The Effect of Risk Aversion, Loss Aversion and Impulsivity on Delay Discounting

by

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ABSTRACT

Delay discounting is the decline in the present value of a reward with delay to its receipt. (Mazur,1987). The delay discounting task is used to measure delay discounting rate, which requires the participants to choose between two options: one involves immediate delivery of a reward, and other involves delivery after a delay, and the immediate rewards are adjusted in value until the subject feels there is no difference between the immediate and the delayed reward. Some previous studies (Robles and Vargas, 2007; 2008; Robles et al., 2009) found that the order of presentation of the immediate rewards (ascending or descending) significantly influenced the estimated delay discounting rate, which is known as the order effect. Uncertainty about the future and impulsivity could explain delay discounting behavior. The purpose of this study was to explore the order effect in delay discounting assessment. The current study found that the order effect in the delay discounting task can be explained by risk aversion, loss aversion and impulsivity. In the current study, the two kinds of fixed procedure (ascending and descending), and the titrating delay discounting task were used to estimate the degree of delay discounting. Also, two gambling tasks were applied to measure risk and loss aversion indices. The BIS-11 scale was used to assess the level of trait impulsivity. The results indicated that impulsivity biases individuals to choose the immediate small reward rather than the large delayed reward, resulting in lower area under the discounting curve (AUC) when estimated with the ascending-sequence delay discounting task. Also, impulsivity moderated the relationship between loss aversion and AUC estimated with the descending-sequence delay discounting task.

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CHAPTER 1

INTRODUCTION

We make countless decisions in our daily life. If the choices we make only differed on one dimension, our preferences would be predictable. For example, would you prefer to get $10 or $20? Almost everyone would choose the larger amount over the smaller one. On the other hand, if the options were to get $10 today or $10 tomorrow, individuals would tend to choose the money sooner. However, the real world is more complicated. We usually encounter choices that require considerations regarding both benefits and costs over a range of time frames. For example, would you prefer to win $20 but have to wait one hour, or would you rather get $10 without waiting? If you choose the sooner smaller rewards, you have shown *delay discounting*.

Delay discounting refers to the decline in the present value of a reward with delay to its receipt. (Mazur,1987). Delay discounting behavior was initially documented by economists in the late 19th and early 20th centuries. In the mid-20th century, economic research started exploring the relationship between delay discounting and internal processing (Samuelson, 1937). Psychological researchers found that delay affects the value of reinforcement in both humans and non- humans (Ainslie, 1975).

Delay discounting has an enormous and varied impact on human and nonhuman behavior. The features of delay discounting decision map onto the ability to self-control in remarkable ways (Ainslie, 1992). A large body of research found that delay discounting behavior is positively correlated with many forms of self-control and clinically important behavior; for example, discounting rate of substance abusers is higher than non-drug users (see Reynolds, 2007). And individuals with higher delay discounting rate are more likely to smoke (AudrainMcGovern et al., 2004; Odum et al, 2002; Reynolds et al., 2004, 2006), drink (e.g. Petry, 2001a), use drugs (e.g., Kirby et al., 1999), have gambling problems (e.g., Petry, 2001) attention deficit hyperactivity disorder (Barkley et al, 2001), and obesity (Komlos et al. 2004).

The main parameter used to describe delay discounting is delay discounting rate. A high rate of delay discounting means decisions are biased toward smaller immediate rewards or failure to consider long-term potential consequences, a form of impulsivity.

The Measurement of Delay Discounting

The core purpose of the delay discounting task is to estimate the rate of discounting by finding the indifference point at a series of delays. The indifference point (IP) is where the preference of the individual switches from the immediate rewards to the delay rewards or from the delay rewards to the immediate rewards. In other words, the indifference point is where there is no difference in subjective value between immediate and delayed rewards.

The methods used to measure indifference points of delay rewards can be divided into two categories: Fill-in-the-blank and binary forced choice.

Fill-in-the-blank task. In a fill-in-the-blank delay discounting task, there are two options: one includes the magnitude of the delay and the specific reward. Another option includes the magnitude of delay, and the value of the reward is missing. The participants are asked to fill a specific value in the blank, which would be the estimated indifference point on this delay (Chapman, 1996; Thaler, 1981). The individual’s indifference points on a given delay are determined by a single question. For example:

What number would make this statement true for you?

$500 now or $_______ 1 year from now

Because the participants do not have an explicit answer of what should they fill in, this fill-in-blank task will lead to inconsistent or nonsensical responses. Frederick et al. (2003) found that participants probably apply a simple rule to determine their answer, such as to multiply the immediate reward by 2 or 10, even though they rarely rely on these rules to determine their preferences in the real world.

Binary forced choice task. In order to avoid these problems, most studies apply a series of binary forced choices, which ask the participants choose between immediate smaller rewards and large delayed rewards. Typically, in this method the amount of the large delayed rewards is kept constant and only the amount of the small immediate rewards is gradually increased or decreased on each delay. Table 1 shows an example of binary forced trials. There are three ways to do this: *ascending*, the immediate amounts are presented in ascending order (i.e., by increasing the immediate reward), *descending*, the immediate amounts of rewards are presented in descending order (i.e., by decreasing the immediate reward) and *random*, the immediate amounts are presented randomly. The participants are asked to make a choice between each pair of smaller immediate rewards and large delay rewards. The indifference point for each delay can be captured by observing the switching point from choosing a smaller immediate reward to choosing large delay rewards or vice versa. There are two ways to estimate the indifferent point; the first one is the mean of the last immediate rewards chosen at each delay and the amount of immediate rewards of the previous trial. For example, if the participant is asked to make a choice between the alternatives in Table 1, he/she may start by choosing the immediate small rewards ($1000 now) and continue to choose this option until the amount of the small reward decreases to $800. The indifference point for $1000 for 1 year would be $ 825 (the mean of $850 and $800). Another way treats the last immediate rewards chosen at each delay as the indifferent point (Robles &Vargas, 2007; 2008; Robles et al., 2009). Based on this method, the indifference point for this participant would be $850.

Table 1

The Immediate Small Rewards and Delay Later Rewards in Binary Forced Choice Task

Trial	Immediate smaller rewards	Delay later rewards
1	$1000 now	$1000 in one year
2	$990.00 now	$1000 in one year
3	$960.00 now	$1000 in one year
4	$920.00 now	$1000 in one year
5	$850.00 now	$1000 in one year
6	$800.00 now	$1000 in one year
…	…	$1000 in one year
24	$20.00 now	$1000 in one year
25	$10.00 now	$1000 in one year
26	$5 now	$1000 in one year
27	$1now	$1000 in one year

Thus, although the binary forced choice task is better than the fill-in-blank task, it is not ideal. This method seems to ask the participants to answer many questions to determine each indifference point. In order to reduce the time, one of the solutions is to terminate the trials in each delay when the preference between small immediate rewards and large delay rewards switches. Robles and Vargas (2007) compared the full-length method delay discounting task and an abbreviated task, where once the indifference point is observed, the remaining trails for that delay are omitted. Their results indicated that there were no significant differences between the full-length and abbreviated version of delay discounting task. The value of the immediate reward on this delay discounting task does not change based on the previous response but follows a pre-set sequence; it can be called a fixed-sequence procedure.

Another solution to reduce the number of forced binary trials in a delay discounting task is using an adjusting procedure, such as titration. (e.g., Du et al., 2002; Odum &Baumann, 2007). In an adjusting procedure, the immediate rewards are modified by the previous choice the participants made. The immediate reward will increase if the delayed reward is chosen, and it will decrease if the immediate reward is chosen; the size of the change is half the value of each choice. For example, the task asked the participant to choose between $500 now and $1000 in 1 year. If the participant chooses the immediate reward ($500 now), the immediate reward of next trial will be $250, decreased by half of the current immediate reward. While if the delay reward is chosen ($1000 in 1 year) the immediate reward for next trial will be $750, increased by half of the current immediate reward. For each delay, it will take 10 such adjustments to determine the indifference point. Rodzon el at (2011) compared the fixed sequence procedure with the descending order and the titrating procedure. According to the results, there was no systematic difference between the delay discounting rate estimated by the fixed procedures and titrating procedures.

The Description Model of Delay Discounting

As the research on delay discounting evolves, some mathematical function have been proposed to fit the empirical delay discounting data. The reason for building a mathematical function is to accurately describe how future rewards are devalued over time.

Exponential function. Economists generally use an exponential model to describe delay discounting. It assumes that the present value of a delayed reward is exponentially decreases at a constant rate per unit of delay (Fishburn & Rubinstein, 1982; Koopmans, 1960; Loewenstein, 1992). The exponential function has the following form.

$$V = Ae\text{-}^{kD} \quad (1)$$

V is the subjective value of the delayed reward, A is the objective value of the reward, D is the delay, and k is the discounting rate, while e is the base of the natural logarithm. For example, if the rewards are to be delivered in one year, the subjective value of $100 with an annual discounting rate of 10% would be $90.54. On the other hand, if the person chooses to receive the reward after five years, his/her subjective value of $100 will be $60.85. Figure 1 shows the exponential discounting function with a 10% delay discounting rate per unit delay.

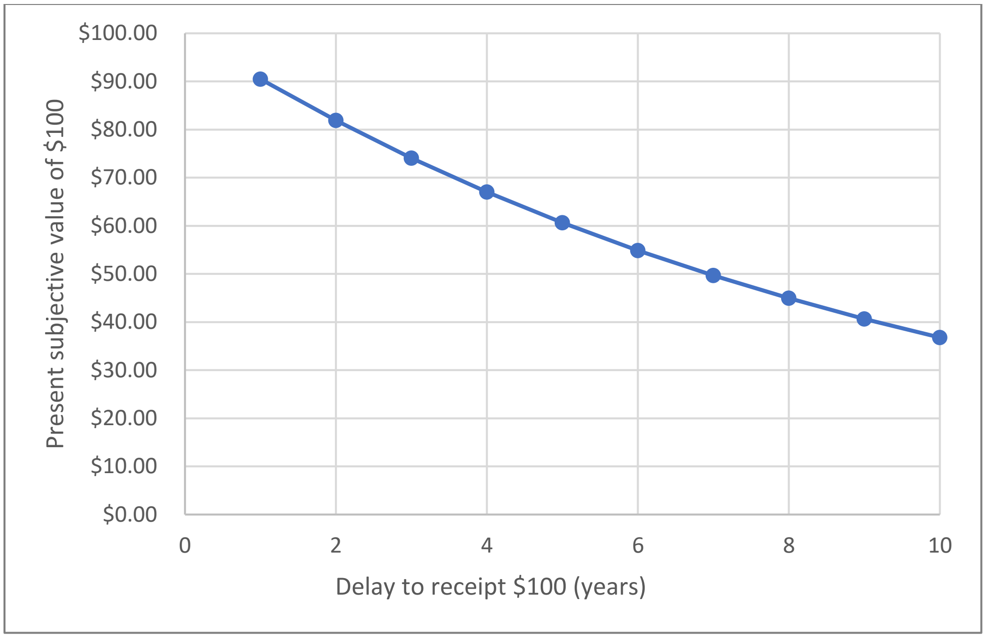


Figure 1. Exponential Discounting Function for a Future Reward of $100, with a Discounting Rate k = 0.1.

The exponential discounting function supports the stationarity assumption of economic theory (Koopmans, 1960), which emphasize the consistency of the delay discounting rate over time. However, a large body of empirical evidence indicates that discounting behavior is more accurately modeled by a hyperbolic than an exponential function. (e.g., Kirby, 1997).

Hyperbolic discounting function. In contrast to the exponential function, the hyperbolic function implies that discounting rate is not constant over time. In this case, the discounting rate decreases as the delay increases. (e.g., Johnson & Bickel, 2002)

$$V = \frac{A}{(1+KD)} \tag{2}$$

where k represents an empirically derived hyperbolic delay discounting rate, V represents the subjective value of the delayed reward; A is the reward amount and D is the delay.

Figure 2 shows the difference between the exponential and hyperbolic functions at the same discounting rate. As the delay increases, the steepness of the hyperbolic function decreases.

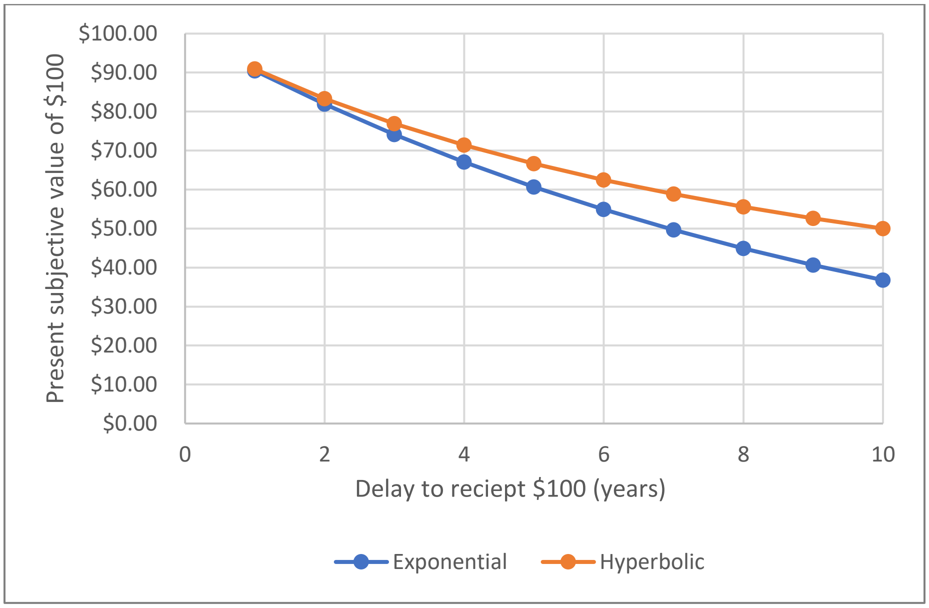


Figure 2. Exponential and Hyperbolic Discount Functions for the Future Reward of $100, with Delay Discounting Rate: $k = 0.10$.

One of the common criticisms of Equation 1 is that it cannot predict preference reversals (Green & Myerson 2004). Preference reversals violate the stationarity assumption. When the delays to both rewards are large enough, people usually prefer the larger later reward than the smaller-sooner reward. However, as the delays to both rewards decreases, people tend to reverse their preference and choose the smaller sooner reward instead. As an example, one person probably prefers $20 in 100 days rather than $15 in 75 days, and simultaneously prefer $15 today than $20 in 25 days. The exponential discounting function cannot reflect this phenomenon, whereas such preference reversal is consistent with the hyperbolic function (Ainslie,1975, 1992; Rachlin, 1974).

Hyperbolic-like discounting function. Based on the idea that the perceived magnitude of a reward can be described by the power function, Green el at (1994) modified the hyperbolic function. The hyperbola-like discounting function introduced parameter s, which represent the non-linear scaling of amount and time and is generally equal or less than 1 (Myerson & Green, 1995).

$$V = \frac{A}{(1+KD)^{S}} \tag{3}$$

Few studies have used the hyperbolic-like discounting function to describe their delay discounting data. Green and Myerson (1995) suggested that the fit of hyperbolic-like function is better than the hyperbolic model. However, a large body of studies has found that empirical data can be well described by the hyperbolic function with a single parameter. Thus, it is unclear whether adding an additional parameter is necessary. One of the objectives of the current study is to compare the goodness of fit of different delay discounting functions to determine which equation best describes our human delay data.

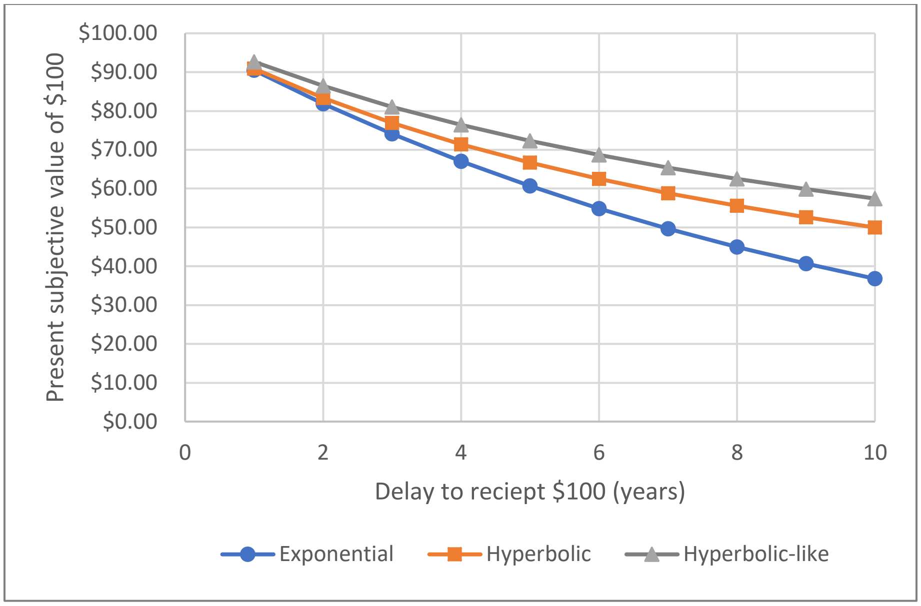


Figure 3. Exponential, Hyperbolic and Hyperbolic-like Discount Functions for the Future Reward of $100, with Delay Discounting Rate: k = 0.10 and s=0.9.

Estimation of Delay Discounting

Delay discounting rate (*k*). The magnitude of an individual's delay discounting is typically described as delay discounting rate (k). Delay discounting rate is estimated based on the hyperbolic function. However, there are several limitations to this method.

First, individual delay discounting rate tends to be significantly positively skewed. This is problematic if inferential statistics are to be used. The skewed distribution requires using the non-parametric tests. However, compared to parametric statistics, non-parametric statistics are generally less powerful. The solution is to use a log transformation to normalize the discounting rate (k) data and then proceed with the parametric analysis. However, such transformation will cause some information of the original data to be lost and will introduce the systematic errors in the model.

Area-under-the-curve (AUC). Thus, Myerson et al. (2001) suggested using AUC to measure the magnitude of delay discounting. The AUC is calculated directly from observed indifference points, avoiding equation-dependent systematic errors. Also, the distribution of AUC is normally distributed, which allows the use of parametric and inferential statistics. The following equation is used to calculate AUC (see Myerson et al., 2001):

$$AUC = \sum (X_2 - X_1)[(y_1 + y_2)/2] \tag{4}$$

Where X_2 and X_1 are successive delays, and y_1 and y_2 represent the indifference points corresponding to these delays, respectively. Before calculating AUC, the x and y values are normalized by dividing each value by the largest x and y values, respectively, thus producing a range of scores between 0 and 1. A larger AUC indicates less delay discounting.

Explanation of Delay Discounting

Most research on delay discounting has focused on demonstrating the phenomenon in different conditions, such as among drug users, or smokers, or on how to best describe discounting behavior mathematically. Even though such research may indirectly reflect the mechanisms underlying delay discounting behavior, few studies have directly explored what causes delay discounting behavior.

Uncertainty for the future. One potential cause for delay discounting is uncertainty about the future. Individuals are less sure the will receive rewards in the distant future than the immediate future, and thus devalue rewards accordingly. Individuals may not believe that the large delayed reward will be actually delivered or may be uncertain of the value the large delay reward will have when they eventually receive it; for example, economic inflation will decrease the value of the reward. Moreover, it is not necessary that this uncertainty be conscious. Some researchers (Critchfield & Atteberry, 2003; Kacelnik, 2003) propose that humans evolved in an environment where future rewards were often no longer available when delivery was delayed. Thus, a mechanism (specifically, devaluing future rewards) probably evolved to adjust to this environment. Even though future rewards are hypothetical or relatively certain for the participants in the laboratory environment, the evolved mechanism may affect a person's behavior at an unconscious level.

As Kacelnik (2003) puts it, "…although animals in the laboratory ought not to discount at all, if they do so it is because they respond to the ghost of uncertainty in their environment of evolutionary adaptation" (p. 119). However, there is little empirical evidence to support this assumption. Some researchers (Patak and Reynolds, 2007; Reynolds et al., 2007) had found that the participants explicitly report feeling less certain that they will receive the large delayed rewards when they asked to make such judgments when they asked the participants to report their certainty of receiving the delayed rewards. Further, they found that participants report greater uncertainty about delayed rewards with increasing length of delays. This suggests that participants automatically evaluate delayed rewards as uncertain, with more uncertainty being associated with increasingly delayed monetary rewards.

Other supporting evidence for the uncertainty hypothesis is that the same functional form (hyperbolic function) provides the best fit for both delay discounting and probability discounting (Green & Myerson, 2004; Rachlin, et al1991). The same mathematical function is used to estimate how people decrease the value of the rewards as delivery time increases or the probability of delivery decreases. However, this does not prove that the same cognitive process is shared by those two types of discounting. Some researchers propose that delay and probability can be substituted for one another. Rachlin et al. (1991), for example, figured out a constant of proportionality that allows transforming delay into subjectively equivalent probability. Furthermore, the work by Weber and Chapman (2005) added uncertainty to the smaller-sooner rewards and added delay to the probabilistic option; they found that the immediacy effect and certainty effect were reduced or eliminated, respectively. Thus, the study supported the hypothesis that delay and uncertainty are interchangeable. Also, Read et al. (2005) found that if the delay is framed as a specific date (e.g., March 30, 2019), the resulting delay discounting rate estimate will be less steep than if the delay is represented in calendar units (e.g., 1 year). This result implies that using specific dates helps to reduce the uncertainty of the delayed rewards, resulting in decrease of the estimated delay discounting rate.

Some economic factors, such as inflation, provide indirect evidence for the uncertainty theory. Inflation refers to the decrease in value that goods show over time; therefore, it is reasonable that people who believe that the smaller amount consumed at an earlier time would be worth more than the larger reward consumed at a later time would prefer the smaller-sooner reward. Some empirical evidence supports this assumption. For example, Ostaszewski et al. (1998) found that at the time when inflation was extremely high in Poland but not in the U.S., delayed rewards in Polish Zlotys were discounted more steeply than delayed rewards in U.S. dollars. The results demonstrated that experience with inflation affects decisions regarding future rewards but does not affect decisions regarding the immediate rewards. Because the experience with inflation exacerbates the influence of uncertainty of the value of the delayed rewards, people discount the delayed rewards more steeply. The author also found that the discounting of both delayed and probabilistic rewards was well fitted by the same hyperbolic model (hyperbolic function), which implies that similar decision-making processes underlie both phenomena, and that delay discounting reflects the risk inherent in waiting for delayed rewards.

Because the phenomenon of delay discounting can be explained by uncertainty about the future, it can be related Prospect Theory (Bleichrodt & Gafni, 1996). Prospect theory (Kahneman and Tversky, 1979,1992) assumes that for humans utility functions are typically concave, which implies that as total assets increase, smaller changes in utility are produced by constant increases in as sets (K.N. Kirby & Santiesteban, 2003). For example, the difference in utility perceived by individuals between getting $10 and getting $20 is greater than the difference between getting $990 and $1000. Similarly, obtaining $20 is obviously better than obtaining $10 but it is not twice as good. Prospect Theory suggests that decision making under risk, in particular the commonly observed preference for certain outcomes over risky outcomes with equal or higher expected value, can be explained by combination two phenomena: the diminishing sensitivity to outcome value as total value increases, resulting in risk aversion, and the tendency to weigh potential losses more than potential gains, resulting in loss aversion.

The classical representation of gains and losses are regarded as increases and decreases of consumption. The changes in utility derived from a gain or a loss are only evaluated by comparing the differences of the final assets. For example, the changes from $100 to $200 and from $200 to $100 are equivalent, differing only in sign (increase or decrease). However, Prospect theory (Tversky & Kahneman,1992) provides an alternative explanation of the changes in utility. It poses that the changes in utility of gains and losses should not be evaluated independently of the initial assets. Thus, losses and gains have different value functions. According to this theory, the changes from $100 to $200 is a gain of $100, which would be described by the gain function. A change from $200 to $100 is a loss of $100, which would be described by the loss function. Tversky and Kahneman (1992) found that the losses and gains function would be well fitted by a different mathematical model (i.e., a power function). For Gains:

$$V = X^{\alpha} \tag{5}$$

where V is the subjective value and α is the risk aversion coefficient.

For losses:

$$V = -\lambda * (-X)^{\beta} \tag{6}$$

Impulsivity. Another explanation of delay discounting behavior is impulsivity. Impulsivity has been defined as the inability to wait, a tendency to act without forethought, insensitivity to consequences, and the inability to inhibit inappropriate behaviors (e.g., Ainslie, 1975; Barkley, 1997). Decisions made without considering the consequences of the outcome are considered to be impulsive decisions (Moeller et al., 2001). It is evident that impulsivity results in preference of immediate small rewards. Discounting rate is reflected on the steepness of the devaluation in subjective value of the delayed rewards. With increasing delay discounting rate, the subjective value of the delay rewards decreases, resulting in higher preference for the impulsive choice. It is obvious that an individual with high level of impulsivity would tend to choose the immediate reward over the delayed reward, leading to a greater delay discounting rate. Higher levels of impulsivity bring about higher delay discounting rate. Thus, the delay discounting paradigm has emerged as a simple but effective assessment of impulsive decision making across various populations (e.g., Johnson, Bickel, & Baker, 2007).

On the other hand, Reynolds et al. (2006) compared three personality scales (BIS-11, I7, and MPQ) of impulsivity, delay discounting, and another behavioral measurement of impulsivity in 70 participants, and showed that delay discounting rate and the personality scales were not significantly related. On the other hand, a study by Kirby and Finch (2010) with 407 college students revealed a significant relationship between impulsivity scales and delay discounting rate.

It still unclear why similar studies would yield contradictory results, although Reynolds et al. (2006) used an adjusting-amount procedure to estimate delay discounting rate, while Kirby and Finch used a paper-based delay discounting task. The delayed rewards used in those studies were also different ($10 for Reynolds and $100 for Kirby). Green et al. (1997) found that delay discounting rate decreased as the amount of delayed reward increased. It appears that estimates of delay discounting rate can be affected many factors, such as the magnitude of rewards, frame and order of presentation. Nevertheless, Rosalyn et al. (2008) using an adjusting-amount procedure (titration method) with a $1000 delay reward to estimate delay discounting rate did not find a significant relationship between delay discounting rate and impulsivity.

Furthermore, it remains unclear why delay discounting rate might be unrelated to trait impulsivity. Other factors, such as risk aversion, which are negatively related or unrelated with impulsivity, affect the individual’s preference for immediate rewards. Thus, one of the purposes of the current study is exploring the relationship between impulsivity and delay discounting rate while controlling for the effect of risk aversion to further test if risk aversion has an impact on the relationship between delay discounting rate and impulsivity.

The Order Effect

Much evidence to date suggests that delay discounting can be regarded as a trait (de Wit, 2008; Kirby, 2009; Reimers et al., 2009; Odum, 2011) because delay discounting rate is consistent across time and across circumstances. However, a growing body of evidence suggests that delay discounting can be changed by variations in the framing of the delays during the assessment, even though delay discounting seems trait-like.

Robles & Vargas (2007, 2008) and Robles et al. (2009) found that the order of presentation of the immediate rewards between trials moderates the estimated rate of delay discounting. The results of a between-subject design (Robles & Vargas, 2008) revealed the delay discounting rate is significantly lower for the participants who were assessed using a descending order of presentation of an immediate reward than the one who was measured by an ascending order delay discounting task. To eliminate the influence of individual differences and further explore the effect of the order, Robles et al. (2009) used a within-subject design to test whether the order effect exists. The results of the two studies were consistent as the AUC was significantly larger when using the descending sequence compared to the rate obtained with the ascending order.

It is unclear why the presentation order would alter the estimate of delay discounting rate, given that delay discounting has a trait like a tendency. Current models cannot provide an account of this finding. We previously mentioned that uncertainty about the future could explain the occurrence of the delay discounting phenomenon if the delayed option is regarded as an option with uncertainty. According to Prospective Theory, risk aversion is defined as the weighing of certain outcomes higher than risky outcomes with equal or higher expected value. As the value of the immediate reward increases, the strength of the temptation from the delayed reward decreases, resulting from the diminishing sensitivity to outcome value. Thus, one of possible explanation is that risk aversion makes the immediate certain rewards more attractive, which causes individuals to switch their preference from delayed large reward to immediate smaller rewards earlier in ascending sequence and to switch their preference later during the descending sequence. Based on Prospect Theory, people treat a change from $200 to $100 as a loss of $100. Hence, in the descending-sequence delay discounting task, participants seem to be in a loss frame; i.e., loss aversion makes people weight losses more than gains. Therefore, in order to avoid a massive loss, the participants choose the delayed reward to stop the immediate rewards from decreasing. In contrast to the effect of risk aversion, loss aversion diminishes the temptation of the immediate rewards. Also, previous research suggests that impulsivity pushes people to prefer the immediate reward rather than the delayed reward. In the present study, we attempt to replicate the order effect, and further explore the effects of the context of choice on delay discounting rate.

Hypotheses

The current study aims to replicate the order effect in delay discounting task and attempt to use risk aversion, loss aversion and impulsivity to explain the order effect.

Hypothesis 1: The hyperbolic model provides the best fit for the current data.

Hypothesis 2: The differences in delay discounting tasks are significant. Specifically, the discounting rate estimated with the ascending task is greater than the rate estimated with the descending task. Also, the difference between the descending delay discounting rate and titrating delay discounting task is not significant.

Hypothesis 3: The order of exposure to the tasks will have an impact on the order effect.

Hypothesis 4: Risk aversion will mask the relationship between impulsivity and degree of delay discounting.

Hypothesis 5: In the ascending-sequence delay discounting task: risk aversion and impulsivity will jointly contribute to increasing the degree of delay discounting. Specifically, a higher level of risk aversion leads to a relatively lower AUC and a greater delay discounting rate.

Hypothesis 6: In the descending-sequence delay discounting task: loss aversion, risk aversion, and impulsivity jointly influence the individual's choice. However, the effects of risk aversion and impulsivity, and loss aversion will be opposite. The higher the level of loss aversion, the lower the delay discounting rate in the descending task estimated as a greater AUC.

CHAPTER 2

METHOD

Participants

Participants were recruited on Amazon MTurk and they received a $2 Amazon gift card compensation after finishing the session. Before performing any analysis, problematic data were removed based on the algorithm developed by Johnson & Bickel (2008). Specifically, the criterion is that if an indifference point is greater than the preceding point by 20% of the larger delay reward, and if the last indifference point (25 years delay) is not lower than first indifferent point (6 hours) by at least 10% of the larger delay reward, the data are regarded as nonsystematic and should be removed. After deleting any problematic data, 96 participants (54 Male, 42 Female) were included in the final sample. Comparison of age and gender did not identify differences between participants whose data were removed and those whose data remained. Their age range was 19-59 years, and all signed informed consent. The demographic characteristics of participants are reported in Table 2.

Table 2

Characteristic of Participants

Participants		N (%)
Age (Years)	*M(SD)*	39.27 (8.27)
Gender	Male	54 (56.3%)
	Female	42 (44.7%)

Measures

The fixed procedure delay discounting task. All the participants were asked to complete two delays discounting tasks in which the immediate rewards were presented in either ascending or descending order. In both the ascending and descending delay discounting tasks, participants were required to make a choice from two options between 30 amounts of immediately available hypothetical cash ($1000, $999, $995, $990, $960, $940, $920, $850, $800, $750, $700, $650, $600, $550, $500, $450, $400, $350, $300, $250, $200, $150, $100, $80, $60, $40, $20, $10, $5, $1) and a constant delayed option ($1000). The immediate amounts were presented in descending order (in the descending task) and ascending order (in the ascending task). The delay magnitudes of the descending task and ascending task were 6 hours, 1 day, 1 week, 2 months, 6 months, 1 year, 5 years and 25 years. In this experiment, we used an abbreviated delay discounting task (Robles & Vargas, 2007). In the abbreviated *ascending* and *descending* task, once a participant shows indifference between the immediate and delayed rewards, the rest of the immediately available reward values at that delay are omitted.

Participants were randomly assigned to receive either the ascending or descending task first. In the current study, we regarded the last immediate rewards chosen at each delay as the indifferent point.

Titrating procedure of delay discounting task. At the beginning of the titrating-delay discounting task, participants were required to make a choice between $500 now and $1000 after a delay. The immediate reward was then adjusted based on a participant’s previous response, and the delayed amount remained at a constant $1000. Then, adjustment to the immediate reward were made according to the following rules. If the immediate outcome is selected, the amount of the next immediate outcome decreases, and if the delayed outcome is selected, the amount of the next immediate outcome increases. The adjustment on the first trial is half of the difference between the immediate and the delay reward; for each subsequent trial, the magnitude of the adjustment is half of the previous adjustment. There were a total of 10 trials at each delay. The estimated indifference point in the titrating sequence procedure is the last value of the immediate outcome for each delay. For consistency, the last value of the immediate reward for each delay was counted as the indifference point in both the titrating and the fixed-sequence delay discounting tasks. The delay values assessed were the same as those in the fixed-sequence delay discounting tasks.

The Gambling Tasks. A gambling task adapted from a previous study (Charpentier al et, 2016) was used to estimate risk and loss aversion coefficients for every participant. The participants first went through a practice phase of gambling the task that involved a tailoring procedure to estimate each participant's indifferent point (the indifference point is the point that indifference in expected value between the gambling option and the certain option). The practice phase started with a series of extreme-value trials where the value of the two options were clearly different (e.g., making a decision between a 50% chance of losing $12 and 50% chance of winning $2, and a 100% chance of winning noting). Then these values were dynamically adjusted in each trial, depending on the participant's previous choice. The decisions were of two types: mixed gamble tasks, for which the certain option was always $0 and the gamble option involved a potential gain and a potential loss, and gain-only gambles, which involved a choice between a sure gain and a risky gamble with 50% chance of winning a higher amount and 50% chance of winning nothing ($0).

Specifically, on each trial of the mixed gamble task (see Appendix A), participants were presented with two options: one was a gambling option in which there was a 50% probability of winning the amount of money written in green (e.g., “WIN $12”), and a 50% probability of losing the amount of money written in red. Another option was a certain option in which there was 100% probability of obtaining noting ($0) written in black. The potential wins and losses were varied parametrically according to the following rules. The gamble’s expected value (EV = 0.5 * win amount + 0.5 * loss amount) was adjusted after two trials reached the participant’s indifference point. Each set of two trials contains one “high” EV gamble and one “low” EV gamble. The EV of the accepted gambles is then decreased by 0.5, while the EV of rejected gambles increased by 0.5. The range of potential gains was between $6 and $24, and between $1 and $12 for potential losses. For each trial, the gain/loss pairs were chosen randomly from all pairs with the same desired EV.

On each trial of the gain-only task (see Appendix A), participants were presented with two options: one was a gains gambling option in which there was a 50% probability of winning a large amount of money written in green (e.g., “WIN $12”), and a 50% probability of winning $0 written in black; the other was a certain option in which there is a 100% probability of obtaining a small amount of money written in green (e.g., “WIN $3”). The left/right location of the gambling and certain options was randomly assigned. Participants were asked to choose between the gambling option and the sure option by clicking the left button of the computer mouse over a command button associated with that option. During the practice phase of the gain-only task, the procedure was the same as the mixed gamble task, except for the way the expected value (EV) is calculated. The gamble expected value was calculated by the equation: EV = 0.5* amount of win in risk option- amount of win in sure option. The range of certain gains was between $2 and $12 and the range of risk gains between $3 and $20. The participants randomly experienced the mixed gamble task practice phase or the practice phase of the gain-only task first.

After the practice phase, the experimental phase was held. The design of the experimental phase was similar to the practice session. On every trial, participants were presented with two options: one was a mixed gambling option in which there is a 50 % probability of winning the amount of money written in green (e.g., “WIN $12”) and a 50% probability of losing the amount written in red (e.g., “LOSE $8”). The other was a sure option in which there was a 100 % probability of obtaining a $0 written in black. The left/right location on the screen of the gambling and sure option was randomly assigned. Participants would choose the gambling or the sure option by clicking the left button of the computer mouse over a command button associated with that option.

The experimental phase of the gambling task also had two conditions, the first condition requires participants to make a choice between two options: the sure option (the value of this option is always $0) and the potential gain and potential loss option (the value for this option is taken from an 8 by 8 gain-loss matrix which was centered on each participant’s own indifference point). The second condition was a gain-only gambling task. The participants were asked to choose between two options: a sure gain of a smaller amount, and a risky gamble with 50% chance of winning a higher amount and 50% chance of not winning anything (the value of this option was taken from a 5 by 5 gain-only matrix centered around each participant's own indifference point). There were 64 mixed gambles and 25 gain-only gambles, randomly interleaved (examples of the loss and gain matrix and gain-only matrix are shown in Appendix B). The specific choice for every participant of the gain-only and mixed gambles depended on the gambles matrix.

Impulsivity. The Barratt Impulsiveness Scale (BIS) was used to measure impulsivity. In its current form (BIS-11; Patton et al., 1995) it consists of 30 items that are responded to on a 4-point Likert scale. The BIS-11 consists of three factors: Attentional Impulsiveness, Motor Impulsiveness, and Nonplanning Impulsiveness. (the BIS-11 is reproduced in Appendix C) Cronbach's Alpha coefficient for the current research was 0.87.

Procedure

Participants completed the all the tasks through MTurk online. Each task in the experiment was programmed using Java software. All participants completed an informed consent form approved by the ASU Institutional Review Board. Each session lasted approximately 40 minutes. Participants completed two fixed sequence delay-discounting tasks, a gambling task, the impulsivity scale, and the titrating-procedure delay discounting task. The order of the tasks was randomly assigned to each participant.

Data Analysis

Delay discounting task. The three models of delay discounting (Exponential function, Hyperbolic function, and Hyperbolic-like function) were fit to the median group indifference points for the different delay discounting tasks (ascending, descending and titrating) using nonlinear regression. Because the three models are not nested, to compare the model fit we used the Bayesian Information Criterion (BIC) as basis for model selection, which determines the relative quality of the models by comparing their goodness of fit in terms of parsimony (i.e., complexity). Smaller BIC score indicates that the model fits the data better.

Typically, R^2 is used to assess the goodness-of-fit of a model, and researchers commonly use it as a criterion (e.g., $R^2 < 0.5$) to remove problematic data (e.g., Green &Myerson, 1995). The R^2 is calculated by nonlinear regression to fit the data to a mathematical discounting model (e.g., the hyperbolic function).

The R^2 is defined as the proportion of the variance explained by the model. Thus, the R can be obtained through the following equation:

$$R^2 = 1 - \frac{SSE_{model}}{SSE_{mean}} \tag{6}$$

Where the SSE_{model} represents the sum of squares error, and SSE_{mean} represents the variance of the observed data.

Even though R^2 is a good criterion to evaluate linear regression models, it is unsatisfying in the case of nonlinear models. In linear regression, the ratio in equation 6 is never greater than 1 or less than zero, because the SSE of the mean is the maximum SSE possible for the model. That is, a horizontal line through the mean of the data will always result in equivalent or greater than the sum of squares error (Ratkowsky, 1990). By contrast, with nonlinear regression, the SSE for the mean does not represent the maximum SSE possible for the model.

Taken the hyperbolic function as an example, if the indifference point for the first delay (6 hours) is low (e.g., 200), the SSE for the mean does not represent the maximum SSE possible for the model. The mean may provide less error than the nonlinear curve, resulting in a negative R^2 value (Motulsky & Christopoulos, 2003). Johnson & Bickel (2008) found that *k* was significantly and positively correlated with R^2. Thus, higher delay discounting rates lead to overestimation of R^2.

Given the drawback of R^2, some researchers use other measures to evaluate the models' goodness of fit. For example, the root means squared error (RMSE) is not influenced by comparison to the mean of the data (e.g., Kirby & Santiesteban, 2003). The Akaike information criterion (AIC) and Bayesian information criterion (BIC; Burnham & Anderson, 2002) were also used as evidence for model selection. In the current study, R^2, RMSE, and BIC were calculated for each delay discounting task as a criterion for model evaluation.

Once the model was selected, the best delay discounting function was applied to each participant's data. An indifference point was first estimated for each delay (0.25, 1, 7, 60, 180, or 365, 1825, 9125 days) based on each participant's choices. Thus, a dataset for each participant included 8 indifference points. The hyperbolic function was used to model each set of indifference points for each participant. Half of the participants were exposed to the titrating discounting task first (coded as 0) and the rest were exposed to the fixed procedure delay discounting first (code as 1). Thus, a 3 (ascending, descending and titrating procedure) by 2 (order exposure [first vs. second]) Mixed factor ANOVA was used to test for an order effect.

Because the distribution of delay discounting rate in each discounting task was positively skewed (skewness values 6.8 for ascending order delay discounting task, 6.4 for descending order and 5.4 for titrating task), they were log-transformed before running the statistical tests. To quantify the degree of delay discounting, in the current research AUC was also estimated for each task.

Loss aversion and risk aversion coefficients. Three-parameters (ρ, λ, μ) are used in Prospect Theory-derived models to calculate loss aversion and risk aversion coefficients. The parameters of the model were estimated using Maximum Likelihood with the following equations:

$$U(\text{gamble}) = 0.5 * \text{gain}^{\rho} + 0.5 * \lambda *(-\text{loss})^{\rho} \tag{7}$$

$$U(\text{sure}) = \text{sure}^{\rho} \tag{8}$$

$$P = \frac{1}{1+e^{-\mu*(u(gamble)-u(sure))}} \tag{9}$$

Where the ρ represents risk aversion, and λ represents the parameter of loss aversion which is only estimated by the mix gambling task. Mu is the inverse temperature parameter, which used in the softmax function (Equation 9) to estimate the probability of choosing a gamble on each trial.

Our models capture loss and risk aversion effects by entering the difference between the utility of the gamble (Equation 7) and the utility of the sure option (Equation 8) in a softmax function (Equation 9) that estimates the probability of choosing the gamble. On mixed gamble trials, because both loss and risk aversion contribute to choosing, both λ and ρ are present in the model, and the utility difference is calculated by Equation 7 (the utility of the sure option is always 0).

$$U(\text{gamble})-U(\text{sure})= 0.5 * \text{gain}^{\rho} + 0.5 * \lambda *(-\text{loss})^{\rho} \tag{10}$$

On gain-only trials, only risk aversion is relevant, since there are no losses involved. Therefore, only ρ is present in the model, and the utility difference is as follows:

$$U(\text{gamble}) - U(\text{sure}) = 0.5 * \text{gain}^{\rho} - \text{sure}^{\rho} \quad (11)$$

The utility difference was entered, for every trial, in the softmax function (Equation. 9). The resulting estimated probability of choosing the gamble is then compared to the participant's actual choice and converted into a negative loglikelihood value. The model-fitting procedure iterates in MATLAB until it converges on the set of parameters that minimize the negative loglikelihood (hence maximizing the likelihood of the data given that set of parameters).

The distribution of ρ is positively skewed (skewness values 1.8) and λ is negatively skewed (skewness value -1.2). So, prior to running statistical tests, the parameters were log-transformed to reduce the skewness of the distributions. Because risk aversion is highest for the lowest value of ρ, the -log(ρ) was treated as the final index of risk aversion.

Spearman correlations were performed first to test the correlations between parameters, and the correlations between parameters and personality measures of impulsivity. Then, multiple regression analysis and moderation analysis were used to test how the loss aversion coefficient, risk aversion coefficient, and impulsivity score affect AUC obtained with the ascending, descending and titrating tasks.

CHAPTER 3

RESULTS

Model Fits

In order to verify my hypothesis 1, the hyperbolic model provided the best fit for the current data; the median indifference points for each delay in each task were used to fit the three models of delay discounting. We used the BIC, R^2 and RMSE as our criteria to evaluate and select the model. The free estimate parameter, BIC, R^2, and RMSE are reported in Table 3. The hyperbolic model provided a good fit to the current data as assessed by the R^2. The median R^2 for the hyperbolic model ranged from 0.98 to 0.99, whereas the range of R^2 for the exponential function varied between 0.69 and 0.74, and for the hyperbolic-like model between 0.86 and 0.87. However, the hyperbolic-like model has the lowest RMSE and BIC. Considering the drawbacks of R^2 for evaluation of nonlinear models and other sources of evidence (BIC and RMSE), the hyperbolic-like model provided the best fit to the data for every task.

Table 3

Free Parameters, R^2, *RMSE* and *BIC* for Three Delay Discounting Model

		k	*s*	R^2	*RMSE*	*BIC*
Exponential	Descending	0.0008		0.71	115.86	102.90
	Ascending	0.0008		0.69	115.86	102.89
	Titrating	0.0008		0.74	115.86	102.89
Hyperbolic-like	Descending	0.0018		0.87	42.22	88.83
	Ascending	0.0081		0.86	42.22	88.82
	Titrating	0.0027		0.87	42.22	88.82
Hyperbolic	Descending	0.02	0.61	0.98	84.17	97.78
	Ascending	0.02	0.61	0.99	93.76	99.51
	Titrating	0.02	0.61	0.98	80.97	97.17

The Order Effect

In view of the complexity of the hyperbolic-like model, most of the data cannot converge using the hyperbolic-like model. Therefore, the hyperbolic model was applied to estimate the individual's delay discounting rate for each delay discounting task. Thus, the delay discounting rate (*k*) for different tasks was estimated using Mazur's (1987) hyperbolic model, resulting in k = .008 (ascending), k = .0018 (descending) and k=.003 (titrating).

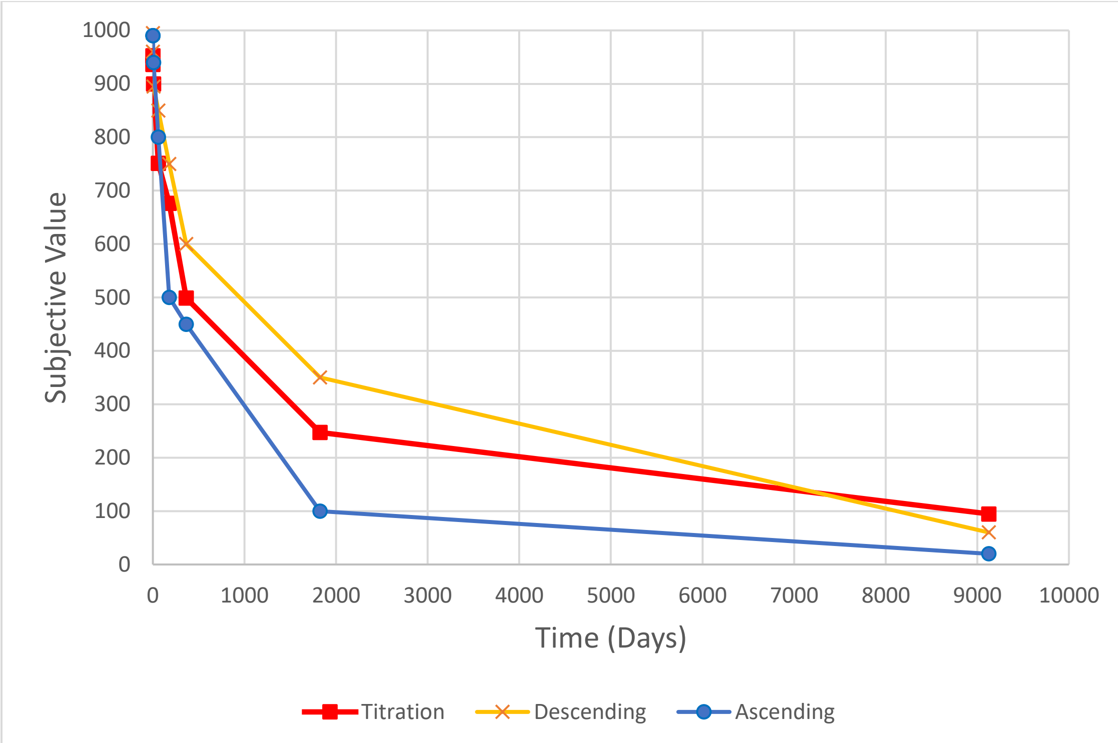


Figure 4. The Subjective Value of $1000 at Each Delay When the Immediate Rewards were Presented in Ascending, Descending and Titrating Order.

One of the aims of the current research was to replicate the order effect observed between in delay discounting tasks. Specifically, that the order of presentation of the immediate rewards would affect the estimated degree of delay discounting. Also, we needed to assess the effect of order of exposure to the degree of delay discounting tasks. Because exposure to the tasks was in a computer-generated random order, half of the subjects were randomly assigned to complete the titrating task first. In addition, based on the second hypothesis of this study, the order of exposure (whether expose the titrating delay discounting task first) has an impact on the results. Thus, a 2 (exposure order) by 3 (three delay discounting tasks) two-way mix factor ANOVA was performed to compare the AUC and log-transformed delay discounting rate (see Table 6 and Table 7). The test revealed a significant difference between the three delay discounting tasks (log-*k*: F (1.78, 168) = 16.21, p < .001, η^2=0.32; AUC: F (1.6,151.98) = 248.62, p < .001, η^2 =0.73) and the interaction between tasks and exposure order was also significant (log-*k*: F(1.78,168)=15.77, p<.001, η^2=0.33; AUC: F(1.6,151.98)=5.8, p=.006, η^2 =0.06). In order to further explore the relationship among the three delay discounting tasks, I split the file based on the order of exposure and ran a post hoc comparison. The results revealed a significant difference between the descending and ascending delay discounting task (log-*k*: p<.001; AUC: p<.001). The difference between descending and titrating procedure delay discounting task was not significant in terms of delay discounting rate (p=.13). Conversely, the difference was significant when assessed by AUC (p<.001). Our results were congruent with the previous research (Robles et al., 2009) and corroborated Hypothesis 2 (The differences in delay discounting tasks are significant) and Hypothesis 3 (The order of exposure to the tasks will have an impact on the order effect).

Table 4

Descriptive Statistics for Delay Discounting Rate

	Exposure titrating first		Exposure titrating second	
Tasks	n	M(SD)	n	M(SD)
Ascending	41	-2.65(1.18)	55	-1.73(0.77)
Descending	41	-2.74(1.17)	55	-2.67(0.70)
Titrating	41	-2.37(1.57)	55	-2.38(0.75)

Table5

Descriptive Statistics for AUC

	Exposure titrating first		Exposure titrating second	
Tasks	n	M(SD)	n	M(SD)
Ascending	41	0.13 (0.12)	55	0.05 (0.07)
Descending	41	0.54 (0.23)	55	0.60(0.19)
Titrating	41	0.26 (0.18)	55	0.31(0.25)

Table 6

The 2-way ANOVA of the Effect of Delay Discounting Task and Exposure Order on Log-transformed Delay Discounting Rate

	F	*df*	*p*	η^2
Delay discounting tasks	16.21**	1.78	<.00	0.50
Exposure order	3.18	1	.08	0.03
interaction	15.77**	1.78	<.00	0.14

** p<.001

Table 7

2-Way ANOVA of the Effect of Delay Discounting Task and Exposure Order on AUC

	F	*df*	*p*	η^2
Delay discounting tasks	248.62**	1.6	<.00	0.73
Exposure order	0.72	1	.08	.008
interaction	5.8*	1.6	.006	0.06

** p<.001; *p<.05

Risk Aversion and Loss Aversion

We used the negative log-transformed risk aversion (-log(ρ)) and log-transformed loss aversion coefficients (log (λ)), estimated with the gambling tasks to, describe the magnitude of risk aversion and loss aversion in the study participants. Both risk and loss aversion can contribute to safe choice on mixed gambles, while only risk aversion contributes to safe choices on gain-only gambles, given that the task involves no losses. The mean of indifference point (IP) for mixed gamble trials was IP = 0 ± 2.85, and the mean of indifference point (IP) for the gain-only gambles trials was IP = 3.01 ± 3.29.

The average loss aversion parameter λ was 2.34 ± 0.51 across all participants, and was greater than 1, consistent with loss-averse decisions and with the existing literature suggesting that people weigh losses about twice as much as gains (Tversky&Kahneman, 1992). Risk aversion was also evident in people's choices, with an average parameter ρ = 0.82 ± 0.35, lower than 1, indicating a diminishing sensitivity to changes in value as value increases. A ρ smaller than 1, which represents the utility function, is concave for gains and convex for losses; and a λ, greater than 1, indicates overweighing of losses relative to gains.

The correlation between loss and risk aversion is not significant ($r = .18$, $p = .07$), implying that distinct processes underlie risk and loss aversion, and that the parameters do not trade off against each other in the Prospect-Theory model.

Relationship between Impulsivity, Delay Discounting, Risk Aversion and Loss Aversion.

Based on the previous research (Reynolds et al, 2006), degree of delay discounting and impulsivity are independent. However, I assumed that risk aversion masks the relationship between impulsivity and degree of delay discounting, appearing as a non-significant correlation between impulsivity and delay discounting (Hypothesis 4). In order to confirm this assumption, we applied the Spearman correlation test to explore the relationship between impulsivity and degree of delay discounting (measured as *k* and AUC), and the relationship between risk aversion, loss aversion and impulsivity. Also, a hierarchical regression was preformed to test the assumption that risk aversion plays a moderator (masking) role in the relationship between impulsivity and delay discounting. Results of the Spearman tests between the log-delay discounting rate for the three delay discounting tasks, AUC, log-risk aversion, log-loss aversion, and the impulsivity are shown in Table 8.

Table 8

Correlation Between Delay Discounting Rate and AUC of Three Delay Discounting Tasks, Risk Aversion, Loss Aversion and Impulsivity.

	1	2	3	4	5	6	7	8	9
1 Ascending k	1.00								
2 Descending k	.62**	1.00							
3 Titrating k	.62**	.54**	1.00						
4 Descending AUC	-0.15	-.14	.19	1.00					
5 Ascending AUC	-.75**	-.38**	-.48**	.14	1.00				
6 Titrating AUC	-.58**	-.52**	-.43*	.28**	.69*	1.00			
7 λ	.45**	.16	.15	-.02	-.42**	-.37**	1.00		
8 ρ	.39**	.22*	.11	-.25*	-.22*	-.18	.06	1.00	
9 BIS-11(impulsivity)	-.27*	.19	-.22*	.07	.17	.04	-.47**	.04	1

*p<.05; **p<.001

Impulsivity score and log-transformed delay discounting rate for both the ascending (r = -0.27, p = .006) and titrating task (r = -0.22, p = .03) were negatively correlated. These results are inconsistent with the previous research (Reynolds et al., 2006). A probable reason for the incongruent results is that in Reynolds et al. individual delay discounting rate was estimated with the hyperbolic model, which does not provide the best model fit (see Table 3). In addition, the accuracy of estimated delay discounting rate is model dependent. Thus, it is likely that the hyperbolic model biased the estimation of delay discounting rate. On the other hand, AUC is a model-independent method to assess degree of delay discounting, and the accuracy of AUC does not rely on the model used. Thus, we also tested the relationship between impulsivity and the AUC. In contrast to our results on delay discounting rate, the AUC estimated from the three delay discounting tasks were not related with impulsivity (ascending: r = .07, p = 0.5; descending: r = .17, p = 0.09; titrating: r = .04; p= 0.7). Reynolds (2006) suggests that the probable reason for the inconsistency between behavioral measures (i.e., delay discounting task) used to assess impulsivity, and scale measurement of impulsivity might be that impulsivity is a multi-dimensional concept and only part of this concept can be captured by the delay discounting task. Thus, I tested for correlation between the AUC of delay discounting tasks and the subscales of the BIS. The results indicated that the Motor Impulsivity subscale is significantly related with the log-transformed delay discounting rate from the three delay discounting tasks (descending: r = .276, p = 0.007; titrating: r = .31, p = 0.02; r = .25; p = 0.02), and it is also associated with AUC from the descending and titrating tasks (descending: r = -0.31, p = 0.002; titrating: r = -0.25, p = 0.015). The results of the Spearman test confirmed the explanation of the non-significant relationship between impulsivity and delay discounting in Reynolds et al. (2006).

Based on what the delay discounting task is supposed to measure, the entire construct of impulsivity assessed by the BIS-11 should be correlated with degree of delay discounting. However, the results show no relationship between AUC and impulsivity ($r = .04$, $p = 0.7$). One probable reason is that risk aversion masks the effect of impulsivity on delay discounting as measured by area under the discounting curve. Because in the titrating task the immediate rewards are not presented in strict ascending or descending order, it is likely that the AUC estimated by the titrating task might not be show the order effect, and can, thus, be treated as a (reference) baseline. Also, I assumed that risk aversion plays a role in moderating the relationship between AUC and both, the titrating task and trait impulsivity. To substantiate this assumption, a moderation analysis (hierarchical regression) was performed (see Table 9).

Table 9

Hierarchical Multiple Regression Analysis of the Effect of Impulsivity and Risk Aversion on Delay Discounting (AUC)

Predictors		ΔR^2	β
Step 1			
	Impulsivity		-0.18
	Risk Aversion		-0.14
Step 2			
	Impulsivity × Risk Aversion	0.05*	-0.25*
	Total R^2	0.13**	
	n	96	

** p<.001; *p<.05

Risk aversion (centered), impulsivity (centered), and an interaction term calculated from these centered variables were entered as predictors of AUC estimated with the titrating delay discounting task. None of the conditional main effects for risk aversion and impulsivity emerged. However, the risk aversion by impulsivity interaction was significant, B = -1.26, SE = 0.56, t (95) = -2.25, p = 0.03, $\Delta R2$ = .05. Simple slopes analyses revealed that for a participant with relatively low-risk aversion (at 1 SD below the mean) or with moderate levels (at mean) of risk aversion, impulsivity was uncorrelated with AUC. This pattern would not hold for participants with high levels of risk aversion (at 1 SD above the mean), with more impulsivity predicting lower AUC, B= -0.39, SE = 0.13, t (95) = -3.1, p =.002.

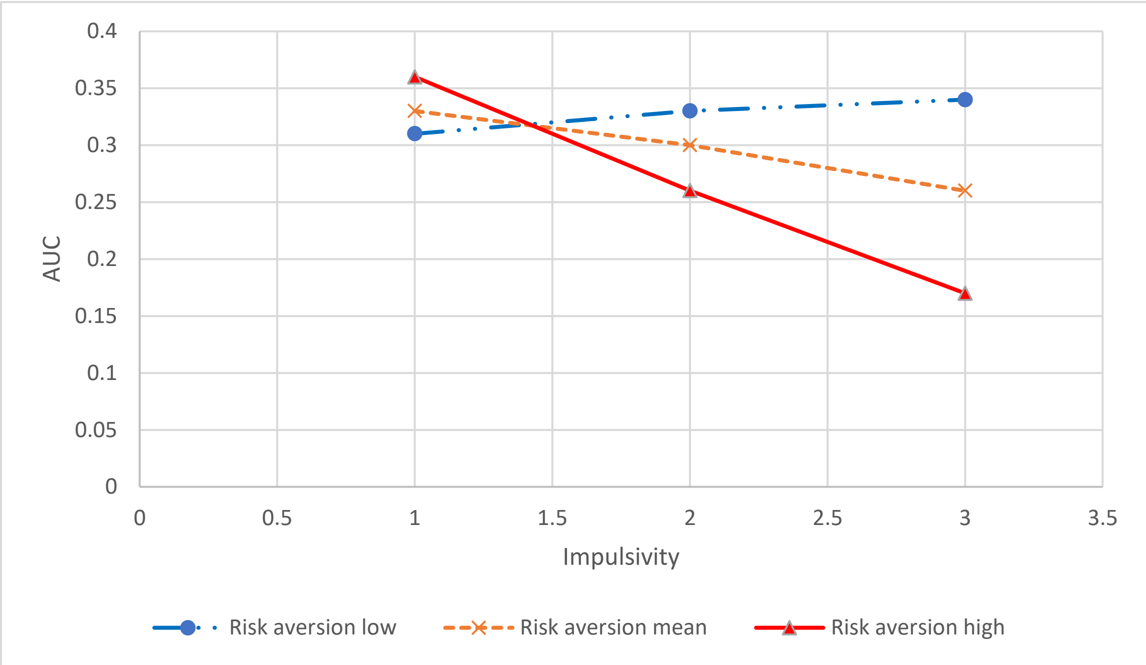


Figure 5. Regression Slopes for AUC Predicted by the Impulsivity for Different Levels of Risk Aversion

Explanation of the Order Effect

The main goal of this study was to explain the order effect observed between thein the fixed sequence procedures in terms of risk aversion, loss aversion, and impulsivity. therefore, we used multiple regression to analyze the data in an attempted to provide support my hypotheses. Given the effect of order of exposure to the tasks on the estimation of delay discounting rate, and the accuracy of delay discounting rate, we only used AUC as the outcome variable to guarantee the sample size and veracity in the regression analysis. Also, because AUC is indirectly obtained from the observed indifference points it would not be biased by the mathematical model.

The AUC from the titrating discounting task, in which the presentation order of the immediate rewards does not follows a strict ascending or descending order, is not subjected to the order effect. Thus, AUC measured by the titrating discounting task was regarded as the baseline from which to further explore the order effect. Accordingly, the order effect can be split into two parts in relation to the baseline: an order effect for the ascending task and an order effect for the descending task.

Order effect for the ascending task. Based on previous research (reviewed above under Explanation of Delay Discounting) the AUC from the ascending delay discounting task can be explained by a combination two parts: the effect from the order of presentation of the immediate rewards, and the participant’s uncertainty about the future. With this research, I want to explain why an order effect exists. For that, we need to test the effect of the presentation order of the immediate rewards on AUC independently. Thus, we excluded the effect of uncertainty about the future from the value of AUC by using as the outcome variable the AUC from titrating discounting task minus the AUC of from the ascending delay discounting task (see Figure 6). A regression was performed to explore my assumption regarding the order effect (results shown in Table 10).

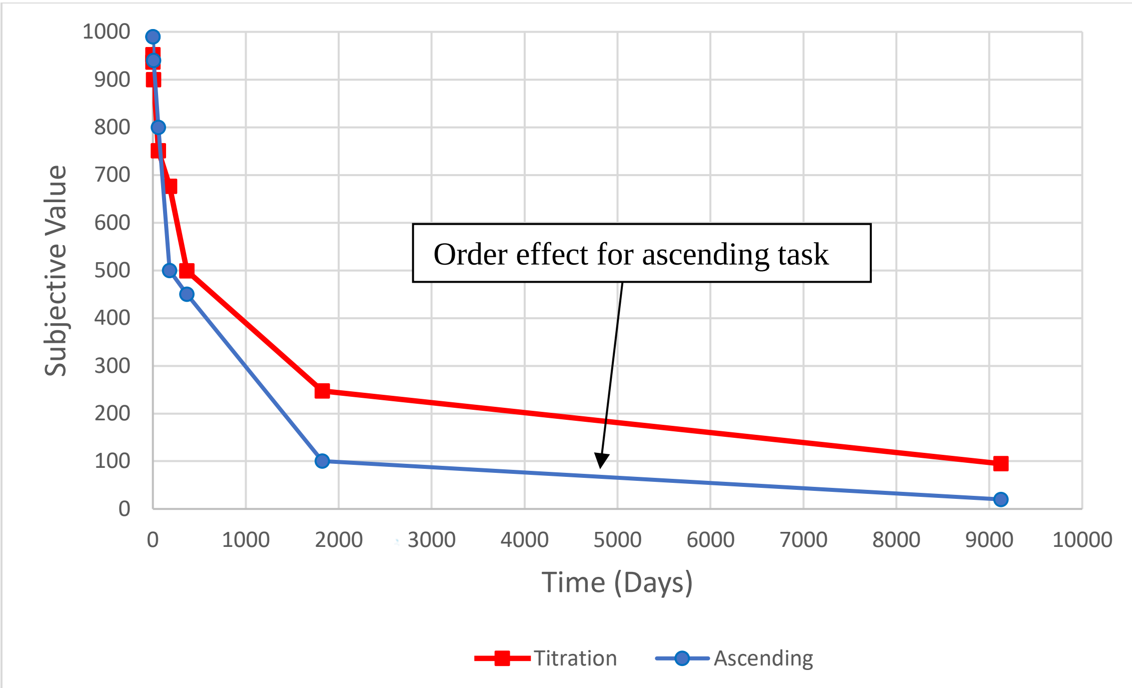


Figure 6 Order Effect for Ascending Delay Discounting Task

Table 10

Regression Analysis of Risk Aversion and Impulsivity on the Difference in AUC between the Ascending and Titrating Delay Discounting Tasks.

	β	*SE*	*t*	*p*
Risk aversion	-0.10	0.08	-0.98	0.33
Impulsivity	-0.20*	0.65	-1.91*	0.05
F	2.93*			
R^2	.06*			
n	96			

*p<.05

Given our outcome variable, risk aversion cannot predict the changes in AUC anymore, whereas the impulsivity can negatively predict the changes in AUC (= -.20, *t* (95) = -1.91, *p* = .05).

According to my hypothesis, risk aversion and impulsivity would have an impact on the ascending delay discounting task. However, based on the regression analysis, in contrast to my hypothesis, risk aversion does not predict the order effect for the ascending task. However, according to the correlation analysis (see Table 8), risk aversion is negatively related with AUC from the ascending task (*r* = -.22, *p* = .03). And impulsivity is not related to AUC from the ascending discounting task (*r* = -.17, *p* = .09), as it was excluded by the regression function. Thus, a regression analysis was preformed to test the relationship between risk aversion and AUC from the ascending delay discounting task. The results showed in Table 11.

Table 11

Regression Coefficients of Risk Aversion on AUC

	β	*t*	*p*
Risk Aversion	-0.23*	-2.27*	.03
F	5.17*		
R^2	.05*		
n	96		

**p*<.05

The results showed that delay discounting could be explained by risk aversion. Risk aversion can explain about 5% of the variance in discounting rate from the ascending. Risk aversion negatively predicted AUC in delay discounting (β = -0.23, p = .03).

Order effect for the descending task. The second part of the order effect lays with the descending delay discounting task (see Figure 7). Thus, we need to change the AUC of the descending discounting task subtracting the AUC assessed by the titrating discounting task to obtain the area of the order effect for descending task. My hypothesis 6 is that loss aversion would increase the AUC measured by the descending discounting task. In order to confirm this assumption, first, I tested the correlation between variables.

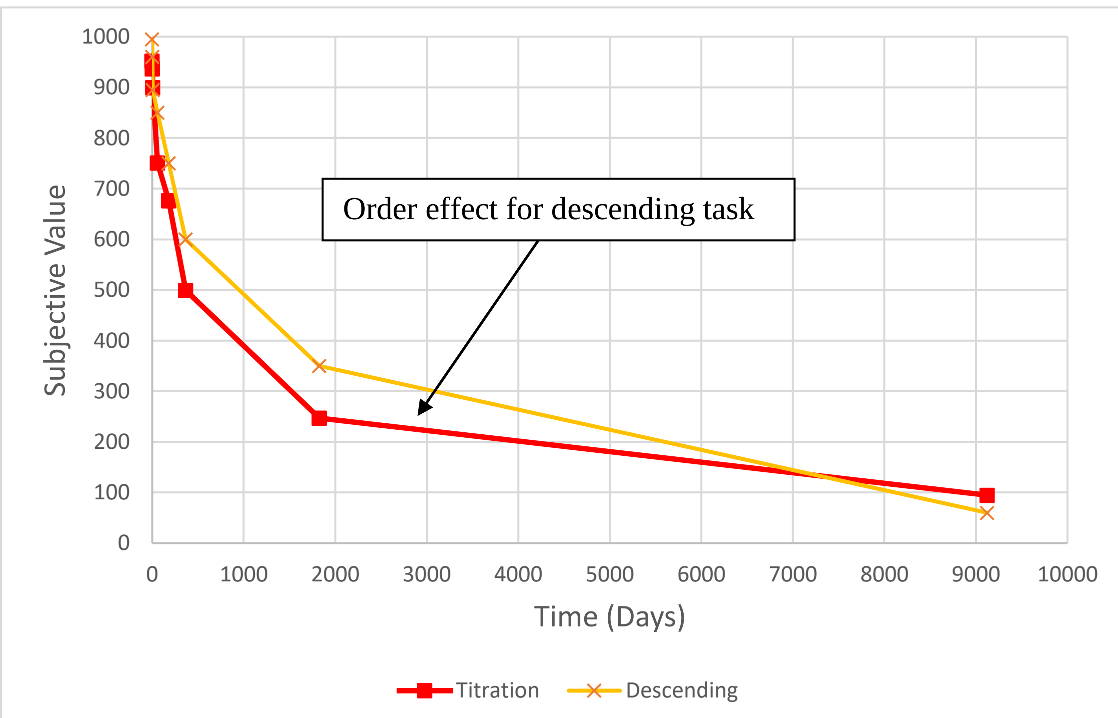


Figure 7 Order Effect for Descending Delay Discounting Task

Both risk aversion and loss aversion are unrelated to the calculated AUC value (r = -0.14, p = .017; loss aversion: r = 0.06, p = .59). In contrast, impulsivity can negatively predict the new AUC (r = -0.27, p = .006). However, loss aversion is the one and only factor the can account for the size of the AUC from the delay discounting task. Thus, I assumed that impulsivity plays a role in moderating the relationship between the new value of AUC from the descending task and loss aversion. To substantiate this assumption, a moderation analysis was performed.

Table 12

Hierarchical Multiple Regression Analysis of the Effect of Impulsivity and Loss Aversion on Order Effect for Descending Task

Predictors			
Step 1		ΔR^2	β
	Impulsivity		-0.31^{**}
	Loss Aversion		0.14
Step 2			
	Impulsivity × Loss Aversion	0.03[a]	-0.17[a]
	Total R^2	0.12^{**}	
	n	96	

Note. p-value for the interaction of impulsivity and loss aversion is p=.06, which is marginally significant. **, p<.01.

Loss aversion (centered), impulsivity (centered), and an interaction term calculated from these centered variables were entered as predictors of AUC from the descending discounting task. Conditional main effects for impulsivity emerged, such that participants who have a high level of impulsivity, b = -0.26, SE = 0.09, t (95) = -3.04, p = .003, show lower AUC. However, there was no main effect of loss aversion. These effects were qualified by a marginally significant risk aversion by impulsivity interaction, b = -0.3, SE = 0.16, t (95) = -1.89, p = 0.06, ΔR^2 = .03. Simple slopes analyses revealed that for a participant with a relatively high level of impulsivity (at 1 SD above the mean) or with moderate levels (at mean) of impulsivity, loss aversion was uncorrelated with AUC. This pattern would not hold for a participant with lower levels of impulsivity (at 1 SD below the mean), with more loss aversion predicting higher AUC, b =13, SE = 0.06, t (95) = 2.06, p =0.04.

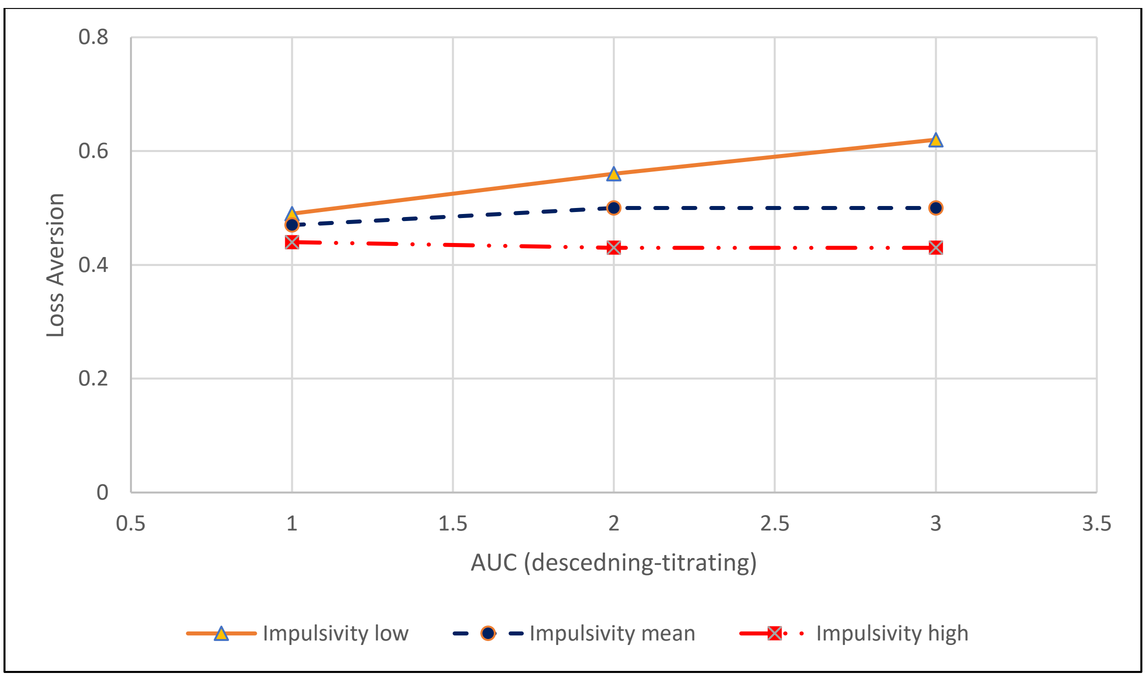


Figure 8. Regression Slopes for Order Effect for Descending Task as Predicted by Loss Aversion in Different Level of Impulsivity.

CHAPTER 4

DISCUSSION

There were three main findings in the present experiment. First, the effect of risk aversion masks the positive relationship between impulsivity and delay discounting. Second, the discounting function was more hyperbolic than exponential, and more hyperbolic-like than hyperbolic. Finally, impulsivity and loss aversion cause the order effect.

Through a comprehensive assessment of indices of goodness of fit, the hyperbolic-like model provides to be a better fit to the indifference point data than either the exponential or hyperbolic models. In contrast to what much delay discounting research suggests (e.g., Loewenstein & Elster, 1992), the estimates of delay discounting rate showed a hyperbolic trend. However, the data from a variety of studies show that at least for human data, the hyperbolic-like model provides a better description of the indifference points obtained from delay discounting tasks (McKerchar et al., 2009). However, the hyperbolic-like model adds an additional free parameter; therefore, the BIC criterion must be used to evaluate goodness of fit given that it penalizes models for the added complexity inherent to having more parameters. The BIC of the hyperbolic-like model is smaller than the hyperbolic-like model. Thus, the hyperbolic-like model was regarded as a better function to describe the current data. The hyperbolic-like model seems 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 hyperbolic, and at longer delays, the indifference points decrease less steeply than the simple hyperbolic (see Odum et al., 2006). In the current study, we also found that R^2 of the hyperbolic model is higher than the hyperbolic-like model. Johnson & Bickel (2008) mentioned that the R^2 is biased and is not a good evaluation indicator for the nonlinear model. Still, we do not have a perfect indicator to assess model fit. Even though RMSE and BIC were treated as indicators to evaluate model fit, RMSE and BIC have some drawbacks. The R^2 more clearly shows how much of variance can be explained by the model and it makes it easier to understand its meaning than that of the RMSE. Also, there is no threshold of RMSE for removing data or evaluating a model. Nevertheless, BIC is a good indicator of model fit, it was only used for model selection. To date, a comprehensive comparison of the models is still necessary when we evaluate nonlinear models.

In the current research, none of the significant correlations between impulsivity and AUC of the delay discounting task were evident, which is consistent with the results from Coffey et al. (2003) and Reynolds et al. (2006). Inconsistent with the results of AUC, impulsivity was significantly related to delay discounting rate. One possible interpretation is that the hyperbolic function may not be the best model to describe the current data, because parameter estimation is probably biased. Also, delay discounting rate is still positively skewed after being log-transformed. Reynolds et al. (2006) explain the inconsistency between self-report and behavior tests results arguing that the self-report scale requires participants to recognize and report their behavioral tendencies, which may not accurately reflect their behavior. In contrast, behavior tasks such as the delay discounting task may be less affected by the individual's biased self-perceptions.

Another possible interpretation is that risk aversion would account for the uncorrelated relationship. Risk aversion biases individual preference in favor of the immediate rewards, which would further lead to a higher delay discounting rate. Even if a participant has a low level of impulsivity, having a high level of risk aversion would lead to a higher delay discounting rate or lower AUC. Through the moderation analysis we found that if a person has a relatively high level of risk aversion, a high level of impulsivity leads to a lower AUC or higher delay discounting rate. We can draw the conclusion that the variance in AUC of delay discounting could be accounted for by impulsivity, under high levels of risk aversion.

The current empirical results replicated the order effect reported by Robles et al. (2007, 2009). The ascending order delay discounting rate is significantly higher than the descending delay discounting rate, which is consistent with results from Robles et al. (2009). The result is also identical to Rodzon et al. (2011), in that delay discounting rate from the descending task is similar to the rate estimated by the titrating task. However, comparing the AUC from descending and titrating tasks, we found the opposite result. The AUC from the descending discounting task is significantly higher than the AUC estimated with the titrating procedure. In their research, Rodzon et al. (2011) use non-parametric statistical methods to explore the effect from a different kind of task on AUC. A drawback of non-parametric statistics is that they involve losing some essential information of the data.

The results appear to generally support the two main hypotheses the study was designed to test: that risk aversion and impulsivity bias the degree of delay discounting in ascending discounting task. Nevertheless, the significant interaction of exposure order and type of delay discounting task needs to be investigated. One possible speculation is that the current study includes both fixed procedures and an adjusting procedure (the titrating task). The adjusting-amount delay discounting task may provide some hints about what the individual's exact indifference point is for each delay. Thus, the strength of the order effect decreases. If a participant is exposed to the titrating procedure task first, he/she would have opportunities to identify the indifference points for each delay and remember those values unconsciously, resulting in elimination of the order effect. The results of the differences in delay discounting rate between different delay discounting tasks supports this assumption. Exposure to the titrating discounting task prior to the fixed procedure task, removes the order effect. In contrast, if delay discounting is estimated by AUC, the exposure order cannot remove the effect of the order of presentation of immediate rewards. It still can be observed in the group of participants who were exposed to the titrating task. In future research, we need to investigate whether the participant's ambiguous awareness of their indifference points before the delay discounting task leads to the order effect.

Also, the results of the study appear to generally support the two hypotheses: 1. impulsivity biases delay discounting in the ascending delay discounting task, and 2. impulsivity is negatively related with AUC estimated by the ascending delay discounting task, which means that a higher-level of impulsivity would intensify the temptation exerted by the immediate rewards. Furthermore, risk aversion only has an impact on AUC from the ascending discounting task. In order to further explore the influence of risk aversion on the order effect, we split the effect of risk aversion into two orthogonal parts: one is the effect on uncertainty about the future; another is the effect of order of presentation. We found that risk aversion has a little impact on the order effect. Conversely, the level of impulsivity would predict the magnitude of the order effect on the ascending delay discounting task. Based on the analysis, we found that risk aversion is strongly correlated with uncertainty about the future, resulting in delay discounting behavior. While risk aversion cannot account for the order effect in delay discounting task. Thus, the current study proves that uncertainty about the future could be one of the reasons why delay discounting behavior occurs in human. However, we still do not have sufficient evidence to verify that the same underlying mechanism exists in both delay discounting and probability discounting.

According to my hypothesis, loss aversion is the one and only factor that can account for the fact that the descending order delay discounting task has a significantly higher AUC than AUC measured by the titrating procedure. However, the correlation between loss aversion coefficients and the differences in AUC from the descending task and the titrating procedure was not significant. The results indicated that impulsivity masks the relationship between loss aversion and AUC in the descending discounting task. For a person with lower impulsivity, the higher of the loss aversion he/she has, the higher value of the AUC.

Loss aversion makes individuals weigh losses more than gains, resulting in quickly shifting from the immediate rewards to the delayed reward. When we controlled for the effect of risk-aversion and impulsivity, loss aversion significantly and positively predicted the order effect in the descending discounting task.

CHAPTER 5

CONCLUSION AND FUTURE RESEARCH

In conclusion, the order effect can be separated into two parts: one concerns the ascending delay discounting task (differences between the ascending and titrating tasks), explained by impulsivity, and another concerns the descending discounting task (differences between the descending and titrating tasks), resulting from loss aversion and impulsivity.

Even though, in the current study, we found that impulsivity and loss aversion can explain the order effect, and that risk aversion can account for the occurrence of the delay-discounting phenomenon, it is still unclear how risk aversion and loss aversion affect degree of delay discounting mathematically. It is possible that as the magnitude of delay increases, the impact of risk aversion is enhanced as an exponential function or as a logistical regression function. The new mathematical model with risk aversion would provide information about why the hyperbolic or hyperbolic-like function is the best model to describe the delay discounting behavior. In future research, we will attempt to build a mathematical delay discounting function that takes risk aversion into account.

Although much empirical research proves that the delay discounting task is a simple and effective tool to measure the impulsivity, some drawbacks exist in current used delay discounting tasks. On the one hand, the fixed-sequence discounting task takes a long time to complete and leads to fatigue and practice effects. On the other hand, even though the titrating procedure effectively shortens the procedure, one accidental invalid selection would severely bias the results. One of the practical solutions is to use Item

Response Theory (IRT) methods in delay discounting tasks, which will not only increase the reliability of the task but will also reduce its duration.

There are some potential limitations of the present study. First, we used hypothetical outcomes instead of real rewards in both delay discounting tasks and gambling tasks. Perhaps the results would differ if people actually received the consequences of their choices.

Second, the delayed reward in all the delay discounting tasks was $1000. Taking the magnitude effect into account, the order effect would differ if we used smaller or larger delayed reward.

Third, even though log-transformation was used to reduce the skewness of the distributions, some variables were still positively skewed, including delay discounting rate in the descending task. A skewed distribution would bias the results from inferential statistics. Alternatively, another approach to reducing the skewness in the distribution of parameter estimates is to use a maximum a posteriori estimation procedure and run a Bayesian analysis.

Furth, in the current research, I used MTurk to recruit the participants. The subjects recruited in MTurk typically have lower socio-economic status. It is unclear whether the order effect exists and whether the loss aversion and impulsivity can still account for the order effect across a wider range of the population.

Regardless of these potential limitations of our current experiment, the present study successfully replicated the order effect in delay discounting task and found that loss aversion and impulsivity could explain this effect.

REFERENCES

Ainslie, G., & Haslam, N. (1992). Self-control. *Choice over time*, *177*, 209.

Audrain-McGovern, J., Rodriguez, D., Tercyak, K. P., Cuevas, J., Rodgers, K., & Patterson, F. (2004). Identifying and characterizing adolescent smoking trajectories. Cancer Epidemiology and Prevention Biomarkers, 13(12), 2023-2034.

Bleichrodt, H., & Gafni, A. (1996). Time preference, the discounted utility model and health. Journal of health economics, 15(1), 49-66.

Barkley, R. A., Edwards, G., Laneri, M., Fletcher, K., & Metevia, L. (2001). The efficacy of problem-solving communication training alone, behavior management training alone, and their combination for parent–adolescent conflict in teenagers with ADHD and ODD. *Journal of consulting and clinical psychology*, *69*(6), 926.

Chapman, G. B. (1996). Temporal discounting and utility for health and money. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22*, 771–791.

Critchfield, T. S., & Atteberry, T. (2003). Temporal discounting predicts individual competitive success in a human analogue of group foraging. *Behavioural Processes*, *64*(3), 315-331.

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

Fishburn, P. C., & Rubinstein, A. (1982). Time preference. *International economic review*, 677-694.

Green, L. & Myerson, J. (2004). A discounting framework for choice with delayed and probabilistic rewards. *Psychological bulletin*, *130*(5), 769.

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.

Kacelnik, A. (2003). The evolution of patience. In: Time and Decision: Economic and Psychological Perspectives on Intertemporal Choice (eds. Loewenstein, G., Read, D. & Baumeister, R.), pp. 115-138. Russell Sage Foundation, New York.

Kirby, K. N., & Santiesteban, M. (2003). Concave utility, transaction costs, and risk in measuring discounting of delayed rewards. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(1), 66.

Koopmans, T. C. (1960). Stationary ordinal utility and impatience. *Econometrica: Journal of the Econometric Society*, 287-309.

Komlos, J., Smith, P. K., & Bogin, B. (2004). Obesity and the rate of time preference: is there a connection? *Journal of biosocial science*, *36*(2), 209-219.

Reynolds, B., Patak, M., & Shroff, P. (2007). Adolescent smokers rate delayed rewards as less certain than adolescent nonsmokers. *Drug & Alcohol Dependence*, *90*(2), 301-303.

Loewenstein, G., & Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *The Quarterly Journal of Economics*, *107*(2), 573-597.

Loewenstein, George, and Jon Elster, eds. Choice over time. pp. 115-138. Russell Sage Foundation, 1992.

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. Behavioral processes, 81(2), 256-259.

Myerson, J., & Green, L. (1995). Discounting of delayed rewards: Models of individual choice. *Journal of the experimental analysis of behavior*, *64*(3), 263-276.

Myerson, J., Green, L., & Warusawitharana, M. (2001). Area under the curve as a measure of discounting. *Journal of the experimental analysis of behavior*, *76*(2), 235-243.

Ostaszewski, P., Green, L., & Myerson, J. (1998). Effects of inflation on the subjective value of delayed and probabilistic rewards. *Psychonomic Bulletin & Review*, *5*(2), 324-333.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, *5*(4), 297-323.

Rachlin, H., Raineri, A., & Cross, D. (1991). Subjective probability and delay. *Journal of the experimental analysis of behavior*, *55*(2), 233-244.

Reynolds, B., Patak, M., Shroff, P., Penfold, R. B., Melanko, S., & Duhig, A. M. (2007). Laboratory and self-report assessments of impulsive behavior in adolescent daily smokers and nonsmokers. *Experimental and clinical psychopharmacology*, *15*(3), 264.

Robles, E., & Vargas, P. A. (2008). Parameters of delay discounting assessment: Number of trials, effort, and sequential effects. Behavioral Processes, 78(2), 285-290.

Robles, E., Vargas, P.A., 2007. Parameters of delay discounting assessment tasks: order of presentation. Behave. Process. 75, 237–241.

Robles, E., Vargas, P. A., & Bejarano, R. (2009). Within-subject differences in degree of delay discounting as a function of order of presentation of hypothetical cash rewards. Behavioural Processes, 81(2), 260-263.Tversky A, Kahneman D (1992): Advances in prospect theory: Cumulative representation of uncertainty. J Risk Uncertain 5:297-323.

Reynolds, B. (2004). Do high rates of cigarette consumption increase delay discounting?: A cross-sectional comparison of adolescent smokers and young-adult smokers and nonsmokers. *Behavioural processes*, *67*(3), 545-549.

Reynolds, B., Ortengren, A., Richards, J. B., & de Wit, H. (2006). Dimensions of impulsive behavior: Personality and behavioral measures. *Personality and Individual Differences*, *40*(2), 305-315.

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.

Petry, N. M. (2001). Pathological gamblers, with and without substance abuse disorders, discount delayed rewards at high rates. *Journal of abnormal psychology*, *110*(3), 482.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics letters*, *8*(3), 201-207.

Odum, A. L., Baumann, A. A., & Rimington, D. D. (2006). Discounting of delayed hypothetical money and food: Effects of amount. *Behavioural processes*, *73*(3), 278-284.

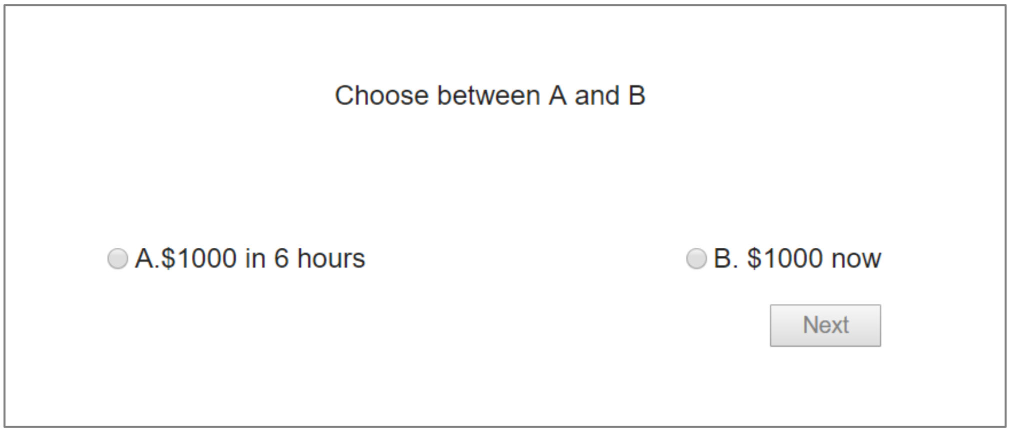
Odum, A. L., Madden, G. J., & Bickel, W. K. (2002). Discounting of delayed health gains and losses by current, never-and ex-smokers of cigarettes. *Nicotine & Tobacco Research*, *4*(3), 295-303.

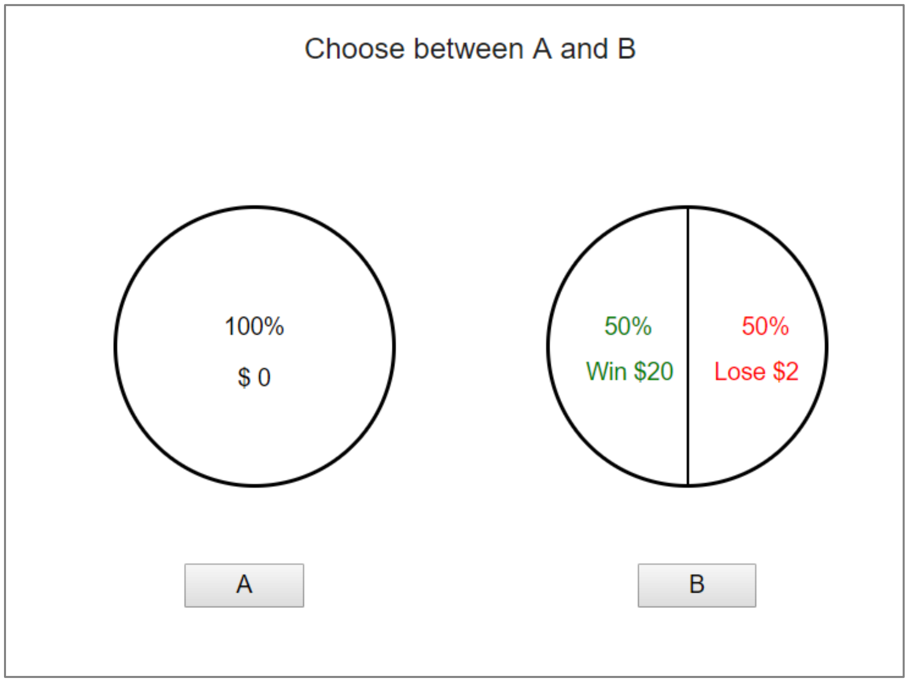
Weber, B. J., & Chapman, G. B. (2005). The combined effects of risk and time on choice: Does uncertainty eliminate the immediacy effect? Does delay eliminate the certainty effect? *Organizational Behavior and Human Decision Processes*, *96*(2), 104-118.

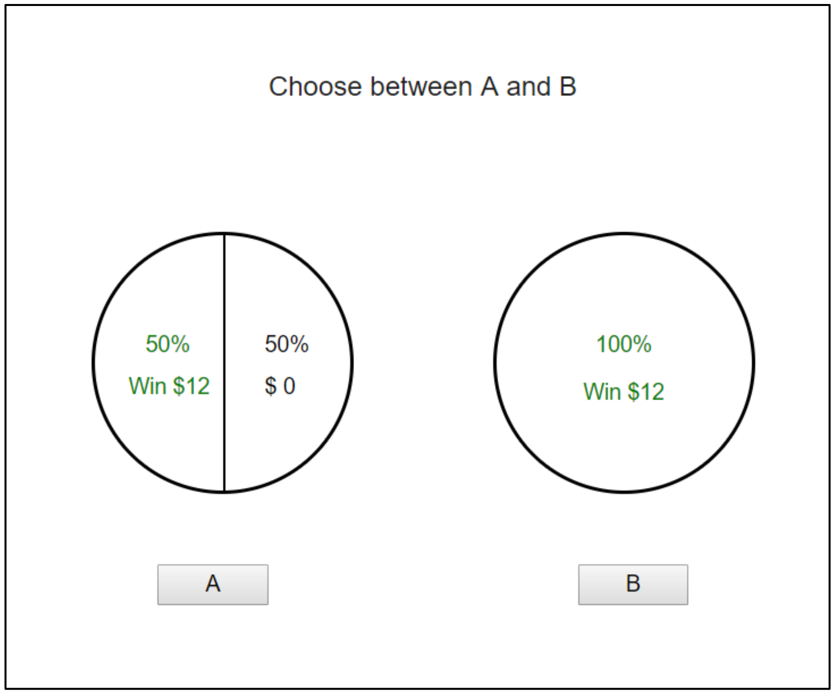
Weller, R. E., Cook III, E. W., Avsar, K. B., & Cox, J. E. (2008). Obese women show greater delay discounting than healthy-weight women. Appetite, 51(3), 563-569.

APPENDIX A

THE TRIAL DESIGN OF EXPERIMENTAL TASKS


Choose between A and B
A.$1000 in 6 hours
B. $1000 now
Next


Choose between A and B
100%
$ 0
50%
Win $20
50%
Lose $2
A
B


Choose between A and B
50%
Win $12
50%
$ 0
100%
Win $12
A
B

APPENDIX B

EXAMPLE MATRIX OF GAIN-LOSS AND GAIN-ONLY MATRIX

(IP CENTED TO ONE)

	9	-3.5	-3	-2.5	-2	-1.5	-1	-0.5	1
	7	-2.5	-2	-1.5	-1	-0.5	0.5	1	2
	5	-1.5	-1	-0.5	0	0.5	1	2	3
	4	-1	-0.5	0	0.5	1	2	3	4
Potential loss	3	-0.5	0	0.5	1	1.5	2.5	3.5	4.5
	2	0	0.5	1	1.5	2	3	4	5
	1	0.5	1	1.5	2	2.5	3.5	4.5	5.5
	0	1	1.5	2	2.5	3	4	5	6
	Expect Value	2	3	4	5	6	8	10	12
IP=1	Potential Gain								

Sure Gain	8	5	4	3	2	0
	6	3	2	1	0	-2
	5	2	1	0	1	-3
	4	1	0	-1	-2	-4
	3	0	-1	-2	-3	-5
	EV	6	8	10	12	16
IP=0	Potential Gain					

APPENDIX C

BIS-11

	① Rarely/Never	② Occasionally	③ Often	④ Almost Always/Always
1 I plan tasks carefully.	①	②	③	④
2 I do things without thinking.	①	②	③	④
3 I make-up my mind quickly.	①	②	③	④
4 I am happy-go-lucky.	①	②	③	④
5 I don't "pay attention."	①	②	③	④
6 I have "racing" thoughts.	①	②	③	④
7 I plan trips well ahead of time.	①	②	③	④
8 I am self controlled.	①	②	③	④
9 I concentrate easily.	①	②	③	④
10 I save regularly.	①	②	③	④
11 I "squirm" at plays or lectures.	①	②	③	④
12 I am a careful thinker.	①	②	③	④
13 I plan for job security.	①	②	③	④
14 I say things without thinking.	①	②	③	④
15 I like to think about complex problems.	①	②	③	④
16 I change jobs.	①	②	③	④
17 I act "on impulse."	①	②	③	④
18 I get easily bored when solving thought problems.	①	②	③	④
19 I act on the spur of the moment.	①	②	③	④
20 I am a steady thinker.	①	②	③	④
21 I change residences.	①	②	③	④
22 I buy things on impulse.	①	②	③	④
23 I can only think about one thing at a time.	①	②	③	④
24 I change hobbies.	①	②	③	④
25 I spend or charge more than I earn.	①	②	③	④
26 I often have extraneous thoughts when thinking.	①	②	③	④
27 I am more interested in the present than the future.	①	②	③	④
28 I am restless at the theater or lectures.	①	②	③	④
29 I like puzzles.	①	②	③	④
30 I am future oriented.	①	②	③	④