^s} \tag{3-2}$$

Equations 3-1 and 3-2 were fit to both group median and individual indifference points using curvilinear regression (Graphpad Prism®). To compare the quality of models, the Akaike Information Criterion (AIC) was used. To determine the quality of a model fit, AIC weighs the goodness-of-fit against the number of free parameters in the model. Therefore, if both models fit equally well, the model with fewer parameters is favored. The lower the AIC value, the better the quality of the fit. Inferential statistics were not conducted on model parameters because the *k* and *s* parameters interact in Equation 3-2. Therefore, a comparison of *k* values between tasks would be inappropriate. The best fitting model (based on AIC comparisons) is displayed (Franck, Koffarnus, House, & Bickel, 2015).

Delay discounting was also assessed using Area Under the Curve (AUC; Myerson, Green & Warusawitharana, 2001). AUC is the sum of the trapezoidal area between each indifference point: x_2-x_1[(y_1+y_2)/2] where x_1 and x_2 are successive delays and y_1 and y_2 are successive indifference points at those delays. AUC can range between 0 and 1, with lower AUC values indicating greater delay discounting. AUCwas compared between conditions using generalized estimating equation (GEE) analyses and pairwise comparisons. GEE analysis is a regression technique for repeated dependent variables that are correlated (Hanley, Negassa, Edwardes, & Forrester, 2003). A Bonferroni adjustment was applied to all pairwise comparisons. For all analyses, the no-delay indifference points were not included in model fits or AUC comparisons but were analyzed separately. Data from all participants were included in the analyses.

Results

Two key analyses are presented. First, the results of the model fits to group median and individual indifference points are reported and the best fitting model is identified. Second, the results of the GEE analysis are reported.

Model fits. The two models of discounting were first fit to the group median indifference points for each task using nonlinear regression. Table 3-1 reports the model fit parameter estimates (*k* and *s*) as well as the goodness of fit and quality of fit measures (R^2 and AIC). Equation 3-1 was the better fitting model (lower AIC value) for clear delayed money, clear probabilistic money, and fuzzy probabilistic money. Equation 3-2 was the better fitting model for fuzzy money, clear food, and fuzzy food.

Figure 3-1 displays the model fits for all six outcomes. The best fitting model (lower AIC) is displayed for each outcome. Indifference points for all outcomes

Table 3-1

Experiment 1: Equation 3-1 (Hyperbolic) vs. Equation 3-2 (Hyperboloid) Model Fits to Group Median Indifference Points

		Hyperbolic (Mazur, 1987)			Hyperbooid (Rachlin, 2006)			
Condition	Outcome	*k*	R^2	AIC	*k*	*s*	R^2	AIC
Delay	Clear money	**0.005**	**.985**	**12.45**	0.011	0.869	.993	18.15
Delay	Fuzzy money	0.026	.824	27.38	**0.107**	**0.590**	**.973**	**26.05**
Delay	Clear Food	0.037	.754	28.48	**0.164**	**0.527**	**.973**	**25.29**
Delay	Fuzzy food	0.186	.757	27.32	**0.470**	**0.535**	**.962**	**26.21**
Probability	Clear money	**0.076**	**.993**	**11.07**	1.068	0.947	.994	20.47
Probability	Fuzzy money	**0.994**	**.996**	**8.33**	0.994	1.00[a]	.996	18.33

Note. Bold model fit values indicate a superior model fit. [a] indicates that the parameter estimate would have exceeded the constraint.

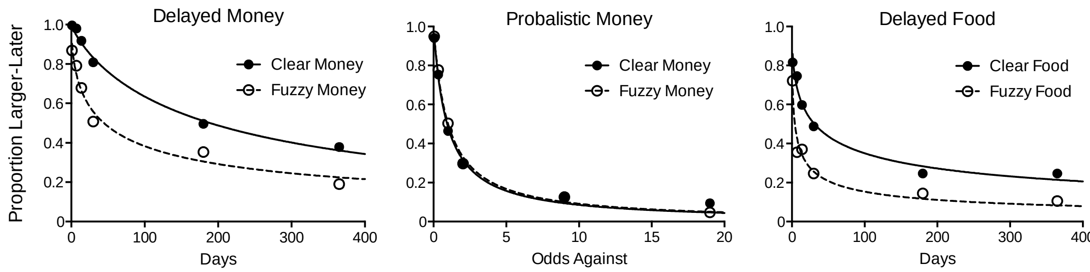

Figure 3-1. Discounting functions for clear and fuzzy framed outcomes. Delay discounting functions for clear and fuzzy unit outcomes. Points show median indifference points for $50, converted to proportion larger-later, as a function of delay. Lines show the best-fitting discounting functions for each task. Equation 3-1 is displayed for clear delayed money, clear probabilistic money, and fuzzy probabilistic money whereas Equation 3-2 is displayed for fuzzy delayed money, clear delayed food, and fuzzy delayed food. The no-delay condition indifference points are not presented in the model fits.

decreased as a function of delay. Overall, money was discounted less by delay than was food. Clear-framed money was discounted less than fuzzy-framed money. Clear-framed food was also discounted less than fuzzy-framed food. There was no effect of framing on the indifference points from the probability discounting tasks for money.

Next, the two models of delay discounting were fit to the indifference points for each participant. Table 3-2 reports the median R^2 and AIC values for model fits to individual participant data. Equation 3-1 provides a better quality of fit (i.e., lower AICc value) for all tasks at the individual participant level, despite Equation 3-2 having a higher R^2 value. This finding suggests that the additional goodness of fit provided by Equation 3-2 (compared to Equation 3-1) does not justify the greater complexity of that model. The model fits for money (delayed and probabilistic) were better than the model fits for food.

The difference in the quality of fits between clear and fuzzy framed outcomes was

Table 3-2

Experiment 1: Median Fit Values of Equation 3-1 (Hyperbolic), and Equation 3-2 (Hyperboloid) Model Fits to Individual Indifference Points

Condition	Outcome	Median R^2 Mazur	Median AIC Mazur	Median R^2 Rachlin	Median AIC Rachlin
Delay	Clear money	0.861	**25.85**	0.899	32.51
Delay	Fuzzy money	0.702	**28.47**	0.826	30.84
Delay	Clear food	0.546	**28.51**	0.816	33.79
Delay	Fuzzy food	0.031	**31.90**	0.685	34.09
Probability	Clear money	0.928	**-22.60**	0.962	-15.29
Probability	Fuzzy money	0.875	**-19.67**	0.918	-14.04

Note. Median R^2 value is the median of the R^2 values for the model fits to individual participant indifference points. Median AIC value is the median of the AIC values for the model fits to individual participant indifference points. Bold values indicate the superior fitting model.

compared by conducting a Wilcoxon matched-pairs test (e.g., nonparametric *t* test) on the R^2 values of the model fits to individual data. A nonparametric test was chosen because of the highly skewed distribution of R^2 values. The R^2 values derived from Equation 3-1 (Mazur, 1987) were used in the analyses because the median AIC score for individual fits favored Equation 3-1 in all cases. A statistically significant difference in the overall model fits was found between clear and fuzzy money (W = -643, $p < .001$) and clear and fuzzy food (W = -523, $p < .05$). This result indicates that Equation 3-1 fit clear-framed outcomes better than fuzzy outcomes.

Generalized estimating equation. GEE analyses were conducted to investigate the overall effects of clear versus fuzzy framing as well as the differences between individual tasks. Probability discounting results were not included in this model because visual analyses indicate that unit framing had no effect on probability discounting. Table 3-3 reports the parameter values for each factor. An unstructured correlation matrix was included in the model to control for the correlation between repeated measures. A

Table 3-3

Generalized Estimating Equation Results

Coefficient	β	Robust S.E.	Robust z
Intercept	0.821	0.086	9.500***
Framing condition	-0.186	0.048	-3.841***
Task type	-0.129	0.039	-3.349***

Note. Framing condition coefficient represents change from clear to fuzzy framing.

*** $p < .001$.

statistically significant main effect for the framing condition was found with a 0.186 average reduction in AUC in the fuzzy framing condition, indicating that fuzzy-framed outcomes were discounted more steeply than clear-framed outcomes. A statistically significant main effect for task type was also found. Pairwise comparisons revealed a statistically significant difference between clear money and fuzzy money (*MD* = 0.177, $p < .01$), clear money and clear food (*MD* = 0.166, $p < .01$), clear money and fuzzy food (*MD* = 0.250, $p < .001$) and clear food and fuzzy food (*MD* = 0.084, $p < .05$).

Figure 3-2 reports the mean AUC values with standard error bars for the delayed money and food conditions. The brackets identify significant pairwise comparisons as determined by the GEE analysis. Consistent with the indifference points displayed in Figure 3-1, Figure 3-2 shows that clear-framed outcomes were discounted less steeply by delay than were their fuzzy-framed alternatives. Also, fuzzy-framed money was discounted similarly to clear-framed food and fuzzy-framed food was discounted the most of any outcome.

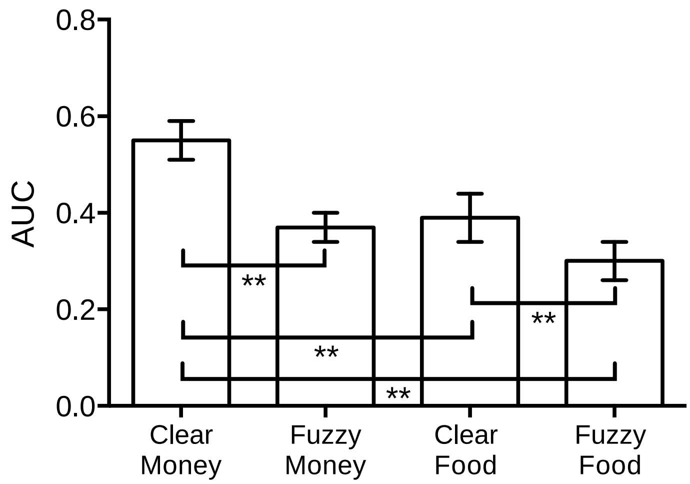

Figure 3-2. Graphic depiction of generalized estimating equation results. Mean area under the curve with structural equation model. Brackets connote statistically significant pairwise comparison. Asterisks indicate statistically significant differences.

We also analyzed the no-delay and 100% probability indifference points across all participants in all delay- and probability-discounting tasks in Experiment 1. These conditions were included to investigate if participants will choose the larger outcome when there is no delay or if the outcome is guaranteed. Most participants reliably selected the larger option (i.e., for most participants, the indifference point was greater than 80% of the larger outcome) when both outcomes were immediate. However, the proportion of individuals who did not select the larger option (i.e., the proportion of people whose indifference points were not greater than 80% of the larger outcome) when the outcomes were immediate were 0.017 for clear delayed money, 0.186 for fuzzy delayed money, 0.322 for clear delayed food, and 0.458 for fuzzy delayed food, 0.050 for clear probabilistic money, and 0.050 for fuzzy probabilistic money. For the majority of cases, when participants chose a smaller amount of food over a larger amount of food in the now condition, the indifference point for the first delay was larger.

Finally, AUC for each outcome was correlated to AUC for all other outcomes to investigate how the discounting of outcomes was related within individuals (Table 3-4). Pearson correlations were conducted on all possible outcome pairings. All outcomes from the delay-discounting tasks were moderately to strongly correlated indicating that how steeply one outcome was discounted was directly related to how steeply other outcomes were discounted.

Discussion

The goal of Experiment 1 was to extend the previous research on framing (DeHart & Odum, 2015) in delay-discounting tasks to the framing of the outcomes. Traditionally, monetary outcomes are framed as dollars (Bickel et al., 1999; Green, Myerson, Oliveira, & Change, 2013; Rachlin, Raineri, & Cross, 1991) whereas food outcomes are framed as servings or bites. In Experiment 1, we found that framing monetary outcomes in fuzzy units (i.e., handfuls of quarters) resulted in steeper discounting than when monetary outcomes were framed in clear units (i.e., dollars). We also found that framing food in clear units (e.g., 250 grapes) resulted in less discounting than when food was framed in

Table 3-4

Correlation Matrix

Task	Clear money	Fuzzy food	Clear food
Fuzzy money	0.752***	0.433**	0.339*
Clear food	0.558***	0.401***	
Fuzzy food	0.413**		

* $p < .05$.
** $p < .01$.
*** $p < .001$

fuzzy units (e.g., 25 servings). However, a direct comparison between the two food tasks is limited. In the clear food condition, participants chose a food outcome from a list of six food options previously selected by the researchers. In the fuzzy food condition, participants were asked about their favorite food. For most participants, the food choices were different for the two tasks. Finally, unit outcome framing did not affect discounting of probabilistic outcomes, providing additional evidence that delay and probability discounting are not affected the same way by some manipulations (Myerson et al., 2003). These findings provide further evidence that differential framing of the outcome can change how delayed outcomes are discounted.

One novel finding in the food delay-discounting tasks is that a large percentage (32-45%) of participants did not choose the larger outcome when both outcomes were to be delivered immediately. Many participants elected to receive a smaller amount of food now instead of a larger amount of food now, but almost exclusively choose the larger amount of money in the same scenario. Such behavior is not necessarily irrational in regards to food, but does limit direct comparisons between the discounting of money and food. For example, an individual may prefer one pizza now over 100 pizzas now because that individual can only consume one pizza and imagines that most of the 100 pizzas would be wasted. Research has indicated that humans have an aversion to waste (Bolton & Alba, 2012). Though we did not explicitly state food storage options, it is possible that participants interpreted that larger amounts of food would be wasted. Importantly, the indifference point for the first delay was typically larger than the now condition indifference point. Therefore, it was not possible to include the now indifference point in the model fit analyses. Further research should investigate if informing participants that they do not have to eat all of their food choice at that moment but can instead prepare to store surplus food reduces the proportion of participants that choose a smaller amount in the now condition.

Finally, the model fits for clearly framed outcomes were superior to fuzzy framed outcomes. One possibility, which does not appear to be the case, is that fuzzy-framed outcomes are discounted less hyperbolically than clear-framed outcomes. To evaluate this possibility, we fit the hyperbolic model (Equation 3-1) and an exponential model (Samuelson, 1937) to the individual data from Experiment 3-1 for clear and fuzzy framed money and food. The hyperbolic model (Equation 3-1) was favored over the exponential model for all outcomes, although the proportion of data sets for which the hyperbolic model was favored differed between clear and fuzzy framed outcomes. Sign tests were conducted to determine how likely the reported proportion of hyperbolic model fits to exponential model fits would be found due to chance. In all cases, the sign test results were statistically significant suggesting that the proportion of hyperbolic model fits was larger than would be expected by chance. The hyperbolic model fit to individual indifference points was chosen (had a lower AIC) over an exponential model fit to individual indifference points in 38 of 59 individuals ($p < .05$) in the clear money condition and 51 of 59 individuals ($p < .001$) in the fuzzy money condition. The hyperbolic model fit to individual indifference points was also chosen over the exponential model fit to individual indifference points in 43 of 59 individuals ($p < .001$) in the clear food condition and 52 of 59 individuals ($p < .001$) in the fuzzy food condition.

Another possible explanation for the finding that fuzzy-framed outcomes yielded lower R^2 values than clear-framed outcomes is that fuzzy-framed outcomes produced less orderly data than clear-framed outcomes. This possibility does appear to be the case. Two suggested criteria for identifying nonsystematic data were applied to the data (Johnson & Bickel, 2002). The first criterion identifies participant data for which an indifference point is larger than the previous indifference point by 20% of the amount of the delayed outcome. The second criterion identifies participant data in which the final indifference point is larger than 90% of the first indifference point. More participant data met at least one of the two suggested criteria for identifying nonsystematic discounting when the outcomes were framed in fuzzy units than when the outcomes were framed in clear units (48 out of a total of 118 for fuzzy-framed outcomes versus 25 out of 118 for clear-framed outcomes; $\chi^2 = 9.073$, $p < .01$). Thus, fuzzy-framed outcomes resulted in a greater degree of discounting by delay as well as less systematic patterns of discounting compared to clear-framed outcomes.

Experiment 2

One possible explanation for the finding that fuzzy money is discounted more than clear money is the increased handling cost associated with the fuzzy option (i.e., having $10 in quarters is more burdensome than having a $10 bill). The goal of Experiment 2 was to investigate the difference in delay discounting of quarters and dollars when both outcomes are framed using clear units. On one hand, if the difference in delay discounting found in Experiment 1 was due to increased handling costs, quarters should be discounted more than dollars. On the other hand, if the difference was due to clear versus fuzzy outcome unit framing, quarters should be discounted similarly to dollars.

Method

Participants. Twenty-three participants (19 males, 4 females, mean age of 20 years) were recruited from introductory courses at Utah State University via an online recruitment tool. Prior to any experimental tasks we obtained informed consent from each participant and answered any questions about the study. Participants received course credit for participating.

Procedure. All portions of this experiment were conducted in a private office. All experimental tasks were controlled with custom-written E-Prime (Psychology Software Tools, Inc.) experimental programs. Sessions were completed within 20 minutes. The Institutional Review Board at USU approved all procedures.

Participants completed two randomly presented tasks: discounting of delayed money for $50 (displayed in dollars), discounting of delayed money for $50 (in units of quarters). The adjusting amount procedure (Du et al, 2002; Frye et al., 2016) was used to establish indifference points and was identical to the procedure described for Experiment 1.

Results

Equation 3-1 and Equation 3-2 were fit to the group median indifference points (with the exception of the no-delay data indifference point) for each task using nonlinear regression. The no-delay indifference points were not included because they did not differ from the one-day indifference points. Table 3-5 reports the parameter estimates and goodness and quality of fit measures (R^2 and AIC) for each model. Equation 3-1 (Mazur, 1987) was a higher quality fit for all conditions. Equation 3-1 and Equation 3-2 were also fit to individual participants' indifference points. Table 3-6 reports the median R^2 and AIC values for model fits to individual participant data. Equation 3-1 provides a better quality of fit (i.e., lower AICc value) for all tasks at the individual participant level, despite Equation 3-2 having a higher R^2 value. This finding shows that the additional goodness of fit provided by Equation 3-2 (compared to Equation 3-1) does not justify the greater complexity of that model.

The left panel of Figure 3-3 shows the line of best fit (Equation 3-1) for the median indifference points (with the exception of the no-delay indifference point) for dollars and quarters. Indifference points for $50 and 200 quarters decreased as a function of delay. Dollars and quarters were discounted similarly. To provide a summary measure of the steepness of discounting, the right panel of Figure3-3 shows mean AUC compared

Table 3-5

Experiment 2: Equation 3-1 (Hyperbolic) vs. Equation 3-2 (Hyperboloid) Model Fits to Group Median Indifference Points

		Hyperbolic (Mazur, 1987)			Hyperboloid (Rachlin, 2006)			
Condition	Outcome	k	R^2	AIC	k	s	R^2	AIC
Delay	Dollars	**0.003**	**.909**	**18.98**	0.012	0.711	.939	26.61
Delay	Quarters	**0.002**	**.909**	**19.52**	0.002	1.000[a]	.909	29.55

Note. Bolded model fit values indicate a superior model fit. The [a] indicates that the model arrived at the parameter constraint.

Table 3-6

Experiment 2: Median Fit Values of Equation 3-1 (Hyperbolic), and Equation 3-2 (Hyperboloid) Model Fits to Individual Indifference Points

Condition	Outcome	Median R^2 Mazur	Median AIC Mazur	Median R^2 Rachlin	Median AIC Rachlin
Delay	Dollars	**0.752**	**24.15**	0.871	27.32
Delay	Quarters	**0.867**	**23.22**	0.922	33.21

Note. Median R^2 value is the median of the R^2 values for the model fits to individual participant indifference points. Median AIC value is the median of the AIC values for the model fits to individual participant indifference points.

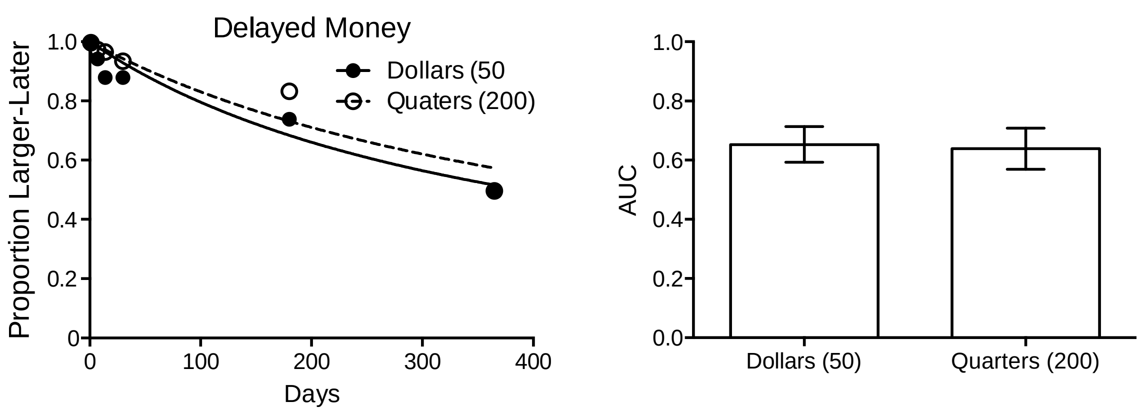

Figure 3-3. Discounting functions and AUC comparison of 50 dollars and 200 quarters. Left Panel: Delay discounting functions for money when the outcome unit was expressed as dollars (closed circles) or quarters (open circles). Points show median group indifference points for \$50, converted to proportion larger-later, as a function of delay. Lines show the best-fitting discounting functions for each task. Equation 3-1 is displayed for both outcomes. Right Panel: mean AUC from individual participants with SEM bars.

across outcomes (dollars and quarters). There was no significant difference in AUC between dollars (M = 0.653, SEM = 0.060) and quarters (M = 0.736, SEM = 0.068; $t(23) = 0.320$, $p = .752$, $d = 0.057$). Area Under the Curve for dollars and quarters was significantly positively correlated ($r = 0.788$, $p < .001$) demonstrating that how one outcome was discounted was strongly related to how the other outcome was discounted. Finally, we analyzed the no-delay indifference points. All participants chose the larger immediate outcome over the smaller immediate outcome for both the $50 and $50 in quarters conditions.

Discussion

Experiment 2 sought to clarify the results of Experiment 1 by framing the unit outcome as clear units of dollars or clear units of quarters. Although dollars and quarters were both discounted by delay in an orderly manner, there was no difference in the degree of discounting by delay between them. This finding suggests that the difference in delay discounting between clear money (dollars) and fuzzy money (handfuls of quarters) in Experiment 1 was not a result of the increased handling cost of handfuls of quarters. If the difference in Experiment 1 were due to handling costs, we would have expected quarters to be discounted more than dollars regardless of framing.

General Discussion

The purpose of these experiments was to further explore the effects of framing on delay discounting. Previous research has demonstrated that differential framing of delay to the receipt of the larger outcome can affect delay discounting (Read et al., 2005; DeHart & Odum, 2015); however, this is the first study to extend those findings to framing of the unit of the outcome. In Experiment 1, we demonstrated that framing the outcome in clear units (e.g., $50, 100 pieces of candy) resulted in less discounting than framing the outcome in fuzzy units (e.g., 4 handfuls of quarters, 2 servings of pizza). Experiment 2 clarified that the difference in discounting of money framed in dollars versus money framed in quarters is likely not due to the increased handling cost of quarters. How framing affects delay discounting, however, remains unclear. Finally, delay discounting was strongly correlated across outcomes, indicating that how one outcome is discounted is predictive of how other outcomes are discounted.

Research suggests that the value of an outcome is not absolute, but is strongly influenced by context (Lempert & Phelps 2016). Context can incorporate a variety of concepts including the presence of outcome-related stimuli, previously made choices, and motivational states of the individual. For example, one important context is how an outcome compares to other available outcomes (Kahneman & Tversky, 1991). Dai, Grace and Kemp (2009) found that if participants completed a delay-discounting task for a small amount of money ($50) first, they discounted $500 less on a subsequent task. However, if participants first completed a delay-discounting task for a large amount of money ($5,000), they discounted $500 more on a subsequent task compared to the first group. In our experiments, the framing of the unit of the outcome served as the context manipulation.

There are several possible explanations for why outcomes framed in clear units were discounted less by delay than outcomes framed in fuzzy units. The simplest explanation is that larger numbers (i.e., $50) are discounted less steeply than smaller numbers (i.e., 5 handfuls of quarters). The tendency to discount larger numbers less then smaller numbers of an outcome, the magnitude effect, has been consistently demonstrated (e.g., Green, Myerson, & McFadden, 1997; Green et al., 2013; Kirby, 1997). A variety of processes may be involved that account for magnitude effects, beyond the objective magnitude of the numerical representation of the outcome, such as satiation in non-monetary outcomes, etc. However, regardless of the process, neurological evidence supports the finding that large numbers are evaluated differently from small numbers. Arshad et al. (2016) demonstrated that different neural systems are involved in the processing of small and large numbers, which may result in different delay discounting processes for large and small amounts. It is possible that the observed difference in delay discounting between clear and fuzzy money in Experiment 1 is a result of the clear condition presenting larger numbers than the fuzzy condition. However, in Experiment 2, no difference was found between discounting of $50 and 200 quarters, suggesting that the difference in numerical amount did not account for the observed differences, but instead is something unique to fuzzy framing. Further research should combine a wider range of magnitudes (e.g., thimblefuls vs. handfuls) and delays to rule out alternative explanations.

Attentional processes may explain the way participants simplified the choice scenario to “big versus small.” Radu et al. (2011) demonstrated that the inclusion of an explicit 0 in the framing of the immediate and delayed outcomes decreased choice of smaller-sooner outcomes. They posit that the inclusion of an explicit 0 shifts attention from the now option to the delayed option. Differential framing of the outcome may serve to shift attention from the more complex complete unit (amount + unit) to the amounts. For example, the fuzzy framing of the handfuls of quarters may have caused an attentional shift from the more complicated objective amount of the outcome (e.g., 10 handfuls of quarters = $40) to simply focusing on the numerals of the choice (e.g., 10 handfuls of quarters = 10).

Individual differences in numeracy may also explain why, for some individuals, outcomes that are framed in fuzzy units are discounted more steeply than outcomes framed in clear units. Numeracy refers to an individual's ability to understand basic mathematical concepts such as amount, distance, and probability (Lipkus, Samsa, & Rimer, 2001). Research in numeracy has shown that individual differences in number processing ability influence how strongly framing manipulations affect decision making (Peters et al., 2006). Participants high in numeracy are more likely to process the entire choice decision (e.g., amounts, probability, etc.) whereas participants low in numeracy are more strongly influenced by how the decision is framed. Individuals low in numeracy may have been primarily responsible for the effects of framing on delay discounting because they were unable to translate the fuzzy framed outcomes into their clear equivalents. Future research should explore numeracy as a possible moderator of the effects of framing on delay discounting.

Finally, more complex framing may require greater effort to fully evaluate the choice and this increase in effort may result in steeper discounting. Previous findings indicate that as the required cognitive resources of evaluating a choice increases, the propensity for impulsive decision making increases (Deck & Jahedi, 2015). This finding has been extended to delay discounting. Hinson, Jameson and Whitney (2003) found that taxing working memory in participants through various techniques resulted in greater delay discounting (see Franco-Watkins, Rickard, & Pashler, 2010 for an alternative explanation of the effects of taxing working memory on delay discounting). Bickel et al. (2011) further investigated the relation between working memory and delay discounting. Participants that received working-memory training reported a decrease in delay discounting whereas participants in the control group did not. Certain ways of framing have been shown to increase the effort required to make a choice (Gonzalez, Dana, Koshino, & Just, 2005; Kuo, Hsu, & Day, 2009), which in turn may tax working memory and increase delay discounting. For example, Gonzalez et al. found that outcomes framed as a sure gain resulted in lower neural activity (suggesting lower effort in evaluating the choice) than when outcomes were framed as an uncertain gain.

We also found that for the discounting of food, participants did not consistently choose the larger outcome when there was no delay to its receipt. In human discounting research, participants are seldom asked to choose between small and large outcomes that are both immediately received. Not consistently choosing the largest possible outcome may be attributed to avoiding waste (Bolton & Alba, 2012) but there is another possible explanation.

Paglieri, Addessi, Sbaffi, Tasselli, and Delfino (2015) theorize that one explanation for the difference in delay discounting between outcomes is not due to the differential effects of delay on those outcomes but is a result of differing baseline motivations to maximize those outcomes. Similar to our findings, Paglieri et al. found that participants were more likely to maximize (e.g., choose the largest possible outcome) monetary outcomes than food outcomes. Paglieri et al. posit that one method to measure baseline motivation is to measure preference for different amounts of the outcome in the absence of delay. Future research should devise methods of incorporating baseline motivation into the theoretical models of delay discounting.

Finally, we found that delay discounting was significantly correlated across outcomes. People who showed relatively steep discounting for one outcome were likely to show relatively steep discounting for another outcome. This finding was true regardless of the framing condition. Previous research has also found that delay discounting is correlated across different outcomes (Friedel, et al., 2014, 2015) and framing conditions (DeHart & Odum, 2015). This finding adds to the growing body of evidence that delay discounting has trait-like characteristics (Odum, 2011) meaning that it is consistent within individuals across outcomes and also across time (Kirby, 2009).

In conclusion, we have extended the findings of the effects of framing on delay discounting to include outcome-unit framing. Regardless of the mechanism of how framing affects delay discounting, how the choice is presented can have an important impact on decision-making. One benefit of using framing to reduce impulsivity is that it can be relatively easy to employ. Although more intensive interventions have proven effective at reducing delay discounting such as working-memory training (Bickel et al., 2011) and mindfulness interventions (Morrison et al., 2014), framing provides a relatively simple way of affecting choice. For example, retirement savings could be increased or unhealthy eating behaviors decreased by properly framing relevant choice scenarios for the decision-maker. Interventions aimed at training individuals to take more time and attend fully to the choice may also reduce impulsivity. Miu and Crişan (2011) demonstrated that instructing participants to assess a choice carefully and increase decision-making time (e.g., cognitive reappraisal) improved economic decision making. A similar strategy could be extended to delay discounting by training individuals to reframe choice scenarios in a way that encourages self-control. Framing presents a promising avenue for better understanding the mechanisms of delay discounting as well as developing better methods for behavioral change.

References

Ainslie, G. (1974). Impulse control in pigeons. *Journal of the Experimental Analysis of Behavior, 21*, 485-489.

Arshad, Q., Nigmatullina, Y., Nigmatullin, R., Asavarut, P., Goga, U. … Malhotra, P. A. (2016). Bidirectional modulation of numerical magnitude. *Cerebral Cortex, 26*, 2311-2324. doi: 10.1093/cercor/bhv344

Bickel, W. K., Odum, A. L., & Madden, G. J. (1999). Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. *Psychopharmacology, 146*, 447-545. dio: 10.1007/PL00005490

Bickel, W. K., Yi, R., Landes, R. D., Hill, P. F., & Baxter, C. (2011). Remember the future: Working memory training decreases delay discounting among stimulant addicts. *Journal of Biological Psychiatry, 69*, 260-265. doi: 10.1016/ j.biopsych.2010.08.017

Bickel, W. K., Jarmolowicz, D. P., Mueller, E. T., Koffarnus, M. N., & Gatchalian, K. M. (2012). Excessive discounting of delayed reinforcers as a trans-disease process contributing to addiction and other disease-related vulnerabilities: Emerging evidence. *Pharmacology and Therapeutics*, *134,* 287-297. doi: 10.1016/ j.pharmthera.2012.02.004

Bolton, L. E., & Alba, J. W. (2012). When less is more: Consumer aversion to unused utility. *Journal of Consumer Psychology, 22*, 369-383. doi: 10.1016/ j.jcps.2011.09.002

Dai, Z., Grace, R. C., & Kemp, S. (2009). Reward contrast in delay and probability discounting. *Learning and Behavior, 37*, 281-288. doi: 10.3758/LB.37.3.281

Daugherty, J. R., & Brase, G. L. (2010). Taking time to be healthy: Predicting health behaviors with delay discounting and time perspective. *Personality and Individual Differences, 48*, 202-207. doi: 10.1016/j.paid.2009.10.007

de Wit, H. (2008). Impulsivity as a determinant and consequence of drug use: A review of underlying processes. *Addiction Biology, 14*, 22-31. doi: 10.1111/j.1369-1600.2008.00129.x

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review, 75*, 97-119. doi: 10.1016/j.euroecorev.2015.05.004

DeHart, W. B., & Odum, A. L. (2015). The effects of the framing of time on delay discounting. *Journal of the Experimental Analysis of Behavior, 103*, 10-21. doi: 10.1002/jeab.125

Du, W., Green, L., & Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *The Psychology Record, 52*, 479-492.

Estle, S. J., Green, L., Myerson, J., & Holt, D. D. (2007). Differential effects of amount on temporal and probability discounting of gains and losses. *Memory & Cognition, 34*, 914-928. doi: 10.3758/BF03193437

Fields, S. A., Sabet, M., & Reynolds, B. (2013). Dimensions of impulsive behavior in obese, overweight, and healthy-weight adolescents. *Appetite, 70*, 60-66. doi: 10.1016/j.appet.2013.06.089

Franck, C. T., Koffarnus, M. N., House, L. L., & Bickel, W. K. (2015). Accurate characterization of delay discounting: A multiple model approach using approximate Bayesian model selection. *Journal of the Experimental Analysis of Behavior, 103*, 218-233. doi: 10.1002/jeab.128.

Franco-Watkins, A. M., Rickard, T. C., & Pashler, H. (2010). Taxing executive processes does not necessarily increase impulsive decision making. *Experimental Psychology, 57*(3), 193-201. doi: 10.1027/1618-3169/a000024

Friedel, J. E., DeHart, W. B., Madden, G. J., & Odum, A. L. (2014). Impulsivity and cigarette smoking: Discounting of monetary and consumable outcomes in current and non-smokers. *Psychopharmacology, 231*, 4517-4526. doi: 10.1007/s00213-014-3597-z

Friedel, J. E., DeHart, W. B., Frye, C. C. J., Rung, J. M., & Odum, A. L. (2015). Discounting of qualitatively different delayed health outcomes in current and never smokers. *Experimental and Clinical Psychopharmacology, 24*, 18-29. doi: 10.1037/pha0000062

Frye, C. C. J., Galizio, A., Friedel, J. E., DeHart, W. B., & Odum, A. L. (2016). Measuring delay discounting in humans using an adjusting amount task. *Journal of Visualized Experiments, 107*, e53584-e53584. doi: 10.3791/53584

Gonzalez, C., Dana, J., Koshino, H., & Just, M. (2005). The framing effect and risky decisions: Examining cognitive functions with fMRI. *Journal of Economic Psychology, 26*, 1-20. doi: 10.1016/j.joep.2004.08.004

Green, L., Myerson, J., & McFadden, E. (1997). Rate of temporal discounting decreases with amount of reward. *Memory & Cognition, 25*, 715-723. doi: 10.3758/BF03211314

Green, L., Myerson, J., Oliveira, L., & Change, S. E. (2013). Delay discounting of monetary rewards over a wide range of amounts. *Journal of the Experimental Analysis of Behavior, 100*, 269-281. doi: 10.1002/jeab.45

Gurm, H. S., & Litaker, D. G. (2000). Framing procedural risks to patients: Is 99% safe the same as a risk of 1% in 100? *Academic Medicine, 75*, 840-842. doi: 10.1097/00001888-200008000-00018

Hanley, J. A., Negassa, A., Edwardes, M. D., & Forrester, J. E. (2003). Statistical analysis of correlated data using generalized estimating equations: An orientation. *American Journal of Epidemiology, 157*, 364-375. doi: 10.1093/aje/kwf215

Heil, S. H., Johnson, M. W., Higgins, S. T., & Bickel, W. K. (2006). Delay discounting in currently using and currently abstinent cocaine-dependent outpatients and non-drug-using matched controls. *Addictive Behaviors, 31*, 1290-1294. doi: 10.1016/j.addbeh.2005.09.005

Hendrickson, K. L., & Rasmussen, E. B. (2013). Effects of mindful eating training on delay and probability discounting for food and money in obese and healthy-weight individuals. *Behaviour Research and Therapy, 51*, 399-409. doi: 10.1016/j.brat.2013.04.002

Hinson, J. M., Jameson, T. L., & Whitney, P. (2003). Impulsive decision making and working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29*, 298-306.* doi: 10.1037/0278-7393.29.2.298

Hoffman, W. F., Moore, M., Templin, R., McFarland, B., Hitzemann, R. J., & Mitchell, S. H. (2006). Neuro-psychological function and delay discounting in methamphetamine-dependent individuals. *Psychopharmacology, 188*, 162-170. doi: 10.1007/s00213-006-0494-0

Holt, D. D., Newquist, M. H., Smits, R. R., & Tiry, A. M. (2014). Discounting of food, sex, and money. *Psychological Bulletin and Review, 21*, 794-802. doi: 10.3758/s13423-013-0557-2

Johnson, M. W., & Bickel, W. K. (2002). An algorithm for identifying nonsystematic delay-discounting data. *Experimental and Clinical Psychopharmacology, 16*, 264-274. doi: 10.1037/1064-1297.16.3.264

Kahneman, D., & Tversky, A. (1991). Loss aversion in riskless choice: A reference dependent model. *Quarterly Journal of Economics, 106*, 1039-1061.

Kirby, K. N. (1997). Bidding on the future: Evidence against normative discounting of delayed rewards. *Journal of Experimental Psychology: General, 126*, 54-70. doi: 10.1037/0096-3445.126.1.54

Kirby, K. N. (2009). One-year temporal stability of delay-discount rates. *Psychonomic Bulletin & Review, 16*(3), 457-462. doi: 10.3758/PBR.16.3.457

Klapproth, F. (2012). The date-delay framing effect in temporal discounting depends on substance abuse. *Behavioural Processes, 90*, 420-423. doi: 0.1016/j.beproc.2012.03.013

Koffarnus, M. N., Jarmolowicz, D. P., Mueller, E. T., & Bickel, W. K. (2013). Changing delay discounting in the light of the competing neurobehavioral decisions systems theory: A review. *Journal of the Experimental Analysis of Behavior, 99*, 32-57. doi: 10.1002/jeab.2

Kuo, F, Y., Hsu, C. W., & Day, R. F. (2009). An exploratory study of cognitive effort involved in decision under framing: An application of the eye-tracking technology. *Decision Support Systems, 48*, 81-91. do: 10.1016/j.dss.2009.06.011

Kühberger, A. (1998). The influence of framing on risky decisions: A meta-analysis. *Organizational Behavior and Human Decision Processes, 75*, 23-55. doi: 10.1006/obhd.1998.2781

LeBoeuf, R. A. (2006). Discount rates for time versus dates: The sensitivity of discounting to time-interval description. *Journal of Marketing Research, 43*, 59-72. doi: 10.1509/jmkr.43.1.59

Lempert, K. M., & Phelps, E. A. (2016). The malleability of intertemporal choice. *Trends in Cognitive Sciences, 20*, 64-74. doi: 10.1016/j.tics.2015.09.005

Lipkus, I. M., Samsa, G., & Rimer, B. K. (2001). General performance on a numeracy scale among highly educated samples. *Medical Decision Making, 21*, 37-44. doi: 10.1177/0272989X0102100105

Magen, E., Dweck, C. S. & Gross, J. J. (2008). The hidden zero effect: Representing a single choice as an extended sequence reduces impulsive choice. *Psychological Science, 19*(7), 648-649. doi: 10.1111/j.1467-9280.2008.02137.x

Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. In M. L. Commons, J. E. Mazur, J. A. Nevin, & H. Rachlin (Eds.) *Quantitative analysis of behavior: Vol. 5 The effect of delay and intervening events on reinforcement value* (pp. 53-73). Hillsdale, NJ: Erlbaum.

Mitchell, S. H. (1999). Measures of impulsivity in cigarette smokers and non-smokers. *Psychopharmacology, 146*, 455-464. doi: 10.1007/PL00005491

Miu, A. C., & Crişan, L. G. (2011). Cognitive reappraisal reduces the susceptibility to the framing effect in economic decision making. *Personality and Individual Differences, 51*, 478-482. doi: 10.1016/j.paid.2011.04.020

Morrison, K. L., Madden, G. J., Odum, A. L., Friedel, J. E., & Twohig, M. P. (2014). Altering impulsive decision making with an acceptance-based procedure. *Behavior Therapy, 45*, 630-639. doi: 10.1016/j.beth.2014.01.001

Myerson, J., Green, L., & Warusawitharana, M. (2001). Area under the curve as a measure of discounting. *Journal of the Experimental Analysis of Behavior, 76*, 235-243. doi: 10.1901/jeab.2001.76-235

Myerson, J., Green, L., Hanson, J. S., Holt, D. D., & Estle, S. J. (2003). Discounting delayed and probabilistic rewards: Processes and traits. *Journal of Economic Psychology, 24*, 619-635. doi: 10.1016/S0167-4870(03)00005-9

Odum, A. L. (2011). Delay discounting: I'm a *k*, you're a *k*. *Journal of the Experimental Analysis of Behavior*, *96*, 427-439. doi: 10.1901/jeab.2011.96-423

Odum, A. L., Baumann, A. A., & Rimington, D. D. (2006). Discounting of delayed hypothetical money and food: Effects of amount. *Behavioral Processes, 73*, 278-284. doi: 10.1016/j.beproc.2006.06.008

Odum, A. L., Madden, G. J., Badger, G. J., & Bickel, W. K. (2000). Needle sharing in opioid-dependent outpatients: psychological processes underlying risk. *Drug and Alcohol Dependence, 60*, 259-266. doi: 10.1016/S0376-8716(00)00111-3

Odum, A. L., & Rainaud, C. (2003). Discounting of delayed hypothetical money, alcohol, and food. *Behavioral Processes, 64*, 305-313. doi: 10.1016/S0376-6357(03) 00145-1

Paglieri, F., Addessi, E., Sbaffi, A., Tasselli, M. I., & Delfino, A. (2015). Is it patience or motivation? On motivational confounds in intertemporal choice tasks. *Journal of the Experimental Analysis of Behavior, 103*, 196-217. doi: 10.1002/jeab.118

Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science, 17*, 407-413. doi: 10.1111/j.1467-9280.2006.01720.x

Petry, N. M. (2001). Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology, 154*, 243- 250. doi: 10.1007/s002130000638

Rachlin, H. (2006). Notes on discounting. *Journal of the Experimental Analysis of Behavior, 85*, 425-435. doi: 10.1901/jeab.2006.85-05

Rachlin, H., Raineri, A., & Corss, D. (1991). Subjective probability and delay. *Journal of the Experimental Analysis of Behavior, 55*, 233-244. doi: 10.1901/jeab.1991.55-233

Radu, P. T., Yi, R., Bickel, W. K., Gross, J. J., & McClure, S. M. (2011). A mechanism for reducing delay discounting by altering temporal attention. *Journal of the Experimental Analysis of Behavior, 96*, 363-385. doi: 10.1901/jeab.2011.96-363

Rasmussen, E. B., Lawyer, S. R., & Reilly, W. (2010). Percent body fat is related to delay and probability discounting for food in humans. *Behavioral Processes, 83*, 23-30. doi: 10.1016/j.beproc.2009.09.001

Rass, O., Schacht, R. L., Buckheit, K., Johnson, M. W., Strain, E. C., & Mintzer, M. Z. (2015). A randomized controlled trial of the effects of working memory training in methadone maintencne patients. *Drug and Alcohol Dependence, 156*, 38-46. doi: 10.1016/j.drugalcdep.2015.08.012

Read, D., Frederick, S., Orsel, B., & Rahman, J. (2005). Four score and seven years from now: The date/delay effect in temporal discounting. *Management Science, 51*, 1326-1335. doi: 10.1287/mnsc.1050.0412

Reynolds, B., Richards, J. B., Horn, K., & Karraker, K. (2004). Delay discounting and probability discounting as related to cigarette smoking status in adults. *Behavioral Processes, 65*, 35-42. doi: 10.1016/S0376-6357(03)00109-8

Reynolds, B. (2006). A review of delay-discounting research with humans: Relations to drug use and gambling. *Behavioral Pharmacology, 17*, 651-667. doi: 10.1097/FBP.0b013e3280115f99

Samuelson, P. A. (1937). A note on the measurement of utility. *Review of Economic Studies, 4*, 155-161. doi: 10.2307/2967612. doi: 10.2307/2967612

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211*, 453-458. doi: 10.1126/science.7455683

CHAPTER 4

A LATENT DISCOUNTING MODEL: STRUCTURAL EQUATION MODELING ANALYSES OF DELAY DISCOUNTING

Introduction

Substance abuse, both illicit and nonillicit, costs more than half a trillion dollars per year in health care, lost productivity, crime, incarceration, and law enforcement (National Institute on Drug Abuse [NIDA], 2008). Unfortunately, substance abuse treatments are moderately effective at best, with 40-60% of participants experiencing relapse (NIDA, 2012). It is necessary to understand the psychological processes related to addiction if substance abuse treatments are to be improved. One process related to substance abuse is impulsive choice, as measured by delay discounting, which can be defined as choosing an immediate outcome over a larger delayed outcome (de Wit, 2008).

Various costly behaviors, including cigarette smoking (Bickel, Odum, Madden, 1999; Friedel, DeHart, Frye, Rung, & Odum, 2016; Friedel, DeHart, Madden, & Odum, 2014), cocaine (Coffey, Gudleski, Saladin, & Brady, 2003; Heil, Johnson, Higgins, & Bickel, 2006), methamphetamine (Hoffman et al., 2006), heroin (Madden, Petry, Badger, & Bickel, 1997), and alcohol (Petry, 2001) abuse can all be conceptualized as choosing the smaller, immediate outcome of substance abuse over the larger, delayed outcome of improved health and avoidance of negative legal and social consequences. Other costly behaviors such as risky sexual activity (Herrmann, Johnson, & Johnson, 2015; Reimers, Maylor, Swewart, & Chater, 2009), obesity (Fields, Sabet, Peal, & Reynolds, 2011; Fields, Sabet, & Reynolds, 2013; Weller, Cook, Edwin, Avsar, & Cox, 2008), and problematic gambling (Petry, 2001; Reynolds, 2006) show similar relationships, with greater impulsivity positively correlating with participation in the risky behavior.

Because of its pervasive relationship to many maladaptive behaviors, delay discounting has been referred to as a “trans-disease” process (Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012; Bickel, Koffarnus, Moody, & Wilson, 2014). In this view, delay discounting is a general process that underlies impulsive decision-making. Individuals that discount delayed outcomes steeply are at a higher risk for engaging in these behaviors. Some evidence exists to support that steep delay discounting precedes acquisition of such behaviors. Using a longitudinal design, Audrian-McGovern et al. (2009) found that steep delay discounting predicted acquisition of cigarette smoking and that delay discounting did not increase as a function of smoking acquisition. Fernie et al. (2013) similarly found that steep delay discounting predicted future problematic alcohol use in adolescents. They also did not find that alcohol use increased delay discounting. Evidence that steep delay discounting precedes addiction does not exclude the possibility that substance abuse also increases delay discounting (Landes, Christensen, & Bickel, 2012). There is a growing body of evidence that suggests that steep delay discounting plays a causal role in substance abuse acquisition and therefore supports the trans-disease theory.

Delay discounting could be referred to as trait (Odum, 2011) because it is consistent across time and by outcome. How an individual discounts one delayed outcome is strongly correlated with how they discount other delayed outcomes, providing further evidence for the general process view of delay discounting. Friedel et al. (2014) found that how an individual (both smokers and nonsmokers) discounted one outcome significantly correlated with how they discounted other outcomes. For example, a participant that steeply discounted delayed money was also likely to steeply discount delayed food, alcohol, and music. In a separate study, Friedel et al. (2016) also found that the delay discounting of qualitatively different outcomes (e.g., health and money) was strongly correlated within individuals. In one example, how participants discounted a monetary gain and a temporary improvement in overall health function was strongly correlated. Although some exceptions exist (Lawyer & Schoepflin, 2013), an individual that discounts one delayed outcome steeply will tend to discount other delayed outcomes steeply as well.

Finally, the general process/trait view of delay discounting is supported by the temporal consistency of delay discounting. Ohmura, Takahashi, Kitamura, and Wehr (2006) demonstrated that delay discounting, including individual indifference points, was stable over the course of three months. Kirby (2009) found that without intervention, delay discounting was stable over a year. In summary, these findings support the view of delay discounting as a trait because of its consistency between outcomes and across time.

One of the most widely used theoretical models of delay discounting, the hyperbola (Mazur, 1987), reflects this general process view. In this hyperbolic model (Equation 4-1),

$$V = \frac{A}{1+kD} \tag{4-1}$$

A is the amount of the delayed outcome, *D* is the delay and *k* is a free parameter that measure the rate at which the delayed outcomes lose value. Historically, Mazur derived this equation from the Matching Law and specifically from the idea that delay reduces the reinforcing value of an outcome (Mazur, 1987; Rachlin, 2006). In this context *k* is a descriptor that quantifies the effects of delay on reinforcer value. However, the parameter *k* may also represent the combination of different underlying psychological processes that combine to result in a reduction of the reinforcing value of a delayed outcome.

An alternative view of delay discounting posits that the devaluation of delayed outcomes as measured by delay-discounting tasks is the aggregate of multiple psychological processes. Individual differences in any one of these aggregated processes may in turn account for the differences in delay discounting found between groups. Some proposed psychological processes have been included in quantitative models of delay discounting such as nonlinear time perception, nonlinear amount perception, and marginal utility and cardinal utility.

Time Perception

Nonlinear time perception is one underlying process that has been explicitly incorporated into quantitative models of delay discounting. A vast body of literature has explored human (Grondin, 2001; Wearden, 1991; Zauberman, Kim, Malkoc, & Bettman, 2008) and nonhuman (Crystal, 2001) time perception and the general finding is that time is perceived nonlinearly. As with many psychophysical processes, the Weber-Fechner law describes subjective time perception as a logarithmic function (Dehaene, 2003; Grondin, 2001). For example, the perceived temporal distance between 1 week and 2 weeks is greater than the perceived temporal distance between 50 weeks and 51 weeks, despite the objective distance between the two being equal.

Two extensions of the hyperbolic model (Equation 4-1; Mazur 1987) incorporate the nonlinear perception of time. Myerson and Green (1995; Equation 4-2) proposed an additional free parameter:

$$V = \frac{A}{(1+kD)^s} \tag{4-2}$$

in which *s* scales for delay and/or amount. Rachlin (2006; Equation 4-3) proposes a similar model:

$$V = \frac{A}{1+kD^s} \tag{4-3}$$

in which *s* only scales delay. Importantly, both of these models frequently fit delay-discounting results better than the hyperbolic model (Franck, Koffarnus, House, & Bickel, 2015; McKerchar et al., 2009).

One difficultly of validating the inclusion of nonlinear time perception in the modeling of delay discounting in the above models is that *k* and *s* share variance. Therefore, examining the independent contributions of nonlinear time perception on the devaluation of delayed outcomes is not possible in these models. However, other research has found a relation between time perception and delay discounting.

Using a temporal bisection task, Baumann and Odum (2012) investigated the relationship of delay discounting and timing, as measured by a temporal bisection task. In the temporal bisection task, participants were asked to categorize the duration of a circle (range of 2-4 s) as either short or long, in reference to short (2 s) and long (4 s) comparison stimuli. They reported a moderate positive correlation (r = 0.228) between delay discounting and timing as measured by the temporal bisection task, meaning that an overestimation of time was related to greater delay discounting. Importantly, they did not find a significant correlation between probability discounting and timing.

On a larger time-scale than the temporal bisection task, Zauberman et al. (2008) further demonstrated that nonlinear time perception is one underlying components of delay discounting. Participants indicated on a number line how far into the future they perceived a delay to be. Participants did not report linear increases in subjective time perception as objective time increased. Instead, the researchers found that subjective time increased logarithmically as objective time increased, further supporting that Weber-Fechner Law's description of time perception is valid. The researchers also found evidence that logarithmic time perception accounts for why delayed outcomes are discounted hyperbolically (e.g., devaluation occurs rapidly at short delays and then slows and long delays). By statistically controlling for logarithmic time perception, the researchers found that the discounting of delayed money was consistent across time (e.g., exponential discounting).

Further supporting the role of logarithmic time perception in delay discounting, Takahashi (2005) presented a mathematical proof that demonstrates that by incorporating logarithmic time perception into exponential discounting (e.g., the rate of devaluation of a delayed outcome is constant across delays), delay discounting becomes hyperbolic-like. Specifically, Takahashi derives the Myerson and Green (1995) hyperboloid. This mathematical proof further supports the role of time perception as a key component of the delay discounting process.

Amount Perception and Utility

The nonlinear perception of amount may also influence how delayed outcomes are discounted. Halberda, Mazzocco, and Feigenson (2008) found individual differences in the accuracy of amount perception using pictures that displayed two groupings of colored (blue and yellow) dots. Participants were asked to indicate which group, blue or yellow, had more dots. Their findings suggest a nonlinear decrease in accuracy of amount perception as the difference between the two groups of colored dots decreased. Ren, Nicholls, Ma, and Chen (2011) found shared neurological processes for estimating the magnitude of a number, physical size of an object, and luminance, which indicates that amount is also perceived logarithmically.

Quantitative models of delay discounting have also incorporated nonlinear amount perception; however, with similar problems as time perception in that s and k cannot be investigated independently. The s parameter in Equation 4-2 (Myerson & Green, 1995) is actually a ratio that describes the nonlinear scaling of both time and amount. Roelofsma (1996) also presented a model that assumes nonlinear amount-perception and applies a Weber-Fechner law scaling to both the amount of the outcome and time.

The perceived utility of the outcome, and not just its objective amount, may also serve as an underlying components of delay discounting. Utility is a complex term that can refer to a variety of qualities of an outcome including the increase in subjective value from a unit increase in the outcome (marginal utility) and the hedonic (e.g., pleasure) value that a unit of an outcome brings (cardinal or experienced utility; Kahneman, Wakker, & Sarin, 1997). Like time perception, utility appears to be perceived nonlinearly (Harinck, Van Dijk, Van Beest, & Mersmann, 2007). For example, the increase in the utility of receiving $100 compared to $10 is not 10 times greater. Assuming logarithmic marginal utility, the increase in utility from $10 to $100 is closer to four times greater.

Other researchers have posited that similar conceptualizations of utility may play an important role in the discounting of delayed outcomes. The utility of an outcome, in part, may manifest in delay discounting tasks through the motivation to obtain that outcome. Paglieri, Addessi, Sbaffi, Tasselli, and Delfino (2015) theorize that one explanation as to why different outcomes are discounted at different rates (e.g., money vs. food; Friedel et al., 2014) is the motivation to obtain that outcome is different. Paglieri et al. suggest that the motivation to obtain an outcome could be investigated by asking participants to choose between a small amount of an outcome now and a large amount of an outcome now. Participants should universally choose the largest amount of money now; however, how they should respond regarding food is less clear. The utility of food is less than money, meaning that it would not be uncommon for a participant to choose a smaller amount of food now. Alternatively, as the amount of food increases, an individual may reach a saturation point and now the utility of food has converted to disutility. This same process does not apply to money, as money typically has no saturation point. Both explanations may account for why food is discounted more than money. Unfortunately, though Paglieri et al. offer an interesting explanation as to why different outcomes are discounted differently, there is little empirical evidence to test this hypothesis (see DeHart, Friedel, Frye, Galizio, & Odum, 2017, for a tentative example).

Various models of delay discounting have attempted to incorporate the nonlinear perception of utility. Read (2001) and Doyle and Chen (2012) both propose models that incorporate nonlinear utility. A recently proposed model of delay discounting, the additive-utility model (Killeen, 2009, 2015), attempts to incorporate both utility and time perception but is difficult to test directly. In this model:

$$U(v,t) = w(k_v v)^\alpha - (1-w)(k_t t)^\beta \qquad (4\text{-}4)$$

the value (v) of an outcome as a function of time (t) is calculated as the utility of the outcome ($(k_v v)^\alpha$) a combination of cardinal and marginal utility) minus the disutility of waiting for that outcome ($(k_t t)^\beta$). To date, only one attempt has been made to directly test this model (Friedel, 2016). Friedel independently derived the free parameters of the additive utility model and then compared the quality of the model fit (imputing those the independently derived parameters into the model) to the fit of the hyperbolic model of delay discounting (Mazur, 1987). He found that the additive utility model fit the results of a delay-discounting tasks at least as well as the hyperbolic model. These findings provide tentative evidence for utility and time perception as underlying components of delay discounting, but further evidence is needed.

Other psychological processes are also associated with delay discounting. Working memory capacity (Wesley & Bickel, 2014), numeracy (Peters, Västfjäll, Slovic, Mertz, Mazzocco, & Dickert, 2006), and general intelligence (Shamosh et al., 2008) all appear to be related to how individuals discount delayed outcomes. However, how these processes serve as underlying components or interact with other underlying processes such as time perception is unclear.

Changing Delay Discounting

The general process perspective of delay discounting (e.g., delay discounting as the basic process) is valuable in identifying differences between groups and predicting maladaptive behaviors. However, the aggregate processes approach (e.g., delay discounting as the combination of multiple underlying components) can provide greater insight into why differences exist between groups and how impulsive choice can be improved. Various interventions have been developed to reduce delay discounting (Koffarnus, Jarmolowicz, Mueller, & Bickel, 2013) including working memory training, engaging in episodic future thinking, and reframing the decision. However, the general process view does not describe why these changes occur. A change in *k* does not necessarily explain why an intervention reduced delay discounting.

Framing. Framing effects are one example of an effective manipulation that cannot be explained by many models of delay discounting. DeHart and Odum (2015) demonstrated that framing the delay to an outcome in either specific dates (results in less discounting) or in units of days (results in greater discounting) was sufficient to alter delay discounting within individuals. It could be theorized that different ways of framing the delay affect the subjective perception of time. Read, Frederick, Orsel, and Rahman (2005) found that when delays in an intertemporal choice task were framed as specific dates, delay discounting was reduced and the pattern of discounting more closely approximated an exponential decrease in value, not hyperbolic.

Framing manipulations may also alter the utility of the outcome. Radu, Yi, Bickel, Gross, and McClure (2011) found that explicitly including a 0 in the delay discounting task choices reduced delay discounting. For example, participants were more likely to choose the delayed outcome when choosing between “$25 now and $0 in 1 week or $0 now and $50 in 1 week” than when choosing between “$25 now or $50 in 1 week.” This manipulation may have increased the utility of the outcome by shifting the choice comparison from $25 and $50 to $0 and $50. DeHart et al. (2017) have also demonstrated that differentially framing the unit of the outcome in clear or fuzzy units altered delay discounting. For example, they found that framing the outcome in handfuls of quarters (fuzzy framing) resulted in greater discounting than when the outcome was framed as dollars (clear framing). This method of framing may have reduced the utility of the outcome, thereby increasing delay discounting.

Financial education. The underlying psychological processes of other interventions demonstrated to alter delay discounting are less clear. For example, Black and Rosen (2011) administered a financial management program to individuals in a treatment facility for cocaine abuse. Delay discounting increased in the group that did not receive the financial management program over the course of their treatment, whereas delay discounting did not change in the group that did receive the financial management program. DeHart, Friedel, Lown, and Odum (2016) also report financial education to be an effective intervention for impulsive decision making. They compared delay discounting in university students at the beginning and end of a four-month semester. Participants enrolled in a semester long financial education course reported a decrease in delay discounting at the end of the semester whereas participants in a control group did not. Although it is clear that delay discounting can be changed, current quantitative theories of delay discounting do not identify processes to explain those changes. Even models that define possible processes (e.g., Killeen, 2015) do not easily allow evaluation of the interaction of those individual processes and the intervention.

Identifying the Underlying Components

One possible solution for identifying the underlying components of delay discounting is through latent factor modeling. A latent factor is a variable that has been statistically derived from a series of observed variables. Latent factors can be interpreted as representing the true score (e.g., error-free) of a set of observed variables that are not perfectly reliable (e.g., are confounded by measurement error; Bollen, 2002).

Latent factors are derived by grouping variables according to their covariance and extrapolating a common factor. This method of comparing multiple measurements is superior to bivariate correlations as it allows for the comparison of many variables at once and adjusts for the shared measurement error across tasks (MacCallum & Austin, 2000). Two latent factor methods are commonly used: exploratory and confirmatory. In exploratory factor analysis, observed variables are grouped in factors according to their covariance without *a priori* theoretical considerations. Latent factors are then derived that represent these groupings. These latent factors have no *a priori* theoretical meaning but are instead interpreted based on how observed variables were grouped together. Confirmatory factor analysis superimposes an *a priori* model on the data to determine if the covariance structure of the data aligns with the theoretical model. A poor fitting model indicates that the covariance structure (how the variables are correlated) does not align with the *a priori* theoretical model.

Latent factor analysis could be applied to delay discounting to better identify the underlying processes involved. For example, most individuals discount delayed food outcomes more than delayed monetary outcomes. However, if an individual steeply discounts food they will likely also steeply discount money. This would suggest that there are multiple processes involved that allow for different degrees of discounting but are consistent across outcomes. Current theoretical models do not explain these seemingly contradictory findings. Latent factor modeling can help to identify the different underlying processes and how they contribute to differences in the discounting of different outcomes.

Limited research has applied factor analysis to delay discounting. Weatherly, Terrell, and Derenne (2010) administered five delay-discounting tasks to two groups of participants and analyzed the results using exploratory factor analysis. In the first group, two factors were derived from the delay discounting tasks. Delay-discounting task results for winning $1,000, winning $100,000, and 100 cigarettes comprised factor one and body image (some improvement to physique now versus greater improvement to physique at a delay) and dating (less-than-ideal mate now versus ideal mate at delay) comprised factor two. These two factors suggest a difference between how these consumable and non-consumable outcomes are discounted. The two factors were moderately correlated at 0.349.

In the second group, two factors were also derived from the delay discounting tasks. Delay-discounting task results for owing $1,000, and owing $100,000 comprised factor one and medical treatments (immediately effective but not guaranteed to work versus effective after a delay but guaranteed to work) and federal legislation (a less-than-perfect bill now versus a perfect bill at a delay) comprised factor two. Retirement savings was included in both factors. The factors for this group were also moderately correlated at 0.362. Again, these results suggest a difference between how these consumable and non-consumable outcomes are discounted with retirement savings having both consumable and non-consumable aspects but the modest correlations suggest that they are not completely separate processes. Weatherly and Terrell (2010) replicated these findings by administering the same delay-discounting tasks to a new set of participants. Instead of using exploratory factor analysis, they used confirmatory factor analysis. The authors report a good-fitting model, suggesting that the factor groupings found in the first study are consistent.

Green and Myerson (2013) explored the distinction between delay and probability discounting by reanalyzing the results of a previous study (Estle, Green, Myerson, & Holt, 2007). In the original study, participants completed delay- and probability-discounting tasks for a variety of outcomes such as money and candy. In their reanalysis, Green and Myerson applied exploratory factor analysis and found clear distinctions between delayed and probabilistic outcomes, suggesting that delayed and probabilistic outcomes engage different processes. In a similar study, Green, Myerson, Oliveira, and Change (2014) administered delay-discounting tasks for gains and losses as well as probability discounting-tasks for gains and losses. Again, using exploratory factor analysis, they found two factors: a factor for delayed outcomes (both gains and losses) and a factor for probabilistic outcomes (both gains and losses).

These studies exemplify the ability of factor analysis to compare the discounting of many outcomes at once, but are limited in their abilities to identify underlying components. The purpose of this study was to apply structural equation modeling to better understand the underlying components of delay discounting. Specially, the underlying components of marginal utility, cardinal utility, and nonlinear time perception were investigated. First, a pilot study was conducted to provide evidence that latent factor modeling can be effectively used to identify those components. An overview of the pilot study is given here. Please see Appendix 4-A for a full description of the methods and results.

Pilot Study

A preliminary study was conducted to evaluate the ability of latent factor modeling to identify the underlying components of delay discounting. Appendix 4A reports the methodology, model creation steps, and model values. Only a figure and description of the final model will be given here. Appendix 4B contains a glossary that defines the key terms for understanding the confirmatory factor analysis results. Two-hundred fifty-eight participants completed twelve delay-discounting tasks in the Fall of 2015 and Spring of 2016. The delay discounting outcomes varied by commodity type and magnitude and the delay distribution was the same between all tasks. Several models were tested, beginning with the simplest one-factor model. The final model was selected because of its superior model fit indices compared to other models and the model's theoretical relevance. The chi-square value for final model was statistically significant, which indicates that the superimposed model did not fully fit the data. The significant chi-square value may be due to the strong correlations between manifest variables. Other model fit indices (e.g., CFI, TLI, RMSEA, and SRMR; Appendix 4A) did indicate an acceptably fitting model.

The results of the final latent model suggest that separate components of cardinal utility (commodity factor) and marginal utility (amount factors; Kahneman et al., 1997) interact to determine the overall utility of an outcome (Figure 4-1). This model supports the utility component of the additive-utility model put forth by Killeen (2009, 2015). However, two limitations of the model remain. First, residual covariances between the magnitude latent factors were highly significant. The high covariance between magnitude factors suggests how individuals discount one amount of the outcome is strongly related

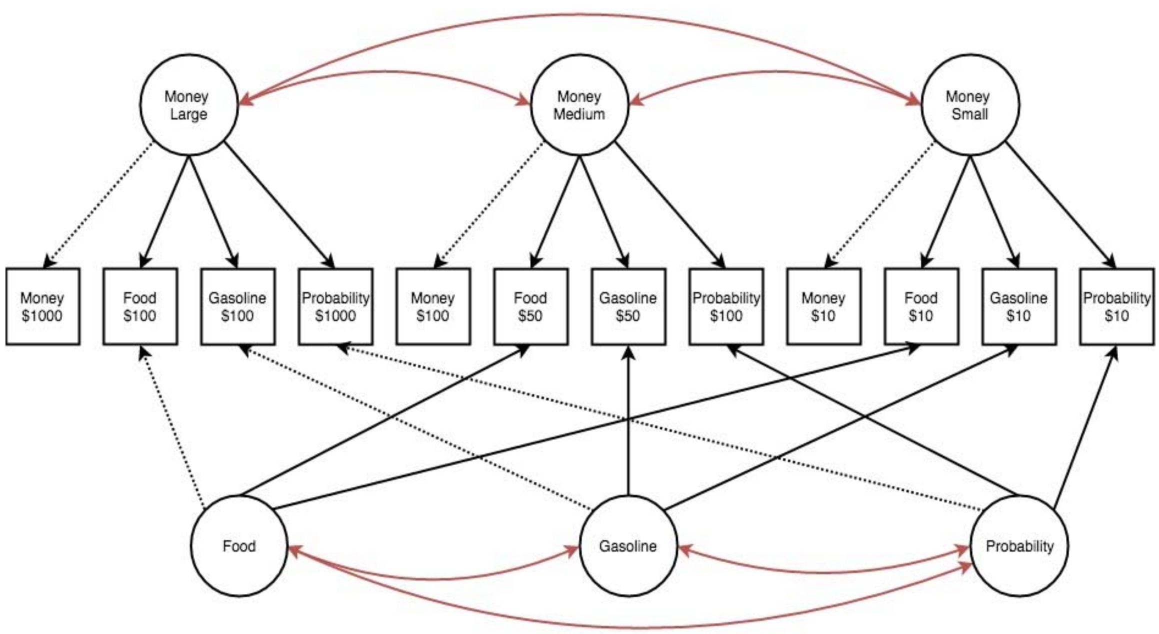

Figure 4-1. Pilot structural equation modeling results. Small, medium, and large factors represent marginal utility of the outcomes. The Food, Gasoline, and Probabilistic Money factors represent the cardinal utility in the outcome in comparison to the money delay-discounting tasks.

to how they discount other amounts of that outcome. Finally, it is important to note that this model cannot address the separate influence of delay on the value of the outcome because the delays did not differ by task.

Conclusions

The results of the pilot study indicate that CFA can be an effective in exploring the underlying components of delay discounting. This study was an extension of the pilot study and improved on two of its limitations. This study included independent measures of time perception, marginal utility, and cardinal utility to further support the derived latent factors. This study also increased the sample size to ensure that the sample size is sufficiently large to derive the proposed model.

Method

Participants

A power analysis was conducted in the R statistical computing environment (Kim, 2005) indicating that a minimum sample size for 300 participants is required for a latent factor model with 35 degrees for freedom (17 manifest variables). Three-hundred fifty-two participants completed the survey (mean age = 34 years, mean income = $9,722, female = 47%) participants were recruited through Amazon Mechanical Turk, an online survey distribution forum. All participants received $2 for participating.

Procedure

Participants completed the study online using Qualtrics survey software.

Participation took approximately 45 minutes. Participants completed eighteen tasks: delay discounting (12 tasks), marginal utility (3 tasks), cardinal utility (two tasks), time perception (1 task), and demographics. The tasks were presented randomly except for the demographics questions, which were presented at the end.

Delay discounting. All participants completed 12 delay-discounting tasks: four money, four food, and four gasoline. These outcomes were chosen because they represent a range of possible marginal utilities meaning that the hedonic value derived from each differs. Gasoline is of particular interest because like food, gasoline is consumable but unlike food, it is not perishable but does entail substantial storage costs. Finally, money is necessary to serve as a proxy in the calculation of cardinal utility (see cardinal utility subheading). For the three outcomes, participants completed two small and two large magnitude tasks. They also completed two short and two long delay tasks (Table 4-1). The delay distribution of the short tasks was: 1 hour, 2 hours, 4 hours, 1 day, and 10 days. The delay distribution of the long tasks was: 1 week, 2 weeks, 1 month, 6 months, and 5 years. Multiple delay distributions were required to investigate the specific role time perception in delay discounting. Previously unpublished research from our laboratory has

Table 4-1

Discounting Tasks for the Three Outcomes

	Delay distribution	
Magnitude	Short delays	Long delays
$10	Small-short	Small-long
$100	Large-short	Large-long

indicated that both delay distributions yield orderly data for the discounting of food (Appendix 4C, Figure 4-1c).

Prior to participants completing the discounting tasks, the survey determined the favorite type of food and favorite brand of gasoline and the relative value of those favorites for each participant. Participants were asked if they owned a car; however, they were not excluded from participation if they did not. Independent samples *t* tests did not reveal any difference in the discounting of delayed gasoline (all four tasks), gasoline cardinal utility, or gasoline marginal utility between car owners and non-owners. To determine the favorite food and brand of gasoline, the text “Please type in your favorite [food/brand of gasoline]. Press the ‘Enter’ key when you are done” was presented to the participants. After hitting the Enter key, the participants completed a question to determine the relative value, in dollars, of each outcome. The text “You said your favorite [food/brand of gas] was [participant’s favorite]. How much does a [serving/gallon] of your favorite [food/brand of gas] cost?” was presented to the participants. The text was accompanied by a text box in which participants entered a monetary value of a serving of their favorite food or a gallon of their favorite brand of gasoline. A content validation on the text box was in place to only accept numeric characters. The task did not allow participants to continue until they have entered a numeric value.

The cost of a single unit (i.e., serving of a favorite food or a gallon of gas) was used to equate the relative value of the outcomes across the different delay discounting tasks. For example, if in a delay-discounting task the larger outcome was $100 and the cost of a serving of a favorite food was $5 and the cost of a gallon of gas was $2, then the delayed amount of the food was 20 servings and the delayed amount of the gasoline was 50 gallons. In this example, 20 servings of food and 50 gallons of gas are equivalent in monetary value to $100. The amounts of $10 and $100 were chosen to provide a sufficiently large contrast between the different amounts. These values were successfully used for money and food delay discounting tasks in the pilot study.

For all the tasks, indifference points were obtained for each delay using an adjusting amount procedure (Du, Green, & Myerson, 2002 Frye, Galizio, Friedel, DeHart, & Odum, 2015). Within a given trial, two choice alternatives were simultaneously presented to the participant, and the participant chose their most preferred alternative. The choice alternatives consisted of a smaller amount of the outcome to be delivered immediately and a larger amount of the outcome to be delivered after a delay. For the first trial within a block of trials, the amount of the immediate outcome was set to half of the larger delayed outcome.

After the first trial within a block, the amount of the immediate outcome was changed based on the participant's choices on the preceding trial. If a participant selected the immediate outcome, on the following trial the amount of that outcome was decreased. If a participant selected the delayed outcome, on the following trial the amount of the immediate outcome was increased. The amount of the immediate outcome was adjusted after the first trial by one fourth of the delayed amount. For each successive trial within a block, the adjustment was one half of the previous adjustment (e.g., after the second trial in a block the adjustment was one eighth of the delayed amount). A block consisted of five trials with a single delay to the larger outcome. The indifference point was taken as the amount of the immediate outcome after the participant makes the final choice within the block.

Marginal utility. Marginal utility was measured by asking participants to indicate how pleasant it would be to receive various amounts of money (Harinck et al., 2007). Participants first read the following instructions:

> "Imagine that the researcher was to give you a prize (e.g., money, food, gasoline) at random with no strings attached. On a scale from 0-100, how happy would you be if you received the prize? Zero is not happy and 100 is completely happy."

Participants then indicated on a number line from 0 to 100 how much pleasantness that amount would bring them. Participants were asked about the following monetary (and converted food and gasoline) amounts: $1, $5, $10, $20, $35, $50, $65, $80, $90, and $95. For food and gasoline, the amounts were determined by dividing the monetary amount (e.g., $10 or $100) by the participant-reported serving/gallon cost.

Cardinal utility. Cardinal utility is the amount of utility that is gained when receiving a unit of an outcome (Köbberling, 2006). Historically, this increase in utility is conceptualized as an increase in "utiles" or "value." Value in this context is difficult to measure directly. In measuring cardinal utility, money appropriately serves as a proxy for utiles or value. However, using money as a proxy for utiles does restrict the analysis to deriving the cardinal utility of food and gasoline but not money. The assumption that money may serve as an appropriate proxy for utiles to measure cardinal utility is appropriate in the context of the proposed latent model.

An alternative method of measuring cardinal utility could be to ask participants how much they would pay for a specific quantity of an outcome (the opposite of what is stated in the above paragraph) and then deriving the rate of change of elasticity (e.g., essential value) of the demand curve as a summary value of cardinal ulitity. The demand task was choosen instead because of the large body of literature demonstrating the validity of the demand task (Bidwell, MacKillop, Murphy, Tidey, & Colby, 2012; MacKillop et al., 2009, 2016). For this reason, cardinal utility for food and gasoline were approximated using demand curve analyses (Hursh & Silberberg, 2008).

Participants reported how much of an outcome (e.g., food or gasoline) they would purchase at a series of unit prices: \$0 (free), \$0.01, \$0.10, \$.25, \$.50, \$1, \$1.50, \$2.00, \$2.5, \$3.00, \$4.00, \$5, \$6.00, \$7.00, \$8.00, \$10, \$15, \$25, \$50, and \$150. At the beginning of the food task, participants read the following instructions (adapted from Koffarnus, Franck, Stein, & Bickel, 2015):

> "Imagine a typical day during which you eat. The following questions ask how many servings of (participant food choice) you would consume if a serving costs various amounts of money. Assume that you have the same income/savings that you have now and NO ACCESS to any other servings of (participant food choice). In addition, assume that you would consume the purchased food on that day; that is, you cannot save the purchased food for a later date. Please respond to these questions honestly. There are no right or wrong answers."

The instructions for the gasoline task were identical but adapted for gallons of gasoline.

Time perception. Subjective time perception was measured by asking the participant to indicate on a line how long they believed a delay was (Zauberman et al., 2008). The further to the right the participant selected on the line, the longer they perceived the delay to be. Participants responded to the following delays: 10 minutes, 1 hour, 12 hours, 1 week, 1 month, 6 months, 5 years, and 25 years. The delays were presented in random order. At the beginning of the time perception task, participants read the following instructions:

> "We are going to ask you to indicate your subjective feeling of duration between right now and various times in the future. Those times will range from 10 minutes to 25 years. Imagine that these time-spans all start right after you wake up in the morning."

Analyses

Before the primary analyses were conducted, the results of the delay-discounting tasks were analyzed to identify unsystematic data. This analysis was done for the purpose of comparing the quality of results collected through Amazon Mechanical Turk to the results of the Pilot Study conducted in the laboratory. Removing unsystematic data is a common practice (e.g., DeHart, Friedel et al., 2016; Lee, Stanger, Budney, 2015; Myerson, Green, van den Berk-Clark, & Grucza, 2015); however, participant data were not removed for the actual analyses. First, the criteria for identifying nonsystematic discounting were developed for "long" delay distributions (e.g., 1 week to 25 years) but are not appropriate for "short" delay distributions. Also, the criteria were developed to identify single task outliers, but it is unclear how to address multiple tasks. For example, it is unclear if all of a participant's data should be removed for violating the criteria for a certain proportion of tasks. Finally, similar criteria do not exist for the other tasks.

I applied two identification criteria similar to that suggested by Johnson and Bickel (2002), but modified to reject fewer participant data, to the individual participant indifference points for each task. The first criterion required that the final indifference point not be greater than 95% of the first indifference point. The second criterion required that no indifference point be 120% greater than the previous indifference point.

Several important limitations exist, however, that impede the ability to directly compare the results of the long delay-discounting tasks to the results of the pilot study. First, the present data only included five indifference points per task whereas the pilot data included six. Also, the length of the delay distributions was slightly different, with different starting and ending delays.

Delay discounting. In the first analysis, theoretical models of delay discounting were fit to the median group indifference points for each delay-discounting task. The models that were selected for analysis were the hyperbola (Mazur, 1987; Equation 4-1) and hyperboloid model of delay discounting (Myerson & Green, 1995; Equation 4-2). For these analyses, curvilinear regression was used to fit the models to the obtained indifference points by determining the best estimates of *k* and *s*.

The two models were then compared across several metrics to determine which model best described the data. Although R^2 is an inappropriate metric for the goodness-of-fit for curvilinear models because the sum of the residuals of curvilinear regression do not always equal one, I report it by convention (Johnson & Bickel, 2002). I also calculated *Sy.x.*, which is the standardized deviation of the residuals and is a more appropriate metric for nonlinear regression (Brown, 2001). Akaike's Information Criteria (AIC) was used to compare the relative quality of each model across outcomes and magnitudes for group level data (Akaike, 1974). As a measure, AIC weighs the relative goodness-of-fit of a model against the number of free parameters in the models. A better fit is indicative of a higher quality but the measure of quality is also penalized for additional free parameters in the model. When comparing AIC values across models, lower AIC values indicate a higher quality model. For this study, AICc, which adjusts for having a low number of data points, was calculated.

Area Under the Curve (AUC) also calculated for each delay discounting outcome (Myerson, Green, & Warusawitharana, 2001). AUC is a nontheoretical summary score of delay discounting. AUC is computed as the sum of the trapezoidal area between indifference points: x_2-x_1[(y_1+y_2)/2] where x_1 and x_2 are successive delays and y_1 and y_2 are successive indifference points at those delays. However, for these analyses, the delays converted to their ordinal values of 1 through 5 (AUCord; Borges, Kuang, Milhorn, & Yi, 2016). This conversion improved comparisons between short and long delay distribution tasks. Ordinal UC can range between 0 and 1, with lower AUCord values indicating greater delay discounting.

Ordinal AUC was compared between conditions using generalized estimating equation (GEE) analyses and pairwise comparisons. GEE analysis is a regression technique for repeated dependent variables that are correlated (Hanley, Negassa, Edwardes, & Forrester, 2003).

Marginal utility. Several models were fit to the marginal utility data. Previous research suggested that a logarithmic function ($U_m = \ln(km)$) may best describe the data (Killeen, 2015). However, exploratory analyses demonstrated that an exponential growth model provided a far superior fit. For the purposes of the latent factor model analyses, the theoretical implications of the specific models are less important than deriving a model parameter that accurately describes the data.

The rate of increase in marginal utility was modeled by fitting an exponential growth equation to the marginal utility task results:

$$U_m = Ymin + (Ymax - Ymin) * \left(1 - e^{(-k*m)}\right) \tag{4-5}$$

where marginal utility (U_m) is the reported pleasantness of the outcome, *Ymin* is the smallest amount of money, *Ymax* is the largest amount of money, *m* is the amount of money, and *k* is the rate of increase in marginal utility. Adjusting for a starting point larger than 0 helped improve the model fit by beginning the function at a reasonable value for the given data. For further analyses, *k* is the value of interest and was natural log transformed to improve its parametric qualities.

Cardinal utility. To analyze the results of the cardinal utility task, a demand curve model was fit to the consumption values at each price point of the outcome:

$$Q = Q_0 * 10^{k(e^{-\alpha Q_0 C} - 1)} \tag{4-6}$$

in which Q is consumption amount of the outcome at a given price, Q_0 is the consumption of the commodity at zero price, α is the demand elasticity (i.e., essential value), and *k* is the span of the function (Koffarnus, et al., 2015). The parameter *k* was calculated by subtracting the $\log_{10}$-transformed average consumption at the highest price ($150) from the $\log_{10}$-transformed average consumption at the lowest price ($0.01; Koffarnus, et al., 2015). For all analyses, *k* was set to 2.584. In this model, α is a free-parameter. Q_0 is also a free parameter though it should closely approximate consumption at $0.00 (free). For further analyses, α is the value of interest and was natural log transformed to improve its parametric qualities.

Time perception. The rate of increase in subjectibve time perception was calculated by fitting a logarithmic equation (Zauberman et al., 2008) to the subjective durations, as indicated on the number line, for each objective delay:

$$T_{Sub} = Y_0 + k * \ln(T_{Obj}) \tag{4-7}$$

In this logarithmic equation, the subjective perception of a delay (T_{Sub}) is the reported distance on the number line, Y_0 is the function's y intercept, T_{Obj} is the objective delay, and k is the rate of increase in subjective time perception.

Structural equation model. The final analysis conducted was the structural equation model (SEM). Ordinal AUC was calculated for each outcome (Borges, et al., 2016). AUCord was used as the dependent measure for the SEM because it is normally distributed and easily compared between outcomes.

A SEM is composed of two parts: a model structure and regression equations (Hox & Bechger, 1988). The model structure is composed of the latent factors. A latent factor is an unmeasured construct that explains the covariance between a series of manifest (measured) variables (Hox & Bechger, 1988). For each latent factor, a reference variable is selected, which serves to set the scale of the latent factor. The covariance between latent factors describes the degree to which the factors uniquely predict their manifest variables. The regression equations measure the ability of a variable (latent or manifest) to account for the variance of another variable (latent or manifest). Consequently, the covariance between latent factors is interpreted as the covariance that remains after the regression variable (latent or manifest) has accounted for a unique portion of the latent factor (Hox & Bechger, 1988). It is also possible to compare factor means; however, that is unnecessary in this study because the GEE analyses provide the same information (e.g., the mean difference between AUCord). Therefore, factor means were set to 0 to allow for the investigation of the covariances between factors.

Several CFAs were conducted, beginning with a one-factor model. This model only included delay discounting measures and simply asserts that one general process is involved in the discounting of delayed outcomes. This model best reflects the hyperbolic model of delay discounting (Equation 4-1, Mazur, 1987). The next model included factors for the different amounts of each outcome and residual factors for the different delay distributions and factors for marginal and cardinal utility. SEM was used to regress the utility factors onto the delay discounting factors to determine the degree to which marginal and cardinal utility predict delay discounting.

Six model fit indices are reported. First, a chi-square test was conducted to compare the hypothesized model to the actual data. A non-significant chi-square value indicates that the hypothesized model and that data align well. Next, comparative fit index (CFI) and Tucker-Lewis index (TLI) values are reported. These values compare the hypothesized model fit to a null model that assumes no covariance between the observed variables. CFI and TLI values above 0.95 are considered to indicate that the proposed latent model fit the actual data better than a null model that assumes no covariance between observed variables (Hu & Bentler, 1999). The root mean square error of approximation (RMSEA) was also calculated. This index measures how well the hypothesized model fits the data's covariance matrix with optimally chosen parameter estimates. Values below 0.08 are considered to indicate a well-fitting model (Hu & Bentler, 1999). Finally, the standardized root mean square residual (SRMR) is reported.

This index measures the discrepancy between the sample covariance matrix and the model covariance matrix. Values below 0.05 are considered to indicate a well-fitting model (Hu & Bentler, 1999). All structural equation models were conducted in the R statistical computing environment (R Core Team, 2015) using the Lavaan package (Rosseel, 2012).

Results

The results are broken into individual tasks. For each task, a full analysis is reported. the latent factor analyses results are reported.

Marginal Utility

First, the exponential model was fit to the median values for each task. The model fits to the median marginal utility values were all very good (Table 4-2). Figure 4-2 displays the model fits to the median values. The exponential model was also fit to individual marginal utility values for the three commodities (Table 4-3). The model fits to individual marginal utility values were very good (high R^2 and low $S_{y.x}$ values), indicating that the derived model *k* parameter well represents the data.

Table 4-2

Marginal Utility Fits to Group Median Values of Subjective Happiness

Outcome	*k*	R^2	$S_{y.x}$
Money	0.053	0.976	2.936
Food	0.089	0.971	4.595
Gasoline	0.042	0.991	2.066

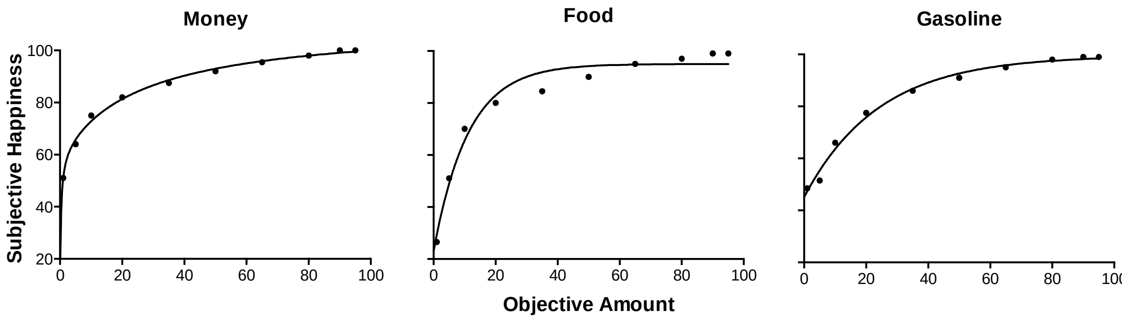

Figure 4-2. Marginal utility model fits. Exponential model fits to the group median subjective happiness values for money, food, and gasoline.[3]

Table 4-3

Median Marginal Utility Fit Values to Individual Values of Subjective Happiness

Outcome	α	R^2	$S_{y.x}$
Money	0.036	0.983	2.908
Food	0.071	0.971	4.250
Gasoline	0.053	0.981	3.160

Cardinal Utility

A demand curve model (Koffarnus et al., 2015) was fit to the consumption amounts at each value for individual responses (Table 4-4). First, the demand curve was fit to the median consumption values (Figure 4-3) for food ($\alpha = 0.013$, $Q_0 = 5.083$, $R^2 = 0.984$, $S_{y.x} = 0.254$) and gasoline ($\alpha = 0.003$, $Q_0 = 21.62$, $R^2 = 0.975$, $S_{y.x} = 1.336$). The

[3] A systematic pattern of model misfit was observed for all three outcomes. Three patterns of misfit were observed. The model under fit the data at the small objective outcome amounts, over fit at the middle objective outcome amounts, and under fit the data at the large objective outcome amounts. A one-parameter model cannot be modified to better fit all three residual patterns without additional free-parameters.

Table 4-4

Median Demand Curve Fit Values to Individual Consumption Amounts

Outcome	α	Q_0	R^2	$S_{y.x}$
Food	0.008	5.482	0.915	0.582
Gasoline	0.002	21.98	0.914	2.862

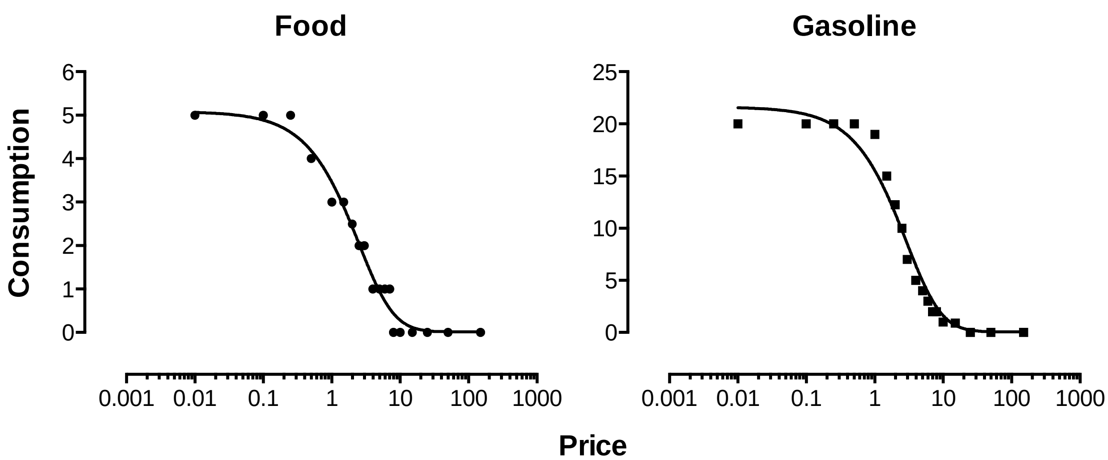

Figure 4-3. Cardinal utility model fits. Demand curve fits to the median consumption values at each price. The left panel displays the demand curve fit to food consumption values and the right panel displays the demand curve fit to gasoline consumption values.

model fits to individual cardinal utility values were very good (high R^2 and low small $S_{y.x}$), indicating that the derived model α parameter well represents the data. A Spearman's correlation was conducted between Q_0 and consumption at \$0.00 to ensure that Q_0 closely approximated consumption at \$0.00 for both outcomes. The correlation for food ($r_{sp} = 0.906$) and gasoline ($r_{sp} = 0.909$) were both strong, indicating that consumption closely approximated Q_0 for both outcomes.

Time Perception

First, the logarithmic model was fit to the median group subjective time perception values. The quality of the model fit to median time perception values was very good ($k = 0.304$, $R^2 = 0.973$, $S_{y.x} = 0.058$). Figure 4-4 shows the logarithmic model fit to median time perception values. The logarithmic model was also fit to individual subjective time perception values. The median fit values indicate that the logarithmic model fit the date moderately well ($k = 0.134$, $R^2 = 0.910$, $S_{y.x} = 0.097$).

Delay Discounting

Delay discounting results were analyzed in several steps. First, two theoretical models (Equations 4-1 and 4-2) were fit to the group median and indifference points of individual participants for each delay-discounting task. Then, the results of the present study were compared to the pilot study. Finally, AUCord was analyzed to identify differences in the discounting of different outcomes, magnitudes, and delay distributions.

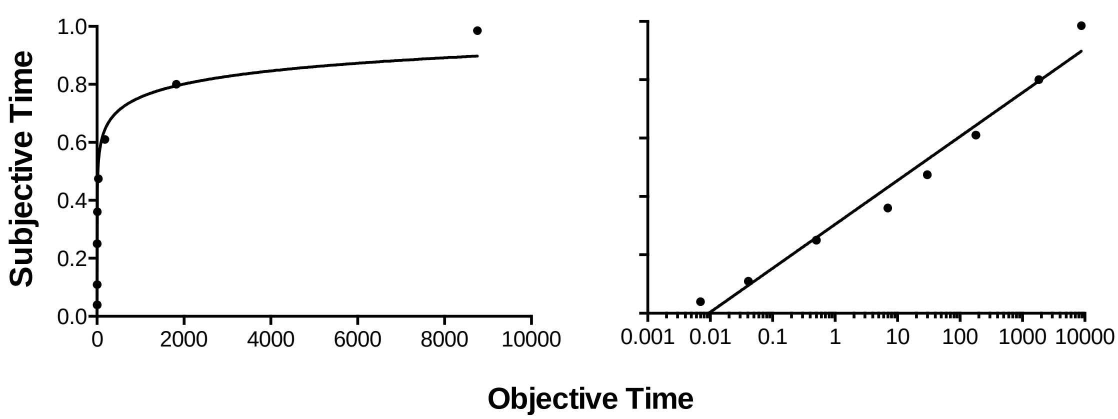

Figure 4-4. Subjective time perspective model fit. Model fits to the group median subjective time perception values. The left panel displays the model fit to objective delays. The right panel displays the model fit to log transformed objective delays.

Model fits. Delay discounting results were fit to two quantitative models (Mazur 1987; Myerson & Green, 1995). First, the models were fit to the median indifference points for each outcome (Table 4-5, Figure 4-5). The hyperbolic model (Mazur, 1987) was favored for 9 out of 12 tasks as indicated by lower AICc values. Table 4-6 reports the median model fit values for each outcome. The delay discounting models were also fit to the indifference points from individual participants. Although the overall fits for the hyperboloid model were superior, the hyperbolic model (Mazur, 1987) was favored for all 12 outcomes despite poor R^2 values because of the lower AICc values.

Finally, to investigate the congruency of discounting between long and short delay distributions, the hyperboloid model was fit to to the long and short delay distribution tasks individually (Figure 4-6). The hyperboloid model was chosen for this

Table 4-5

Equation 4-1 (Hyperbolic) and Equation 4-2 (Hyperboloid) Model Fits to Group Median Indifference Points

	Hyperbolic (Mazur, 1987)				Hyperboloid (Myerson & Green, 1995)				
Task	*k*	R^2	Sy.x	AICc	*k*	*s*	R^2	Sy.x	AICc
Money Long \$100	**0.018**	**0.910**	**0.090**	**-15.216**	0.105	0.363	0.966	0.064	-0.042
Money Long \$10	**0.060**	**0.895**	**0.100**	**-14.155**	0.383	0.345	0.979	0.052	-2.083
Money Short \$100	**0.124**	**0.891**	**0.014**	**-33.918**	13.308	0.043	0.921	0.014	-15.556
Money Short \$10	**0.254**	**0.979**	**0.012**	**-35.313**	1.935	0.210	0.981	0.013	-15.705
Food Long \$100	**211.000**	**0.665**	**0.132**	**-11.355**	1984.201	0.315	0.900	0.084	2.619
Food Long \$10	**252.924**	**0.610**	**0.125**	**-11.952**	3123.350	0.290	0.953	0.050	-2.474
Food Short \$100	15.178	-2.270	0.251	-4.943	**4955.849**	**0.092**	**0.997**	**0.009**	**-19.397**
Food Short \$10	1.422	-2.030	0.241	-5.338	**3448.483**	**0.086**	**0.970**	**0.002**	**-8.350**
Gasoline Long \$100	**23.000**	**0.812**	**0.127**	**-11.736**	243.302	0.296	0.928	0.091	3.506
Gasoline Long \$10	**62.090**	**0.581**	**0.162**	**-9.317**	841.940	0.240	0.946	0.067	0.445
Gasoline Short \$100	**0.321**	**0.569**	**0.057**	**-19.724**	246.225	0.048	0.990	0.010	-18.745
Gasoline Short \$10	0.621	0.235	0.110	-13.215	**498.936**	**0.071**	**0.999**	**0.004**	**-27.574**

Note. Bolded numbers highlight best fitting model.

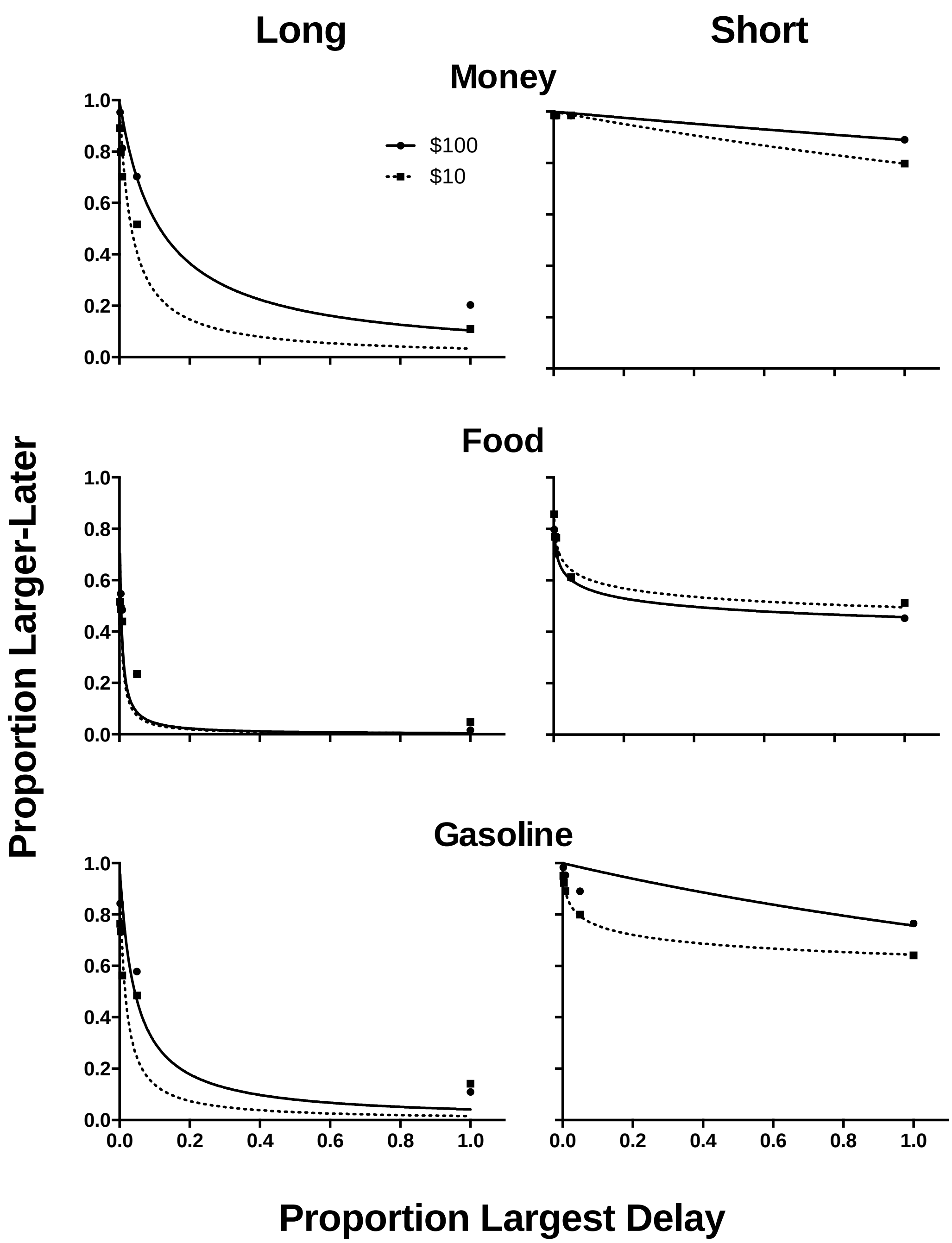

Figure 4-5. Delay discounting model fits to median group indifference points. Model fits to the median indifference points for each outcome. The x-axis is standardized as the proportion of the largest delay. The line representing the best fitting equation, as determined by the AICc value, is displayed for each outcome.

Table 4-6

Median Equation 4-1 (Hyperbolic) and Equation 4-2 (Hyperboloid) Model Fit Values to Indifference Points from Individual Participants

	Hyperbolic (Mazur, 1987)				Hyperboloid (Myerson & Green, 1995)				
Task	*k*	R^2	Sy.x	AICc	*k*	*s*	R^2	Sy.x	AICc
Money Long $100	**0.014**	**0.865**	**0.010**	**-14.292**	0.208	0.313	0.962	0.057	-1.277
Money Long $10	**0.043**	**0.724**	**0.117**	**-12.633**	0.621	0.347	0.913	0.075	1.487
Money Short $100	**0.000**	**0.000**	**0.015**	**-32.886**	8.500	0.018	0.852	0.014	-15.33
Money Short $10	**0.000**	**0.396**	**0.033**	**-25.324**	4.601	0.042	0.888	0.028	-8.159
Food Long $100	**0.339**	**0.302**	**0.114**	**-12.829**	7.073	0.241	0.821	0.086	2.908
Food Long $10	**0.418**	**0.183**	**0.152**	**-9.9797**	8.741	0.219	0.798	0.101	4.560
Food Short $100	**0.011**	**-0.378**	**0.128**	**-11.660**	29.32	0.055	0.778	0.074	1.435
Food Short $10	**0.003**	**-0.319**	**0.187**	**-7.8804**	7.304	0.094	0.762	0.096	4.026
Gasoline Long $100	**0.029**	**0.530**	**0.134**	**-11.246**	1.371	0.277	0.899	0.085	2.747
Gasoline Long $10	**0.094**	**0.477**	**0.149**	**-10.187**	1.864	0.277	0.888	0.094	3.759
Gasoline Short $100	**0.001**	**-0.219**	**0.081**	**-16.273**	9.367	0.041	0.840	0.048	-2.978
Gasoline Short $10	**0.001**	**0.085**	**0.116**	**-12.705**	4.171	0.087	0.857	0.071	1.029

Note. Bolded numbers highlight best fitting model.

analysis because of its superior fit to the indifference points of the short delay distribution delay-discounting tasks. The hyperboloid model was also fit to the combined short- and long-delay distribution task indifference points for each outcome and amount (Figure 4-7).

To determine if separate models fit the indifference points of the short and long delay distribution tasks better than an omnibus model that fit both tasks at once, two analyses were conducted. First, AICc values were compared between the separate model fits and the omnibus model. Second, the free-parameters (e.g., *k* and *s*) of the omnibus model were used in the model fits for the separate short and long delay distribution tasks. The quality of fit was compared to the separate task model fits to determine if the quality of model fit using the omnibus free-parameters approximated the quality of model fit of

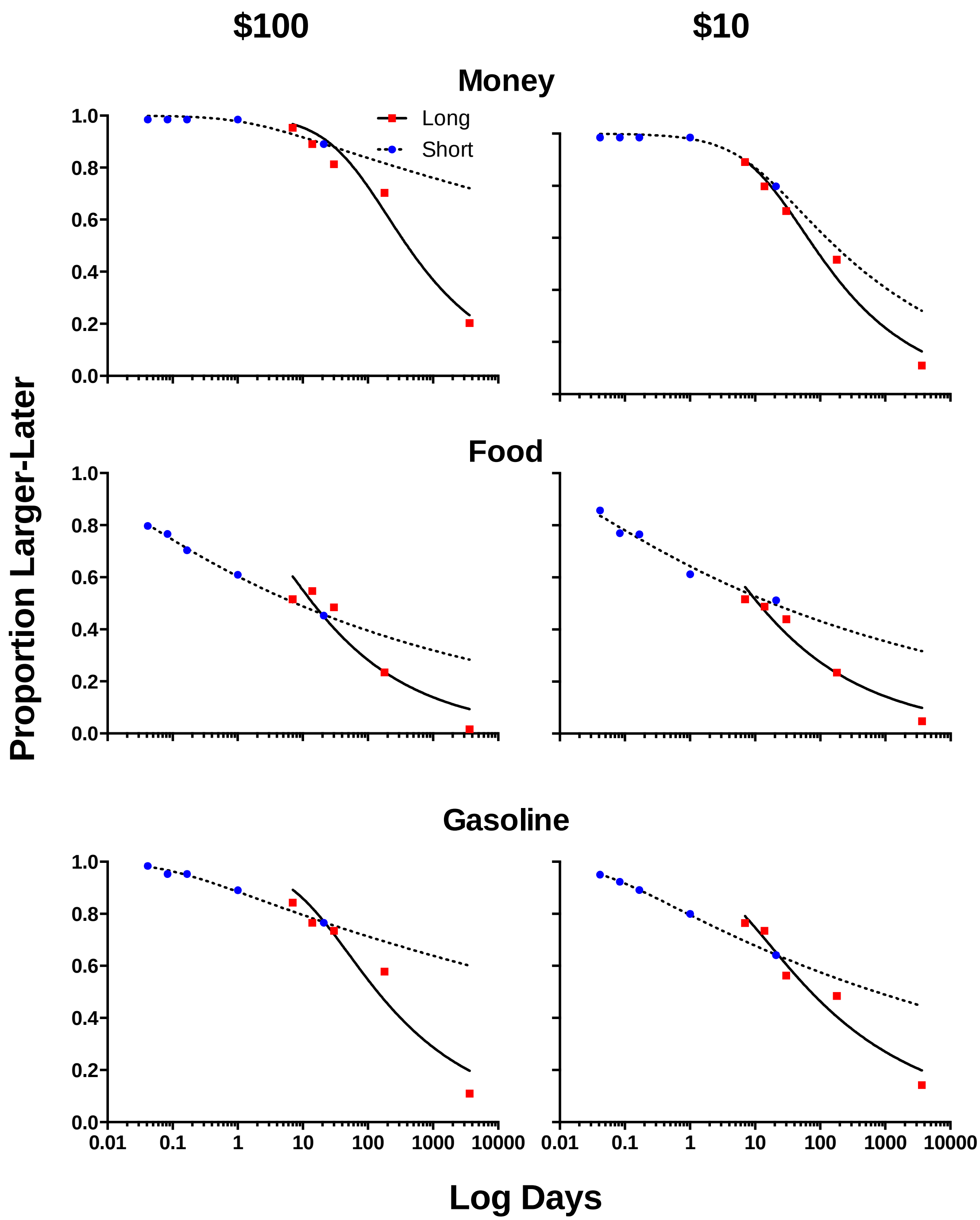

Figure 4-6. Delay discounting of different outcomes with long and short delay distributions. Myerson and Green hyperboloid model fits are displayed. Both delay distributions are plotted on the same graph for each outcome. The x-axis is in a log10 scale to allow for the visualization of both delay distributions. Model curves were extended to allow for comparisons between tasks.

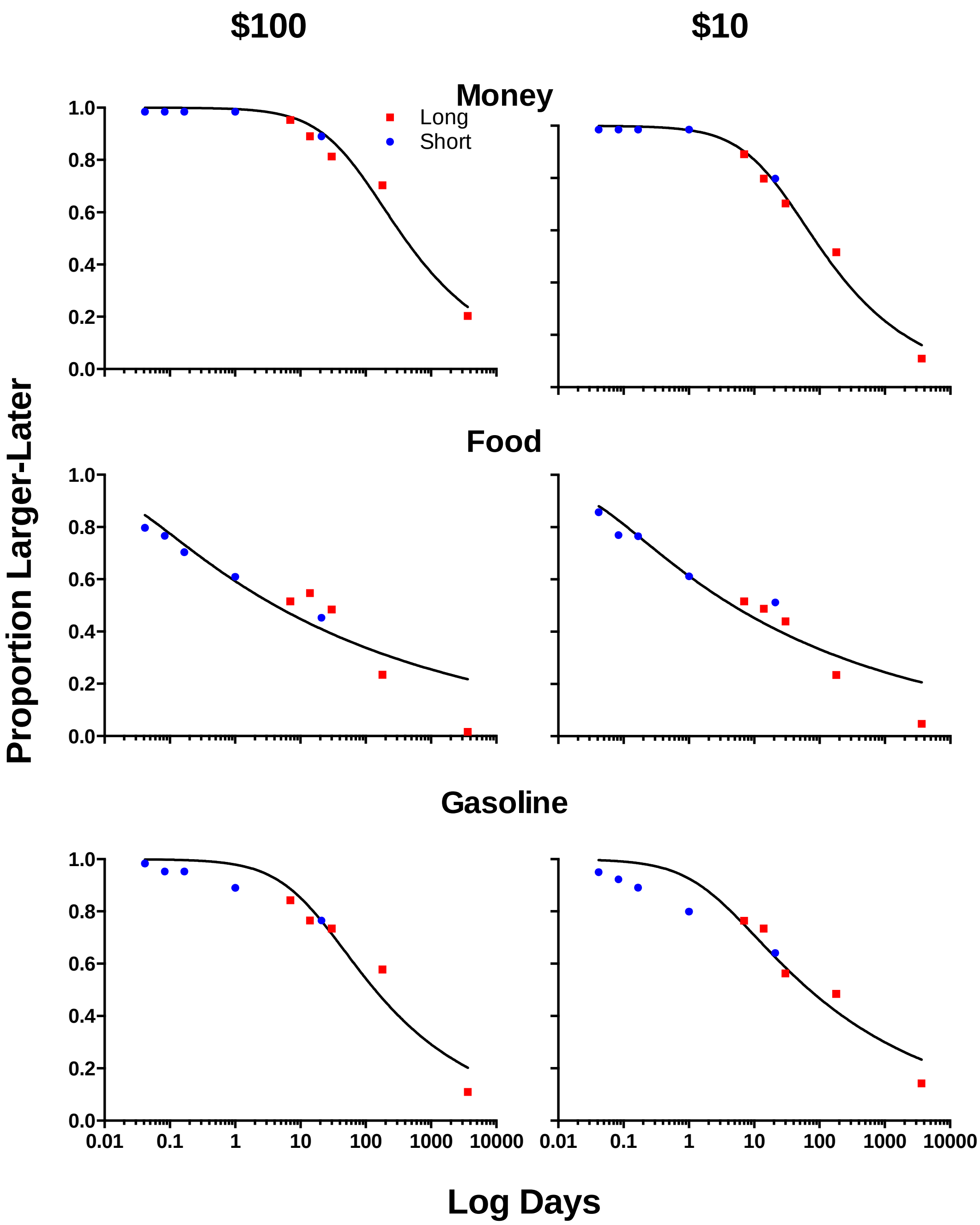

Figure 4-7. Delay discounting of different outcomes with omnibus model fit. Omnibus model fit to combined short and long delay discounting task indifference points for each outcome and amount.

the separate task model fits (Table 4-7). The omnibus model fit AICc values were superior to the individual model fit AICc values because AICc imposes an additional penalty for data sets with fewer points (e.g., 5 versus 10). When the derived parameters of the omnibus model fits were used to fit the indifference points of the individual short and long delay distribution tasks independently, the omnibus model parameters fit the data worse than the individual model fits. However, the margin of improvement in the individual model fits was small in many instances, suggesting that the omnibus model fit the data similarly to the individual model fits.

Table 4-7

Median Equation 4-2 (Hyperboloid) Model Fit Values to Long, Short, and Combined Indifference Points from Individual Participants

Outcome	Model fit	*k*	*s*	R^2	$S_{y.x}$	AICc	Separate fit AICc
Money $100							
	Short			-2.569	0.082	-3.425	-15.33
	Long			0.982	0.071	-5.035	-1.277
	Omnibus	0.037	0.285	0.915	0.062	-47.76	
Money $10							
	Short			-0.301	0.104	-1.187	-8.159
	Long			0.440	0.144	2.036	1.487
	Omnibus	0.245	0.200	0.833	0.096	-39.05	
Food $100							
	Short			-0.172	0.223	6.425	1.435
	Long			0.204	0.212	5.936	2.908
	Omnibus	11.74	0.155	0.675	0.142	-31.22	
Food $10							
	Short			-0.025	0.221	6.328	4.026
	Long			-1.095	1.038	21.82	4.560
	Omnibus	17.50	0.173	0.682	0.156	-29.4	
Gasoline $100							
	Short			-0.354	0.149	2.438	-2.978
	Long			0.475	0.135	1.400	2.747
	Omnibus	0.884	0.162	0.753	0.119	-34.78	
Gasoline $10							
	Short			0.971	0.155	2.805	1.029
	Long			0.422	0.160	3.130	3.759
	Omnibus	1.928	0.195	0.742	0.129	-33.20	

Note. The “Separate Fit AICc” is identical to the Myerson and Green (1995) AICc column from Table 4-6. It is included here to add in comparisons.

Comparisons to pilot data. Where appropriate, results of the pilot study were compared to delay discounting results of the principle study. Results were compared on the degree of nonsystematic data obtained (Table 4-8). Two criteria were applied to the indifference points from individual participants for each delay discounting task (Johnson & Bickel, 2008).

Overall, the present study contained a greater proportion of delay discounting results that failed one of the two modified criteria for nonsystematic discounting. Fisher-Irwin tests were conducted to compare the differences in the proportion of nonsystematic data for each study. For both datasets, more nonsystematic data were identified in the food discounting tasks compared to money and gasoline. Also, more non-systematic data were reported in the present study compared to the pilot study. There are several explanations for the difference in data quality. First, participants in the current study

Table 4-8

Proportion of Individual Delay Discounting Results that Fail a Criterion for Identifying Nonsystematic Data

	Pilot study		Present study	
Task	Criterion 1 (%)	Criterion 2 (%)	Criterion 1 (%)	Criterion 2 (%)
Money $100	8	10	9	19**
Money $10	8	14	8	24**
Food $100	19	32	22	33
Food $10	11	35	16	38
Gasoline $100	16	14	13	31***
Gasoline $10	13	20	16	33***

Note. Asterisk on Present Study values identifies a significantly different proportion from the Pilot Study proportion.

** $p < .01$.
*** $p < .001$.

completed more tasks than participants in the pilot study, and did not have scheduled breaks. Second, it is possible that the compensation for the MTurk participants ($2) was not as valuable as the extra credit for laboratory participants. Third, the pilot study was conducted in a controlled laboratory setting compared to the uncontrolled setting of the participant's personal computer. Participants in the laboratory setting may have attended more to the tasks than the Amazon Mechanical Turk participants did. These results suggest that a researcher should weigh the costs and benefits of collecting data online through Amazon Mechanical Turk (present study) compared to collecting data in the laboratory (pilot study).

Ordinal area under the curve. Finally, ordinal AUC values were computed and GEE analyses were conducted (Table 4-9). No participant data were removed. Dummy variables were created for outcome type, amount, and delay distribution. Significant main effects for the delay distribution and outcome type were found. However, no significant main effect for the magnitude of the outcome was found. Significant interactions were also found for all three possible combinations of delay, magnitude, and commodity. The lack of significant main effect for magnitude is due to its dependence on commodity type and delay distribution.

Pairwise comparisons were also conducted to investigate relevant differences between tasks (Figure 4-8). For money and gasoline, $100 was discounted less than $10 and short delay distributions resulted in less discounting than long delay distributions. However, for food outcomes, no difference between discounting of $100 and $10 for the long delay distribution tasks were found (see red brackets in Figure 4-8). Also, $10 of

Table 4-9

Generalized Estimating Equation Results

Variable	β	Robust S.E.	Robust *z*
Intercept	0.371	0.038	9.71***
Delay	0.297	0.021	14.24***
Magnitude	0.008	0.020	0.40
Commodity	0.032	0.014	2.29**
Delay x magnitude	-0.034	0.009	-3.54***
Magnitude x commodity	0.016	0.006	2.84**
Delay x commodity	-0.064	0.006	-10.30***

**$p < 0.01$.
***$p < 0.001$.

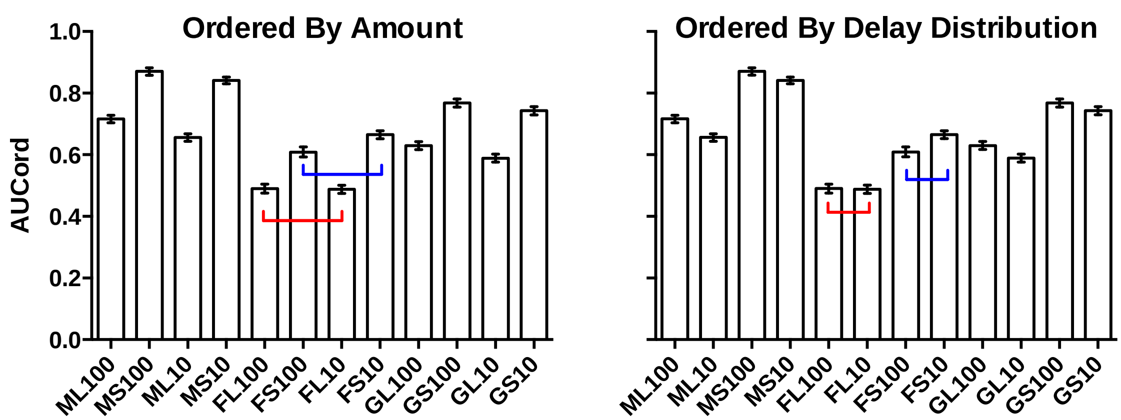

Figure 4-8. Pairwise comparisons of AUCord values for each outcome. The red bracket identifies a nonsignificant difference of interest. The blue bracket identifies a difference in delay discounting that is opposite of what is typically observed with money. Two panels are presented to improve the ease of making meaningful visual comparisons between tasks.

food was discounted less than $100 of food, which is in the opposite direction of the typically observed magnitude effect (e.g., larger amounts are discounted less than smaller amounts). Although this finding is unexpected, the large sample size supports the validity of this finding.

Latent Factor Analyses

Structural equation modeling analyses were conducted to understand the relation between delay discounting, cardinal utility, marginal utility, and time perception. First, the model parameters for cardinal and marginal utility were log transformed to improve their parametric properties. Next, bivariate correlations between all variables of interest were conducted (Figure 4-9). All AUCord values were strongly positively correlated,

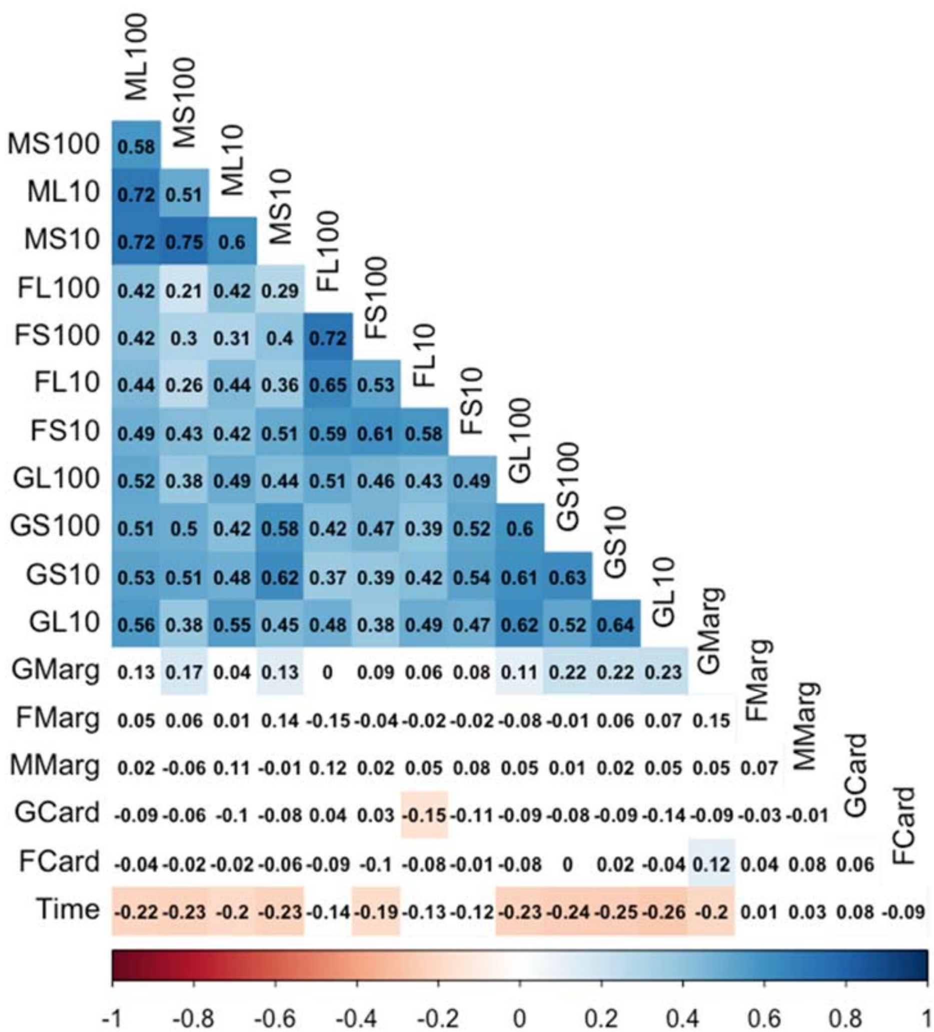

Figure 4-9. Pearson correlations of all outcomes. Squares with no color represent nonsignificant correlations (e.g., p > 0.05). The figure abbreviations are: M = Money, F = Food, G = Gasoline, L = Long, S = Short, Marg = Marginal Utility, Card = Cardinal Utility, and Time = Time perception.

indicating that high AUCord (low discounting) values for one delayed outcome strongly predict high AUCord values for other outcomes. Marginal and cardinal utility (α parameter) were poorly correlated with AUCord or other utility measures. Some significant correlations between marginal utility, cardinal utility, and time perception and delay discounting were found. To aid in replication of the latent factor models, means, standard deviations, and standard error values are reported (Table 4-10). For all latent models, case-wise (or full information) maximum likelihood estimation was used instead of generalized least squares to allow for the inclusion of incomplete participant data.

Table 4-10

Outcome Descriptive Statistics

Variable	Mean	*SD*	*S.E.*
Money Long $100	0.717	0.220	0.012
Money Long $10	0.656	0.222	0.012
Money Short $100	0.870	0.204	0.011
Money Short $10	0.841	0.208	0.011
Food Long $100	0.490	0.280	0.015
Food Long $10	0.488	0.243	0.013
Food Short $100	0.609	0.309	0.016
Food Short $10	0.666	0.245	0.013
Gasoline Long $100	0.630	0.245	0.013
Gasoline Long $10	0.589	0.247	0.013
Gasoline Short $100	0.768	0.253	0.014
Gasoline Short $10	0.743	0.252	0.013
Log Marginal Money	-3.819	2.832	0.158
Log Marginal Food	-3.276	3.377	0.182
Log Marginal Gasoline	0.908	3.475	0.186
Ln Cardinal Food	-2.069	0.564	0.033
Ln Cardinal Gasoline	-6.479	4.722	0.270
Log Time Perception	-3.436	3.204	0.172

Note. Cardinal utility values are α (elasticity) parameter.

Single discounting factor model. First, a model that explored the abilities of the utility outcomes to predict general delay discounting was created (Figure 4-10). A structural equation model was created with a factor for delay discounting, a factor for marginal utility, and a factor for cardinal utility. The two utility factors and time perception were regressed onto the delay discounting factor to analyze the degree to which those measures predict delay discounting. For the cardinal utility factor, it was necessary to set both factor loadings to 1 for the model to converge properly.

The overall model fit was very poor (χ^2(df = 131) = 985.520, p < .001, CFI = 0.688, TLI = 0.636, RMSEA = 0.136, SRMR = 0.079). This is largely because a single

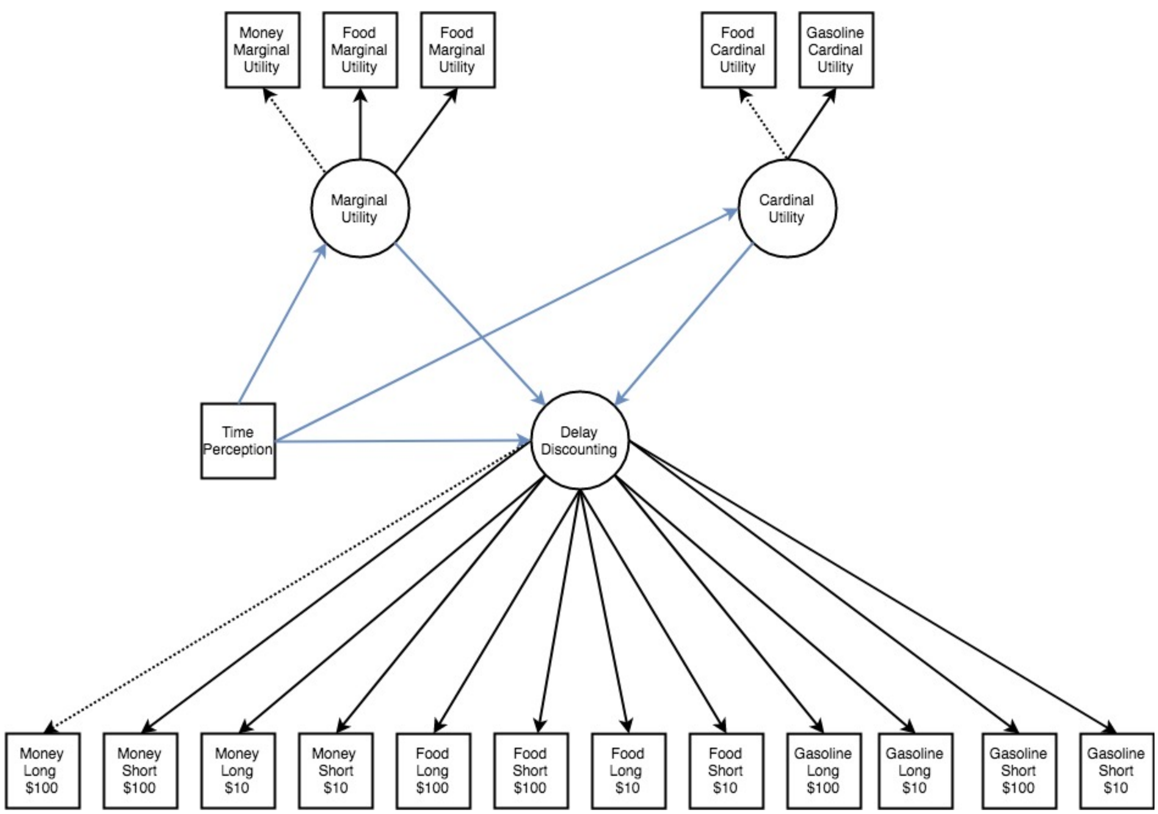

Figure 4-10. Single discounting factor model. SEM of marginal and cardinal utility factors regressed onto a delay discounting factor. Only the model structure is shown.

delay discounting factor is too restrictive. Although all loadings for the delay discounting factor were significant, no loadings for the two utility factors were significant, indicating that the utility factors poorly predicted the observed utility variables. This finding corroborates the poor correlations between these variables. However, time perception did significantly predict delay discounting (Std. loading = -0.259 $p < .001$), indicating that as the perception of time becomes increasingly nonlinear, delay discounting increases. Therefore, future models may include these variables in regression equations; however, they should not have their own factors. Modification indices (report of the residual error covariance between manifest variables that is not explained by a latent factor) suggest additional factors of magnitude and delay distribution for the delay discounting manifest variables.

Bi-factor model. A bi-factor model (Eid, Geiser, Koch, & Heene, in press) was created with unique factors for magnitude and outcome type and residual factors for the short delay scales. This modeling approach is different from more traditional bifactor models (Eid et al., in press). For example, a traditional bi-factor model would include a general discounting factor that loads onto all delay discounting measured variables and residual factors for each specific delay discounting tasks. These models assume that factor representations (e.g., domains) are interchangeable or randomly selected. However, in practice, the assumption that domains are interchangeable is rarely the case. As a result, the meaning of the general factors is unclear.

A more appropriate approach to bi-factor models when facets are non-interchangeable is to define general factors based on a reference facet. In this approach, one facet serves as reference to which the remaining facets are compared. Method (or specific) factors are specified for each non-reference facet. The method factors represent the residual covariance among the measured variables of a domain (e.g., shared characteristics of different measured variables) that is not shared with the reference factor.

The short delay scale tasks were chosen as non-reference facets, because long delay scale tasks are more common and therefore are more appropriate points of reference. Other model structures are possible but they may not reflect the typical way in which delay-discounting task results are compared. Appendix 4D presents the results of the final model with the factors reversed: reference factors for the short delay scale tasks and residual factors for the long delay scale tasks. Comparing the two different model structures can indicate which tasks serve as better reference variables. However, for the purposes of this study, a model structure that closely reflects typical delay progressions and amounts is most appropriate. Because of the short delay methods factors, the magnitude/outcome factors also become magnitude/outcome/long factors. The magnitude/outcome/long factors are reference factors that measure the covariance between the discounting tasks of different amounts in context of the long delay distribution task. The loadings for the non-long variables within the long reference variables represents the amount of variance that is shared with the reference variable (e.g., \$100 long or \$100 short for each outcome). This covariance in part represents the shared covariance related to the amount of the outcome. For the long discounting tasks within the long discounting factors, these are the true scores of these variables because they do not pertain to the methods factors.

The method factor loadings for the short delay distribution tasks account for the variance between short delay distribution tasks not accounted for by the long reference factors. Finally, the marginal utility, cardinal utility, and time perception measured variables were regressed onto their corresponding factors. Therefore, the correlation between factors represents the residual correlations after removing the variance accounted for by marginal utility, cardinal utility, and time perception.

The overall model fit was very good, χ^2(df = 66) = 98.908, p = 0.05, CFI = 0.988, TFI = 0.975, RMSEA = 0.038, SRMR = 0.033. All factor loadings were significant. Also, time perception significantly predicted most reference and methods factors (standardized regression coefficients: money long \$100 = -0.226, money long \$10 = -0.187, food long \$100 = -0.119, gasoline long \$100 = -0.220, gasoline long \$10 = -0.192, money short = -0.166, gasoline short = -0.256). The factor correlation for money \$100 and money \$10 was greater than 1, indicating that the correlation between the different money delay discounting tasks was perfect (within the margin of error) after accounting for the shared measurement error between tasks. The final model combined these two factors into a single factor to address this perfect factor covariance and create a more parsimonious model.

Final model. The final model was similar to the previous bi-factor model but with the Money \$100 factors and Money \$10 factors combined into a Money factor (Figure 4-11—model structure; Figure 4-12—regressions onto factors; Table 4-11) to address the correlation of 1 between the two factors. This change decreased the quality of fit, χ^2(df =

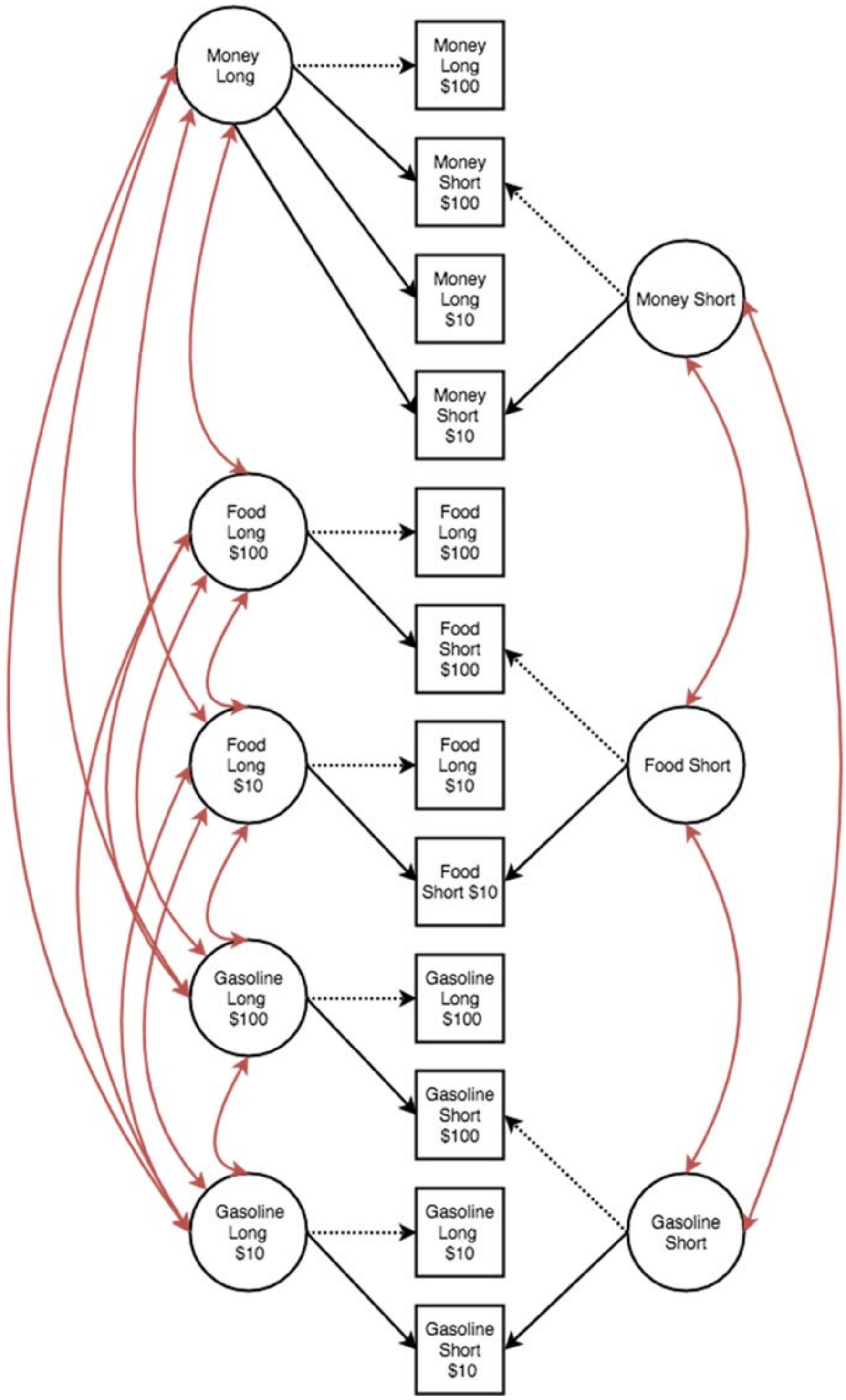

Figure 4-11. Structural model. Red lines are factor covariances.

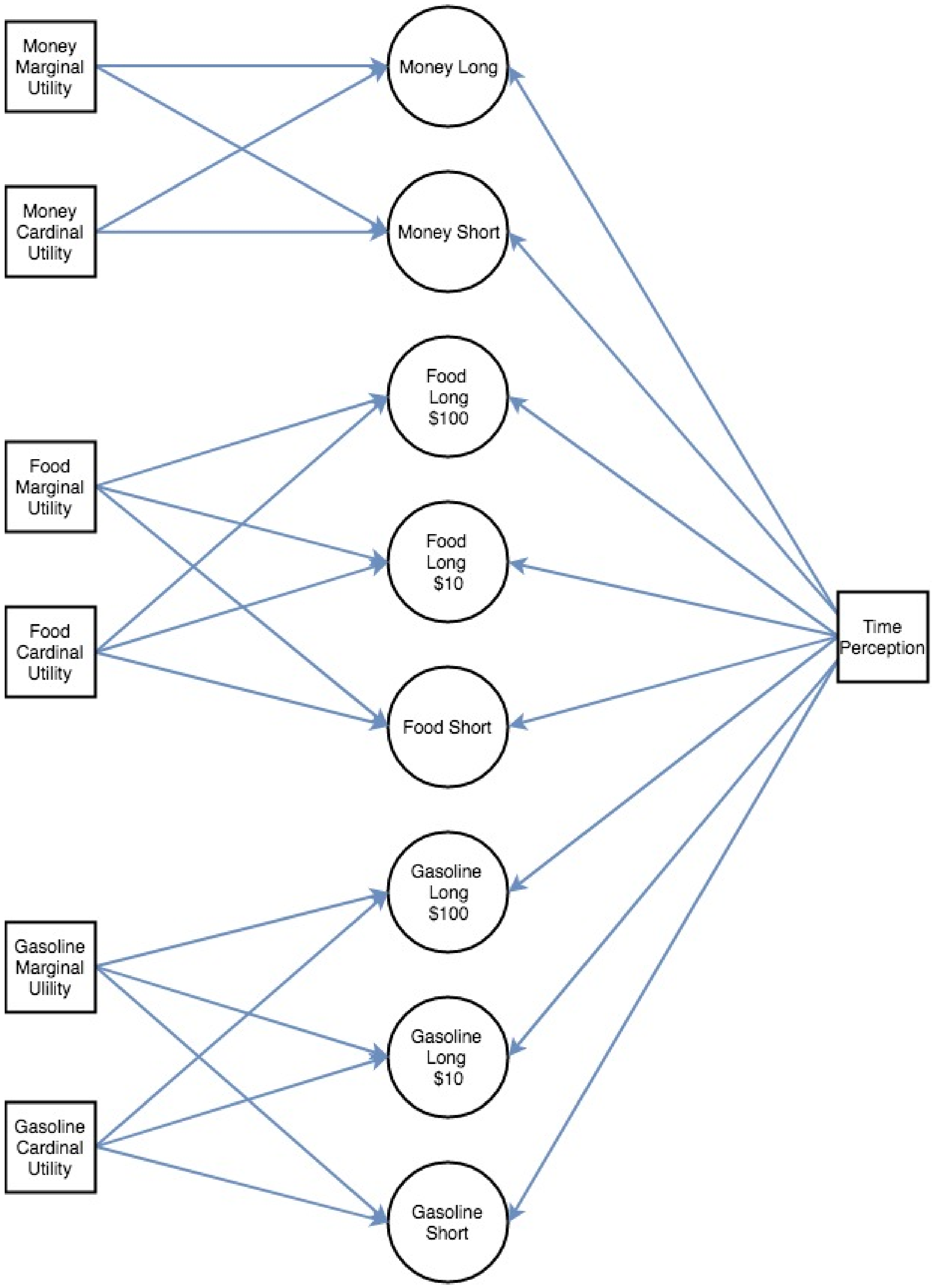

Figure 4-12. Regression model. Blue lines are variable regression lines.

Table 4-11

Final Bi-Factor Model Results

Latent factor	Manifest variable	Estimate	Standardized factor loading	R^2
Reference factors				
Money long				
	Money long $100	1.000	0.882	0.778
	Money short $100	0.674	0.642***	0.412
	Money long $10	0.918	0.803***	0.645
	Money short $10	0.795	0.743***	0.552
Food long $100				
	Food long $100	1.000	0.791	0.626
	Food short $100	0.924	0.764***	0.584
Food long $10				
	Food long $10	1.000	0.791	0.623
	Food short $10	0.952	0.746***	0.557
Gasoline long $100				
	Gasoline long $100	1.000	0.843	0.711
	Gasoline short $100	0.840	0.689***	0.474
Gasoline long $10				
	Gasoline long $10	1.000	0.825	0.681
	Gasoline short $10	0.917	0.743***	0.552
Methods factors				
Money short				
	Money short $100	1.000	0.508	0.258
	Money short $10	1.139	0.568***	0.323
Food short				
	Food short $100	1.000	0.314	0.010
	Food short $10	0.938	0.372***	0.138
Gasoline short				
	Gasoline short $100	1.000	0.370	0.134
	Gasoline short $10	1.148	0.427***	0.182
Regressions	**Manifest variable**	**Estimate**	**Standardized regression coefficient**	**R^2**
Money long				
	Money marginal utility	0.002	0.031	0.000
	Time perception	-0.013	-0.213***	0.045
Food long $100				
	Food marginal utility	-0.004	-0.057	0.003
	Food cardinal utility	-0.034	-0.078	0.006
	Time perception	-0.010	-0.119*	0.014
Food long $10				
	Food marginal utility	-0.002	-0.034	0.001
	Food cardinal utility	-0.015	-0.046	0.002
	Time perception	-0.004	-0.070	0.005

(*table continues*)

Regressions	Manifest variable	Estimate	Standardized regression coefficient	R^2
Gasoline long $100				
	Gasoline marginal utility	0.005	0.092*	0.008
	Gasoline cardinal utility	-0.001	-0.022	0.000
	Time perception	-0.014	-0.220***	0.048
Gasoline long $10				
	Gasoline marginal utility	0.010	0.165**	0.027
	Gasoline cardinal utility	-0.002	-0.037	0.001
	Time perception	-0.012	-0.193**	0.037
Money short				
	Money marginal utility	-0.003	-0.094	0.008
	Time perception	-0.005	0.159*	0.025
Food short				
	Food marginal utility	0.000	0.006	0.000
	Food cardinal utility	0.019	0.117	0.014
	Time perception	-0.003	-0.113	0.012
Gasoline short				
	Gasoline marginal utility	-0.001	-0.019	0.000
	Gasoline cardinal utility	0.002	0.115	0.013
	Time perception	-0.007	-0.255**	0.065

Factor correlations with regressions	Manifest variable	Covariance estimate	Residual correlation
Money long			
	Food long $100	0.021	0.442***
	Food long $10	0.020	0.556***
	Gasoline long $100	0.026	0.682***
	Gasoline long $10	0.026	0.703***
	Food short	0.003	0.188
	Gasoline short	0.002	0.115
Food long $100			
	Food long $10	0.042	0.866***
	Gasoline long $100	0.033	0.659***
	Gasoline long $10	0.032	0.640***
	Money short	-0.004	-0.162*
	Gasoline short	-0.005	-0.200*
Food long $10			
	Gasoline long $100	0.024	0.622***
	Gasoline long $10	0.028	0.749***
	Money short	-0.003	-0.133
	Gasoline short	-0.001	-0.085
Gasoline long $100			
	Gasoline long $10	0.035	0.897***
	Money short	-0.002	-0.092
	Food short	0.004	0.200
Gasoline long $10			
	Money short	-0.004	-0.95**
	Food short	-0.002	-0.116

(*table continues*)

Factor correlations with regressions	Manifest variable	Covariance estimate	Residual correlation
Money short			
	Food short	0.008	0.838***
	Gasoline short	0.008	0.931***
Food short			
	Gasoline short	0.007	0.856***

Factor correlations without regressions	Manifest variable	Covariance Estimate	Factor Correlation
Money long			
	Food long $100	0.022	0.444***
	Food long $10	0.021	0.553***
	Gasoline long $100	0.028	0.698***
	Gasoline long $10	0.028	0.712***
	Food short	0.004	0.222*
	Gasoline short	0.002	0.099
Food long $100			
	Food long $10	0.043	0.866***
	Gasoline long $100	0.035	0.657***
	Gasoline long $10	0.032	0.627***
	Money short	-0.004	-0.167*
	Gasoline short	-0.005	-0.227**
Food long $10			
	Gasoline long $100	0.025	0.627***
	Gasoline long $10	0.029	0.741***
	Money short	-0.003	-0.137
	Gasoline short	-0.003	-0.142
Gasoline long $100			
	Gasoline long $10	0.038	0.906***
	Money short	-0.001	-0.054
	Food short	0.005	0.230*
Gasoline long $10			
	Money short	-0.003	-0.143*
	Food short	-0.001	-0.060
Money short			
	Food short	0.008	0.808***
	Gasoline short	0.009	0.932***
Food short			
	Gasoline short	0.008	0.878***

* $p < .05$.
** $p < .01$.
*** $p < .001$.

75) = 124.234, p < .001, CFI = 0.990, TFI = 0.984, RMSEA = 0.031, SRMR = 0.036. However, besides the now statistically significant chi-square value, the other fit indices still indicated an acceptable model fit. Table 4-11 reports factor loadings and regression

values as well as the factor covariances (with and without regressions) for the final model.

Strong correlations between factors remained (e.g., Gasoline \$100 and Gasoline \$10, Money Short, Food Short, and Gasoline Short) but these factors were kept separate to differentially investigate the regressions of the marginal utility, cardinal utility, and time perception variables on these factors. The factor loadings for both the reference and methods factors for all outcomes were statistically significant, indicating that the latent factors strongly predicted their corresponding measured variables. The large R^2 values for each measured variable (e.g., R^2 for reference measured variables and summed R^2 for measured variables that load onto reference and methods factors) indicate a high degree of reliability for each variable. Finally, the majority of the regression equations did not yield significant results. However, marginal utility of gasoline did predict both the Gasoline \$100 and Gasoline \$10 factors. Also, nonlinear time perception (e.g., k in the model) significantly predicted the Money Long, Food Long \$100, Gasoline Long \$100, Gasoline Long \$10, Money Short, and Gasoline Short. However, most of the R^2 values were less than 5%. Importantly, nonlinear time perception did not predict most food factors.

Discussion

This study is the first to apply structural equation modeling to understand the underlying components of delay discounting. Its goal was to investigate the proposed influence of marginal utility, cardinal utility, and time perception in the discounting of delayed outcomes (Zauberman, et al., 2008; Myerson & Green, 1995; Rachlin, 2006; Killeen 2015). It also sought to understand the degree to which delay discounting has trait-like tendencies. First, the individual measures will be discussed. Next, the latent factor analyses will be interpreted. Finally, general conclusions will be discussed.

Utility

The model fit values for marginal and cardinal utility from individual participants were very good. For cardinal utility, as measured by demand curve analyses, the demand curve equation (Hursh & Silberberg, 2008; Koffarnus et al., 2015) fit individual participant data well. This finding validates the inclusion of the elasticity parameter in the latent factor analysis, because it can be assumed that this parameter measures the proposed construct of demand elasticity. How to properly and quantitatively describe the marginal utility task results was less clear. Previous research (Harinck et al., 2007; Killeen, 2015) has suggested a logarithmic function best describes marginal utility. However, the results of this study (model fits to individual data) suggest an exponential growth function best describes the task results.

Two possibilities can account for the discrepancy between previously proposed models of marginal utility and the model selected here. First, it is possible that the true function of marginal utility is an exponential growth function. A second possibility is that the task used here did not actually measure the true construct of marginal utility because of its reliance on "utiles" or subjective value as its principle unit. Similar limitations exist in the measurement of cardinal utility. This difficulty is evident in the history of these constructs in economics. Utility was initially conceived in terms of marginal and cardinal utility (Bentham, 1789). However, as economics moved towards a greater emphasis of precise quantification in the late 19th century, ordinal utility (e.g., the value of a good in quantities of another good) gained favor (Van Praag, 1990). More recently, psychology and economics have developed common interests and once again marginal and cardinal utility have gained favor as valid conceptualizations of utility (Kahneman et al., 1997). Unfortunately, and in part validating the concerns of the proponents of ordinal utility, methods of directly assessing marginal and cardinal utility are limited. It is possible that although the exponential model fit the marginal utility results very well, the underlying task did not actually measure marginal utility. Additionally, a compromise was necessary in the measurement of cardinal utility with the rate of change in elasticity (e.g., essential value) serving as the proxy for "utiles" or value. A similar compromise was necessary for marginal utility, with "happiness" serving as the proxy for "utiles." Future research should work towards developing better methods of measuring cardinal and marginal utility.

Time Perception

The results of the time perception model were similar to those of Zauberman et al. (2008) with the logarithmic model fitting the data well. A large body of literature confirms our finding that time is perceived logarithmically (e.g., Takahashi, 2005; Takahashi, Oono, & Radford, 2008). The current task was adopted from the Zauberman et al. task but modified to better match the delays from the delay discounting task. This is an important modification because it demonstrates that logarithmic time perception persists across a greater range of delays than previously demonstrated.

Delay Discounting

Three important findings from the delay discounting model fits emerged. First, the hyperbolic model (Mazur, 1987) was almost universally favored, comparing AICc values, over the hyperboloid model (Myerson & Green, 1995) for both model fits to group median and indifference points from individual participants. This finding held true despite low R^2 values for the hyperbolic model fits to individual data. This discrepancy is due to the differences in how theses fit indices are calculated. R^2 can be calculated as:

$$R^2 = 1 - \frac{RSS}{TSS} \tag{4-8}$$

where *RSS* is the residual sums of squares and *TSS* is the total sums of squares. The residual sums of squares represent the total deviation of the model from the actual data. The total sums of squares are the sum of the difference of each data point from the mean of all data points. It is possible to obtain a negative R^2 if the *TSS* is smaller than the *RSS*. For the short delay discounting tasks, a negative R^2 value is possible when the delayed outcome was not discounted. The hyperboloid model (Equation 4-2; Myerson & Green, 1995) can provide a good fit to data with little or no discounting, resulting in a large R^2 value (e.g., small *RSS* and small *TSS*). The hyperbolic model (Equation 4-1; Mazur, 1987) cannot, resulting in a larger *RSS* value compared to the *TSS* value and therefore negative R^2 values.

Akaike's Information Criteria is not affected by the unlikely scenario of *RSS* being larger than *TSS*. Akaike's Information Criteria (AICc in this study) can be calculated as:

$$AIC = n * \ln\left(\frac{RSS}{n}\right) + 2 * K \tag{4-9}$$

where *n* is the number of data points, *RSS* is the residual sums of squares, and *K* is the number of free-parameters in the model. Therefore, a large *RSS* can be offset by the number of free parameters in the model. The additional correction for a small number of data points (AICc) further penalizes models with additional parameters.

The discrepancy between AICc (and to a lesser extent $S_{y.x}$) values and R^2 provides further evidence that R^2 is an inappropriate measure for summarizing the quality of fit for a nonlinear regression model. Additionally, the hyperboloid model was more likely to fail to converge or to provide ambiguous values. Franck et al. (2015) report a similar finding, that the Myerson and Green (1995) hyperboloid is more likely to not converge or to produce ambiguous parameter estimates (different parameter values that produce identical fits).

Another finding of interest is that the model fits for the two delay distributions of a specific magnitude of an outcome aligned. In most instances, the omnibus model fit was superior to the individual model fits. Even when the omnibus model fit parameters were used to fit the individual delay distribution tasks, the difference in the quality of fit from the individual model fits was minimal. These findings suggest that each delay is treated independently from the other delays in a delay discounting task. The quality of the omnibus model fit argues against the view that delays are evaluated in the context of the other delays in a delay-discounting task (Scholten, Read, & Sanborn (2014). There is evidence to suggest global patterns of discounting (as corroborated by the high correlation among the degree of discounting with different delay-discounting tasks) within an individual. If an individual steeply discounted an outcome in the short delay progression task, they were also likely to steeply discount an outcome in the long delay progression task, resulting in the modest alignment of the two discounting functions. Further research should investigate the degree to which the discounting of an outcome at a specific delay is influenced by the other delays that have been presented.

Finally, like the pilot study results, there was no difference in the discounting of small and large food amounts for the long delay distribution tasks. This finding is similar to the non-human animal literature that fails to demonstrate that large amounts of food are discounted by delay less than small amounts of food (Freeman, Green, Myerson, & Woolverton, 2009; Green, Myerson, Holt, Slevin, & Estle, 2004; Richards, Mitchell, de Wit, & Seiden, 1997). Conversely, Food Short $10 was discounted less than Food Short $100, which is opposite of the typical finding in the human literature that large amounts of an outcome are discounted less than small amounts of an outcome (Chapman & Elstein, 1995; Estle, et al., 2007; Green, Myerson, Oliveira, & Chang, 2013). Discounting larger amounts of delayed food more than small amounts has also been found in the non-human literature (Ong & White, 2004). For example, Richards, Mitchell, de Wit, and Seiden (1997) reported that rats discounted larger amounts of food more than smaller amounts (see Grace, Sargisson, & White, 2012, for an example of pigeons discounting larger amounts more than smaller amounts). Interestingly, this finding appears to be unique to food, as large amounts of money and gasoline were discounted less than small amounts of money and gasoline in both this study and the pilot study. Conversely, Jimura, Myerson, Hilgrad, Braver, and Green (2009) found that human participants discounted large amounts of juice less than small amounts of juice using a delay scale that ranged from 5-85 s. Therefore, methodological factors (e.g., hypothetical vs. real rewards) may account for the conflicting results in both the human (Jimura, et al., 2009) and non-human (Grace et al., 2012) literature. The data reported here are some of the first to offer a potential reconciliation of the previously posited contradiction between discounting in human and non-human animals.

Latent Factor Analyses

The SEM results will be discussed in terms of the implications of the model structure and the factor regressions. Typically, AUC is compared using bivariate correlations (Charlton & Fantino, 2008; Friedel, et al., 2014; Johnson et al., 2010). Structural equation modeling is superior to a bivariate correlation matrix in two ways. First, it allows for the comparison of many variables at once. Second, it accounts for the shared measurement error between tasks, which allows for a truer depiction of the covariance between tasks. Both of these benefits are made clear in the model structure results. The model structure describes the covariance between delay-discounting task results of the same amount, outcome type, and delay distribution. The factor regressions describe the ability of marginal utility, cardinal utility, and time perception to account for the factor variances.

The model structure revealed two important findings. First, the revised final model combined the Money Long $100 and Money Long $10 factors because the covariance between the two factors was one. This signifies that after factoring out the shared measurement error among the delay-discounting tasks, the rank order for individuals for the monetary delay-discounting tasks was nearly perfect. Additionally, high factor covariances of the other factors suggest a very high individual rank-order among all delay-discounting tasks. This finding provides more complete evidence that delay discounting has trait-like qualities (Odum, 2011). Although some research has suggested that the discounting of all delayed outcomes is not related (Green & Myerson, 2013; Lawyer & Schoepflin, 2013), superior methods of measure trait variables (e.g., SEM) provide a more complete answer. The results of this study indicate that there is very strong evidence for referring to delay discounting as a trait.

Second, the model structure was successful in accounting for a large proportion of the variance of each delay discounting task. The long factors accounted for the greatest proportion of variance, even for the short delay distribution tasks. However, the short factors also accounted for a significant proportion of the short delay distribution task variances. Therefore, the variance accounted for by the long factors for the short tasks more accurately represents the shared commodity and magnitude, after having accounted for specific variance of the short delay distribution. Because the long factors accounted for a greater proportion of variance in the short delay distribution tasks than the short factors, it can be concluded that commodity type and amount play a larger role in accounting for the similarities in delay discounting than the delay distribution.

The factor regressions did not provide evidence for marginal and cardinal utility as underlying components of delay discounting. Marginal and cardinal utility did not predict their corresponding factors except gasoline marginal utility, which did predict Gasoline Long \$100 and Gasoline Long \$10. However, the R^2 values were minimal (1%). These findings suggest that the Additive Utility Model of delay discounting (Killeen

2009, 2015) may not incorporate the actual underlying psychological processes. Time perception did significantly predict the three short factors, with a small R^2 values averaging 5%. Overall, these three underlying components do not appear to predict delay discounting in a meaningful way. In fact, a latent model that excludes these regression paths fit the data better, $\chi^2(df = 25) = 36.568$, $p = 0.63$, CFI = 0.996, TFI = 0.989, RMSEA = 0.036, SRMR = 0.017. The improved model fit suggests that the regression paths did not provide a greater explanation of the data and actually made the model more complex than necessary. However, it is valuable to maintain the regression paths in the model to test the hypotheses of the proposed underlying components of delay discounting.

Ultimately, the results of the SEM analyses are inconclusive in identifying the underlying components of delay discounting. Marginal and cardinal utility appear to have no explanatory power in understanding delay discounting and nonlinear time perception is less predictive than expected. Two possible explanations for these findings exist. First, the tasks used to measure marginal and cardinal utility may have poor construct validity. Although the quantitative models fit the data well, because of the nebulous nature of utility, further research is needed to identify the tasks that best measure these constructs. Second, the model may be correct in demonstrating that marginal and cardinal utility are not underlying components of delay discounting. An alternative explanation that accounts for differences in outcomes and magnitudes is the scaling of amount (similar to the scaling of time; Halberda et al., 2008). Perhaps larger numbers are perceived differently from smaller numbers (Arshad, et al., 2016), independently of the context in which they are presented. Peters, Slovic, Västfjäll, and Mertz (2008) found that participants who more precisely identified numbers and nonnumerical stimuli (e.g., pictures of dots or lines) as smaller or larger than a target quantity were more likely to choose the larger-delayed outcome in a delay-discounting task compared to participants with less accurate amount perception. The differential perception of amount also provides an explanation for the results of the experiments in Chapter 3 in that larger numerical representations (dollars) were discounted more than smaller numerical representations (handfuls of quarters). Further research should investigate how the perception of amount, independent of utility, predicts delay discounting.

Time perception did account for a statistically significant portion of the variance of several factors, although the degree of prediction was small. The time perception task used here represents one type of time perception. Other tasks, such as the temporal bisection task, measure different forms of time perception. Baumann and Odum (2012) found that the temporal bisection task moderately predicted delay discounting. The temporal-bisection tasks measures time perception on a much shorter time frame and is more concerned with the precision in estimating time intervals. The length of one's temporal window also appears to be related to delay discounting. Quisenbery, Bianco, Gatchalian, and Kim-Spoon (2016) demonstrated that differences in delay discounting between adolescent smokers and nonsmokers can in part be attributed to shorter temporal windows (e.g., how far into the future a consequence can impact immediate behavior) in smokers compared to non-smokers. Stein et al. (2016) found that extending an individual's temporal window through episodic future thinking (e.g., imagining oneself into the future to experience the delayed outcome) reduces delay discounting and subsequent cigarette smoking. Future research should investigate the degree to which these different measures of time perception predict delay discounting.

Conclusions

The results of this study provide powerful evidence for the establishment of delay discounting as a trait. The strong correlation among latent factors demonstrate that how an individual discounts one domain of an outcome (e.g., outcome type/amount/delay progression) is strongly related to how they are discounting other outcome types, amounts, and delay progressions. Classifying delay discounting as a trait does not necessarily mean that delayed outcomes should be discounted equally regardless of the amount, outcome type, or delay scale. Identifying delay discounting as a trait indicates that there is a great deal of consistency within an individual. The SEM results have clearly demonstrated that how one outcome (regardless of amount and delay scale) is discounting by delay is strongly predictive of how other outcomes are discounted by delay. Another characteristic of a trait is its temporal stability. Further research using latent state/trait methods should be conducted to better investigate the temporal stability of delay discounting by accounting for shared measurement error.

Calling a class of behaviors a trait also does not necessarily mean it can never change. Changes in personality traits have been shown (Roberts, Walton, & Viechtbauer, 2006), suggesting that these behaviors, while highly consistent, are not unmovable. The classification of delay discounting as a trait would suggest that any intervention that affects the discounting of one type of outcome should also affect the discounting of other outcomes. Future research can further solidify delay discounting as a trait by addressing this question.

Finally, the underlying components of delay discounting remain unclear. The results of this study perhaps best validate the hyperboloid model first proposed by Mazur (1987) and then reintroduced by Rachlin (2006). This model explicitly addresses nonlinear time perception but does not include additional processes that affect the amount of the outcome. Future research should work towards identifying those underlying components of delay discounting and in turn develop a quantitative model that incorporates those components.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19*, 716-723. doi:10.1109/TAC.1974.1100705

Arshad, Q., Nigmatullina, Y., Nigmatullin, R., Asavarut, P., Goga, U. … Malhotra, P. A. (2016). Bidirectional modulation of numerical magnitude. *Cerebral Cortex, 26*, 2311-2324. doi: 10.1093/cercor/bhv344

Audrain-McGovern, J., Rodriguez, D., Epstein, L. H., Cuevas, J., Rodger, K., & Wileyto, E. P. (2009). Does delay discounting play an etiological role in smoking or is it a consequence of smoking? *Drug Alcohol Depend, 103*, 99-106. doi: 10.1016/j.drugalcdep.2008.12.019

Bentham, J. (1789). *An introduction to the principle of morals and legislations* (Reprinted in 1948). Retrieved from www.earlymoderntexts.com/assets/pdfs/ bentham1780.pdf

Baumann, A. A., & Odum. A. L. (2012). Impulsivity, risk taking and timing. *Behavioural Processes, 90*, 408-414. doi: 10.1016/j.beproc.2012.04.005

Bidwell, L. C., MacKillop, J., Murphy, J. G., Tidey, J. W., & Colby, S. M. (2012). Latent factor structure of a behavioral economic cigarette demand curve in adolescent smokers. *Addictive Behavior, 37*, 1257-1263. doi: 10.1016/j.addbeh.2012.06.009

Bickel, W. K., Jarmolowicz, D. P., Mueller, E. T., Koffarnus, M. N., & Gatchalian, K. M. (2012). Excessive discounting of delayed reinforcers as a trans-disease process contributing to addiction and other disease-related vulnerabilities: Emerging evidence. *Pharmacology and Therapeutics*, *134,* 287-297. doi: 10.1016/ j.pharmthera.2012.02.004

Bickel, W. K., Koffarnus, M. N., Moody, L., & Wilson, A. G. (2014). The behavioral- and neuro-economic process of temporal discounting: A candidate behavioral marker of addiction. *Neuropharmacology, 76*, 518-527. doi: 10.1016/ j.neuropharm.2013.06.013

Bickel, W. K., Odum, A. L., & Madden, G. J. (1999). Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. *Psychopharmacology, 146*, 447-454. doi: 10.1007/PL00005490

Black, A. C., & Rosen, M. I. (2011). A money management-based substance use treatment increases valuation of future rewards. *Addictive Behaviors, 36*, 125-128. doi: 10.1016/j.addbeh.2010.08.014

Bollen, K. A. (2002). Latent variables in Psychology and the Social Sciences. *Annual Review of Psychology, 53*, 605-634. doi: 10.1146/annurev.psych.53.100901. 135239

Borges, A. M., Kuang, J., Milhorn, H., & Yi, R. (2016). An alternative approach to calculating Area-Under-the-Curve (AUC) in delay discounting research. *Journal of the Experimental Analysis of Behavior, 106*, 145-155. doi: 10.1002/jeab.219

Brown, A. M. (2001). A step-by-step guide to nonlinear regression analysis of experimental data using a Microsoft Excel spreadsheet. *Computer Methods and Programs in Biomedicine, 65*, 191-200. doi: 10.1016/S0169-2607(00)00124-3

Chapman, G. B., & Elstein, A. S. (1995). Valuing the future: Temporal discounting of health and money. *Medical Decision Making, 15*, 373-386. doi: 10.1177/ 0272989X9501500408

Charlton, S. R., & Fantino, E. (2008). Commodity specific rates of temporal discounting: Does metabolic function underlie differences in rates of discounting? *Behavioural Processes, 77*, 334-342. doi: 10.1016/j.beproc.2007.08.002

Coffey, S. F., Gudleski, G. D., Saladin, M. E., & Brady, K. T. (2003). Impulsivity and rapid discounting of delayed hypothetical rewards in cocaine-dependent individuals. *Experimental and Clinical Psychopharmacology, 11*, 18-25. doi: 10.1037/1064-1297.11.1.18

Crystal, J. D. (2001). Nonlinear time perception. *Behavioural Processes, 55,* 35-49. doi: 10.1016/S0376-6357(01)00167-X de Wit, H. (2008). Impulsivity as a determinant and consequence of drug use: A review of underlying processes. *Addiction Biology, 14*, 22-31. doi: 10.1111/j.1369-1600.2008.00129.x

Dehaene, S. (2003). The neural basis of the Weber-Fechner Law: A logarithmic mental number line. *Trends in Cognitive Sciences, 7,* 145-147. doi: 10.1016/S1364-6613(03)00055-X

DeHart, W. B., & Odum, A. L. (2015). The effects of the framing of time on delay discounting. *Journal of the Experimental Analysis of Behavior, 103*, 10-21. doi: 10.1002/jeab.125

DeHart, W. B., Friedel, J. E., Frye, C. C. J., Galizio, A.,& Odum, A. L. (2017). *A fistful of quarters: The effects of outcome unit framing on delay discounting.* Manuscript submitted for publication.

DeHart, W. B., Friedel, J. E., Lown, J. E., & Odum, A. L. (2016). The effects of financial education on impulsive decision making. *PLOS ONE, 11*(7)*,* e0159561. doi: 10.1371/journal.pone.0159561

Doyle, J. R., & Chen, C. H. (2012). The wages of waiting and simple models of delay discounting. http://ssrn. com/abstract=2008283.

Du, W., Green, L., Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *Psychological Record*, *52*(4), 479-492.

Eid, M., Geiser, C., Koch, T., & Heene, M. (in press). Anomalous results in G-factor models: Explanations and alternatives. *Psychological Methods.*

Estle, S. J., Green, L., Myerson, J., & Holt, D. D. (2007). Discounting of monetary and directly consumable rewards. *Psychological Science, 18*, 58-63. doi: 10.1111/j.1467-9280.2007.01849.x

Fields, S., Sabet, M., Peal, A., & Reynolds, B. (2011). Relationship between weight status and delay discounting in a sample of adolescent cigarette smokers. *Behavioural Pharmacology*, *22*, 266-268. doi: 10.1097/FBP.0b013e328345c855

Fields, S. A., Sabet, M., & Reynolds, B. (2013). Dimensions of impulsive behavior in obese, overweight, and healthy-weight adolescents. *Appetite, 70*, 60-66. doi: 10.1016/j.appet.2013.06.089

Fernie, G., Peeters, M., Gullo, M., Christiansen, P., Cole, J. C., Sumnall, H. … Field, M. (2013). Multiple behavioral impulsivity tasks predict prospective alcohol involvement in adolescents. *Addiction*, 108, 1916-1923. doi: 0.1111/add.12283.

Franck, C., Koffarnus, M., House, L., & Bickel, W. (2015). Accurate characterization of delay discounting: A multiple model approach using approximate Bayesian model selection and a unified discounting measure. *Journal of the Experimental Analysis of Behavior, 103,* 218-233. doi: 10.1002/jeab.128.

Freeman, K., Green, L., Myerson, J., & Woolverton, W. (2009). Delay discounting of saccharin in rhesus monkeys. *Behavioural Processes, 82,* 214 -218. doi:10.1016/j.beproc.2009.06.002

Friedel, J. E. (2016). *An examination of how qualitatively different delayed outcomes are discounted* (Unpublished doctoral dissertation). Utah State University, Logan UT.

Friedel, J. E., DeHart, W. B., Frye, C. C. J., Rung, J. M., & Odum, A. L. (2016). Discounting of qualitatively different delayed health outcomes in current and never smokers. *Experimental and Clinical Psychopharmacology, 24*, 18-29. doi: 10.1037/pha0000062

Friedel, J. E., DeHart, W. B., Madden, G. J., & Odum, A. L. (2014). Impulsivity and cigarette smoking: Discounting of monetary and consumable outcomes in current and non-smokers. *Psychopharmacology, 231*, 4517-4526. doi: 10.1007/s00213-014-3597-z

Frye, C. C. J., Galizio, A., Friedel, J. E., DeHart, W. B., & Odum, A. L. (2016). Measuring delay discounting in humans using an adjusting amount task. *Journal of Visualized Experiments, 107,* e53584-e53584. doi:10.3791/53584

Grace, R. C., Sargisson, R. J., & White, K. G. (2012). Evidence for a magnitude effect in temporal discounting with pigeons. *Journal of Experimental Psychology: Animal Behavior Processes, 38*, 102-108. doi: 10.1037/a0026345.

Green, L., & Myerson, J. (2013). How many impulsivities? A discounting perspective. *Journal of the Experimental Analysis of Behavior, 99*, 3-13. doi: 10.1002/jeab.1

Green, L., Myerson, J., Holt, D. D., Slevin, J. R., & Estle, S. J. (2004). Discounting of delayed food rewards in pigeons and rats: Is there a magnitude effect? *Journal of the Experimental Analysis of Behavior, 81*, 39-50. doi: 10.1901/jeab.2004.81-39

Green, L., Myerson, J., Oliveira, L., & Chang, S. E. (2013). Delay discounting of monetary rewards over a wide range of amounts. *Journal of the Experimental Analysis of Behavior, 100*, 269-281. doi: 10.1002/jeab.45

Green, L., Myerson, J., Oliviera, L., & Change, S. E. (2014). Discounting of delayed and probabilistic losses over a wide range of amounts. *Journal of the Experimental Analysis of Behavior, 101*, 186-200. doi: 10.1002/jeab.56

Grondin, S. (2001). From physical time to the first and second moments of psychological time. *Psychological Bulletin, 127*, 22-44. doi: 10.1037/0033-2909.127.1.22

Halberda, J., Mazzocco, M. M. M., Feigenson, L. (2008). Individual differences in non-verbal number acuity correlate with math achievement. *Nature, 455*, 655-668. doi: 10.1037/0033-2909.127.1.22

Hanley, J. A., Negassa, A., Edwardes, M. D., & Forrester, J. E. (2003). Statistical analysis of correlated data using generalized estimating equations: An orientation. *American Journal of Epidemiology, 157*, 364-375. doi: 10.1093/aje/kwf215

Harinck, F., Van Dijk, E., Van Beest, I., & Mersmann, P. (2007). When gains loom larger than losses: Loss aversion for small amounts of money. *Psychological Science, 18*, 1099-1105. doi: 10.1111/j.1467-9280.2007.02031.x

Heil, S. H., Johnson, M. W., Higgins, S. T., & Bickel, W. K. (2006). Delay discounting in currently using and currently abstinent cocaine-dependent outpatients and non-drug-using matched controls. *Addictive Behaviors, 31*, 1290-1294. doi: 10.1016/ j.addbeh.2005.09.005

Herrmann, E. S., Johnson, P. S., & Johnson, M. W. (2015). Examining delay discounting of condom-protected sex among men who have sex with men using crowdsourcing technology. *Aids and Behavior, 19*, 1655-1665. doi: 10.1007/ s10461-015-1107-x

Hoffman, W. F., Moore, M., Templin, R., McFarland, B., Hitzemann, R. J., & Mitchell, S. H. (2006). Neuro-psychological function and delay discounting in methamphetamine-dependent individuals. *Psychopharmacology, 188*, 162-170.

Hox, J. J., & Bechger, T. M. (1988). An introduction to structural equation modeling. *Family Science Review, 11*, 354-373.

Hursh, S. R., & Silberberg, A. (2008). Economic demand and essential value. *Psychological Review, 115*, 186-198. doi: 10.1037/0033-295X.115.1.186

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*, 1-55. doi: 10.1080/10705519909540118

Jarmolowicz, D. P., Bickel, W. K., Carter, A. E., Franck, C. T., & Mueller, E. T. (2012). Using crowdsourcing to examine relations between delay and probability discounting. *Behavioral Processes, 91,* 308-312. doi: 10.1016/j.beproc.2012. 09.001

Jimura, K., Myerson, J., Hilgard, J., Braver, T. S., & Green, L. (2009). Are people really more patient than other animals? Evidence from human discounting of real liquid rewards. *Psychonomic Bulletin & Review, 16*, 1071-1075. doi: 10/3758/PBR. 16.6.1071

Johnson, M. W., Bickel, W. K., (2002). An algorithm for identifying nonsystematic delay-discounting data. *Experimental and Clinical Psychopharmacology, 16*, 264-274. doi: 10.1037/1064-1297.16.3.264

Johnson, M. W., Bickel, W. K., Baker, F., Moore, B. A., Badger, G. J., & Budney, A. J. (2010). Delay discounting in current and former marijuana-dependent individuals. *Experimental and Clinical Psychopharmacology, 18,* 99-107. doi: 10/1037/ a0018333

Kahneman, D., Wakker, P. P., & Sarin, R. (1997). Back to Bentham? Explorations of experienced utility. *Quarterly Journal of Economics, 112*, 375-406. doi: 10.1162/003355397555235.

Killeen, P. R. (2009). An additive-utility model of delay discounting. *Psychological Review, 116*(3), 602-219. doi: 10.1037/a0016414

Killeen, P. R. (2015). The arithmetic of discounting. *Journal of the Experimental Analysis of Behavior, 103*, 249-259. doi: 10.1002/jeab.130

Kim, K. H. (2005). The relation among fit indexes, power, and sample size in structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 12*, 368-390. doi: 10.1207/s15328007sem1203_2

Kirby, K. (2009). One-year temporal stability of delay-discount rates. *Psychonomic Bulletin & Review, 16*, 457-462. doi: 10.3758/PBR.16.3.457

Köbberling, V. (2006). Strength of preference and cardinal utility. *Economic Theory*, *27*(2), 375-391. doi: 10.1007/s00199-005-0598-5

Koffarnus, M. N., Franck, C. T., Stein, J. S., & Bickel, W. K. (2015). A modified exponential behavioral economic demand model to better describe consumption data. *Experimental and Clinical Psychopharmacology, 23*(6), 504-512. doi: 10.1037/pha0000045

Koffarnus, M. N., Jarmolowicz, D. P., Mueller, E. T., & Bickel, W. K. (2013). Changing delay discounting in the light of the competing neurobehavioral decision systems theory: A review. *Journal of the Experimental Analysis of Behavior, 99*, 32-57. doi: 10.1002/jeab.2

Landes, R. D., Christensen, D. R., & Bickel, W. K. (2012). Delay discounting decreases in those completing treatment for opioid dependence. *Experimental and Clinical Psychopharmacology, 20*, 302-309. doi: 10.1037/a0027391

Lawyer, S. R., & Schoepflin, F. J. (2013). Predicting domain-specific outcomes using delay and probability discounting for sexual versus monetary outcomes. *Behavioural Processes, 96*, 71-78. doi: 10.1016/j.beproc.2013.03.001

Lee, D. C., Stanger, C., & Budney, A. J. (2015). A comparison of delay discounting in adolescents and adults in treatment for cannabis use disorders. *Experimental and Clinical Psychopharmacology, 23*(2), 130-137. doi: 10.1037/a0038792

MacCallum, R. C., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. *Annual Review of Psychology, 51*, 201-226. doi: 10.1146/annurev.psych.51.1.201

MacKillop, J., Murphy, J. G., Tidey, J. W., Kahler, C. W., Ray, L. A., Bickel, W. K. (2009). Latent structure of facets of alcohol reinforcement from a behavioral economic demand curve. *Psychopharmacology, 203*, 33-40. doi: 10.1007/s00213-008-1367-5

MacKillop, J., Weafer, J., Gray, J. C., Oshri, A., Palmer, A., & de Wit, H. (2016). The latent structure of impulsivity: Impulsive choice, impulsive action, and impulsive personality traits. *Psycholopharmacology, 233*, 3361-3370. doi: 10.1007/s00213-016-4372-0

Madden, G. J., Petry, N. M., Badger, G. J., & Bickel, W. K. (1997). Impulsive and self-control choices in opioid- dependent patients and non-drug-using control participants: Drug and monetary rewards. *Experimental and Clinical Psychopharmacology, 5*, 256-262.

Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. In M. L. Commons, J. E. Mazur, J. A. Nevin, & H. Rachlin (Eds.) *Quantitative analysis of behavior: Vol. 5 The effect of delay and intervening events on reinforcement value* (pp. 53-73). Hillsdale, NJ: Erlbaum.

McKerchar, T. L., Green, L., Myerson, J., Pickford, T., Hill, J. C., & Stout, S. C. (2009). A comparison of four models of delay discounting in humans. *Behavioral Processes, 81*, 256-259. doi: 10.1146/annurev.psych.51.1.201

Myerson, J., & Green, L. (1995). Discounting of delayed rewards: Models of individual choice. *Journal of the Experimental Analysis of Behavior, 64,* 263-276. doi: 10.1901/jeab.1995.64-263

Myerson, J., Green, L., van den Berk-Clark, C., & Grucza, R. A. (2015). Male, but not female, alcohol-dependent African Americans discount delayed gains more steeply than propensity-score matched controls. *Psychopharmacology*, *232*(24), 4493-4503. doi: 10.1007/s00213-015-4076-x

Myerson, J., Green, L., & Warusawitharana, M. (2001). Area under the curve as a measure of discounting. *Journal of the Experimental Analysis of Behavior, 76*, 235-243. doi: 10.1901/jeab.2001.76-235

National Institute on Drug Abuse. (2008). *Drug abuse costs the United States economy hundreds of billions of dollars in increased health care costs, crime, and lost productivity*. Retrieved from http://www.drugabuse.gov/publications/addiction-science-molecules-to-managed-care/introduction/drug-abuse-costs-united-states-economy-hundreds-billions-dollars-in-increased-health

National Institute on Drug Abuse. (2012). *How effective is drug addiction treatment?* Retrieved from http://www.drugabuse.gov/publications/principles-drug-addiction-treatment-research-based-guide-third-edition/frequently-asked-questions/how-effective-drug-addiction-treatment

Odum, A. L. (2011). Delay discounting: Trait variable? *Behavioural Processes, 87*(1), 1-9. doi: 10.1016/j.beproc.2011.02.007

Ohmura, Y., Takahashi, T., Kitamura, N., & Wehr, P. (2006). Three-month stability of delay and probability discounting measures. *Experimental and Clinical Psychopharmacology, 14*, 318-328. doi: 10.1037/1064-1297.14.3.318

Ong, E. L., & White, K. G. (2004). Amount-dependent temporal discounting? *Behavioural Processes, 30*, 201-2012. doi: 10.1016/j.beproc.2004.03.005

Paglieri, F., Addessi, E., Sbaffi, A., Tasselli, M. I., & Delfino, A. (2015). Is it patience or motivation? On motivational confounds in intertemporal choice tasks. *Journal of the Experimental Analysis of Behavior, 103,* 196-217. doi: 10.1016/j.beproc.2004.03.005

Peters, E., Västjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science, 17*, 407-413. doi: 10.1111/j.1467-9280.2006.01720.x

Peters, E., Slovic, P., Västfjäll, D., & Mertz, C. K. (2008). Intuitive numbers guide decisions. *Judgment and Decision Making, 3*, 619-635.

Petry, N. M. (2001). Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology, 154*, 243- 250. doi: 10.1007/s002130000638

Quisenberry, A. J., Bianco, A., Gatchalina, K. M., & Kim-Spoon, J. (2016). The temporal window of valuation is constricted among adolescent smokers. *Behavioural Processes, 132*, 29-33. doi: 10.1016/j.beproc.2016.09.005

R Core Team. (2015). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Rachlin, H. R. (2006). Notes on discounting. *Journal of the Experimental Analysis of Behavior, 85*, 425-435. doi: 10.1901/jeab.2006.85-05

Radu, P. T., Yi, R., Bickel, W., Gross, J. J., & McClure, S. M. (2011). A mechanism for reducing delay discounting by altering temporal attention. *Journal of the Experimental Analysis of Behavior, 96*, 363-385. doi: 10.1901/jeab.2011.96-363

Read, D. (2001). Is time-discounting hyperbolic or subadditve? *Journal of Risk and Uncertainty, 23*, 5-32. doi: 10.1023/A:1011198414683

Read, D., Frederick, S., Orsel, B., & Rahman, J. (2005). Four score and seven years from now: The data/delay effect in temporal discounting. *Management Science, 51*, 1326-1335. doi: 10.1287/mnsc.1050.0412

Reimers, S., Maylor, E. A., Stewart, N., & Chater, N. (2009). Associations between a one-shot delay discounting measure and age, income, education and real-world impulsive behavior. *Personality and Individual Differences, 47*, 973-978. doi: 10.1016/j.paid.2009.07.026

Ren, P., Nicholls, M. E. R., Ma, Y. Y., & Chen. L. (2011). Size matters: Non-numerical magnitude affects the spatial coding of response. *PLOS One, 6*, e23553. doi: 10.1371/journal.pone.0023553

Reynolds, B. (2006). A review of delay-discounting research with humans: Relations to drug use and gambling. *Behavioural Pharmacology, 17*, 651-667. doi: 10.1097/FBP.0b013e3280115f99

Richards, J. B., Mitchell, S. H., de Wit, H., & Seiden, L. S. (1997). Determination of discount functions in rats with an adjusting-amount procedure. *Journal of the Experimental Analysis of Behavior, 67*, 353-366. doi: 10.1097/FBP. 0b013e3280115f99

Roberts, B. W., Walton, K. E., & Viechtbauer, W. (2006). Patterns of mean-level change in personality traits across the life course: A meta-analysis of longitudinal studies. *Psychological Bulletin, 132*, 1-25. doi: 10.1037/0033-2909.132.1.1

Roelofsma, P. H. M. P. (1996). Modeling intertemporal choices: An anomaly approach. *Acta Psychologica, 93*, 5-22.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*, 1-36.

Shamosh, N. A., DeYoung, C. G., Green, A. E., Reis, D. L., Johnson, M. R., Conway, A. R. A., … Gray, J. R. (2008). Individual differences in delay discounting: Relation to intelligence, working memory, and anterior prefrontal cortex. *Psychological Science, 19*, 904-911. doi: 10.1111/j.1467-9280.2008.02175.x

Scholten, M., Read, D., & Sanborn, A. (2014). Weighing outcomes by time or against time? Evaluation rules in intertemporal choice. *Cognitive Science, 38*, 399-438. doi: 10.1111/j.1467-9280.2008.02175.x

Stein, J., Wilson, A. G., Koffarnus, M. N., Daniel, T. O., Epstein, L. H., & Bickel, W. K. (2016). Unstuck in time: Episodic future thinking reduces delay discounting and cigarette smoking. *Psychopharmacology, 233*, 3771-3778. doi: 10.1007/s00213-016-4410-y

Takahashi, T. (2005). Loss of self-control in intertemporal choice may be attributable to logarithmic time perception. *Medical Hypotheses, 65*, 691-693.

Takahashi, T., Oono, H., & Radford, M. H. B. (2008). Psychophysics of time perception and intertemporal choice models. *Physica A: Statistical Mechanics and its Applications, 387*(8-9), 2066-2074. doi: 10.1016/j.physa.2007.11.047

Van Praag, B. M. S. (1990). Ordinal and cardinal utility: An integration of the two dimensions of the welfare concept. *Journal of Econometrics, 50*, 69-89. doi: 10.1016/0304-4076(91)90090-Z

Wearden, J. H. (1991). Do humans possess an internal clock with scalar timing properties? *Learning and Motivation, 22*, 59-83. doi: 10.1016/0023-9690(91)90017-3

Weatherly, J. N., & Terrell, H. K. (2010). Delay discounting of different commodities II: Confirmatory analyses. *The Journal of General Psychology, 138*(1), 35-48. doi: 10.1080/00221309.2010.532522

Weatherly, J. N., Terrell, H., & Derenne, A. (2010). Delay discounting of different commodities. *The Journal of General Psychology, 137*(3), 273-286. doi: 10.1080/00221309.2010.484449

Wesley, M. J., & Bickel, W. K. (2014). Remember the future II: Meta-analyses and functional overlap of working memory and delay discounting. *Biological Psychiatry, 75*, 435-448. doi: 10.1016/j.biopsych.2013.08.008

Weller, R. E., Cook, E. W. III, Avsar, K. B., & Cox, J. E. (2008). Obese women show greater delay discounting than healthy-weight women. *Appetite, 51*, 563-569. doi: 10.1016/j.appet.2008.04.010

Zauberman, G., Kim, B. K., Malkoc, S. A., & Bettman, J. R. (2008). Discounting time and time discounting: Subjective time perception and intertemporal preferences. *Journal of Marketing Research, 46*, 543-556. doi: 10.1509/jmkr.46.4.543

APPENDICES FOR CHAPTER 4

Appendix 4A

Pilot Study

Method

Participants

Participants (n = 258) were recruited from undergraduate courses at Utah State University. Participants were recruited through an online registration system and from in-class announcements. The mean age of participants was 20.5 years. One-hundred eighteen participants were male and 99 were female. All students received course credit for participating. All study procedures were approved by the Utah State University Institutional Review Board and participants signed an informed consent before completing any other tasks.

Procedure

Discounting tasks. All participants completed 12 delay-discounting tasks and 3 probability-discounting tasks. All of the discounting tasks were for hypothetical outcomes and participants were aware that they would not be receiving any of the outcomes. There were three different outcomes for the delay-discounting tasks (3 discounting tasks per outcome): money, food, and gasoline. The outcome for the probability-discounting tasks was money. The tasks were organized into three blocks of four tasks. The blocks were categorized by the magnitude of the outcome: small, medium, and large. The order of the presentation of the three blocks was randomized as was the order of the four discounting tasks within the blocks. All tasks were programmed with custom written E-Prime software.

The process of determining an indifference point for each delay was the same as described in the methods of Chapter 4. There were six delays for each outcome: 1 day, 1 week, 2 weeks, 1 month, 6 months, and 5 years. The algorithm used to determine indifference points in the probability discounting tasks were identical to the algorithm used in the delay-discounting task but the text for the choice alternatives was different across the task types. In the probability discounting tasks, the small outcome was delivered with a 100% probability and the larger outcome was to be delivered with a likelihood that decreased across successive blocks. There were six different probabilities to receive the larger outcome: 95%, 75%, 50%, 33%, 10% and 5%.

The delay discounting tasks were organized into three blocks with four discounting tasks per block. Those blocks were presented in a randomized order to each participant and the order of each task within a block was randomly presented to the participant. Participants were given a brief 5-minute break between each block in which they were allowed to leave the laboratory testing room. Table 4-1a displays the small outcome, medium outcome, and large outcome blocks and the monetary value of each outcome for the discounting tasks.

Table 4-1a

Discounting Tasks

	Outcome type		
Outcome size	Money	Food	Gasoline
Small Outcome	$10	$10	$10
Medium Outcome	$100	$50	$50
Large Outcome	$1000	$100	$100

Note. The amounts of the monetary outcome were for delay discounting of money task and the probability-discounting task

Analyses

The analyses were the same as the analyses of Chapter 4.

Results

Results are organized into three main sections. First, the results of the theoretical model fits to the median group indifference point for each task are reported. Next, the correlations of the twelve tasks are given. Finally, the results of the confirmatory factor analysis are described.

Theoretical Model Fits

Equation 4-1 and Equation 4-3 were fit to the median group indifference points (Table 4-2a). For 8 of the 12 tasks, AIC scores favored Equation 4-1. For delayed monetary and gasoline outcomes, larger outcomes were discounted less than smaller outcomes. No difference in the discounting of difference food amounts was found. Also, no difference in the discounting of different probabilistic monetary amounts was found.

Correlations

Area Under the Curve was calculated for each outcome and bivariate correlations were conducted between every outcome combination (Figure 4-2a). For all but one pairing (probability $10 and Food $100), the bivariate correlation between outcomes were positive and statistically significant. However, the correlation between delayed and probabilistic outcomes was much smaller than the correlation between delayed outcomes.

Table 4-2a

Equation 4-1 (Hyperbolic) and Equation 4-3 (Hyperboloid) Model Fits to Group Median Indifference Points

	Mazur (1987)				Rachlin (2006)				
Task	*k*	R^2	Sy.x	AIC	*k*	*s*	R^2	Sy.x	AIC
$10 delay	**.301**	**.906**	**.010**	**-20.762**	.392	.671	.964	.069	-16.483
$100 delay	.057	.938	.062	-26.373	**.113**	**.694**	**.994**	**.023**	**-30.338**
$1000 delay	.017	.995	.013	-45.067	**.027**	**.877**	**.999**	**.005**	**-47.969**
$10 probability	**.980**	**.993**	**.028**	**-36.104**	.986	.887	.997	.021	-30.714
$100 probability	**1.048**	**.999**	**.012**	**-45.926**	1.049	.980	.999	.013	-36.392
$1000 probability	**1.364**	**.989**	**.038**	**-32.320**	1.364	~ 1	.989	.043	-22.325
$10 food	**1.863**	**.868**	**.102**	**-20.533**	1.337	.563	.971	.053	-19.602
$50 food	**1.347**	**.975**	**.052**	**-28.454**	1.195	.770	.989	.038	-23.578
$100 food	**1.138**	**.958**	**.066**	**-25.638**	1.001	.698	.992	.032	-25.565
$10 gas	**.220**	**.811**	**.121**	**-18.405**	.345	.560	.961	.062	-17.813
$50 gas	.095	.766	.119	-18.683	**.225**	**.540**	**.970**	**.048**	**-20.954**
$100 gas	.060	.601	.151	-16.641	**.206**	**.487**	**.933**	**.064**	**-17.362**

~ Indicates that parameter hit constraint.

Note. Bold indicates the chosen model based on AIC value. Sy.x is the standardized deviation of the residuals.

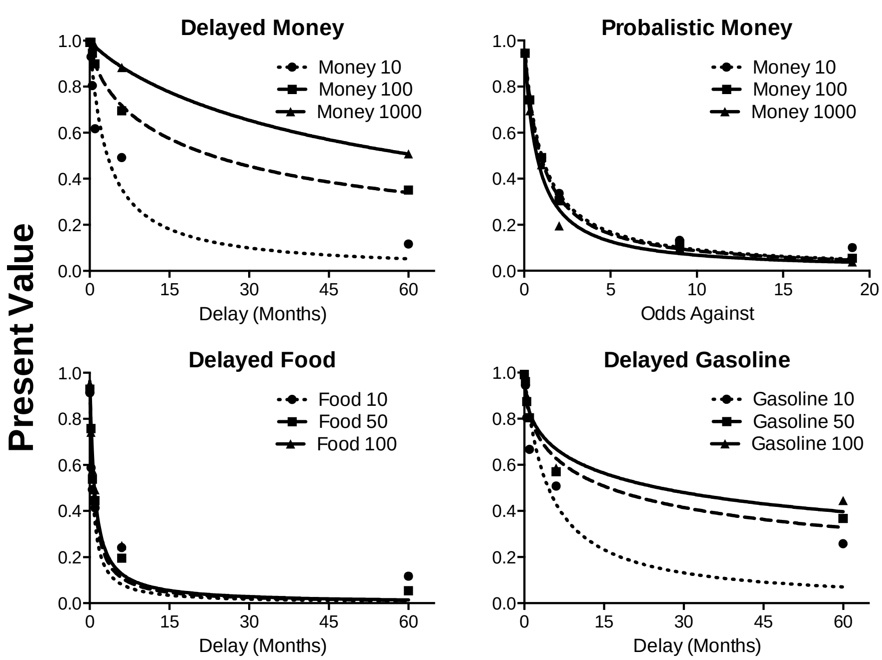

Figure 4-1a. Delay discounting model fits to group median indifference points. Model fits to median group indifference points. The best fitting model for each task is displayed (Table 4-2a).

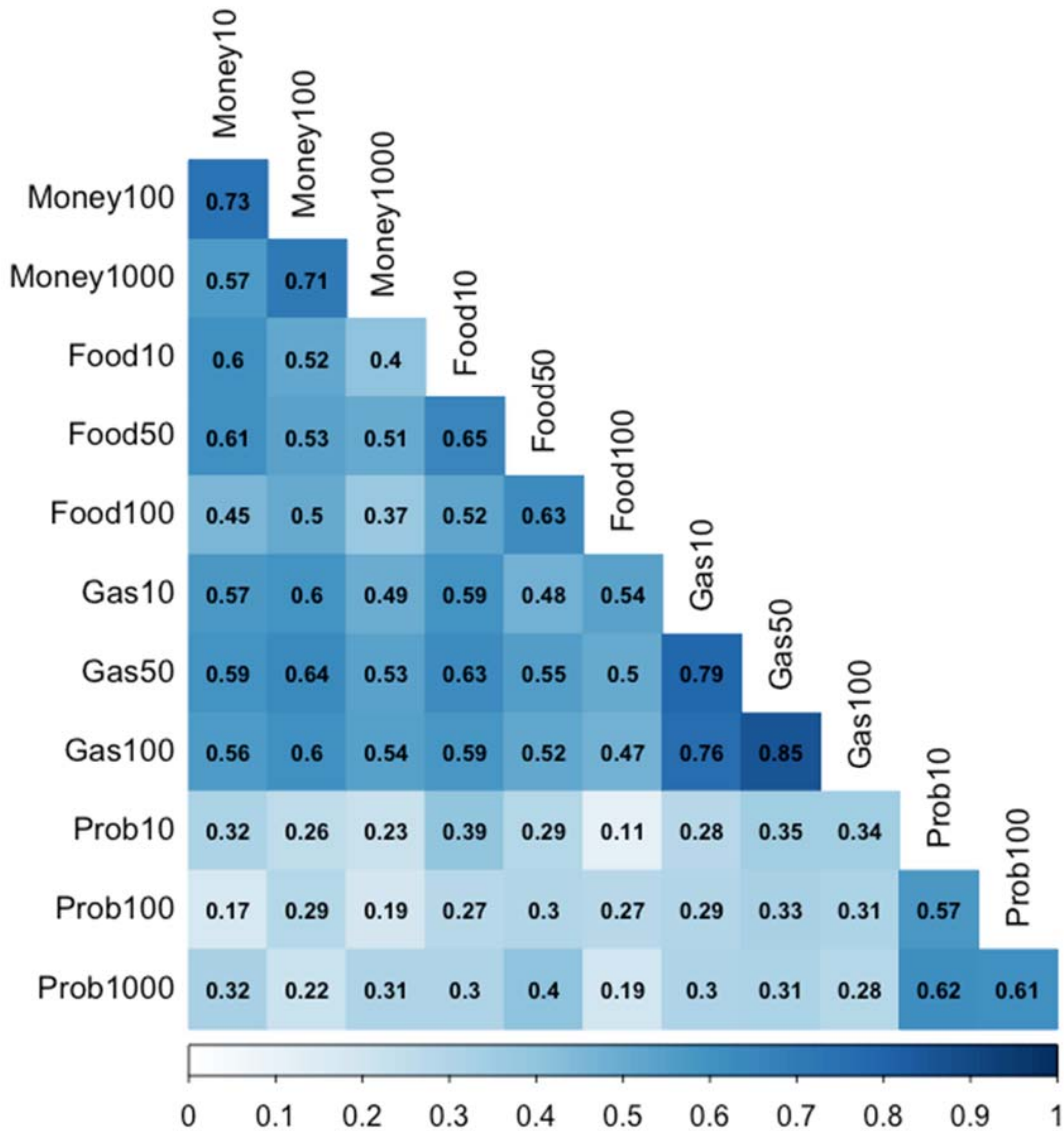

Figure 4-2a. Bivariate correlation matrix between all outcomes. Only the correlation of Food100 and Prob10 is not significant.

The results of the bivariate correlation indicate that how an individual discounts one outcome is highly predictive of how that individual discounts other outcomes. In order to allow for replicating the latent factor models, the means, standard deviations, standard errors (Table 4-3a) are also provided.

Table 4-3a

Delay Discounting Descriptive Statistics

Task	Mean	*SD*	*SE*
Money \$10	0.354	0.237	0.018
Money \$100	0.537	0.269	0.020
Money \$1,000	0.648	0.279	0.021
Food \$10	0.263	0.230	0.017
Food \$50	0.254	0.235	0.018
Food \$100	0.296	0.250	0.019
Gas \$10	0.418	0.282	0.021
Gas \$50	0.470	0.298	0.023
Gas \$100	0.487	0.299	0.023
Probability \$10	0.273	0.171	0.013
Probability \$100	0.222	0.138	0.010
Probability \$1,000	0.176	0.131	0.010

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was used to explore the covariance between outcomes. First, a one-factor latent model (Model 1) was created with one latent factor loading onto all twelve tasks. All factor loadings were statistically significant; however, the overall model fit was poor, $\chi^2(df = 54) = 377.547$, CFI = 0.737, TLI = 0.679, RMSEA = 0.186, SRMR = 0.111. Removing the three probability tasks (Model 2) improved the model fit but the overall model fit was still poor, $\chi^2(\mathrm{df} = 27) = 249.538$, CFI = 0.840, TLI = 0.797, RMSEA = 0.195, SRMR = 0.074.

Next, a four-factor model (Model 3) that compares the discounting of food, gasoline and probabilistic money to delayed money was created. All factor loadings were statistically significant and the overall model fit was greatly improved though the chi-square value was still statistically significant, χ^2(df = 42) = 86.312, CFI = 0.964, TLI = 0.943, RMSEA = 0.078, SRMR = 0.043. The results of this model suggest that there is shared covariance between outcomes but that unique outcomes also share separate covariance.

The final reported model is the best fitting model and explores the different components of the utility of the outcome (Model 4; Figure 4-3a). Latent factors for time are not included in this model because time (e.g., delay scale) did not vary by task, therefore the differential effects of time cannot be extrapolated. Six latent factors were included in the model: small money, medium money, large money, food, gasoline, and probabilistic money. In this model, the amount factors serve as reference factors for true scores of Money $10, Money $100, and Money $1,000. The outcome factors (food, gasoline, and probabilistic money) serve as residual factors that describe the degree to which the discounting of non-monetary outcomes (and probabilistic money) cannot be predicted by monetary delay-discounting factors. The model fit, although more complex than the four-factor model, provided a superior fit, χ^2(df = 39) = 74.791, CFI = 0.971, TLI = 0.951, RMSEA = 0.073, SRMR = 0.041. Though the chi-square value was statistically significant, indicating a less-optimal fit, the other fit indices suggest that Model 4 fits the data well. All factor loadings were statistically significant (Table 4-4a).

The reference factors were strongly correlated. This indicates that correlation between money delay-discounting is very large and that a single factor may more parsimoniously describe the data. The residual factors were also strongly correlated, suggesting strong covariance above what they share with money. This provides evidence that additional (or different) components are involved in the discounting of non-monetary outcomes. This correlation was smaller for probabilistic money, suggesting that money is the uniting aspect of the tasks but that probabilistic outcomes are difference from delayed outcomes. This is in line with previous literature suggesting the delay and probability discounting are two difference processes (Jarmolowicz, Bickel, Carter, Franck, & Mueller, 2012).

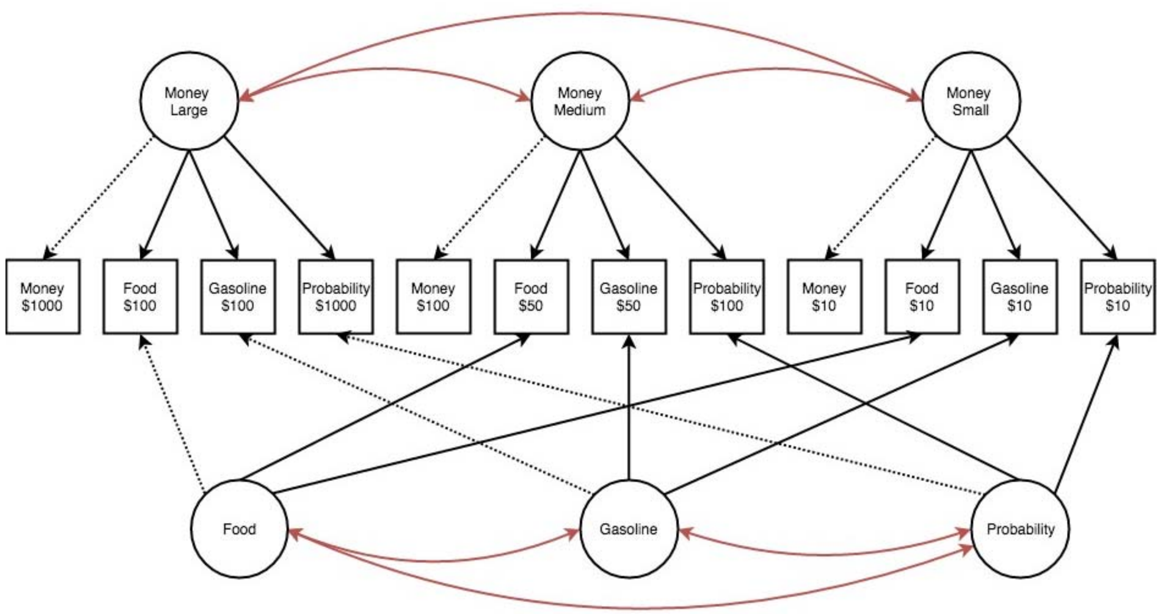

Figure 4-3a. Model 4 model structure.

Table 4-4a

Model 4 Factor Loadings

Latent factor	Manifest variable	Estimate	Standardized factor loading	R^2
Reference factors				
Money small				
	Money $10	1.000	0.805	0.648
	Food $10	0.686	0.571***	0.326
	Gasoline $10	0.893	0.614***	0.377
	Probability $10	0.266	0.297***	0.088
Money medium				
	Money $100	1.000	.962	0.925
	Food $50	0.499	0.549***	0.301
	Gasoline $50	0.785	0.689***	0.475
	Probability $100	0.135	0.252**	0.064
Money large				
	Money $1000	1.000	0.819	0.671
	Food $100	0.489	0.447***	0.200
	Gasoline $100	0.838	0.646***	0.417
	Probability $1000	0.156	0.271**	0.073
Methods factors				
Food				
	Food $10	1.000	0.438	0.192
	Food $50	1.336	0.568***	0.323
	Food $100	1.609	0.644***	0.415
Gasoline				
	Gasoline $10	1.000	0.576	0.332
	Gasoline $50	1.185	0.641***	0.412
	Gasoline $100	1.139	0.615***	0.378
Probabilistic money				
	$10	1.000	0.613	0.376
	$100	1.066	0.803***	0.645
	$1000	0.901	0.718***	0.516

** $p < .01$.
*** $p < .001$.

Appendix 4B

Glossary of Terms

Glossary of Terms

Manifest Variable: Directly measured variable.

Factor: Unmeasured variable that is derived from the covariance of manifest variables.

Degrees of Freedom: The number of known values minus the number of unknown values that are derived from the known values.

Unstandardized Loadings: The slopes of regressing the manifest variable onto the factor.

Standardized Loadings: The correlation of the factor and manifest variable.

Residual Covariance: The remaining correlation between manifest variables not accounted for by the latent factor. Large residual covariances suggest additional factors are needed.

Chi-square: Tests the null hypothesis that the model perfectly fits that data. A significant chi-square value indicates that the model does not completely fit the data.

CFI: Compares performance of the model to a model that assumes no correlation between all observed variables.

TLI: Similar to CFI but with a greater penalty for additional free-parameters.

RMSEA: The root mean square error of approximation. Measures the difference between the hypothesized model with optimally chosen parameters and the population covariance matrix. A value of 0.05 or small is considered an acceptably fitting model. Provides a better estimate of the model fit for large sample sizes than the chi-square.

SRMR: The standardized root mean square residual. Calculated as the difference between the residuals of the sample covariance matrix and the hypothesized covariance matrix. A value of 0.08 or less indicates an acceptably fitting model.

Appendix 4C

Short Delay Discounting Task Example

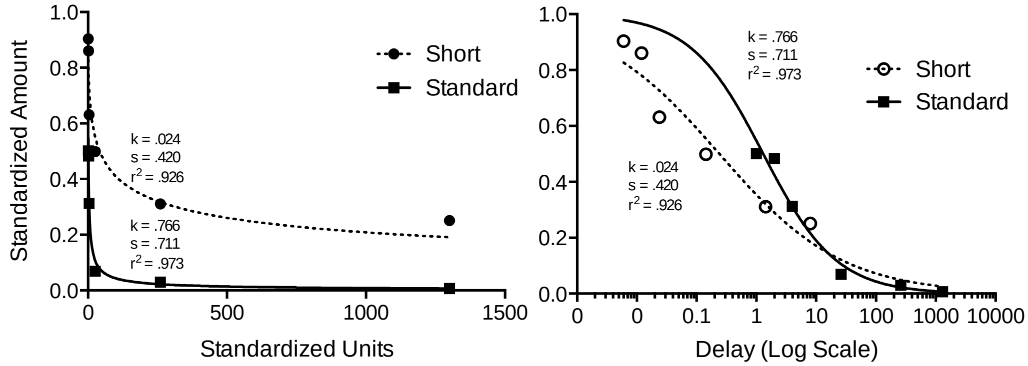

Figure 4-1c. Discounting of food for long- and short-delay distributions. Left panel: Discounting of the same food outcome ($100) for short and long delay distributions. Delays were converted to proportions of the largest delay to aid in comparing the shape of the curve. Right panel: The same discounting results but with the nonconverted delays on a log scale.

Appendix 4D

Reverse Structural Equation Modeling Model

Reverse Structural Equation Modeling Model

In order to investigate the difference model fits by changing the domain of the reference factors, a new model was created with the short $100 task for each outcome type and amount serving as the reference measured variable (and therefore defining the domain of the reference factor) and the long delay progression tasks loading onto the methods factors. The overall model fit was very good, $\chi^2(df = 75) = 100.021$, $p < .05$, CFI = 0.991, TFI = 0.983, RMSEA = 0.031, SRMR = 0.033, and was slightly better than the final model presented in the main text. The pattern of significant regression paths was similar to the main model, with time perception predicting the Money, Food $100, Gasoline $100, and Gasoline $10 reference factors. However, time perception did not predict the residual factors. Table 4-1d presents the results of the SEM model.

A latent factor model without the regression paths was also created in order to report the factor correlations without the regressions. The model fit well, $\chi^2(df = 25) =$ 15.579, $p = 0.927$, CFI = 1.00, TFI = 1.009, RMSEA = 0.000, SRMR = 0.010. Similar to the final model reported in the main text, removing the regression paths from the model improves (in this case, greatly improves) the quality of the model fit.

The model presented here fits the covariance structure of the data slightly better than the final model presented in the main text. This suggests that the short delay progression tasks serve as better reference variables than the long delay progression tasks. However, the marginal, cardinal utility, and time-perception tasks did not predict the latent factors better than in the final model presented in the main text. Therefore, the results of both models are similar in that separate factors for the long and short delay progression tasks describe the data well, are highly correlated, and are not predicted by marginal utility, cardinal utility, and time-perception (some regression paths were weakly predictive).

Table 4-1d

Reverse Bi-Factor Model Results

Latent factor	Manifest variable	Estimate	Standardized factor loading	R^2
Reference factors				
Money short				
	Money short $100	1.000	0.830	0.689
	Money long $100	0.953	0.734***	0.539
	Money short $10	1.168	0.951***	0.904
	Money long $10	0.776	0.593***	0.352
Food short $100				
	Food short $100	1.000	0.848	0.719
	Food long $100	0.878	0.826***	0.682
Food short $10				
	Food short $10	1.000	0.835	0.697
	Food long $10	0.843	0.711***	0.506
Gasoline short $100				
	Gasoline short $100	1.000	0.821	0.674
	Gasoline long $100	0.886	0.748***	0.560
Gasoline short $10				
	Gasoline short $10	1.000	0.880	0.774
	Gasoline long $10	0.783	0.701***	0.491
Methods factors				
Money long				
	Money long $100	1.000	0.436	0.190
	Money long $10	1.467	0.635***	0.104
Food long				
	Food long $100	1.000	0.361	0.130
	Food long $10	0.857	0.355***	0.126
Gasoline long				
	Gasoline long $100	1.000	0.338	0.114
	Gasoline long $10	1.459	0.491***	0.241

Regressions	Manifest variable	Estimate	Standardized regression coefficient	R^2
Money short				
	Money marginal utility	-0.002	0.035	0.001
	Time perception	-0.014	-0.262***	0.069
Food short $100				
	Food marginal utility	-0.004	-0.047	0.002
	Food cardinal utility	-0.015	-0.035	0.001
	Time perception	-0.013	-0.161**	0.026

(*table continues*)

Regressions	Manifest variable	Estimate	Standardized regression coefficient	R^2
Food short $10				
	Food marginal utility	-0.002	-0.030	0.001
	Food cardinal utility	-0.005	0.015	0.000
	Time perception	-0.007	-0.107	0.0.11
Gasoline short $100				
	Gasoline marginal utility	0.004	0.069	0.004
	Gasoline cardinal utility	-0.001	-0.028	0.001
	Time perception	-0.019	-0.296***	0.088
Gasoline short $10				
	Gasoline marginal utility	0.080	0.124***	0.015
	Gasoline cardinal utility	0.001	0.030	0.001
	Time perception	-0.020	-0.288***	0.083
Money long				
	Money marginal utility	0.004	0.116*	0.013
	Time perception	-0.000	-0.004	0.000
Food long				
	Food marginal utility	-0.001	-0.018	0.000
	Food cardinal utility	-0.021	-0.124	0.000
	Time perception	0.002	0.060	0.004
Gasoline long				
	Gasoline marginal utility	0.003	0.119	0.014
	Gasoline cardinal utility	-0.002	-0.101	0.010
	Time perception	0.002	0.091	0.008
Factor correlations with regressions	Manifest variable	Covariance estimate	Residual correlation	
Money short				
	Food short $100	0.020	0.470***	
	Food short $10	0.020	0.614***	
	Gasoline short $100	0.023	0.708***	
	Gasoline short $10	0.024	0.701***	
	Food long	-0.007	-0.450***	
	Gasoline long	-0.004	-0.281***	
Food short $100				
	Food short $10	0.045	0.862***	
	Gasoline short $100	0.034	0.669***	
	Gasoline short $10	0.027	0.500***	
	Money long	0.004	-0.146*	
	Gasoline long	0.004	0.195*	
Food short $10				
	Gasoline short $100	0.028	0.696***	
	Gasoline short $10	0.029	0.680***	
	Money long	0.003	0.149*	
	Gasoline long	0.001	0.085	

(*table continues*)

Factor correlations with regressions	Manifest variable	Covariance estimate	Residual correlation
Gasoline short $100			
	Gasoline short $10	0.036	0.888***
	Money long	0.003	0.154*
	Food long	-0.005	0.254*
Gasoline short $10			
	Money long	0.003	0.164***
	Food long	0.006	-0.055
Money long			
	Food long	0.007	0.723***
	Gasoline long	0.006	0.790***
Food long			
	Gasoline long	0.007	0.828***
Factor correlations without regressions	**Manifest variable**	**Covariance estimate**	**Factor correlation**
Money short			
	Food short $100	0.021	0.482***
	Food short $10	0.021	0.615***
	Gasoline short $100	0.026	0.739***
	Gasoline short $10	0.027	0.722***
	Food long	-0.008	-0.463***
	Gasoline long	-0.004	0.270**
Food short $100			
	Food short $10	0.046	0.864***
	Gasoline short $100	0.037	0.676***
	Gasoline short $10	0.030	0.513***
	Money long	0.004	0.159*
	Gasoline long	0.004	0.296*
Food short $10			
	Gasoline short $100	0.029	0.696***
	Gasoline short $10	0.031	0.677***
	Money long	0.003	0.168*
	Gasoline long	0.003	0.112
Gasoline short $100			
	Gasoline short $10	0.042	0.898***
	Money long	0.003	0.125
	Food long	-0.006	0.298**
Gasoline short $10			
	Money long	0.003	0.145*
	Food long	-0.021	-0.102
Money long			
	Food long	0.007	0.713***
	Gasoline long	0.007	0.803***
Food long			
	Gasoline long	0.007	0.857***

* $p < .05$; ** $p < .01$.; *** $p < .001$.

CHAPTER 5

GENERAL DISCUSSION

Delay discounting, or the devaluation of an outcome as the time to its receipt increases, has become one of the principle behavioral constructs for understanding the acquisition and maintenance of maladaptive behaviors such as substance abuse (Bickel, Moody, & Higgens, 2016), problematic gambling (Amlung, Vedelago, Acker, Balodis, & MacKillop, 2016), and risky sexual behaviors (Johnson, Johnson, Herrmann, & Sweeney, 2015). The consistent predictive power of delay discounting to differentiate between individuals that do and do not engage in risky behaviors has led some to refer to delay discounting as a trait (Odum, 2011) and as one of the general underlying processes of maladaptive behaviors (Bickel, Koffarnus, Moody, & Wilson, 2014).

If delay discounting is one of the underlying mechanisms of the acquisition and maintenance of maladaptive behaviors, then changing delay discounting would result in a change in those behaviors. Chapter 2 and Chapter 3 demonstrate that delay discounting can be changed through the simple manipulation of reframing the choice. In Chapter 2, framing the delay of the larger outcome as a specific date decreased delay discounting whereas framing the delay in units of days increased delay discounting. In Chapter 3, fuzzy unit framing increased delay discounting whereas clear unit framing decreased delay discounting for both food and monetary outcomes. Both of these studies demonstrate that delay discounting can be changed through reframing the choice. These results could lead to promising developments of interventions that teach individuals how to reframe choices in a way that encourages self-control.

While the results of these studies add to the growing body of literature that delay discounting can be changed (Koffarnus, Jarmolowicz, Mueller, & Bickel, 2013), they do not provide a process for how delay discounting was changed. Chapter 4 sought to identify possible underlying components of delay discounting in order to aid in the development of interventions to reduce impulsive choice. Three hypothesized components were cardinal utility, marginal utility, and nonlinear time perception (Killeen, 2009, 2015; Myerson & Green, 1995; Rachlin 2006). Importantly, intervening on these basic components may result in more effect methods of reducing impulsive decision making. For example, if an individual could be taught to perceive time more accurately, delayed outcomes may be perceived as closer than before.

Previously applied methods of evaluating delay discounting across different amounts and outcomes are limited in their ability to evaluate many tasks at once and how the three constructs listed above are related. For example, bivariate correlations can only describe how two variables are related. Multiple regression analyses could analyze how well those three constructs predict a single delay discounting task, but again it does not give a complete description. Even more complex methods such as multilevel modeling would require difficult-to-interpret three-way interactions. Structural equation modeling; however, provides a method of analyses that allows for the evaluation of the relationship of many variables.

Chapter 4 applied structural equation modeling (SEM) to understand the ability of marginal utility, cardinal utility, and nonlinear time perception to predict different components of delay discounting (e.g., amount, outcome type, and the specific delay distribution). Despite the identification of a well-fitting delay discounting structural model, marginal utility and cardinal utility did not predict any aspect of delay discounting (with one small exception). Nonlinear time perception; however, did predict specific factors related to the delay distribution. This finding corroborates theoretical models that incorporate nonlinear time perception (e.g., Myerson & Green, 1995; Rachlin, 2006) but it does not justify the inclusion of utility (Killeen 2009, 2015). This finding does not suggest that nonlinear time perception (included in the hyperboloid models) is the only components involved in delay discounting. Other components such as the nonlinear perception of amount (Halberda, Mazzocco, & Feigenson, 2008), executive functioning (Olson, Hooper, Collins, & Luciana, 2007), and numeracy (Peters, 2012) may play important roles in the discounting of delayed outcomes. Structural equation modeling presents a promising framework for exploring these questions.

Chapter 4 also provided further evidence for the classification of delay discounting as a trait. The high degree of correlation between latent factors, after accounting for the shared measurement error among delay discounting tasks and any predictive qualities of marginal utility, cardinal utility, and nonlinear time perception, suggests that delay discounting is consistent across outcomes, amounts, and delay distributions. For example, if an individual discounts $100 steeply, they are very likely to discounting five servings of pizza steeply. This high degree of consistency is one of the defining characteristics of a trait (McCrae & Costa, 1995). Future research can employ SEM to evaluate other characteristics of delay discounting as a trait. For example, delay discounting is consistently demonstrated to be stable over time intervals ranging from 3 months (Ohmura, Takahashi, Kitamura, & Wehr, 2006) to 1 year (Kirby, 2009). However, measurement error restricts the ability to evaluate delay discounting's true temporal stability. Latent state/trait analyses have the ability to account for the shared measurement error as well as identify the state fluctuations of delay discounting. Structural equation modeling also has the ability to identify differences between groups and further clarify why differences in delay discounting are found between those groups.

The answers from Chapters 2-4 (and the future research it points to) all culminates into a greater understanding of impulsive choice. The ultimate goal of this line of research is to better understand impulsive choice's role in the acquisition and maintenance of problematic behaviors. In doing so, interventions for preventing or reducing these behaviors may become more successful and as a result improve the lives of millions struggling with these behaviors.

References

Amlung, M., Vedelago, L., Acker, J., Baladis, I., & MacKillop, J. (2016). Steep delay discounting and addictive behavior: A meta-analysis of continuous associations. *Addiction, 112*, 51-62. doi: 10.1111/add.13535

Bickel, W. K., Koffarnus, M. N., Moody, L., & Wilson, A. G. (2014). The behavioral- and neuro-economic process of temporal discounting: A candidate behavioral marker of addiction. *Neuropharmacolgy, 76*, 518-527. doi: 10.1016/j.neuropharm. 2013.06.013

Bickel, W. K., Moody, L, & Higgins, S. T. (2016). Some current dimensions of the behavioral economics of health-related behavior change. *Preventive Medicine, 92*, 16-23. doi: 10.1016/j.ypmed.2016.06.002

Halberda, J., Mazzocco, M. M. M., & Feigenson, L. (2008). Individual differences in non-verbal number acuity correlate with math achievement. *Nature, 455*, 655-668. doi: 10.1038/nature07246

Johnson, M. W., Johnson, P. S., & Herrmann, E. S., & Sweeney, M. M. (2015). Delay and probability discounting of sexual and monetary outcomes in individuals with cocaine use disorders and matched controls. *PLOS One, 10*(5), e0128641. doi: 10.1371/journal.pone.0128641

Killeen, P. R. (2009). An additive-utility model of delay discounting. *Psychological Review, 116*(3), 602-219. doi: 10.1037/a0016414

Killeen, P. R. (2015). The arithmetic of discounting. *Journal of the Experimental Analysis of Behavior, 103*, 249-259. doi: 10.1002/jeab.130

Kirby, K. (2009). One-year temporal stability of delay-discount rates. *Psychonomic Bulletin & Review, 16*, 457-462. doi: 10.3758/PBR.16.3.457

Koffarnus, M. N., Jarmolowicz, D. P., Mueller, E. T., & Bickel, W. K. (2013). Changing delay discounting in the light of the competing neurobehavioral decision systems theory: A review. *Journal of the Experimental Analysis of Behavior, 99*, 32-57. doi: 10.1002/jeab.2

McCrae, R. R., & Costa, P. T., Jr. (1995). Trait explanations in personality psychology. *European Journal of Personality, 9*, 231-252. doi: 10.1002/per.2410090402

Myerson, J., & Green, L. (1995). Discounting of delayed rewards: Models of individual choice. *Journal of the Experimental Analysis of Behavior, 64,* 263-276. doi: 10.1901/jeab.1995.64-263

Odum, A. L. (2011). Delay discounting: Trait variable? *Behavioural Processes, 87*(1), 1-9. doi: 10.1016/j.beproc.2011.02.007

Ohmura, Y., Takahashi, T., Kitamura, N., & Wehr, P. (2006). Three-month stability of delay and probability discounting measures. *Experimental and Clinical Psychopharmacology, 14*, 318-328. doi: 10.1002/per.2410090402

Olson, E. A., Hooper, C. J., Collins, P., & Luciana, M. (2007). Adolescents' performance on delay and probability discounting tasks: Contributions of age, intelligence, executive functioning, and self-reported externalizing behavior. *Personality and Individual Differences, 43*,1886-1897. doi: 10.1016/j.paid.2007.06.016

Peters, E. (2012). Beyond comprehension: The role of numeracy in judgments and decision. *Current Directions in Psychological Science, 21*, 31-35. doi: 10.1177/0963721411429960

Rachlin, H. R. (2006). Notes on discounting. *Journal of the Experimental Analysis of Behavior, 85*, 425-435. doi: 10.1901/jeab.2006.85-05

APPENDICES

Appendix A

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Signed: Ann Galizio

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Logan, UT 84322

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Signed: ______________________

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Morgantown, WV 26505

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Signed: ______________________________ 4/16

CURRICULUM VITAE

W. BRADY DeHART

Utah State University
Department of Psychology
2810 Old Main Hill
Logan UT, 84322-2810
801-678-2174
bradydehart@gmail.com

Education

Ph.D., Experimental Psychology, Utah State University, Logan UT, July 2017

G.R.E. General Test	Verbal 163, 93rd percentile Quantitative 159, 82nd percentile Analytical Writing 4.5
G.R.E. Psychology Subject Test	750, 93rd percentile

B.A., Psychology, Utah State University, Logan UT, December 2011
4.00 GPA, Summa Cum Laude, Minor: Spanish

Departmental Honors in Psychology

Valedictorian, Department of Psychology

Research Interests

- **Behavioral Economics:** The impact of environmental and psychological factors on decision-making including emotion, stress, and how situations are worded and presented.

- **Delay Discounting:** How people devalue delayed rewards. What factors contribute to individual differences in delay discounting? How can delay discounting be modulated and what variables influence delay discounting? What are the underlying mechanisms of delay discounting?

- **Emotion and Distress Tolerance:** How the experience of negative affect such as stress impacts decision-making and encourages impulsive behavior. Also, how the ability to tolerate the impact of stress moderates this relationship.

- **Statistical Analyses:** Applying novel statistical methods such latent factor and multilevel modeling to the investigation of behavioral economic constructs.

Manuscripts in Preparation

DeHart, W. B., Friedel, J. E., & Odum, A. L. (2016). *A Latent discounting model: Confirmatory factor analyses of delay discounting.* Manuscript in preparation.

DeHart, W. B., Friedel, J. E., Fryre, C. C. J., Galizio, A., & Odum, A. L. (2016). *The discounting of different outcomes and amounts.* Manuscript in preparation.

Rung, J. M., Frye, C. C. J., **DeHart, W. B.**, & Odum, A. L. (2016). *Alterations of the spacing between delays in discounting tasks: Effects on the form and steepness of discounting.* Manuscript in preparation.

DeHart, W. B., Friedel, J. E., Fryre, C. C. J., Galizio, A., & Odum, A. L. (2016). *Delay discounting of different outcomes by smokers, smokeless tobacco users, e-cigarette users, and non-nicotine users.* Manuscript in preparation.

Manuscripts Submitted for Publication

DeHart, W. B., Galizio, A., Frye, C. C. J., Friedel, J. E., & Odum, A. L. (2016). *A fistful of quarters: The effects of outcome unit framing on delay discounting.* Manuscript submitted for publication.

Frye, C. C. J., Baumann, A. A. L., Friedel, J. E., Galizio, A., **DeHart, W. B.**, & Odum, A. L. (2016). *Exploring domain specificity of delay discounting: Money, food, and gift cards for food.* Manuscript submitted for publication.

Friedel, J. E., Galizio, A., Frye, C. C. J., **DeHart, W. B.**, & Odum, A. L. (2016). *Rapidly obtaining indifference points: Measures of delay discounting from a visual analogue scale and a survey.* Mansucript submitted for publication.

Peer-Reviewed Publications

Berry, M. S., Friedel, J. E., **DeHart, W. B**., Mahamane, S., Jordan, K. E., & Odum, A. L. (2017). The value of clean air: Comparing discounting of delayed air quality and money across magnitudes. The Psychological Record, 67(2), 137-148.

Friedel, J. F., **DeHart, W. B.**, Odum, A. L. (2017). *Turn it up to eleven: The effects of 100 db 1 kHz and 22 kHz tones on level pressing in rats. Journal of the Experimental Analysis of Behavior, in press.*

DeHart, W. B., Friedel, J. E., Lown, J. E., & Odum, A. L. (2016). The effects of financial education on impulsive decision making. *PLOS ONE, 11*(7), e0159561.

Frye, C. C. J., Galizio, A. Friedel, J. E., **DeHart, W. B.**, & Odum, A. L. (2016). Measuring delay discounting in humans using an adjusting amount task. *Journal of Visualized Experiments (107)*, e53584-e53584.

Friedel, J. E., **DeHart, W. B.**, Frye, C. C. J., Rung, J. M., & Odum, A. L. (2015). Discounting of qualitatively different delayed health outcomes in current and never smokers. *Experimental and Clinical Psychopharmacology, 24*(1), 18-29.

DeHart, W. B., & Odum, A. L. (2015). The effects of the framing of time on delay discounting. *Journal for the Experimental Analysis of Behavior, 103*(1), 10-21.

Friedel, J. E., **DeHart, W. B.**, Madden, G. J., Odum, A.L. (2014). Impulsivity and cigarette smoking: Discounting of monetary and consumable outcomes in current and non-smokers. *Psychopharmacology, 231*, 4517-4526.

Hatch, D., **DeHart, W. B.**, & Norton, M. (2014). Subjective stressors moderate effectiveness of a multi-component, multi-site intervention on caregiver depression and burden. *International Journal of Geriatric Psychiatry, 29*(4), 406-4013.

Invited Presentations

DeHart, W. B., & Odum, A. L. (2016). *Delay discounting: Measurement and analysis.* Paper presented at the University of Guadalajara, Mexico.

Odum, A. L., **DeHart, W. B.**, Friedel, J. E., Galizio, A., & Frye, C. C. J. (2016). *Organismic and environmental influences on delay discounting: Evidence for a general process.* Paper presented at the Winter Conference on Animal Learning and Behavior Annual Meeting, Winterpark, CO.

Odum, A. L., Friedel, J. E., & **DeHart, W. B.** (2014, May). *Delay discounting as a process.* Paper presented at the Society for the Quantitative Analyses of Behavior 37th Annual Meeting, Chicago, IL.

Odum, A. L., Friedel, J. E., & **DeHart, W. B.** (2014, February). *Delay discounting across commodities.* Paper presented at the annual meeting of the Texas Association for Behavior Analysis, San Antonio, TX.

Symposium Presentations

DeHart, W. B., J. E., Frye, C. C., Galizio, A, Haynes, J., & Odum, A. L. (2017, May). Delay discounting of non-monetary outcomes: The effects of different magnitudes and delay distributions. *In E. B. Rasmussen (Chair), Delay Discounting in Health with a Focus on Food and Exercise.* Symposium conducted at the Annual Convention of the Association for Behavior Analysis International, Denver, CO.

DeHart, W. B., Friedel, J. E., & Odum, A. L. (2016, May). A Latent Discounting Model: Confirmatory Factor Analyses of Delay Discounting. *In A. L. Odum (Chair), Discounting Across Commodities and Contexts: Evidence for and against a General Discounting Process.* Symposium conducted at the Annual Convention of the Association for Behavior Analysis International, Chicago, IL.

Paper Presentations

DeHart, W. B., & Odum, W. B. (2016, April). *A Latent Discounting Model: Confirmatory Factor Analyses of Delay Discounting.* Paper presented at the Utah State University Research Symposium, Logan, UT.

Friedel, J. E., **DeHart, W. B.**, & Odum, A. L. (2014, May). *The generality of steep discounting in smokers.* Paper presented at the Association for Behavior Analysis International 40th Annual Convention, Chicago, IL.

DeHart, W. B. (2014, April). *Math and the apocalypse: Exponential growth of a zombie outbreak.* Paper presented at the Utah State University Graduate Symposium, Logan, UT.

DeHart, W. B. (2011, March). *Psychological junk-food: satisfaction of intrinsic needs in a superficial way through immersive online video games.* Paper presented at the Utah State University Student Showcase, Logan, UT.

DeHart, W. B., & Bates, S. C. (2010, April). *SI dosage: Impact on exam performance in introductory courses.* Paper presented at the Rocky Mountain Psychological Association, Denver, CA.

Bates, S. C., & **DeHart, W. B.** (2009, July). *Findings from a national sample of introductory psychology syllabi using the project syllabus rubric.* Paper presented at the International Conference on the Teaching of Psychology, Vancouver, B.C., Canada.

Posters Presentations

DeHart, W. B., Friedel, J. E., Frye, C. C., Galizio, A., & Odum, A. L. (2016, May). *Delay discounting of different outcomes by smokers, smokeless tobacco users, e-cigarette users, and non-nicotine users.* Poster presented at the Society for the Quantitative Analyses of Behavior 39th Annual Meeting, Chicago, IL.

Galizio, A., Frye, C. C. J., Friedel, J. E., **DeHart, W. B.**, & Odum, A. L. (2016, May). *Timing and delay discounting.* Poster presented at the Annual Convention of the Association for Behavior Analysis International, Chicago, IL.

Frye, C. C. J., Rung, J. M., Galizio, A., Friedel, J. E., **DeHart, W. B.**, & Odum, A. L. (2016, May). *Explaining the magnitude effect in delay discounting research: It is all about the contrast.* Poster presented at the annual Association for Behavior Analysis International convention, Chicago, IL.

DeHart, W. B., Friedel, J. E., Lown, J., & Odum, A. L. (2015, May). *The effects of a semester long financial education course on delay discounting.* Poster presented at the Association for Behavior Analysis International 41th Annual Convention, San Antonio, TX.

Friedel, J. E., **DeHart, W. B.**, Frye, C. C. J., Galizio, A., & Odum, A. L. (2015, May). *Impulsivity and tobacco use: Discounting of qualitatively different outcomes in non-smokers, cigarette smokers, and smokeless tobacco users.* Poster presented at the Society for the Quantitative Analyses of Behavior 38th Annual Meeting, San Antonio, TX.

DeHart, W. B., Chowning, L., & Odum, A. L. (2015, May). *A fistful of quarters: The effects of outcome unit framing on delay discounting.* Poster presented at the Society for the Quantitative Analyses of Behavior 38th Annual Meeting, San Antonio, TX.

Mahamane, S., **DeHart, W. B.**, Friedel, J. E., Odum, A. L., & Jordan, K. (2015, March). *Blue Goes Green III: Does visual pollution affect nature/built categorization?* Poster presented at the Intermountain Sustainability Summit 6th Annual Meeting, Ogden, Utah.

Friedel, J. E., **DeHart, W. B.**, Mahamane, S, Odum, A. L., & Jordan, K. (2015, March). *Blue Goes Green I: increased delay discounting for better air quality.* Poster presented at the Intermountain Sustainability Summit 6th Annual Meeting, Ogden, UT.

DeHart, W. B., Mahamane, S., Friedel, J. E., Odum, A. L., & Jordan, K. (2015, March). *Blue Goes Green II: Implicit preference for natural vs. man-made environments.* Poster presented at the Intermountain Sustainability Summit 6th Annual Meeting, Ogden, UT.

DeHart, W. B., Friedel, J. E., Frye, C., Rung, J., & Odum, A. L. (2014, November). *Differences in delay discounting across outcomes in smokers and non-smokers.* Poster presented at the Society for Judgment and Decision Making 44th Annual Meeting, Long Beach, CA.

DeHart, W. B., Mendenhall, M., Stopnecipher, J., & Odum, A. L. (2014, May). *The effects of the framing of time on delay discounting.* Poster presented at the Society for the Quantitative Analyses of Behavior 37th Annual Meeting, Chicago, IL.

Frye, C., Rung, J., Friedel, J. E., **DeHart, W. B.**, & Odum, A. L. (2014, May). *Assessing differences in discounting using linear vs. exponential delay progressions.* Poster presented at Association for Behavior Analysis International 40th Annual Convention, Chicago, IL.

Hatch, D., **DeHart, W. B.**, & Norton, M. (2013, April). *Contextual factors moderate the effectiveness of a multi-component, multi-site intervention on caregiver depression and burden.* Poster presented at The Gerontological Society of America's 66th Annual Scientific Meeting, New Orleans, LA.

DeHart, W. B., & Odum, A. L. (2013, May). *The effect of mood induction on delay discounting.* Poster presented at the Society for the Quantitative Analysis of Behavior 36th Annual Meeting, Minneapolis, MN.

DeHart, W. B., & Bates, S. C. (2011, April). *Females who play video games: Differences in mobile phone video game usage.* Poster presented at the Rocky Mountain Psychological Association, Salt Lake City, UT.

DeHart, W. B., & Bates, S. C. (2011, April). *Psychological junk-food: Satisfaction of intrinsic needs in a superficial way through immersive online video games.* Poster presented at the Western Psychological Association, Los Angeles, CA.

Editorial Boards

- *Journal of the Experimental Analysis of Behavior*

Invited Reviews

- May 2017 - *The Behavior Analyst*
- August 2016 - *Psychological Reports*
- July 2016 - *PLOS ONE*
- May 2016 - *PLOS ONE*
- May 2016 - *Journal of the Experimental Analysis of Behavior*
- March 2016 - *Journal of the Experimental Analysis of Behavior*
- February 2016 - *Journal of the Experimental Analysis of Behavior*
- February 2016 - *Psychopharmacology*
- October 2015 - *Behavior Analysis: Research and Practice*
- September 2015 - *Journal of the Experimental Analysis of Behavior*
- June 2015 - *Emotion*
- August 2014 - *Journal of the Experimental Analysis of Behavior*
- July 2014 - *Journal of the Experimental Analysis of Behavior*

Research Experience

- Project Manager, TANF, Dr. Amy Odum & Dr. Michael Twohig, 2012-present
- Graduate Research Assistant, Dr. Amy Odum, 2012-present
- Laboratory Technician, Dr. Amy Odum, 2011-2012
- Undergraduate Research Assistant, Dr. Scott Bates, 2008-2012
- Undergraduate Research Assistant, Dr. Amy Odum, 2010-2012
- Undergraduate Animal Laboratory Assistant, Psych 3400, 2011

Teaching Experience

- Independent Instructor
    - Psych 3010 Online: Psychological Statistics, Spring 2017
    - USU 1010: University Connections, Fall 2016
    - Psych 1010: Introduction to Psychology, Fall 2016
    - Psych 3510: Social Psychology, Spring 2016
    - USU 1010: University Connections, Fall 2015
    - Psych 3500: Research Methods, Fall 2015
    - Psych 3400 Online: Advanced Behavior Analysis, Fall 2014

- Supplemental Instructor
    - Justin Barker Spring, 2011
    - Joseph Baker Fall, 2010
    - Dr. Jenna Glover, Spring 2010
    - Dr. Scott Bates, 2008-2009
- Supplemental Instructor Group Coordinator, 2010-2011
- Undergraduate Teaching Fellow, Dr. Scott Bates, 2009-2010
- College Reading and Learning Association Level 1 Tutor

Awards and Scholarships

- Summer 2016 Scholarly Communications Funding Award - $1495
- Spring 2016 USU Student Research Symposium Oral Presentation Award
- 2015-2016 USU Department of Research and Graduate Studies Travel Award - $600
- 2014-2015 USU Department of Research and Graduate Studies Travel Award - $600
- 2014-2015 Aubrey Daniels International Research Grant - $1,500
- 2014-2017 TANF Grant, Project Manager, State of Utah - $210,000
- 2014-2015 Borg Scholarship and Research Productivity Award - $3,000
- 2014-2015 Alvord Scholarship - $1,000
- 2013-2014 Blue Goes Green Grant - $2,000
- Undergraduate Research Scholar, Honors Department of Utah State University
- 2011-2012 Robins Award: University Undergraduate Researcher of the Year
- 2011-2012 Psychology Department Valedictorian
- 2011-2012 Psychology Department Outstanding Undergraduate Student
- 2011-2012 Undergraduate Researcher of the Year, College of Education
- 2011-2012 Undergraduate Student Representative
- Spring 2011 Honors Department Research Funds, $400
- Fall 2010 Undergraduate Research and Creative Opportunities Grant, $506.62
- Various Department of Psychology Student Travel Scholarship, $200-$300
- 2009-2010 Undergraduate Teaching Apprentice of the Year, Psychology Department
- 2008-2011 Presidential Scholarship, Utah State University

Popular Press Recognition

- bSci21.org - http://www.bsci21.org/jeab-how-we-think-about-time-affects-impulsivity/

- The Wall Street Journal - https://www.wsj.com/articles/the-key-to-financial-discipline-it-may-be-as-simple-as-taking-a-class-1490582293

Professional Affiliations

- Association for Behavioral Analysis International 2013-Present
- Society of the Quantitative Analysis of Behavior 2012-Present
- Psi Chi 2009-Present
- Rocky Mountain Psychological Association 2010-Present
- Industrial/Organizational Club Vice President 2011-2012

Software Skills and Technical Skills

- Inquisit: Rich survey and IAT programming
- SPSS
- E-prime programming for psychological research
- Qualtrics survey software
- Breathalyzer use and calibration
- CO monitor use and calibration
- Saliva collection
- R Statistical Environment

Relevant Trainings

- September 2014 Acceptance and Commitment Therapy Workshop

Additional Languages

- Fluent in Spanish including reading, writing and speaking