Delay Discounting as a Measure of Impulsivity

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Lidan Gu （古丽丹）

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Abstract

Delay discounting as a behavioral measure of impulsivity has been widely used in neuroeconomy, psychopathology, clinical neuroscience, and drug addiction studies. Previous psychological studies have suggested that: 1) a hyperbolic function best describes the decision behaviors of humans and other animals; 2) drug users tend to have higher delay discounting rates than controls; and 3) the associations between delay discounting rate and personality measures of delay discounting are inconsistent across studies. However, neuroimaging studies have often observed two neural systems involved in delay discounting, and a number of neural models have been proposed to describe delay discounting. The studies reported in this dissertation investigated delay discounting as a behavioral measure of impulsivity when considering the neural models.

In Chapter 1, delay discounting and its designs, task procedures, analysis models, reliability, and validity are reviewed. Based on previous studies, the delay discounting rate is influenced by the design of delay discounting tasks such as reward magnitude; the delay discounting rate reliably differentiates drug users from controls; and its reliability is high within a normal population but is relatively lower in clinical populations. In Chapter 2, the current studies are introduced.

In Chapter 3, three neural model fitting equations are compared with the standard exponential model and hyperbolic model. The studies suggest the saturating-hyperbolic model fits better than the standard models when the reward magnitude is low ($10). The superiority of the saturating-hyperbolic model is even more robust when clinical populations are involved. However, the saturating-hyperbolic model does not fit the

empirical data better than the standard models when the reward magnitude is high ($1000).

In Chapter 4, cocaine users are compared with matched controls and with individuals with binge eating disorder on their delay discounting rates; the parameters are analyzed by the saturating-hyperbolic function. The results show that cocaine users do not have significantly higher delay discounting rates; rather, they have significantly higher saturation indices, indicating the observed decision making bias in cocaine users is associated with the decision factor related to reward utility instead of the decision factor related to time utility. Furthermore, the findings suggest the observed decision making bias in cocaine users is not associated with binge eating disorder, indicating the decision preference is likely to be specific to drug users.

In Chapter 5, a personality measure based on the construct of time preference (the Time Preference Scale) is introduced. Its psychometric properties and its association with delay discounting and with the Barrat Impulsiveness Scale are investigated. The Time Preference Scale appears to have high reliability and validity. The latent trait of time preference is significantly associated with delay discounting rate. In addition, time preference is better than the overall score on the Barrat Impulsiveness Scale, but not better than the score on the non-planning subscale of the Barrat Impulsiveness Scale, in predicting the delay discounting rate. In Chapter 6, overall conclusions are drawn based on results of the current studies, and practice implications and research recommendations are provided.

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Chapter 1.

Delay Discounting as a Behavioral Measure of Impulsivity : A review

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Impulsivity

Our daily life is full of decisions that require considerations regarding benefits and costs over a range of time frames. For instance, would you prefer to wait one hour for a table at a popular restaurant, or would you rather dine at a less favorable restaurant without waiting? When you are upset, do you tend to spend most of your monthly income shopping without considering your soon-to-be due rent? Some decisions may reflect a personal life style, and others may cause serious consequences. A decision made without considering the consequences of the outcome is considered to be an *impulsive decision* (Moeller et al., 2001). Impulsive decision making is an important component of impulsivity research. Individual differences in decision making bias can predict an individual's chemical use status, treatment effectiveness, and other health behaviors (Alessi & Petry, 2003; Warren K. Bickel et al., 2010; Petry, 2001a; Yoon et al., 2007).

Impulsivity is also an important construct in psychopathology. Impulsivity has been associated with various disorders, including drug abuse (Gregory J. Madden, Petry, Badger, & Bickel, 1997), alcohol abuse/dependence (Flory et al., 2006), binge eating disorder (Volkow & Wise, 2005), depression and attention-deficit/hyperactivity disorder (e.g., Avila, Cuenca, Felix, Parcet, & Miranda, 2004), antisocial behavior (Cale, 2006), borderline personality disorder (e.g., Bagge et al., 2004), and suicide (e.g., Dougherty, Mathias, Marsh, Moeller, & Swann, 2004).

Traditionally, impulsivity is perceived as a personality trait, and it has been studied extensively using personality assessments. Over the past decade, there has been a growing amount of interest in the use of laboratory-based simulated paradigms in, for example, the fields of neuroeconomy, psychopathology, clinical neuroscience, and drug addiction (Busemeyer & Stout, 2002). In order to better understand the neuropsychological basis of impulsivity, studies have employed some of these paradigms to assess behavioral correlates of impulsivity, such as inattention, disinhibition, and impulsive decision making (Madden & Johnson, 2009). In particular, the delay discounting paradigm has been demonstrated to be a simple but effective assessment of impulsive decision making across various populations (e.g., Johnson, Bickel, & Baker, 2007).

The purpose of this chapter is not to discuss the individual difference variable of delay discounting, but rather to review the basic science of delay discounting. First, delay discounting is described, including a brief history, the procedure used in animal studies and human studies, and procedure variations. Second, major analysis models are presented. These models are categorized into description models and interpretation (neural) models. Third, reliability and validity of delay discounting tasks are reviewed. Finally, conclusions are drawn regarding the application and interpretation of delay discounting models.

Delay Discounting

Economists were the first social scientists to document the phenomenon of delay discounting in the late 19^{th} and early 20^{th} centuries. In the mid-20^{th} century, some economists began to associate the phenomenon with internal processing (Samuelson, 1937; Strotz, 1956). Early research on delay discounting focused on personality correlates and social contexts. Social class status, achievement, time perception, and prediction of life events have been associated with delay discounting using self-report questionnaire methods (Ainslie, 1975). In Analytical Psychology, delay discounting is associated with the id's pleasure principle (Freud, 1956). In developmental psychology, delay is believed to develop due to external circumstances (i.e., unavailability of immediate reward), and it is internalized as an ability to delay (Rapaport, 1950). Klein (1954) emphasizes the ability to delay as a self-regulation mechanism.

In experimental psychology, the influence of time delay on the reinforcement effect was observed by many psychologists who used experiments to study animal and human behaviors (Ainslie, 1975). Davenport (1962) and Logan (1965) employed two-way choices between rewards of different amounts at different time delays in their experiments with rats and found the reward value rapidly declined as a function of delay. Mischel and colleagues (1958, 1966, 1989, 1990) studied preschoolers' delay of gratification behavior and found the individual difference of choice behavior could predict academic achievement and coping in adolescence.

A similar discounting effect was also proposed by Rotter (1954) who noted that long delay is often associated with lower probabilities when considering the uncertainty of the future. Rachlin, Raineri, and Cross (1991) extended the delay discounting procedure to a probability discounting procedure in which individuals chose between small but certain reward, and larger but probabilistic reward. Similar to the delay discounting function, the subjective value of the larger reward decreased as the odds against receiving it were increased.

Currently there are many versions of delay discounting tasks. A typical delay discounting task examines the complex interplay between reward processing and temporal processing. Such tasks often involve choices between a larger and a smaller reward, where the smaller reward is available sooner than the larger one (Green & Myerson, 2004). The main parameter is the delay discounting rate. A high delay discounting rate represents a decision bias toward smaller and more immediate reward or a failure to consider long-term potential consequence, a bias that has been attributed to impulsivity.

Designs

Animal Designs

Studies assessing delay discounting in animals assess the delay effect on the reinforcement of the animals' behavior. In these studies, the rewards (or reinforcers) are operationally defined as food, liquid, or drugs (e.g., cocaine), and the animal subjects receive rewards by pressing a lever, pecking a key, etc. The association between the decreasing subjective value of a reward and the delay for receipt of the reward has been assessed by two major procedures: the adjusting-delay procedure (Mazure, 1987), and the adjusting-amount procedure (Richards, Zhang, Mitchell, & de Wit, 1997).

Mazur (1987) developed the adjusting delay procedure in which the delay to receive a small reinforcer is adjusted until the subjective values of the small reinforcer and the large reinforcer are equal (indifference point). The indifference point refers to the situation in which the subject has equal chances to select either one of the pair alternatives. In a delay discounting task, the indifference points for a series of reward options can be plotted to form a discount curve that describes the delay discounting rate.

Richards, Mitchell, De Wit, and Seiden (1997) modified the adjusting-delay procedure by adjusting the reward amounts rather than the delays. In their experiment, eight rats chose between an adjusting amount of immediate water and a fixed amount of water given after a delay. Comparing the adjusting-delay procedure and the adjusting-amount procedure has yielded consistent results (Green, Myerson, Shah, Estle & Holt, 2007).

Another popular procedure in animal studies is the T-maze procedure. In this procedure, rats are placed at a starting point from which they can approach the maze in either of two ways: one with smaller-sooner reward, and one with a larger-later reward (Thiébot, Bihan, Soubrie, & Simon, 1985). The reward choices are delivered at the end of the T arms, and delays are preceded by confining the rats in the arm to the larger reward.

The animal studies have the benefit of using tightly controlled experimental manipulations to attain causal relationships between independent variables and dependent variables. Also, the target behavior can be studied in a systematic way. For instance, Perry, Larson, German, Madden, and Carroll (2005) tested their rats' delay discounting rates, then divided the rats into high/low impulsive groups according to the rats' delay discounting rates and examined the group difference in cocaine self-administration. This kind of systematic investigation has made important contributions to the pioneering work of understanding delay discounting. However, there are some concerns regarding some specific procedures in the animal model. For example, there is potential confounding of the labor effort in the T maze procedure—that is, the effort involved in running before getting a reward--making it harder to discern whether or not the choices are merely due to delay discounting (Green & Myerson, 2010).

Human Designs

The procedures in animal studies have established the foundation for the development of designs for studying the delay discounting task in humans. Unlike the animal designs, the human designs often involve hypothetical rewards rather than real reinforcers. Based on the adjusting procedures, Rachlin et al. (1991) developed an early human design in which human participants were required to choose between hypothetically receiving a certain amount of money (< $1000) immediately and hypothetically receiving $1000 after a delay. The delayed amount ($1000) was fixed, while the more immediate amounts were adjusted at each of 7 delays until the participant reached an indifference point for each delay. The immediate amounts ranged from $1 to $1000, and the 7 delays ranged from 1 month to 50 years.

Some researchers (e.g., Bickel & Marsch, 2001) have voiced concerns regarding the hypothetical nature of rewards used in the Rachlin et al. study (1991). They developed a procedure involving real rewards to increase the construct validity of delay discounting measures. Studies comparing both hypothetical rewards and real rewards have supported a consistency between these two procedures when the rewards are monetary (Johnson & Bickel, 2002; Madden, Begotka, Raiff, & Kastern, 2003). However, when the rewards are stimulant drugs, the procedure using hypothetical rewards may fail to yield expected results (cf. Richards et al., 1999).

To better detect state changes after certain experimental manipulations (e.g., sleep deprivation/consumption of alcohol or diazepam), Reynolds and Shiffbauer (2004) developed an experiential discounting task (EDT) which allowed participants to directly experience the choice consequence. In this procedure, participants were required to make decisions on choices such as 15 cents immediately, or 35% chance of 30 cents in 15 seconds. The delays used in this procedure were short (seconds). According to the authors, the purpose of combining probability and delay was to make it a "real-life" situation because delay often involves some uncertainty in real life. However, it is unknown whether the short duration of delay (less than 1 minute) is a sensitive measure of the delay function (Green & Myerson, 2010). It is also unclear whether or not the delay is confounded with uncertainty (Reynolds & Shiffbauer, 2004).

Another widely used procedure is a titrating method in which the amounts of rewards as well as the first delay are fixed, while the length of the second delay is titrated until an indifference point is reached. This titrating procedure, together with the real reward delivery (in which the participant directly experiences the choice consequences), is a procedure often used in functional magnetic resonance imaging (fMRI) studies to investigate the neural correlates of delay discounting (cf. Wittmann, Leland, & Paulus, 2007).

Compared with the procedure designs in animal studies, the human designs require more sophisticated cognitive processes. Furthermore, most animal designs are based on the choices between immediate and delayed rewards, while many human models involve situations in which both choices are delayed. Within the human model, the different delay discounting procedures appear to generate qualitatively consistent conclusions when rewards are general (i.e. money). One advantage of human studies is that they are likely to have better external validity, as conclusions drawn from human studies are more readily applicable to human behavioral interventions. Moreover, their cost and efficiency are likely better than those in animal studies. One disadvantage of human studies is that it is harder to detect causal relationship due to the limitation of the manipulation (e.g., it is unethical to use cocaine self-administration behavior as a dependent variable).

Design Variations and Group Characteristics

Various studies have supported the observation that delay discounting parameters in human studies are influenced by a number of factors. Both manipulations of the task procedure and group characteristics can affect the delay discounting rate. These observed effects include domain effect, magnitude effect, frame effect, and characteristics of age, physiological state, and intelligence.

Domain effects. Although food is the major reward type in animal studies, money is the most commonly used reward in human studies. Nonetheless, researchers have started to investigate the delay discounting function in humans using food, a topic that can be informative in understanding eating disorders and/or unhealthy food choices. Some authors found a higher delay discounting rate for real food rewards than for hypothetical food rewards and hypothetical monetary rewards (Odum & Rainaud, 2003; Odum, Takahashi, Kitamura, & Wehr, 2006). Other reward types have also been examined by various researchers. In particular, heroin (Madden et al., 1997), cocaine (Coffey, Gudleski, Saladin, & Brady, 2003), cigarettes (Bickel, Odum, & Madden, 1999), alcohol (Odum & Rainaud, 2003), and even abstract outcomes such as health care utilization (Chapman, 1996; Odum, Madden, & Bickel, 2002) have been used as rewards in delay discounting studies. The various types of rewards often lead to different delay discounting rates; thus a domain effect should be considered when multiple reward domains are involved.

Magnitude effects. When the rewards being chosen are large (e.g., >$1000), the delay discounting rate tends to be more shallow, indicating a magnitude effect (Baker, Johnson, & Bickel, 2003). Green, Myerson, and McFadden (1997) compared delayed hypothetical rewards of different amounts ($100, $2,000, $25,000, and $100,000) in a sample of 24 undergraduate students. They found the delay discounting rate decreased as the amount of reward increased. In addition, the duration of delay scale may affect the delay discounting rate. Evidence from an fMRI study suggests a longer time-period (>1 year) may involve a different type of processing (Wittmann et al., 2007).

Frame effect. Another noteworthy effect is the frame effect (Bickel et al., 2003), which refers to the tendency for the delay discounting rate to be higher when the delayed outcome is presented as a gain rather than a loss. The effect has been demonstrated in various studies with undergraduate samples (Chapman, 1996; Shelley, 1993).

Age and state. Younger participants appear to have higher delay discounting rates (the future reward is discounted more rapidly) than older subjects, suggesting an age effect on the delay discounting rate (Green & Myerson, 2004). Certain states (e.g., sleep deprivation or opiate deprivation) also increase the delay discounting rate (e.g., Giordano et al., 2002; Reynolds & Shiffbauer, 2004).

Intelligence. Intelligence was significantly correlated with delay discounting performance as participants with higher WAIS-III scores had lower delay discounting rates in one study (Monterosso, Ehrman, Napier, O'Brien, & Childress, 2001). The negative association between intelligence and delay discounting performance has been supported by a number of other studies involving young adults (e.g., Bobova, Finn, Rickert, & Lucas, 2009) and middle-aged adults (e.g., de Wit, Flory, Acheson, McCloskey, & Manuck, 2007).

Studies of these factors have increased our understanding of delay discounting phenomena. Current literature indicates that delay discounting parameters should be considered within context.

Analysis Models

Economists and psychologists investigated delay discounting phenomena from different angles and on different levels. As the research on delay discounting expands, various analysis models have been proposed to fit empirical data or to explain the underlying mechanisms. Some of the models focus on describing delay discounting mathematically, while others also link to theoretical frameworks associated with neural processes. In this section, the former are referred to as *description models*, while the latter are referred to as *neural models*.

Description Models

Exponential discounting function. The "exponential discounting model" is commonly used in economics and artificial intelligence (A.D. Redish & Z. Kurth-Nelson, 2010). The exponential discounting function can be described by the following equation:

$$V = A \cdot e^{-kD}$$

In this equation, V is the subjective value of the delayed outcome; D is the delay for receipt of the outcome; and k is the discounting rate. This model assumes the delay involves a constant probability against the receipt of delayed reward. It is often used in economics as economists often are concerned with the phenomena of impulsivity at a macro level. Although this model does not predict discounting reversals commonly demonstrated in animal and human studies (Green & Myerson, 2004), it adequately describes human performance under some conditions such as time constraint, and it has proved to be more appropriate when the decision makers are trying to maximize gains using certain strategies (Schweighofer et al., 2006).

Hyperbolic discounting function. In contrast to research in the economic field, one widely accepted model in human and animal studies is the "hyperbolic discounting function." The hyperbolic delay discounting function refers to a decrease in discounting rate when the delay increases. The discounting is steep when the delay is relatively short, and it is shallow when the delay is relatively long. This function can be represented by the following formula:

$$V=A/(1+kD)$$

In this formula, V refers to the subjective value of a delayed outcome; A represents the objective amount of the delayed outcome; D equals the delay of the outcome; and k represents the delay discounting rate (Mazur, 1987). A higher k means there is a steeper discounting function and stronger preference for more immediate and smaller outcome (or greater impulsivity).

The hyperbolic function was found to fit the empirical data well in many psychology studies (K.N. Kirby & Santiesteban, 2003; G.J. Madden, W.K. Bickel, & E.A. Jacobs, 1999). This model assumes the reward choices at different times are actually choices with different rate of rewards. However, the change of the discounting rate could be interpreted in many different ways (K.N. Kirby & Santiesteban, 2003).

Extended hyperbolic model. Some authors theorize that the perceived magnitude of a reward/outcome and the physical magnitude of the reward/outcome can be described by a power function (Stevens, 1957). Based on this theory, Green, Fry, and Myerson (1994) further modified the formula of hyperbolic function by adding one more parameter "s," which represents the nonlinear scaling of time. They noted the s parameter is generally ≤ 1 (Myerson & Green, 1995):

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

This model is defined as an "extended hyperbolic" model. Although many studies support that the hyperbolic function is a better fit than the exponential function for animal and human subjects, Green and Myerson (2004; 1995) further argue that the "extended hyperbolic" model provides a better fit than the hyperbolic model.

Estimate of within-individual difference. The delay discounting rate (k) is often normalized using log transformation for further analysis. To directly estimate the within-individual change, Landes et al. (2010) proposed a mathmatical model based on Mazur's (1987) hyperbolic discounting. In this model, the log transferred delay discounting rate, ln(k), is directly estimated by k*. This model assesses the within-individual change (e.g., due to procedure difference) by defining $\ln(Y) = \ln(k_1) - \ln(k_0)$ and using d(w) as the direct estimation for the within-individual change. In the equation, w represents the dummy code indicating the condition of the data (e.g., \$10 version = 0 and \$1000 version = 1):

$$\frac{V}{A} = (1 + \exp[d(w)]\,D)^{-1} = (1 + \exp[w\mathrm{In}(\gamma) + k_0^*]\,D)^{-1}$$

Neural Theories and Models

From a decision-making perspective, it is relatively easy to make a rational decision when only one dimension (e.g., only compare values or only compare times) is involved (Green & Myerson, 2004). The decision making process becomes more difficult when multiple dimensions are involved. In these situations, individuals tend to make decisions according to their preference (Green & Myerson, 2004). In the case of delay discounting, at least two dimensions are involved: time and reward. Further, decision-making involves a higher order cognitive functioning; thus, the decision preference, as measured by delay discounting rate, may result from a combination of multiple psychological processes. A number of neural models have been proposed to explain the underlying mechanisms. Some models focus on time processing, and some emphasize value processing, while others attempt to integrate multiple processes.

Time perception. Time perception may play an important role in delay discounting function (Staddon & Cerutti, 2003; Takahashi, 2006). In general, an individual's sensitivity to time is lower and more malleable than his or her sensitivity to money (Ebert & Prelec, 2007). The perception of experienced time can be described by the Weber-Fechner Law or Stevens' Power Law, but the perception of future time can be described by log or power functions (Zauberman, Kim, Malkoc, & Bettman, 2009).

Based on their study, Kim and Zauberman (2009) proposed a "perceived-time–based discount model," which separated effect of "internal discounting" from the effect of time perception. The "internal discounting" can be described by the exponential function ($e^{-k \cdot D'}$), while time perception can be defined by the power function ($D' = \alpha \cdot D^{\beta}$). Together, the perceived-time-based discount model can be described by the following equation:

$$V = A \cdot e^{-k \cdot \alpha \cdot D^{\beta}}$$

One study of time perception tasks showed that the power function for time perception fit the empirical data better than a linear function based on the maximum likelihood estimation (Kim & Zauberman, 2009).

Evidence supporting the connection between time perception and delay discounting also comes from pharmacological studies and neuroimaging studies. Several neuro-psychopharmacological studies with human subjects have demonstrated that dopaminergic drugs affect participants' time perception (Odum & Ward, 2004; Rammsayer, 1997), and that subjects with chronic administration of dopaminergic drugs tend to have higher delay discounting rates (Rammsayer, 1993). Recent fMRI studies also indicate that time perception strongly involves brain activities in the striatum and insular cortex areas (Craig, 2009; Wittmann, Leland, Churan, & Paulus, 2007). In an effort to identify the brain regions associated with immediate reward versus delayed reward, and the brain regions involved in processing delays of different durations, Wittmann et al. (2007) examined the delay discounting rates for both shorter (<1 year) and longer delays (≥1 year) among 13 healthy subjects. They found that neural activations associated with short delay versus long delay increased in the caudate and putamen, which support the idea that dopamine neurotransmission is associated with duration estimation. These results are further supported by Wittmann's (2010) fMRI study involving 13 healthy subjects.

Prospect theory. Value processing often involves comparisons and evaluations. One of the reference points is expectation. Prospect theory is a theoretical framework for relative evaluations for choice under uncertainty (Tversky & Kahneman, 1992). The theory assumes the individual engages in an editing process in which choices are simplified, and the probability of a choice is transformed based on a weighting function that overweighs the lower probability and underweights the higher probability. The theory is often associated with delay discounting because delay often involves uncertainty (Bleichrodt & Gafni, 1996). For a reward, the subjective value can be illustrated as a gain function:

$$V_g = A^{\alpha}$$

For a loss, the relative value can be illustrated as a power function:

$$V_l = -\lambda \cdot (-V)^{\beta}$$

These two equations can be integrated in the exponential model to describe the delay discounting that involves both gain and loss (K.N. Kirby & Santiesteban, 2003). The equation is as follows:

$$-\lambda \cdot (-V)^{\beta} = A^{\alpha} e^{-rD}$$

After solving for V, the subjective value for delayed reward can be described as:

$$V = -\left(\frac{A^{\alpha} e^{-rD}}{-\lambda}\right)^{\frac{1}{\beta}}$$

The prospect theory appears to have good explanatory power with respect to choices under uncertainty. Yet, it is still unclear whether this theory is sufficient to interpret delay discounting, as the association of delay duration and uncertainty remains unclear (Green & Myeron, 2004). If delay is a form of uncertainty, delay discounting and probability discounting should be positively correlated. This hypothesis is supported by the results of some studies (e.g., Rachlin et al., 1991). However, choice under uncertainty may only reflect the effect of one of the motives associated with time preference—the expectancy.

Heuristic processing model. The heuristic processing model emphasizes using strategies to decrease one's effort for a complex decision. When considering multiple dimensions simultaneously for a decision, people often employ some strategies to minimize the effort involved in information processing. Part of the reason for using heuristics is an individual's cognitive constraints (Simon, 1990). A decision maker may have a number of strategies to decrease their efforts (Shah & Oppenheimer, 2008). One common strategy is the weighted additive rule, a version of expected value maximization, in which the decision maker considers the value of each choice and gives a weight to each choice to determine the importance of that choice; these products of weight and value are summed to generate the value of a decision (Payne, Bettman, & Johnson, 1988). Given that a full calculation with the weighted additive rule may be constrained by limited cognitive capacity, a recent heuristic processing model (Shah & Oppenheimer, 2008) posits that a quick decision is based on processing fewer cues, simplifying strategies, and examining fewer alternatives. Hogarth and Karelaia (2007) provided a mathematical model to describe the heuristic judgment. According to their model, it is essential to calculate the criterion (Y_e) and the judgment (Y_s) using the cues (X_j) and the match weights (β), as shown below. These parameters are further used to calculate secondary parameters (such as correlations between Y_e and Y_s) according to different models, such as the Lens model (Tucker, 1964):

$$Y_e = \sum_{j=1}^{k} \beta_{e.j} X_j + \varepsilon_e$$

and

$$Y_s = \sum_{j=1}^{k} \beta_{s.j} X_j + \varepsilon_s$$

and the equation of the Lens model that evaluates decision performance:

$$\rho_{Y_e Y_s} = G R_e R_s + \rho_{\varepsilon_e \varepsilon_s} \sqrt{(1 - R_e^2)(1 - R_s^2)}$$

There are also discussions about the temporal heuristic, which is associated with temporal construal and temporal distance (Trope & Liberman, 2003). In general, heuristic models focus on the limited capacity of individuals' cognitive resources in decision making (Newell & Bröder, 2008). Theories about heuristic decisions have been connected to delay discounting and have been closely related to the prospect theory (Schwarz, 2004; Shah & Oppenheimer, 2008). Computational models based on heuristic theories have been applied rarely in studies of delay discounting.

Saturating-hyperbolic model. The saturating-hyperbolic model considers the amount of the reward and the discounted utility (Doya, 2008). This model proposed that a choice value is determined by the amount of the reward, delay of the reward, and probability of getting the reward (see also Jozefowiez, Staddon, & Cerutti, 2009). The following equation describes the model:

$$V_i = \sum_i f(amount_i) \times g(delay_i) \times h(probability_i)$$

In this model, the function for the amount follows a saturation function, where A is the amount of the reward, and Q determines the amount with which the utility curve saturates:

$$f(A) = \frac{A}{A + Q}$$

The function for the delay follows a hyperbolic function in which k represents the delay discounting rate:

$$g(d) = \frac{1}{(1 + kD)}$$

The function for probability also follows a hyperbolic function in which H represents the probability discounting rate:

$$h(p) = \frac{p}{p + H(1 - p)}$$

Jozefowiez et al. (2009) argued that a model with all three of these aspects can explain the interaction between reinforcement and time perception. Staddon (2005) noted that time perception is associated with memory strength and habituation because memory strength weakens as time passes, just like response weakens after repeated stimuli. Thus, time representation is associated with a particular payoff for each possible response or choice, and the individual selects the response or choice to maximize the reward based on the probability.

Doya (2008) proposed 3 ways of learning values in uncertain situations: 1) memory traces to form an association between specific conditions and actions; 2) temporal difference, a method of learning how to predict the reward for future situations based on previous ones; and 3) an action-dependent and state-transition probability model that allows flexibility in both situations and actions. Doya's proposed ways of learning may correspond to Rangel et al.'s (2008) 3 valuation systems: Pavlovian, habitual, and goal-directed systems. Differences between the habitual and goal-directed systems are associated with the approach to changes in the situation. The habit system relies on repeated experiences, while the goal-directed system is flexible and it updates the value of an action according to feedback.

Dual processes models. One of the dual processes models is the quasi-hyperbolic model (often referred to as the β and δ models) (Laibson, 1997; Phelps & Pollak, 1968). Based on theory about competition between two brain systems and empirical data from neuroimaging studies, the parameters in the quasi-hyperbolic model can be described as β system and δ system, in which β system represents the short-term reward processing, while the δ system is associated with both short-term and the long-term reward processing; thus, the β system involves specific processing, while the δ is a non-specific system (McClure, Ericson, Laibson, Loewenstein, & Cohen, 2007; McClure, Laibson, Loewenstein, & Cohen, 2004). The following equation describes the model:

$$V = A \cdot \beta \cdot \delta^{D}$$

On the right side of the equation, the "β" system is often associated with limbic reward processing that responds to immediate rewards (often within a few minutes), a person's rigid behavior manner, and risk-taking tendency. The "δ" system is often associated with the prefrontal deliberation processing that responds to delayed rewards and planning.

McClure and colleagues (2004) also identified 5 β areas in the brain. These areas include: the ventral striatum (VStr), medial orbitofrontal cortex (MOFC), medial prefrontal cortex (MPFC), posterior cingulate cortex (PCC), and left posterior hippocampus. They also identified the δ areas: the right dorsolateral prefrontal cortex

(DLPFC), right venrolateral prefrontal cortex (VLPFC), right lateral orbitofrontal cortex (LOFC), and inferoparietal cortex. McClure et al. (2007) further extended the model to adapt to situations where both choices are delayed. Their results suggest the β system did not show higher activation when the earliest delay was higher than 10 minutes, indicating that the β system responds to the absolute (rather than the relative) immediate rewards.

Several other models also stress the interaction of two conflicting systems. Based on drug addiction research, Bechara (2005) argued that impulsivity related to addiction involves two separate yet interacting systems that control decision making. One is the impulsive system centered at the amygdala whose function is to signal the pain or pleasure of immediate prospects; the other system is the reflective system, centered at the prefrontal cortex, whose function is to signal the pain/pleasure of future prospects. Powerful reinforcers (e.g., drugs) can trigger bottom-up, involuntary signals from the amygdala system which can dominate the decision making process and hinder the normal operation of the prefrontal system to resist drugs.

Similarly, Bernheim and Rangel (2004) proposed that a decision maker operates in either a "cold" mode or a "hot" mode. The "hot" mode is associated with the hedonic effect and reacting to the most immediate rewards, while the "cold" mode is associated with cognitive control and considering the long-term consequence. A "hot" mode may be triggered and dominate decision making processes when some elements (e.g., the intensity of the environment cues, the state of nature, the expectancy of the event) exceed a certain threshold. Benhabib and Bisin (2005) suggested a model that describes the automatic system and the executive system in which the automatic system operates in a default manner, while the executive system expends resources to control the automatic processes.

Loewenstein and O'Donoghue (2004) similarly assumed that behavior is the result of the interaction between "deliberative" and "affective" systems. However, rather than assuming the determination of which system is in control is a stochastic process, they assumed the affective system is normally in control of behavior, and the deliberative system can influence the affective system's preference by exerting costly cognitive effort or "willpower." Benhabib and Bisin (2005) proposed that controlled, executive processes "constrain" automatic processes, monitoring the decisions of automatic processes and intervening only when those decisions become excessively suboptimal.

Some evidence of two systems also comes from animal studies. Using delay discounting and the odor reversal task on rats, Churchwell et al. (2009) found that the disconnection of the medial prefrontal cortex and basolateral amygdala is associated with impulsivity (inability to wait for rewards) while the disconnection of the orbitofrontal cortex and amygdala is associated with the compulsivity (inflexibility).

Associated Factors

Although some cognitive processes are not formally included in analysis models, they have been observed to be associated with the decision bias as measured by delay discounting.

Attention and working memory. The effect of attention on decision making has been discussed and demonstrated in a number of studies (E. U. Weber & Johnson, 2009). Kahneman (1973) described attention as characterized by limited resources, and thus it can define the significance of stimuli. External stimuli, such as the reward domains, may result in different amount of focus and decision weights. The proposed relationship between attention and external stimuli may explain the domain effect or magnitude effect of delay discounting. Task orders, such as which choice options are presented first, may also influence decision making, as the early options attract more attention and thus are more likely to be used as reference for subsequent evaluations (Kahneman, 2003). Further, the capacity of working memory also has an effect on the performance of delay discounting (Hinson, Jameson, & Whitney, 2003).

Stimulant-dependent individuals often have impaired working memory and attention (Wittmann, Leland, Churan, & Paulus, 2007). Shamosh and colleagues (2008) found that the delay discounting rate was negatively correlated with both intelligence and working memory in 103 healthy participants, but working memory did not account for more variance in delay discounting beyond what could be accounted for by intelligence. While performing working memory tasks, the participants showed significant activations in their left anterior prefrontal cortex and lateral frontopolar cortex. A path analysis indicated that intelligence was associated with delay discounting rate indirectly through the working memory-related activities in the left prefrontal cortex.

Motivation and emotion. Decision making is also influenced by motivation that is associated with goals and emotions. When multiple goals conflict, a person's decision making behavior depends on selective attention (Krantz & Kunreuther, 2007). Different emotions may direct decision makers to focus on different aspects of stimuli. Feelings of fear may cause the decision maker to become more sensitive to the threat feature of the stimuli, while sadness may motivate the decision maker to change one's state (Lerner, Small, & Loewenstein, 2004; G. F. Loewenstein, Weber, Hsee, & Welch, 2001).

Strong emotions often lead to automatic and "effort-free" inputs that influence decision making processes through attention, motivation, and evaluations (E. U. Weber & Johnson, 2009). Specific choices may elicit immediate emotions that influence decisions. Current emotions and expected emotions may influence decisions through different processes. Current emotions may influence the evaluation of the choices by increasing the value (when emotions are positive) or decreasing the value (when emotions are negative). These relationships are supported by evidence that extraverted individuals are more likely to have decision making bias toward immediate reward over delayed and bigger rewards when in a positive mood than when in a negative mood stimulated by the situation (Hirsh, Guindon, Morisano, & Peterson, 2010).

Summary and Discussion

Delay discounting has been described using different models that are based on different assumptions. The exponential model fits better in economic studies, as the risk associated with time delay is more constant; while the hyperbolic model fits better in studies of the decision making processes of humans and animals, as the decision making often involves subjective evaluations and irrational components, such as emotions. The hyperbolic function is consistent across species and has been widely accepted as a computational model for delay discounting in psychology studies. However, further investigation is needed to determine whether the extended hyperbolic model serves as a better fit than the hyperbolic model for most empirical data.

Delay discounting can be explained using different neural models that focus on different neural systems. Each candidate underlying mechanism appears to focus on different components of decision making processes. Some emphasize time processing, such as the time perception model. Some emphasize the value processing associated with time, such as the prospect theory. Some stress the interaction between time processing, value processing, and other cognitive processes, such as the saturation-hyperbolic model, heuristic processing model, the β/δ model, and Bernheim and Rangel's (2004) hot/cold model.

From the perspective of the cognitive system, cognitive theories can be categorized into 3 types: theories that focus on neurophysiologic substrate, theories that aim to understand the dynamic processes, and theories that emphasize a goal-oriented system (Marr, 1982). In decision making processes for a typical delay discounting task, all 3 of these systems likely are involved. The function of the neurophysiology system may explain the domain effect on delay discounting rate (i.e., real food reward leads to higher delay discounting rate than the hypothetical food reward). The state effect or the deprivation effect (e.g., due to sleep deprivation) is also likely to be associated with the neurophysiology system. This system can be associated with the emotions, automatic processes, and the cold system, discussed previously. The neural models described previously appear to focus more on the dynamic processes, which involves time processing, value processing, and memory. Some of the models (e.g., prospect model, saturation-hyperbolic model, and β/δ model) involve functions of reward utility, function of time valuation, and interactions of both. The differences of these models lie in the ways to describe functions of processes and emphasis of the underlying mechanisms associated with these processes. To illustrate, the prospect theory emphasizes uncertainty and uses a power function to describe the subjective value; the saturation-hyperbolic model emphasizes the saturation effect and function; the β/δ model emphasizes an overall preference for the current reward and uses a linear function to describe reward utility. The time perception model appears to focus more on rational processes that involve exponential discounting (internal discounting) and power discounting (due to time perception). As reported earlier, the exponential function may be a good model when rational strategies are involved (Schweighofer, et al., 2006). Thus this function is more likely to be associated with the goal-oriented system or motivational system.

Valuation systems (Pavlovian, habitual, and goal-directed systems) may provide additional interpretation for the decision processes discussed above (Rangel, et al., 2008). Doya (2008) indicated that reward utility is associated with classical conditioning, while time utility is associated with a habitual system through repeated experiences. Further empirical studies may provide evidence for these hypotheses.

Reliability

In general, delay discounting rate is a relatively stable measure (Simpson & Vuchinich, 2000). Thus, delay discounting represents an important psychometric index of individual differences in the ways future outcome is discounted (Hariri, 2009). Yoon and colleagues (2007) reassessed the delay discounting rate of participants over time using a repeated-measures analysis of variance and found no significant change in delay discounting rate. Similarly, Ohmura and colleagues (2006) examined the long-term reliability of discounting rates for both delay (Range: 1 week to 25 years) and probability (Range: .05 to .95) by comparing indifference points from the same subjects over a 3-month period. In their sample of 22 undergraduates, they found that both the delay discounting rate and probability discounting rate were stable.

Test-retest consistency within participants is supported by a number of other studies (e.g., Simpson & Vuchinich, 2000; Yoon et al., 2007). Simpson and Vuchinich (2000) studied 17 student volunteers, using a hypothetical reward procedure, and retesting participants 1 week later. The test-retest correlation was .91. In Baker's (2003) study involving 26 smokers and 20 nonsmokers, test-retest correlations ranged from .71 to .78 in smokers, and .82 to .90 in nonsmokers. In summary, delay discounting rate appears to be a highly reliable index in healthy populations. However, all of these results are based on the one-parameter model.

Validity

Correlations between Delay Discounting Rate and Impulsivity as Assessed by Personality Measures

Studies with samples from a normal population. Reynolds, Ortengren, Richards, and de Wit (2006) tested 3 personality measures of impulsivity (BIS-11, I_7, and MPQ), delay discounting, and other behavioral measures of impulsivity on 70 healthy participants. The delay discounting rate was analyzed using the hyperbolic model. The correlations between delay discounting rate and the subscale scores of the 3 personality measures were not statistically significant. One possible explanation is that the construct of impulsivity involves multiple dimensions, whereas delay discounting measures a specific process characteristic of impulsivity (Reynolds, et al., 2006). In contrast, Kirby and Finch (2010) asked 407 college students to complete a delay discounting task and a self-reported measure including items from a variety of impulsivity scales (e.g., BIS, EASI, I_7). They found the delay discounting rate was significantly and positively correlated with impulsiveness and venturesomeness scores on the I_7 scale.

It remains unclear why such similar studies yielded contradictory results. One explanation is that these two studies used different versions of delay discounting tasks. Kirby and Finch (2010) used a questionnaire-based delay discounting task (monetary choice questionnaire) that involved 9 questions, while Reynolds et al. (2006) used a computerized adjusting-amount procedure. An alternative explanation is that the personality inventories measure broader situations than the decision making task (Coffey et al., 2003; Odum & Baumann, 2010). Given the multiple influences on decision making performance, some authors suggest researchers should include multiple personality measures in studying the association between discounting performance and the individual difference of impulsivity (Bickel & Marsch, 2001).

Studies with samples from clinical populations. In one study, 30 adolescent smokers completed the BIS-11 and other behavioral tasks including a delay discounting task (Krishnan-Sarin et al., 2007). The correlations between scores on the subscales of the BIS-11 and the delay discounting rate were not statistically significant, although they were positive and all were in a .2 range. In many studies the researchers combined the clinical groups and control groups in evaluating the correlations between delay discounting rate and the personality measures (Matthew W. Johnson et al., 2010). However, the delay discounting rate tends to be less stable in clinical populations. For instance, in a study by Takahashi et al. (2007) involving 33 alcoholics over a two month interval, the test-retest reliability for delay discounting rate ranged from .31 to .37. These results indicated that the reliability of delay discounting rate in clinical populations seemed to be lower. Thus, the results of these studies should be interpreted carefully.

Construct Validity of Delay Discounting

Convergent validity. Although test-retest correlations of delay discounting are low in clinical populations, delay discounting rates in clinical population are consistently higher than controls. Delay discounting reliably differentiates members of some impulsive populations from members of non-impulsive populations, providing support for its construct validity. In particular, delay discounting has been consistently associated with various impulsive symptoms, particularly with drug addictions (W.K. Bickel & Marsch, 2001). Preferences for smaller and sooner rewards have been reported for problematic drinkers (Vuchinich & Simpson, 1998), opiate addicts (G.J. Madden, et al., 1999), smokers (W.K. Bickel, Odum, & Madden, 1999), and pathological gamblers (Petry, 2001b).

Delay discounting has been found to be associated with other types of decision making tasks. Monterosso et al. (Monterosso, Ehrman, Napier, O'Brien, & Childress, 2001) studied the associations between delay discounting performance, the Gambling Task, the Rogers Decision-Making Task, personality measures of impulsivity, and WAIS-III scores for 32 cocaine dependent subjects. They found positive and significant correlation between delay discounting rate and the Gambling Task performance as well as negative correlation between delay discounting rate and WAIS-III scores.

Discriminant validity. Within the domain of decision making, studies investigating the constructs of delay discounting and probabilistic discounting (in which the subjective value of an outcome changes as a function of probability) indicated delay discounting function and probabilistic discounting function are different processes (Green & Myerson, 2004; Mitchell, 1999; Ohmura, et al., 2006). Specifically, consistent findings of a higher delay discounting rate were obtained for drug addicts compared to controls (Richard Yi, Xochitl de la Piedad, & Warren K. Bickel, 2006), while drug addicts did not differ significantly from controls on probabilistic discounting rates (Mitchell, 1999). However, some studies support a same underlying process of delay and uncertainty in gamblers (Holt, Green, & Myerson, 2003) and undergraduate students (B. J. Weber & Chapman, 2005).

Summary and discussion. Empirical studies using the hyperbolic model support a significant correlation between delay discounting rate and personality measures of impulsivity in normal populations when the sample size is large. However, when the sample size is small and when the sample involves a clinical group, the correlation is inconsistent across studies. One possible explanation is lack of power due to a small sample size. Another concern is the low test-retest reliability of delay discounting in samples from clinical populations. Further, the hyperbolic model tends to absorb various effects in one delay discounting parameter; thus it may lead to inconsistencies in the results when multiple potential influences are involved. One of the factors that may account for the inconsistency between normal samples and samples of drug users is the state that results from drug use. If drug use or other factors do temporarily change an individual's delay discounting rate, the delay discounting rate in such a situation is more likely to serve as a "state" assessment rather than a "trait" assessment. A model that includes a parameter for detecting sensitivity to the current reward may help disentangle the different influences.

Delay discounting has been found to be associated with impulsivity because it differentiates people with impulsive disorders from controls. Delay discounting has also been found to be associated with decision making processes in general. Future studies need to compare delay discounting tasks with other specific decision making tasks to further identify the unique mechanism of delay discounting.

Summary and Conclusions

In summary, impulsivity is a multi-dimensional construct associated with a range of psychological concerns. The delay discounting task measures impulsive decision making that involves both time processing and value processing. Delay discounting has been used to measure both human subjects and nonhuman subjects, in studies employing varying experimental procedures and data analysis models. Different experimental procedures appear to have yielded qualitatively consistent results. However, different procedures do affect the delay discounting rate. Observed procedure effects include domain effect, magnitude effect, and sign effect, among others. The exponential model is often used in economic studies, and it has been found to provide a good description for human performance when certain conditions are involved and when rational strategy thinking is emphasized. The hyperbolic model has been found to be a good fit for data generated in human studies on impulsivity and in animal studies on learning.

Neuropsychological studies suggest the delay discounting function involves multiple dynamic processes. A number of neural models are available to explain delay discounting from different angles. However, few studies have compared the differences among these models, and there is no consensus as to which model provides the best interpretation. Given the low test-retest reliability of delay discounting in clinical populations, models that allow researchers to differentiate varied neural processes may provide better theoretical bases for studies on impulsivity, especially when those involving clinical populations. Correlation between the delay discounting parameters and other parameters of cognitive processes may also provide useful explanations.

The delay discounting rate reliably differentiates various clinical samples from controls with respect to impulsivity. Thus, delay discounting can be used as a measure of individual differences. As stated previously, test-retest reliability of delay discounting tasks is high among normal samples but is comparatively lower in clinical samples when only one delay discounting parameter is involved. Because the delay discounting task involves a number of underlying processes, the contributing causes to the delay discounting rate are difficult to assess when the model is using only one parameter. Two parameter models (such as the saturation-hyperbolic model, or the β and δ model) may be helpful in accounting for different underlying processes.

Chapter 2.

Preface to the Subsequent Studies

To summarize the previous chapter, impulsivity is a multi-dimensional construct associated with a range of psychological concerns. The delay discounting task measures impulsive decision making that involves both time processing and value processing. Researchers have studied delay discounting in human and nonhuman subjects, using varying experimental procedures and data analysis models. Different experimental procedures appear to have yielded qualitatively consistent results. Different procedures do affect the delay discounting rate, however. Observed procedure effects include domain effect, magnitude effect, and sign effect, among others.

The exponential model is often used in economic studies and is found to provide a good description of human performance when certain conditions are involved and when rational strategy thinking is emphasized. The hyperbolic model has been found to be a good fit for empirical data in human studies on impulsivity and in animal learning studies. Findings of neuropsychological studies suggest the delay discounting function involves multiple dynamic processes. A number of neural models are available to explain delay discounting from different angles. However, few studies have compared the differences among these models, and there is no consensus as to which model provides the best interpretation. To address this concern, a series of studies were designed to compare selected models when different procedures and various populations are involved. These studies are described in Chapter 3.

Studies of the concurrent validity of delay discounting suggest the delay discounting rate reliably differentiates various clinical populations from controls with respect to impulsivity when the data are analyzed with the hyperbolic function. It is unclear whether this is still the case when the data are analyzed with other neural models.

Furthermore, the specificity of decision bias associated with delay discounting observed in drug users is still unclear. Therefore, studies described in Chapter 4 were designed to investigate these gaps in the literature.

Studies on the convergent validity of delay discounting have yielded inconsistent results regarding the associations between delay discounting and personality measures of impulsivity. One possible factor that likely contributes to this inconsistency is that personality measures assess a broader situation associated with impulsivity, while delay discounting only measures a specific component of impulsive decision making. To investigate whether a specific personality measure associated with the construct of delay discounting will provide a stronger association, the Time Preference Scale based on the construct of time preference theory was developed. Its psychometric properties and its association with delay discounting are described in Chapter 5.

Chapter 3.

Fitting Three Neural Models of Delay Discounting:

Population Effect and Magnitude Effect

Introduction

The delay discounting task is a behavioral measure commonly used in neuroeconomics, psychopathology, clinical neuroscience and drug addiction research (Busemeyer & Stout, 2002; M.W. Johnson, Bickel, & Baker, 2007). Economists and psychologists have investigated the phenomenon of delay discounting from different angles and at different levels. Various models have been proposed to fit the delay discounting data or to explain the underlying mechanisms. These models can be divided into two major categories: those that focus on describing the phenomenon and fitting the empirical data mathematically, and those that aim to provide a theoretical base for analyzing the neural process and explaining performance differences.

The Indifference Point

Measuring the subjective value of delayed rewards often involves a titrating scaling based on a series of decisions (Mazur, 1987). A common procedure is the adjusting-amount procedure in which a smaller and immediate reward is adjusted until the value of that small reward is equal to the subjective value of a large and delayed reward (which means that an indifference point is reached)(Richards, Mitchell, De Wit, & Seiden, 1997). The indifference point refers to a situation in which the subject has equal chances of selecting either one of a pair of alternatives (e.g., $5 now, or $10 in 30 days). When fitting delay discounting data, the indifference points for a series of reward options can be plotted to form a discount curve that describes the delay discounting parameter(s). The nature of the functions describing these indifference points is subject to a great deal of debate. Five of these competing models are described next.

The Exponential Model

The exponential discounting model is commonly used in economics (Frederick, Loewenstein, & O'donoghue, 2002; Samuelson, 1937). The exponential discounting function can be described by the following equation in which V represents the subjective value of the delayed outcome while d is the delay time for receipt of the outcome, and k is the discounting rate:

$$V = A \cdot e^{-kd}$$

This model involves a constant temporal discounting (e^{-k}) over time. A higher k means there is a steeper discounting function and stronger preference for a more immediate and smaller outcome (or greater impulsivity). Although this model describes human performance well under some conditions (e.g., time constraints) and could be more appropriate when decision makers are trying to maximize gains using certain strategies (Schweighofer, et al., 2006), it does not predict choice reversal commonly demonstrated in animal and human samples (Green & Myerson, 2004). As an example of choice reversal, an individual prefers $9 in 3 weeks over $8 in two weeks, yet switches his/her preference to $8 immediately over receipt of $9 in one week. This example implies a non-constant temporal discounting over time.

The Hyperbolic Model

The hyperbolic discounting model describes a decrease in discounting when the delay is increased; thus it allows for non-constant temporal discounting. This function can be described by the following equation (Mazur, 1987):

$$V = \frac{A}{(1 + kd)}$$

When compared with the exponential model, the hyperbolic model makes a steeper discounting when the delay is relatively short, and a shallower discounting when the delay is relatively long (see Figure 3.1). This model has been widely used in the psychology literature (e.g. Ainslie, 1975; G. J. Madden, Begotka, Raiff, & Kastern, 2003; Gregory J. Madden, Warren K. Bickel, & Eric A. Jacobs, 1999; Mazur, 1985). However, neuropsychological studies suggest that at least two processes or two neural systems are involved in delay discounting (Bernheim & Rangel, 2004; G. Loewenstein & O'Donoghue, 2004; McClure, et al., 2004). As a result, novel models based on neuropsychological theories that allow two parameters to explain discounting behavior are receiving increased attention (McClure, et al., 2007; McClure, et al., 2004; Yi, Landes, & Bickel, 2009).

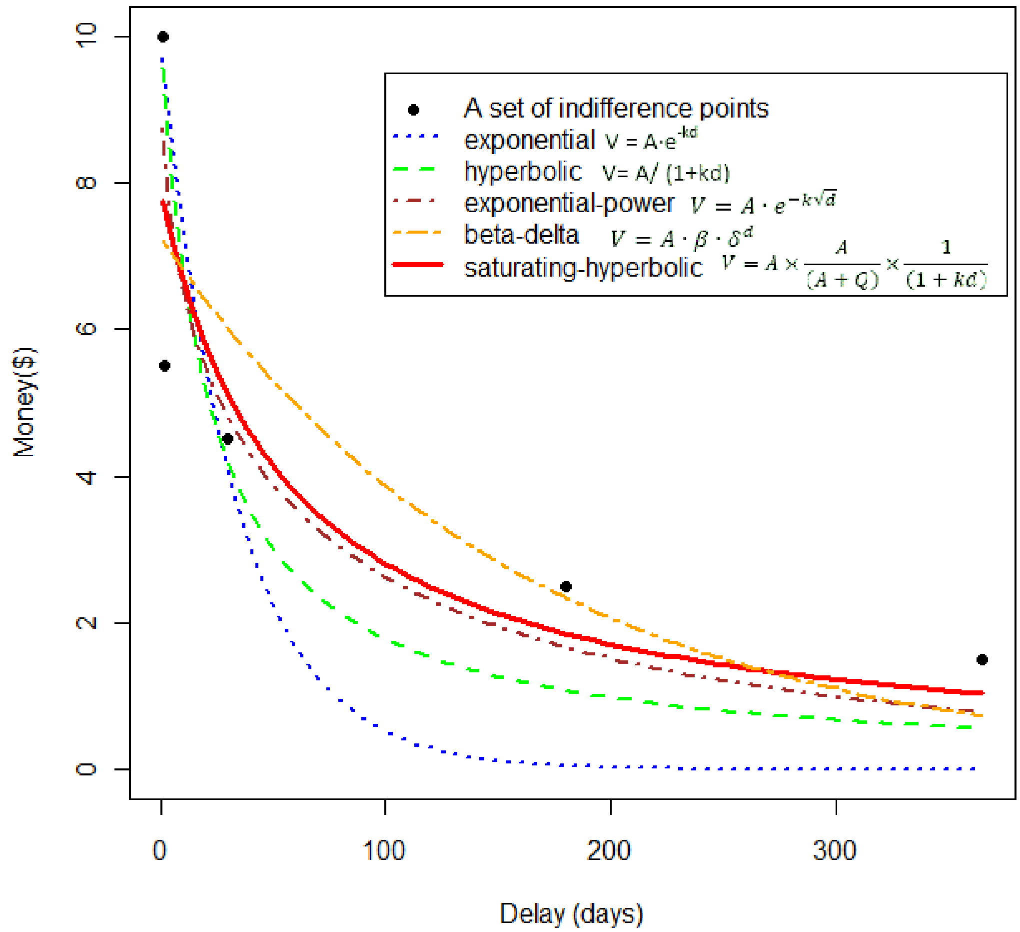


Figure 3.1 Fitting one subject's data with 5 delay discounting functions

The Exponential-Power Models

The exponential-power models consist of a group of neural models based on the theories of time perception and memory decay. From the perspective of time perception, an individual's sensitivity to time is less sufficient and more malleable than his/her sensitivity to money (Ebert & Prelec, 2007). The perception of future time can be described by log or power functions (Zauberman, et al., 2009). From the perspective of memory decay, an individual's estimation of future time or future event is based on the experience and memory of the past time or past event (Rachlin, 2004; Yi, et al., 2009). In their study, Yi et al. (2009) demonstrated that the following equation best fit their data:

$$V = A \cdot e^{-k\sqrt{d}}$$

In this model, the experience of time is described with a power function ($\sqrt{d}$). Similar to Kim and Zauberman's model, this model allowed the researchers to separate the effect of discounting (e^{-k}) and the effect of time experience (D'=$\sqrt{d}$). A comparison of this model with the exponential model and the hyperbolic model, indicates the following: this model supports a constant exponential discounting, as in the exponential model, but it also predicts a shallower discounting curve over time, as in the hyperbolic model, due to the power function of time experience.

The Beta-Delta Model

The Beta-Delta model is similar to the exponential-power model in that it supports a constant exponential discounting for time. This model can be described using the following equation:

$$V = A \cdot \beta \cdot \delta^{d}$$

In this model, the discounting rate is constant (k=log $\frac{1}{\delta}$), and the subjective value of the delayed reward can be influenced by monetary utility (β) and time discounting (-log (δ)). The equation can also be written as:

$$V = A \cdot \beta \cdot e^{-(-\log(\delta)) \cdot d}$$

When β=1, the model is the same as the exponential model. However, when 0<β<1, the model is very similar to the hyperbolic model; thus it is also called the "quasi-hyperbolic model" (Laibson, 1997; Phelps & Pollak, 1968). Figure 3.1 shows an example of a Beta-Delta curve in which β=0.73 and δ=0.99. The curve is relatively steep when the delay is short, while it is relatively shallow when the delay is long (shallower than the exponential curve).

Based on the theory about competition of two brain systems and neuroimaging data, the β and δ parameters can be described as β system and δ system, in which β system represents the specific short-term reward processing, and the δ system is associated with rational and non-specific processing of both the short-term and the long-term reward (McClure, et al., 2007; McClure, et al., 2004).

Based on the theory, McClure and colleagues (2004) identified five β areas in the brain: the ventral striatum (VStr), medial orbitofrontal cortex (MOFC), medial prefrontal cortex (MPFC), posterior cingulate cortex (PCC), and left posterior hippocampus. Using the same method, they identified five δ areas: the right dorsolateral prefrontal cortex (DLPFC), right ventrolateral prefrontal cortex (VLPFC), right lateral orbitofrontal cortex (LOFC), and inferoparietal cortex. In addition, a number of other theories echo this two system model. These theories include but are not limit to, impulsive-reflective systems (Bechara, 2005), hot-cold modes (Bernheim & Rangel, 2004), and affective-deliberative systems (G. Loewenstein & O'Donoghue, 2004).

The Saturating-Hyperbolic Model

Both exponential-power models and the beta-delta model provide descriptions of different aspects of decision making performance on a delay discounting task. The former focuses more on time perception and memory decay, while the latter focuses more on different valuation systems in the brain. However, an explanation of the formation of these preference differences in delay discounting may rely on learning theory.

Doya (2008) proposed 3 ways of learning values in uncertain situations: 1) memory traces to form an association between specific conditions and action; 2) temporal difference, a method of learning how to predict the reward for future situations based on the previous one; and 3) an action-dependent and state-transition probability model that allows flexibility in both situation and in the action. Doya's proposed ways of learning may correspond to Rangel et al.'s (2008) 3 valuation systems: Pavlovian, habitual, and goal-directed.

Based on Doya's theory, a choice value is determined by the amount of the reward, delay of the reward, and the probability of getting the reward. The function for the amount of the reward follows a saturating function where A is the amount of the objective reward and Q determines the amount with which the utility curve saturates:

$$f(A) = \frac{A}{A + Q}$$

Further, the function for the delay time follows a hyperbolic function in which k specifies the delay discounting rate:

$$g(d) = \frac{1}{(1 + kd)}$$

The function for probability also follows a hyperbolic function in which H represents the weight parameter for evaluating the rewards:

$$h(p) = \frac{p}{p + H(1 - p)}$$

Given that the probability of receiving a reward is often not assessed in a delay discounting task, and the risk of receiving a reward could be an inherited component of the delayed condition (Green & Myerson, 2004; A. David Redish & Zeb Kurth-Nelson, 2010), a simpler equation of subjective value in a delayed time can be described as:

$$V = A \times \frac{A}{(A + Q)} \times \frac{1}{(1 + kd)}$$

The saturating function that describes the utility of the reward can reflect an individual's physiological needs, psychological desires, or economic needs, while temporal discounting reflects reinforcement learning (Doya, 2008). A comparison of this model with the hyperbolic model, suggests this model is the same as the hyperbolic model when Q = 0. When Q > 0, this model produces a shallower curve than the hyperbolic model when the delay is relatively long, as shown in Figure 3.1.

Model Comparison

A number of studies have compared mathematical fits of some models (K.N. Kirby & Santiesteban, 2003; J. Myerson & Green, 1995; Yi, et al., 2009). The hyperbolic model was observed to fit better than the exponential model in a sample of 45 undergraduate students (Kirby & Santiesteban, 2003), and in a sample of 18 heroin-dependent adults for a hypothetical $1000 reward and a hypothetical heroin-reward (G.J.

Madden, et al., 1999). In addition, the exponential-power model provided superior fit when compared with exponential, hyperbolic, logarithmic, power, and hyperbolic power models in a sample of 29 adults (Yi, et al., 2009). In their study of 16 healthy adults, Ballard and Knutson (2009) did not report the results of model comparing, but they stated the exponential, hyperbolic, and quasi-hyperbolic model all fit their data "reasonably well." In a study involving 24 normal adults, Pine et al. (2009) found that an exponential utility-hyperbolic discounting model fit better than the exponential utility-exponential discounting model, exponential utility-quasi-hyperbolic discounting model, general quasi-hyperbolic discounting model, hyperbolic discounting model, and the exponential discounting model. In addition, the quasi-hyperbolic discounting model had a higher sum of AIC scores than the hyperbolic and exponential models. All of these studies used hypothetical rewards in the discounting tasks.

These findings suggest that, in normal samples, the hyperbolic model can better describe the data than the exponential model; the β-δ model (quasi-hyperbolic model) does not necessarily fit better than the hyperbolic model or the exponential model mathematically; and the exponential-power model may be better than the hyperbolic model and the exponential model. In psychiatric samples, the hyperbolic model fits better than the exponential model. However, it is still unknown how the β-δ model and the exponential-power model fit the data in individuals from a psychiatric population. Further, to this author's best knowledge, there is very little empirical evidence for the saturating-hyperbolic model, let alone its comparison with other models.

A recent neural-imaging study supports a neural region (dorsal striatum) that processes the reward utility over and above the objective reward magnitude (Pine et al., 2009). The β parameter in the Beta-Delta model is often considered as a reward utility. However, there is inconsistent evidence regarding the β and δ system. Regarding the β system, there is some evidence the β system (mesolimbic dopamine projection regions), proposed from the McClure studies (2007; 2004), is also associated with both delayed reward magnitude and the delay; thus it is more subject specific (encodes subjective value) rather than time specific (Ballard & Knutson, 2009; Kable & Glimcher, 2010). Regarding the δ system, some evidence suggests it is associated with decision making in general (when compared with rest) and with reaction time, but not when the delayed reward is chosen (Kable & Glimcher, 2010). Together, these findings suggest it is necessary to include a reward utility in the delay discounting model, yet β may not be a good indicator for the reward utility.

Studies in this Chapter

Although neural imaging studies have provided important evidence in evaluating the neural models, there is little evidence from studies using personality measures to validate how well these neural models can predict individual's general behavior. The delay discounting rate analyzed by the hyperbolic model has been associated with the nonplanning subscale on the Barrat Impulsivity Scale(de Wit, Flory, Acheson, McCloskey, & Manuck, 2007), but the observed correlation is inconsistent across studies (Dom, De Wilde, Hulstijn, & Sabbe, 2007; Matthew W. Johnson, et al., 2010; Reynolds, et al., 2006). It is unclear whether these neural models would help to disentangle the relationship between decision making bias and personality measure of impulsivity.

In addition, most studies of neural models have involved only normal samples and have not considered the magnitude difference. It is well documented that delay discounting phenomena often change due to magnitude and population differences. The delay discounting rate is more shallow when the magnitude is large (>1000)(F. Baker, M.W. Johnson, & W.K. Bickel, 2003). Further, the delay discounting rate for drug users have been found to be steeper (W.K. Bickel, et al., 1999; G.J. Madden, et al., 1999).

Given the apparent gap in this regard, three studies were designed to evaluate the three neural models (exponential-power, β-δ, saturating-hyperbolic) comparing them with the standard models from the behavioral literature (exponential model and hyperbolic model). These studies tested the following hypotheses:

1. The exponential-power model will fit better than the exponential model and the hyperbolic model for the delay discounting data, but the β-δ model will not necessarily fit better than the standard models. In addition, the saturating-hyperbolic model is expected to fit better than the standard models.
2. The temporal discounting parameters in the exponential model (k.Exp), hyperbolic model (k.Hyp), exponential-power model (k.ExPo), saturating-hyperbolic model (k.SaHy), and the β-δ model (δ) will all be highly correlated, while the monetary utility parameters in the saturating-hyperbolic model (Q) and β-δ model (β) will be highly correlated (β is considered as a monetary utility here in a broader way which assumes that the utility of money increases linearly with the objective magnitude).
3. The temporal discounting parameters from all five models will be significant predictors of strong self-regulation and a lack of impulsivity, while the

monetary utility parameters will be significant predictors of reward sensitivity.

4. The models fits will be consistent regardless of (i) population difference and (ii) differences in reward magnitude.

General Methods

Participants

Participants were recruited either from undergraduate courses at the University of Minnesota or from the Twin Cities community through newspaper advertisements. Their age range was 18-49 years, and all provided informed consent. The demographic characteristics of participants across all three studies are reported in Table 3.1.

Table 3.1 *Characteristics of Participants*

Characteristic	Group		
	Study 1	Study 2	Study 3
Population	Undergraduate students	Cocaine addicts	Undergraduate students
Final n	87	36	40
Mean Age[a]	20.07 (2.89)	38.81 (7.25)	19.73 (1.70)
Gender (% male)	33.3	81.09	33.3
Education (in years)	13.03 (2.04)	13.14 (1.82)	13.60 (1.65)

Race (% Caucasian)	69.0	36.1	72.5
% Native American	0	5.6	0
% Native Hawaiian	0	2.8	0
% Asian	21.8	0	20
% African American	4.6	47.2	5
% Hispanic	1.1	2.8	2.5
% Other	3.4	5.6	0

Note. [a]Numbers in parentheses are standard deviations.

Measures

The Choice Delay Discounting Task (Richards, Zhang, & de Wit, 1999). The delay discounting task measures the subjective values after certain delays. This measure uses a computerized random adjusting-amount procedure in which the smaller and immediate reward is adjusted until the value of the small reward is equal to the subjective value of a large and delayed reward (which means an indifference point is reached). In this study, the task allowed participants to choose from $10 after a delay (1, 2, 30, 180, or 365 days) or an immediate and smaller reward. For example, participants were offered the following choice: Would you rather have $5 now or $10 in 30 days?

After the participant made a choice, the answer was used by the program to narrow the range of the immediate rewards for the subsequent questions. A series of questions were presented until an indifference point at a certain delay time was reached.

In addition, the adjusting nature of the task was masked by mixing the delay discounting questions and probability discounting questions. Because there were 5 delay times, completing the task would lead to 5 indifference points which yielded a delay discounting curve. A higher delay discounting rate meant there was a steeper discounting function and a stronger preference for more immediate and smaller outcome (or greater impatience). There were two versions of delay discounting tasks with different reward magnitudes in the current studies. The $10 version used a highest hypothetical reward magnitude of 10 dollars, while the $1000 version used a highest hypothetical reward magnitude of 1000 dollars.

Self-Report Personality Measures

Adult Externalizing Scale (Krueger, Markon, Patrick, Benning, & Kramer, 2007). The Adult Externalizing Scale (AES), contained in Appendix A, was used to measure the disinhibition personality characteristics. This is a 100-item version of the Adult Externalizing Scale that includes three factors related to disinhibition: general externalizing, aggression, and substance use. All scales showed adequate internal consistency (Alpha coefficients > .90 in a mixed sample of 480 respondents).

Barratt Impulsiveness Scale (BIS-11; Patton, Stanford, & Barratt, 1995). The BIS-11, contained in Appendix B, was used to measure personality traits of impulsiveness. This 30-item scale consists of three factors: Attentional Impulsiveness, Motor Impulsiveness, and Nonplanning Impulsiveness. The Alpha coefficients for the total BIS scores are around .80 or higher in undergraduate students, psychiatric patients, and prison inmates. In addition, significant group differences were demonstrated between undergraduate students and patients or prisoners.

Behavioral Inhibition System and Behavioral Approach System (BIS/BAS) Scales (Carver and White, 1994). The BIS/BAS Scales, contained in Appendix C, were used to measure Gray's (1990) approach/avoidance personality system. This 20-item questionnaire is composed of four subscales: BAS Drive, BAS Fun Seeking, BAS Reward Responsiveness, and BIS. The Cronbach's Alpha for these four subscales are .76, .66, .73, and .74, respectively. Convergent validity is demonstrated by results indicating the BIS is significantly correlated with the Tridimensional Personality Questionnaire (TPQ) scales as follows: Harm Avoidance ($r=.59$, $p<.001$), Reward Dependence ($r=.42$, $p<.001$), and Manifest Anxiety Scale (MAS) ($r=.58$, $p<.001$); the BAS Drive is correlated with Extraversion ($r=.41$, $p<.001$); the BAS Reward is correlated with Extraversion ($r=.39$, $p<.001$); the BAS Fun Seeking is correlated with Extraversion ($r =.59$, $p<.001$) and TPQ Novelty Seeking ($r=.51$, $p<.001$) (Carver and White, 1994).

Time Preference Scale. The Time Preference Scale, contained in Appendix D, is recently developed by MacDonald, Rusticini and Krueger. This is a 9-item inventory used to measure self-report tendencies to take immediate rewards compared to larger, long term rewards. The current version of the scale is a 9-item questionnaire developed from a larger pool of 19 items. The Cronbach's Alpha of the scale was .81 in a sample of 188 undergraduate students and community subjects.

General Procedures

Each participant completed a choice delay discounting task (Richards, Zhang, Mitchell, & De Wit, 1999) and a computerized personality inventory that comprised of items from the Barratt Impulsiveness Scale (Patton, Stanford, & Barratt, 1995), Adult Externalizing Scale (Krueger, Markon, Patrick, Benning, & Kramer, 2007), Behavioral Inhibition System and Behavioral Approach System (BIS/BAS) Scales (Carver & White, 1994), Time Preference Scale (TiPs, see Appendix E), among others that will not be discussed in the current study. All tasks were administered individually on a desktop computer. Thirty-four of the undergraduate participants completed two versions of the delay discounting task (the $10 version and $1000 version).

General Data Analysis

The delay discounting function was analyzed individually for each participant. An indifference point was first estimated for each delay time (1, 2, 30, 180, or 365 days) based on each participant's choices. Thus, a set of data for each participant included 5 indifference points.

Before performing any analysis, problematic data were removed based on the algorithm developed by Johnson & Bickel (M.W. Johnson & Bickel, 2008). We adopted the first criterion that an indifference point was greater than the preceding point for more than 20% of the largest delayed reward. However, in order to include as many samples as possible, we modified the second criterion (the last indifference point was not less than the first indifference point for at least 10% of the largest delayed reward) to no discounting at all, which means that the last indifference point was not less than the first indifference point.

After the data cleaning, the five functions were used to model each set of indifference points for each participant. These models are: exponential, hyperbolic, saturating-hyperbolic, exponential-power, and beta-delta model (see Figure 1). In these functions, V represents the value (indifferent point); A represents the delayed reward; d represents the delayed time; k represents the delay discounting parameter; Q represents the saturating parameter; β represents the weight for the immediate reward, while δ represents the weight for delayed reward. The goodness-of-fit was evaluated using sums of individual Akaike Information Criterion (AIC) scores. The AIC is a way of measuring the relative performance of models. This approach is based on the concept of Kullback-Leibler information (Burnham & Anderson, 2004) which defines the distance between full reality and a specific model. The AIC is calculated as AIC = -2 (ln (likelihood)) + 2 K, in which likelihood represent the probability of the data given a model and k is the number of free parameters in the model. There were different numbers of parameters (thus different numbers of degree of freedom) involved in these models. Thus, AIC scores were used to balance the potential over-fit effects of models with more parameters (Burnham & Anderson, 2004; Motulsky & Christopoulos, 2004). The sum of individual AIC scores had been used as the primary index for model comparison (e.g., Pine, 2009). Further, Akaike weights (which represent the relative likelihood of a model within all models) were calculated for each model to indicate how likely a model would be the best among the candidate models, based on the likelihood ratio (Burnham & Anderson, 2004). In addition, pair-wise t-tests were conducted to compare individual mean AIC scores for each model to provide additional evidence for the model selection.

Spearman correlations were performed to test hypotheses 2 and 3, which concern the correlations between parameters and the correlations between parameters and personality measures of impulsivity. Results from studies 2 and 3 were compared with the results of study 1 to test hypothesis 4.

Study 1: Model Comparison

Study 1 Introduction

The primary purpose of study 1 was to compare how well the 5 models fit the data. As noted earlier, the exponential-power model has been shown to demonstrate a better fit than the standard models (exponential model and hyperbolic model) in one study (Yi, et al., 2009). However, there is some evidence for including a reward utility in a delay discounting model (Pine, et al., 2009). The β parameter in the β-δ model can be considered as a parameter of reward utility. However, it assumes a linear relationship between the reward utility and the objective magnitude of the reward, which is likely to be violated in practice (Kable & Glimcher, 2010). The Q parameter in the saturating-hyperbolic model is also considered as a parameter of reward utility, and it assumes a saturating function between the reward utility and the objective amount of the reward. However, there is little empirical evidence for this model.

Study 1 Method

Participants. Participants were recruited by the author and other research assistants at the Translational Research in Cognitive and Affective Mechanisms (TRiCAM) Lab through undergraduate psychology courses at the University of Minnesota. After removing problematic data, as described in the general method section, the final sample included a total of 87 students between 18 and 38 years of age (mean =20.1 years; sd = 2.89). Slightly over two-thirds were female and a majority (68%) identified themselves as Caucasian. Detailed demographic information is reported in table 3.1.

Procedure. Participants were told that they were participating in a study on decision making. Each participant completed the $10 version of the delay discounting task and a computerized personality inventory comprised of the BIS-11, AES, BAS/BIS, TiPs, and four other personality measures that will not be discussed in the current study. All of tasks were completed individually in a testing room of the TRiCAM lab.

Data analysis. Methods of data analysis are described in the previous general data analysis section. In particular, when performing the Spearman correlations between the parameters and the personality measures, only some subscales or factors from the personality measures were selected, based on extant literature. These subscales or factors include: Nonplanning subscale of the BIS-11, the general externalizing factor and the substance use factor of the AES, the reward responsiveness subscale of the BAS/BIS, and the TiPs.

Study 1 Results

Model fitting. The sum of individual AIC scores, Akaike weights, and pair wise t-test results are reported in Table 3.2. As shown in that table, the saturating-hyperbolic model appears to be the best fitting model for the $10 version of delay discounting task in an undergraduate sample of 87. The Akaike weight of the saturating-hyperbolic model showed there was 99% of chance for this model to be the best fitting model. The next best fitting model is the hyperbolic model, whose Akaike weight showed a 1% of chance being the best fitting model base on the current data. The pair wise t-tests showed significant differences between individual AIC scores for the exponential-power model and those of those of the saturating-hyperbolic model, but there were no significant differences in individual AIC scores between the saturating-hyperbolic model and either the exponential, hyperbolic, or β-δ model. These findings are partly consistent with the hypotheses, specifically, that the saturating-hyperbolic model would have a better fit than the standard models. However, the fact that the exponential-power model did not fit better than the standard models is inconsistent with the hypotheses.

Table 3.2 *Sum of AICs, Akaike Weight, and t-test Results for Each Model across Three Studies*

Study	Model	AIC (sum)	Akaike weight		t-test (alpha)
Undergrad $10	Exponential (E)	1317.73	3.78E-10	E-S	1.20 (*p*=.233)
n = 87	Hyperbolic (H)	1283.29	0.01	H-S	.369 (*p*=.713)
	Exponential-power (P)	1411.16	1.95E-30	P-S	2.84 (*p*=.006)
	Saturating-hyperbolic (S)	1274.36	0.99	S-S	--
	β and δ model (B)	1313.23	3.59E-09	B-S	1.15 (*p*=.252)
Cocaine $10	Exponential (E)	647.07	2.99E-31	E-S	3.51 (*p*=.001)
n = 36	Hyperbolic (H)	626.57	8.46E-27	H-S	3.78 (*p*=.001)
	Exponential-power (P)	636.05	7.39E-29	P-S	3.86 (*p*<.001)
	Saturating-hyperbolic (S)	506.50	1.00	S-S	--

	β and δ model (B)	536.02	3.89E-07	B-S	1.31 (*p*=.20)
Undergrad $1000 *n* = 40	Exponential (E)	2181.33	0.98	--	--
	Hyperbolic (H)	2189.52	0.02	H-E	.36 (*p*=.723)
	Exponential-power (P)	2297.81	5.01E-26	P-E	2.66 (*p*=.011)
	Saturating-hyperbolic (S)	2221.80	1.60E-09	S-E	1.68 (*p*=.10)
	β and δ model (B)	2213.01	1.30E-07	B-E	2.92 (*p*=.006)

Parameter correlations. The Spearman correlations between parameters from different models are reported on Table 3.3. As shown in this table, the delay discounting rates generated by the exponential model, hyperbolic model, and exponential-power model (k.Exp, K.Hyp, and K.ExPo) in study 1 were all positively and highly correlated (correlation coefficients > .99). The delay discounting parameters generated from the saturating-hyperbolic model (k.SaHy) and from the β-δ model (δ) were also highly correlated with the delay discounting parameter from one parameter models (K.Exp, K.Hyp, and K. Expo). The reward utility parameters (Q.SaHy and β) were negatively and highly correlated. The Q.SaHy was moderately correlated with other temporal discounting parameters, while β had weaker or non-significant correlations with other temporal discounting parameters. These findings suggest all temporal discounting parameters were very consistent, and the two reward utility parameters were also very consistent; these findings are consistent with the second hypothesis. Although the Q.SaHy and β are both reward utility parameters, they reflected opposite characteristics. Similarly, δ was negatively correlated with other discounting parameters, indicating that δ and other discounting parameters reflected the opposite characteristics. These findings are consistent with what can be predicted from the theories of the saturating-hyperbolic model and the β-δ model.

Table 3.3 *Spearman Correlations between Parameters from Different Models within and across Three Studies*

Study	Variable	k.Exp	k.Hyp	k.ExPo	k.SaHy	δ	Q.SaHy
Undergrad $10	k.Hyp	.996**					
	k.ExPo	.998**	.998**				
	k.SaHy	.992**	.987**	.989**			
	δ	-.988**	-.978**	-.982**	-.995**		
	Q.SaHy	-.426**	-.384**	-.399**	-.501**	.528**	
	β	.249*	.200	.220*	.326**	-.366**	-.938**
Cocaine $10	k.Hyp	.993**					
	k.ExPo	.993**	.996**				
	k.SaHy	.590**$_a$	.573**$_a$	.573**$_a$			
	δ	-.585**$_a$	-.565**$_a$	-.567**$_a$	-.993**		
	Q.SaHy	-0.013	0.032	0.032	-.644**	.648**	
	β	-0.182	-0.232	-0.226	.447**	-.480**	-.905**
Undergrad	k.Hyp	.999**					
$1000	k.ExPo	.997**	.998**				
	k.SaHy	.997**	.995**	.993**			
	δ	-.995**	-.993**	-.991**	-.998**		

Q.SaHy	-0.188$_b$	-0.167$_b$	-0.149$_b$	-0.231$_b$	0.23$_b$	
β	0.031$_b$	0.012$_b$	-0.005$_b$	0.077$_b$	-0.086$_b$	-.929**

Note. Study 1 n =87 ; Study 2 n = 36 ; Study 3 n=40; ^{a} indicates a significant Fisher's z-score difference between Study 1 and Study 2, $p < .05$; ^{b} indicates a non-significant Fisher's z-score difference between Study 3 and Study 1, $p > .05$.

Correlations between parameters and personality measures of impulsivity. The Spearman correlations between parameters and the personality measures of impulsivity are reported in Table 3.4. Given the exploratory nature of this study, we did not correct for multiple statistical tests. All temporal discounting parameters were significantly correlated with the general externalizing factor of the Adult Externalizing Scale (AES) at the .05 level. Further, β was significantly correlated with this factor at the .05 level. These findings indicate the participants who assigned higher weights to current reward and lower weights to the future also tended to have higher general externalizing scores. Further, all temporal discounting parameters, but not reward utility parameters, were significantly correlated with the substance use factor of the AES at the .01 level. These results indicate the factor of substance use was associated more with the habituation process rather than physiological needs, psychological desires, or economic needs in this sample drawn from a normal population. Only the temporal discounting parameters from the two parameter models (K.SaHy and δ) were significantly correlated with the non-planning subscale of the Barratt Impulsiveness Scale (BIS) and the Time Preference Score (TiPs) at the .05 level. In addition, the saturating parameter (Q.SaHy) was also significantly correlated with the TiPs at the .05 level.

Table 3.4 *Comparison of Spearman Correlations between Parameters and Scores on Personality Measures across Three Studies*

Study	Variable	k.Exp	k.Hyp	k.ExPo	k.SaHy	δ	Q.SaHy	β
Undergrad	Ext (AES)	.228	0.203	.222	.238	-.253	-0.209	.257
$10	Sub (AES)	.302	.277	.294	.304	-.316	-0.185	0.178
	NoPl (BIS)	0.198	0.200	0.196	.215	-.218	-0.153	0.153
	ReRes (BAS)	-0.058	-0.070	-0.061	-0.038	0.038	-0.119	0.153
	TiPS	-0.207	-0.187	-0.2	-.215	.231	.219	-0.182
	Note: rho >.21 *p*<.05, rho >.26 *p*<.01							
Cocaine	Ext (AES)	-.420	-.409	-.404	-0.089	0.085	-0.098	0.174
$10	Sub (AES)	-0.193	-0.175	-0.173	0.037	-0.036	-0.222	0.284
	NoPl (BIS)	-0.183	-0.197	-0.165	0.146	-0.193	-0.242	.345
	ReRes (BAS)	-0.212	-0.198	-0.193	-0.211	0.200	0.167	-0.111
	TiPS	0.082	0.100	0.079	-0.048	0.073	0.114	-0.189
	Note: rho >.27 *p*<.05, rho >.43 *p*<.01							
Undergrad	Ext (AES)	0.296	0.301	0.284	0.294	-0.291	-0.14	0.098
$1000	Sub (AES)	.393	.400	.383	.395	-.385	-0.115	0.054
	NoPl (BIS)	0.217	0.207	0.187	0.233	-0.217	-0.173	0.113
	ReRes (BAS)	-0.179	-0.196	-0.193	-0.157	0.138	-0.279	0.301
	TiPS	-0.115	-0.118	-0.098	-0.135	0.14	0.307	-.315
	Note: rho >.27 *p*<.05, rho >.43 *p*<.01							

Note. Study 1 *n* = 87; Study 2 *n* =36; Study 3 *n*=40; k.Exp refers to the delay discounting rate in the exponential model; k.Hyp refers to the delay discounting rate in the hyperbolic model; k.ExPo refers to the delay discounting rate in the exponential-power model; k.SaHy refers to the delay discounting rate in the saturating-hyperbolic model; δ refers to the delay discounting parameter in the beta-delta model; Q.SaHy refers to the saturation index in the satuating-hyperbolic model; β refers to the reward index in the beta-delta model.

These findings are also partly consistent with hypotheses. Although all temporal discounting parameters were associated with the general externalizing factor and substance use factor of the AES, only the temporal discounting parameters from the saturating-hyperbolic model and the β-δ model were significantly correlated with the non-planning impulsiveness subscale of the BIS and the total score of TiPs. Inconsistent with hypotheses, however, the two reward utility parameters were not significantly correlated with the reward responsiveness of the BAS/BIS.

Study 1 Discussion and Conclusions

Mathematically, the saturating-hyperbolic model appeared to be the best fitting model among the five models discussed herein, with respect to this study of a $10 version delay discounting task with an undergraduate sample of 87 individuals. However, this conclusion may not be robust enough because the pair wise t-tests showed there were no significant differences in individual AIC scores between the saturating-hyperbolic model and the exponential, hyperbolic, and the β-δ models.

All temporal discounting parameters were highly correlated. The two reward utility parameters were also highly correlated. The temporal discounting parameters of both the saturating-hyperbolic model and the β-δ model showed higher correlations with the personality measures of impulsivity than did the one parameter models.

This initial study provides some evidence that the saturating-hyperbolic model may best describe the present data. However, since there was a non-significant difference in individual AIC scores between this model and the standard models, this conclusion is tentative and these findings require replication in future studies. Further, the results are based on the data from a normal population. Other variables, such as population difference, could possibly accelerate or decelerate the effect obtained in this study. Given these possible limitations and previous evidence that drug users tend to display much steeper discounting than normal controls (W.K. Bickel, et al., 1999; G.J. Madden, et al., 1999), Study 2 was conducted to test the population effect on model fitting.

Study 2: Population Effect on Model Fitting

Study 2 Introduction

Individuals with impulsive disorders, particularly in the area of substance abuse, are thought to discount future reward much steeper than controls (e.g. Bornovalova, Daughters, Hernandez, Richards, & Lejuez, 2005; Heil, Johnson, Higgins, & Bickel, 2006; A.L. Odum, Madden, & Bickel, 2002; R. Yi, X. de la Piedad, & W. K. Bickel, 2006). Within these populations, cocaine addicts appeared to have higher delay discounting rates than other substance users (e.g. alcohol or heroin; Bornovalova, et al., 2005; Heil, et al., 2006; K.N. Kirby & Petry, 2004). In addition, although the delay discounting rate analyzed with hyperbolic model has been associated with Nonplanning on the Barrat Impulsivity Scale (BIS-11) in a normal sample (de Wit, et al., 2007), the delay discounting rate analyzed with the hyperbolic model has no significant correlations with any subscales on the BIS-11 in the psychiatric population (Dom, et al., 2007; Matthew W. Johnson, et al., 2010). These findings suggest that the psychiatric population may respond to the delay associated decisions with a different pattern from the normal population, and thus indicates a potential effect of population difference on model fitting. Study 2 involves using data set from a sample of cocaine addicts to determine the population effect.

Study 2 Method

Participants. In this study, 36 active cocaine users between 18 and 49 years of age (mean =38.81; sd =7.25) were recruited by the research assistants at Dr. Kelvin Lim's Lab in department of psychiatry through postings and newspaper advertisements. These cocaine users were recruited using inclusion criteria and exclusion criteria. The inclusion criteria were: 1) meeting *Diagnostic and Statistical Manual of Mental Disorders* (4th ed.; *DSM–IV*) diagnostic criteria for cocaine dependence for at least 1 year; 2) meeting that criterion within the month prior to enrollment in the study; and 3) having used cocaine at least 6 times in the month prior to enrollment in the study. Exclusion criteria were: 1) a prior history of neurological illness, psychiatric illness, and/or HIV seropositivity; 2) current medication that may alter gamma-aminobutyric acid brain levels; and 3) current dependence on any psychoactive substance (with the exception of cocaine, caffeine, or nicotine).

Procedure. Participants completed the tasks in three sessions, with the third session being an MRI. The first two sessions were completed at Dr. Lim's lab. During the first session, participants finished a clinical interview and underwent an informed consent process. During the second session, these participants completed the $10 version delay discounting task, the same personality inventory as in Study 1, as well as a probability discounting task that will not be discussed herein.

Data analysis. The methods of data analysis are the same as described in Study 1. In addition, tests of the difference between two independent correlation coefficients (Cohen, Cohen, West, & Aiken, 1983) were performed to compare the parameter correlations in Study 2 with those in Study 1.

Study 2 Results

Model fitting. Consistent with Study 1, the saturating-hyperbolic model continued to be the best fitting model for this sample of cocaine addicts, followed by the β and δ model. This superior fit was consistently shown by the lower sum of AIC scores in Table 3.2. The Akaike weights showed that there was almost a 100% chance of the saturating-hyperbolic model being the best fitting model. In addition, the pair-wise t-tests showed the individual AIC scores of the saturating-hyperbolic model were significantly lower than the individual AIC scores generated from the three, one-parameter models, but not the individual AIC scores from the β-δ model. These findings suggest the two-parameter models (with one temporal discounting parameter and one reward utility parameter) can better describe the delay discounting data for a sample drawn from the psychiatric population.

Parameter correlations. Consistent with the findings in Study 1, the Spearman correlations between temporal discounting parameters from the one-parameter models (K.Exp, K.Hyp, and K. Expo) were highly correlated (correlation coefficients > .99).

Also consistent with findings in Study 1, the reward utility parameters and the temporal discounting parameters between two-parameter models were highly consistent (correlations > .90). However, the temporal discounting parameters from the two-parameter models had lower correlations with the temporal discounting parameters from the one-parameter models, although the correlations were still significant (correlation magnitudes ranged from .565 to .59). These results also suggest larger inconsistencies between the phenomena being measured by the one-parameter models and the phenomena being measured by the two-parameter models; this finding was not suggested by Study 1 data.

Correlations between parameters and the personality measures associated with impulsivity. As shown in Table 3.4, the temporal discounting parameters from the one-parameter models were negatively correlated with the general externalizing factor of the AES, indicating that participants who discounted future rewards more steeply tend to have less disinhibition issues. These findings are counter-intuitive and inconsistent with results from Study 1. However, there were no significant correlations between parameters from the two-parameter models and the general externalizing factor of the AES. In addition, none of the parameters was significantly correlated with the substance use factor of the AES, indicating the temporal discounting parameters were not correlated with the substance use issues beyond and above the group membership of cocaine addiction. Finally, β was found to be correlated significantly with nonplanning. The correlation between Q.SaHy and nonplanning approached significance. Therefore, the reward utility parameters from the two-parameter models appear to be more sensitive to the individual differences among cocaine addicts than those from the one-parameter models.

Study 2 Discussion and Conclusions

Results from Study 2 indicate that there were larger differences and inconsistencies between phenomena measured by the one-parameter models and phenomena measured by the two-parameter models. First, although the t-test results in Study 1 suggested that the superior fit of the saturating-hyperbolic model over the standard models was not robust enough at the individual level, the current study indicated the mathematical fit of the saturating-hyperbolic model was significantly better than the standard models at the individual level in a sample of cocaine addicts. Second, the correlations of temporal discounting parameters between one-parameter models and two-parameter models were significantly stronger in Study 1 than in Study 2, indicating larger inconsistencies between these parameters may exist in the cocaine population compared to the normal population. Third, the reward utility parameters from the two-parameter models appeared to be more sensitive to the individual differences within the cocaine addicts than the normal sample. This evidence suggests two parameter models should be used to analyze delay discounting data for samples obtained from the cocaine population.

The results of Study 2 demonstrate that source population variables may influence the nature of model fitting. Yet to be tested, however, is whether the current conclusion will be affected by the reward magnitude. Given some prior evidence that a large reward magnitude leads to shallower delay discounting patterns (e.g. F. Baker, et al., 2003), Study 3 was designed to test the magnitude effect.

Study 3: Magnitude Effect on Model Fitting

Study 3 Introduction

Current literature suggest the discounting rate measured by the hyperbolic model tends to be more shallow when the rewards being chosen are large (e.g., >$1000), indicating a magnitude effect (F. Baker, et al., 2003). Green, Myerson, and McFadden (1997)compared delayed hypothetical rewards of different amounts ($100, $2,000, $25,000, and $100,000) in a sample of 24 undergraduate students. They found that the delay discounting rate decreased as the amount of reward increase. These findings raise the question as to whether the magnitude effect may influence the model fitting. This study involved a $ 1000 version delay discounting task with the larger and later reward being $1000 rather than $10 as in the Study 1.

Study 3 Method

In this study, forty undergraduate students between 18 and 30 years of age were recruited from undergraduate psychology classes. Within the 40 students, 34 overlapped with the Study 1 sample. These participants completed the $1000 version delay discounting task and the same personality inventory as in Study 1. The methods of data analyses were the same as in Study 2.

Study 3 Results

Model fitting. As shown by the sum of AIC scores in Table 3.2, the exponential model was the best fitting model, followed by the hyperbolic model. The Akaike weights showed there was a 98% chance of the exponential model being the best model given the current data with a $1000 version delay discounting task. The pair wise t-tests showed the exponential model was not significantly better than the hyperbolic model or the saturation-hyperbolic model at the individual level, but it was significantly better than the exponential-power model and the β-δ model. Consistent with Study 1 findings, the saturating-hyperbolic model was not significantly different from the standard models in terms of mathematical fit. However, inconsistent with Study 1 results, the one-parameter model appeared to be the best model when the reward magnitude was high. These indicated an effect that was opposite of the population effect shown in Study 2.

Parameter correlations. In this study, all temporal discounting parameters were highly correlated (correlation coefficients > .9). These results are consistent with those of Study 1, further indicating the inconsistency between parameters observed in Study 2 was more specific to population effect. The reward utility parameters appeared to have lower correlations with the temporal discounting parameters than those correlations in Study 1. However, the test of the difference in correlation coefficients suggested these correlations in Study 3 and Study 1 were not significantly different. In other words, the parameter correlations were generally consistent with those in Study 1.

Correlations between parameters and the personality measures associated with impulsivity. Consistent with Study 1, all temporal discounting parameters were significantly correlated with the substance use factor of AES (and correlations were all in the same direction as those in Study 1), suggesting the relationships between delay discounting indices and the substance use factor did not vary across different versions of the delay discounting task, but they did vary in samples from different population. In addition, β was negatively and significantly correlated with scores on the time preference scale. This finding is different from Study 1 in which the δ was positively associated with the time preference scale scores. These results suggest there may be more variance between temporal discounting parameters when the delayed reward is small, where there may be more variance in the reward utility parameters when the delayed reward is relatively large. The findings also indicate that a delay discounting task with a smaller reward magnitude is likely more sensitive in measuring impulsive decision making.

Study 3 Discussion and Conclusions

Overall, results from Study 3 suggest the two-parameter models do not fit better than the standard models when the delay discounting task involves a larger amount of rewards. In fact, one-parameter models (particularly the exponential model) fit better than other models, although this conclusion was not robust given the non-significant t-test results. These findings again challenge standard practice which favors the hyperbolic model over the exponential model in human studies. They support early evidence that the exponential model could be more appropriate under some conditions (Schweighofer, et al., 2006). One explanation is that there are higher consistencies between decision choices within and across individuals. Thus, a constant discounting parameter can describe the data satisfactorily, and there is not enough of variance to indicate the necessity of a second parameter.

Compared with Study 1, the results of Study 3 suggest consistent patterns of correlations between parameters and the correlations between parameters and the personality measures of impulsivity, indicating these correlations do not vary due to the magnitude effect.

General Discussion and Conclusions

The present studies examined the model fitting of 3 neural models compared with the 2 standard models in 3 conditions: $10 version of a delay discounting task in a normal sample, $10 version of a delay discounting task in a sample of cocaine addicts, and $1000 version of a delay discounting task in a normal sample. The 3 models discussed in the current studies are: the exponential-power, saturating-hyperbolic, and the β and δ model; and the 2 standard models are the exponential model and the hyperbolic model.

In these 3 studies, the saturating-hyperbolic model with a reward utility parameter and a temporal discounting parameter likely best described the delay discounting data when the reward magnitude was relatively low. The superiority of this model was manifested by lower overall AIC scores in the normal sample when compared with the standard models. It was also shown by lower overall AIC scores and significantly higher t-test score of individual AIC scores in a clinical sample. However, its superiority decreased when the delay discounting task involved a higher amount of reward. In fact, the exponential model was the best fitting model for the delay discounting data in a normal sample when large amount of reward was involved. These findings challenge the standard practice of using the hyperbolic model across different conditions and populations in human studies. This investigator proposes two guidelines for selecting a model to analyze delay discounting data: 1) it is necessary to include a reward utility parameter when selecting a model to analyze delay discounting data for samples from a clinical population; and 2) It still worth considering the use of the exponential model or other model that indicates a constant temporal discounting parameter under some conditions (e.g., large magnitude, emphasis on strategies).

Inconsistent with Yi's (2009) findings that the exponential-power model fit better than the standard models in their data, the exponential-power model showed worse fit than the standard models across all 3 of the present studies. A comparison of the present delay discounting tasks with those of Yi, reveals their delay discounting tasks involved much longer delays (between 1 day and 25 years), while the delay times in the tasks in Studies 1-3 were relatively short (between 1 day and 365 days). This difference may suggest the length of delay time scale has impact on the model fitting. This effect, as well as other effects (e.g., domain effect), should be examined further in future studies.

Chapter 4

The Specificity of Decision Making Bias in Cocaine Addiction

Introduction

Cocaine addiction is a subcategory of drug addiction characterized by repeated self-administration of cocaine, craving, and withdrawal. Cocaine addicts often make poor decisions about rewards (Heil, et al., 2006; K.N. Kirby & Petry, 2004). However, it remains unclear whether this is a decision-making bias related to impulsive behaviors in general or a specific bias related to impatience (Bornovalova, et al., 2005; Estle, Green, Myerson, & Holt, 2007; Green & Myerson, 2010). Further, it is still unclear whether this bias is associated more strongly with personal desires or more strongly associated with the executive abilities of planning over time. In addition, it is unclear whether this bias is associated with the broader construct of impulsivity, which is often regarded as an underlying predisposition or liability for drug addiction.

Specificity of Cocaine Addiction In Terms of Decision Domains

The classical theory of neuroeconomic decision-making involves two parameters that specify one's attitude toward delayed rewards and one's attitude toward risk. These two parameters can be operationalized by choice behaviors evidenced during delay discounting and probability discounting tasks (Rustichini, 2009). The delay discounting task is thought to measure time preference, or the tendency to choose a small and more immediate reward over a larger and later reward when individuals are faced with rewards in different times. Probability discounting task measures risk aversion, or the tendency to choose a small but certain reward over a larger but probabilistic reward (Rachlin, Raineri, & Cross, 1991).

In psychology research, delay discounting and probability discounting measures are often analyzed using a hyperbolic model (Ainslie, 1975; G. J. Madden, et al., 2003; Gregory J. Madden, et al., 1999; Mazur, 1985, 1987). The delay discounting rate has been associated with a number of impulsive disorders, particularly in the area of substance abuse (Bornovalova, et al., 2005; Heil, et al., 2006; A.L. Odum, et al., 2002; Richard Yi, et al., 2006), and has at times been shown to be central to the definition of impulsivity. Within literature on substance abuse, cocaine addicts appear to have higher delay discounting rates than other substance users (e.g., alcohol and heroin users)(Bornovalova, et al., 2005; Heil, et al., 2006; K.N. Kirby & Petry, 2004).

The research on probability discounting is less thorough than that on delay discounting. Some studies support an association between cocaine addiction and risk taking propensity. For instance, cocaine addiction has been associated with risk taking propensity as measured by the BART task (Bornovalova, et al., 2005). Cocaine users are 10 times more likely to be pathological gamblers (Steinberg, Kosten, & Rounsaville, 1992). Further, risk taking in childhood predicts drug use in early adulthood (Ríos-Bedoya, Wilcox, Piazza, & Anthony, 2008), and cocaine addiction can also predict various risk behaviors, such as sexual risk behavior (Hayaki, Anderson, & Stein, 2006). Although there are some indications that cocaine addicts also have risk-taking propensities, there is little empirical evidence to support that they have a higher risk taking tendency as measured by the probability discounting rate.

Specificity of Decision Bias in Cocaine Addiction in Terms of Individual Differences in Impulsivity

Although literature on drug addiction provides robust evidence to support that cocaine addicts often have a higher delay discounting rate, it remains a question as to whether the decision making bias in cocaine addiction is associated with the personality trait of impulsivity. Impulsivity is a liability that is associated with cocaine addiction. On self-report questionnaires of impulsivity, cocaine addicts consistently have shown greater impulsivity when compared to control groups (e.g. Coffey, Gudleski, Saladin, & Brady, 2003). However, attempts to disentangle the relationships between the delay discounting rate and personality measures of impulsivity have obtained varying levels of success. For instance, the delay discounting rate was observed to be positively and significantly correlated with Nonplanning on the Barrat Impulsivity Scale in a normal sample (BIS-11; de Wit, Flory, Acheson, McCloskey, & Manuck, 2007). However, other studies indicated no significant correlations between delay discounting rate and subscales on the BIS-11 in samples drawn from the normal population (Reynolds, Ortengren, Richards, & de Wit, 2006), or from the clinical population (Dom, De Wilde, Hulstijn, van Brink, & Sabbe, 2006; Johnson et al., 2010). There are several possible explanations for these inconsistent results. One explanation is that decision making performance is often influenced by an individual's current state (i.e., physical state, or mood state); thus the decision making performance is possibly less stable than responses to the personality measures (Hirsh, et al., 2010; Amy L. Odum & Baumann, 2010). Other explanations include variability in sample sizes and/or statistical power, the fact that personality measure assess general tendencies in broader situations than those involved in a given decision making task, and the use of homogeneous samples (Coffey, et al., 2003; Amy L. Odum & Baumann, 2010). Given the multiple influences on decision making performance, some authors suggest researchers include multiple personality measures when studying the associations between discounting performance and individual difference variables (W.K. Bickel & Marsch, 2001).

Are the Decision Making Biases in Question Associated with Other Impulsive Disorders?

Although cocaine addicts have shown a clear propensity for decision biases associated with delayed reward, whether their bias is associated with other impulsivity disorders is less clear. As substance use disorders often involve adaptation of the neurocircuitry due to drug use (Bibb et al., 2001; Hyman, Malenka, & Nestler, 2006), comparing the association between discounting performance and impulsive disorder with cocaine, and discounting performance with impulsive disorder without drugs, will provide further information regarding the specificity of the observed decision making bias associated with cocaine addiction.

One putative impulsive disorder without the pharmacological influence of drugs may be binge eating disorder (BED). Binge eating disorder (BED) is listed under “Criteria Sets and Axes for Further Study” in DSM-IV, and is slated to become a formal diagnosis in the Diagnostic and Statistical Manual – V (DSM-V) (cf. Wilfley, Bishop, Wilson, & Agras, 2007). A binge eating disorder involves complex behavior characterized by overeating, lack of control, and psychological distress.

Binge eating disorder is also considered as an impulsive disorder because clinical observations indicated reward sensitivity or drive may play an important role in developing this condition (Dawe & Loxton, 2004). Further, binge eating disorder and substance use disorder (SUD) co-occur at high rates. For example, Peterson and colleagues (2005) studied the mental health history and responses to self-report questionnaires in a sample of female binge eaters. Of the 84 binge eating respondents, 39 (46%) evidenced SUD. The binge eater and SUD group was reported to have more binge eating episodes on the Eating Behavior-IV and higher impulsivity on the Multidimensional Personality Questionnaire (MPQ) than the non-SUD group.

Research on binge eating disorder is less thorough than that on cocaine addiction. Literature on binge eating disorder studies suggests a commonality between binge eating disorder and cocaine addiction such that both are related to habits and preferences that are learned through the reinforcement of powerful and repetitive rewards (Volkow & Wise, 2005). Binge eaters, however, do not have the adaptation of neurocircuitry due to the drug use. Studies examining the correlations between binge eating disorder and comorbidity have shown that individuals with binge eating disorder are more likely to display psychological distress and to have other psychiatric disorders such as depression, anxiety disorder, and panic attacks (Wonderlich et al., 2009).

The association between discounting performance and binge eating disorder remains unclear. A recent study failed to detect a group effect among binge eaters, obese women, and normal controls on delay discounting after controlling for education level (Davis, Patte, Curtis, & Reid, 2010). However, another study indicated that obese women have significantly higher delay discount AUC (area-under-curve) scores than controls (Weller, Cook, Avsar, & Cox, 2008).

Specificity of the Decision Making Bias in Cocaine Addicts In Terms of Neural Systems

One drawback of previous studies is that the delay discounting rate is analyzed using the standard hyperbolic model; thus researchers are unable to differentiate the decision factor associated with time valuation from the factor associated with reward valuation (value currency). Neural imaging studies suggest there is a common neural system (Ventral striatum and orbitofrontal cortex) that encodes value currency for decisions associated with both delayed rewards and probability rewards (Peters & Büchel, 2009). These regions were originally referred to as a system associated with specific short-term reward processing in a delay discounting task (McClure, et al., 2007; McClure, et al., 2004). Later studies, however, indicated these regions are associated more strongly with valuation specific to reward (value currency) rather than with specific time (Ballard & Knutson, 2009; Kable & Glimcher, 2010). These findings indicate that both common and distinct neural systems are involved in decisions associated with delay and risk. Thus, the standard method of analyzing delay discounting and probability discounting data with one parameter is not specific enough to address the common neural factors and distinct factors involved in decision making bias in cocaine addicts. Instead, novel models that allow two parameters to explain discounting behaviors appear to offer promise.

The present study on model fitting (reported in Chapter 3) suggests the saturating-hyperbolic model fits the delay discounting data better than the hyperbolic model. This model differentiates value currency from time valuation in decision making. Specifically, value currency can be described as a saturation function, while the subjective value of time or risk can be described as a hyperbolic function (Doya, 2008). The equation for the saturating function is listed below, where A is the amount of the objective reward, and Q determines the amount with which the utility curve saturates:

$$f(A) = \frac{A}{A + Q}$$

Further, the function for the delay time follows a hyperbolic function in which k specifies the delay discounting rate:

$$g(d) = \frac{1}{(1 + kd)}$$

The function for probability also follows a hyperbolic function in which H represents the weight parameter for evaluating the rewards:

$$h(p) = \frac{p}{p + H(1 - p)}$$

Based on the theory of this model and literature on neural imaging studies, the common factor between delay discounting and probability discounting is represented by the saturation function.

Studies in this Chapter

Previous studies on delay discounting in cocaine addicts have suggested cocaine addicts tend to have a decision making bias. However, whether this decision making bias is a general bias of decision making and whether this decision making bias is associated with impulsivity remain unclear. In addition, it is unclear whether the decision making bias is related to the common factor associated with both delayed reward and probabilistic reward or a distinct factor associated with only delay discounting. To address gaps in the literature, two studies have been designed to compare two decision making tasks with respect to rewards (delay discounting and probability discounting). The associations between these tasks and the personality characteristic of impulsivity were investigated and compared for individuals diagnosed with cocaine addiction versus those diagnosed with binge eating disorder. In Study 1, the discounting parameters were calculated according to the hyperbolic function. In Study 2, the discounting parameters were calculated according to the saturating-hyperbolic function. Based on the literature, the following hypotheses were tested:

1. Cocaine addicts have significantly higher tendencies of both impatience (higher delay discounting rates) and risk-taking (lower probability discounting rates) than controls.
2. Discounting parameters are significantly correlated with externalizing, non-planning impulsiveness, and reward responsiveness, as measured by personality inventories.
3. Cocaine addicts and binge eaters both exhibit greater decision bias on discounting measures than controls.

General Methods

Participants

Participants were recruited through postings and newspaper advertisements. All participants were told that they would be paid 180 dollars for completing all three sessions. The final samples included 36 active cocaine users, 39 matched healthy, non-cocaine using controls, 20 female adults with binge eating disorder, 16 normal, non-binge eating female controls, and 19 overweight non-binge eating female controls. To rule out the association between weight and decision making bias, both normal controls and overweight controls were included, and their responses were compared to those of the binge eaters. All participants were between age 18 and 46 years.

For the cocaine addicts, inclusion criteria were: 1) meeting *DSM-IV* (4th ed.) diagnostic criteria for cocaine dependence for at least 1 year; 2) meeting that criterion within the month prior to enrollment in the study; and 3) having used cocaine at least 6 times in the month prior to enrollment in the study. Exclusion criteria were: 1) a prior history of neurological illness, psychiatric illness, and/or HIV seropositivity; 2) current medication that may alter gamma-aminobutyric acid brain levels (a criterion related to a different assessment procedure); and 3) current dependence on any psychoactive substance (with the exception of cocaine, caffeine, or nicotine). For the binge eater group, only female participants were enrolled. The inclusion criterion was meeting *DSM-IV* diagnostic criteria for binge eating disorder. The same exclusion criteria for the cocaine user group were also applied to the binge eater group. For healthy controls, exclusion criteria were: 1) any diagnosed psychiatric disorder in the past 3 months prior to enrollment; and 2) a history of substance dependence or substance abuse within the past year (with the exception of caffeine or nicotine). These control participants were matched with either active cocaine users or binge eaters on demographic variables listed in Table 4.1.

Table 4.1 *Demographics for Cocaine-Dependent Participants (CD), CD Controls, Participants with Binge Eating Disorder (BED), BED Overweight Controls, and BED Normal Controls*

Characteristic	Group				
	CDs	CD Controls	BEDs	BED Normal Controls	BED Overweight Controls
n	36	39	20	16	19
Age	38.81 (7.25)	38.79 (7.12)	33.50 (8.22)	31.44 (7.65)	32.74 (7.55)
Gender (% female)	18.91	23.07	100	100	100
Race (% Caucasian)	36.1	76.9	72.7	81.2	89.5
% Native American	5.6	2.6	0	6.2	0
% Native Hawaiian	2.8	0	0	0	0
% Asian	0	0	4.5	0	0
% African American	47.2	12.8	13.6	6.2	10.5
% Hispanic	2.8	0	0	0	0
% Other	5.6	7.7	9	6.2	0
Education (in years)	13.14 (1.82)	14.59 (1.52)	15.60 (1.82)	15.19 (1.76)	14.89 (2.19)
Years of use (cocaine)	14.53 (7.48)	--	--	--	--
Days of use (per week)	3.42 (1.68)	--	--	--	--
BMI	--	--	34.64 (3.68)	23.10 (1.87)	34.27 (4.47)

Note. BMI refers to Body Mass Index, a measure of body fat based on height and weight. A BMI of 30 or higher is considered as overweight.

Behavior Measures

Discounting Measures (Richards, Zhang, & de Wit, 1999). The delay discounting task measured the subjective values after certain delays. This task was a computerized random adjusting-amount procedure in which the smaller and immediate reward was adjusted until the value of the small reward was equal to the subjective value of the large and delayed reward (which meant an indifference point was reached). The task allowed participants to choose from $10 after a delay (1, 2, 30, 180, or 365 days) or an immediate and smaller reward. For example, participants were offered the following choice: Would you rather have $5 now or $10 in 30 days? After the participant made a choice, the answer was used by the program to narrow the range of the immediate rewards for the subsequent questions. A series of questions were presented until an indifference point at a certain delay time was reached. In addition, the adjusting nature of the task was masked by mixing the delay discounting questions and probability discounting questions. Because there were 5 delay times, completing the task would lead to 5 indifference points which yielded a delay discounting curve. A steeper delay discounting curve meant a stronger preference for more immediate and smaller outcome (or greater impatience).

The probability discounting task measured the subjective values with certain probability against receiving the reward. In the task, participants were asked to choose from $10 with a probability (95%, 90%, 75%, 50%, 25%) and a smaller, guaranteed amount of money. For example, one of the questions was “Would you rather take $5 for sure or $10 with a 50% chance?” Again, the smaller and assured reward was adjusted until an indifference point was reached for each probability level. The adjusted procedure was masked by mixing the probability questions with the delay questions. The

5 indifference points generated from the 5 probability levels were used to generate a probability discounting curve. A steeper probability discounting curve meant a stronger preference for more certain and smaller rewards (or higher risk aversion).

Self-Report Personality Measures

Substance Use. The individual difference in substance use problems was measured by the Adult Externalizing Scale. This is a 100-item version of the disinhibition measure (Krueger, Markon, Patrick, Benning, & Kramer, 2007) that include three factors: general externalizing, aggression, and substance use. All scales showed adequate internal consistency (alpha > .90 in a mixed sample of 480 respondents). Sample items associated with substance use include: "My drug use has caused problems with my family"; "I gave up things I used to enjoy because of drugs"; and "I've broken the law to get money for drugs."

Non-Planning Impulsiveness. Non-planning impulsiveness was measured by the Barratt Impulsiveness Scale (BIS-11; Patton, Stanford, & Barratt, 1995). The BIS-11 generally is used to measure personality traits of impulsiveness. This 30-item scale is composed of three factors: Attentional Impulsiveness, Motor Impulsiveness, and Nonplanning Impulsiveness. Sample items associated with non-planning impulsiveness include: "I plan tasks carefully"; "I plan trips well ahead of time"; and "I get easily bored when solving thought problems."

Reward Responsiveness. Reward responsiveness was measured by the Behavioral Inhibition System and Behavioral Approach System (BIS/BAS) Scales (Carver & White, 1994). The BIS/BAS Scales were used to measure Gray's (1990) approach/avoidance personality system. This 20-item questionnaire is composed of four subscales: BAS Drive, BAS Fun Seeking, BAS Reward Responsiveness, and BIS. Sample items associated with reward responsiveness include: "When I get something I want, I feel excited and energized"; "When I see an opportunity for something I like I get excited right away"; and "When good things happen to me, it affects me strongly."

Procedure

Participants completed the tasks in three sessions, with the third session consisting of an MRI scan, which will not be discussed in the current study. During the first session, participants finished a clinical interview and underwent an informed consent process. The cocaine users, the binge eaters, and their controls were interviewed by research assistants in Department of Psychiatry to assess whether or not they met certain *DSM-IV* criteria using a Structured Clinical Interview for Axis I disorders. The cocaine users also completed a cocaine craving questionnaire, brief substance craving questionnaire, and eating disorders examination questionnaire (EDE, Fairburn, 2008). Controls for cocaine users completed the EDE and Stunkard-Messick Eating Questionnaire (SMEQ, Stunkard & Messick, 1985). The binge eaters also completed the EDE. During the second session, all participants completed the personality measures, and the discounting tasks (among other cognitive tasks that are not included in the current study). All of the tasks were administered through a desk-top computer. The sequences of tasks were randomly assigned. Participants were given detailed instructions before starting each task. Upon completing the tasks, participants were debriefed by providing them with an explanation about the purpose of the study and how the data would be used.

Data Analysis

Data check. The final samples were determined after a data check based on an algorithm developed by Johnson and Bickel (2008). We adjusted the second criterion used by Johnson and Bickel given that the longest delay in our delay discounting task is 1 year rather than 25 years. We modified the second criterion (the last indifference point was not less than the first indifference point for at least 10% of the largest delayed reward) to no discounting at all, which meant that the last indifference point was not less than the first indifference point. Nonsystematic discounting data from 3 cocaine users, 3 cocaine controls, 3 binge eaters, 3 normal binge eater controls, and 4 overweight binge eater controls were excluded from further analysis. A follow-up analysis consisting of a t-test, one-way analysis of variance (ANOVA) and X^2 suggested there were no significant differences on the demographic variables between the clinical groups and their matched control groups.

Calculation of discounting. The discounting parameters were analyzed using the hyperbolic function in Study 1 and the saturating-hyperbolic function in Study 2.

Group differences analysis. Subscale scores or factor scores were computed for each personality measure. Multivariate analysis of variance (MANOVA) was performed to investigate the group effect on personality measures. Based on the distribution characteristics of the data, a repeated measures ANOVA or Mann-Whitney U test was performed to detect group differences on discounting parameters. If significant group differences on parameters were found, t tests with bootstrap resampling were used to provide further analysis for group difference at each indifference point.

Correlation analysis. Pearson's correlations or Spearman correlations were calculated to test the correlations between discounting parameters as well as the correlations between discounting parameters and personality measures.

Study 1: Decision Bias Described by the Hyperbolic Function

Study 1 Introduction

The primary purposes for Study 1 was to replicate the previous studies on delay discounting performance in cocaine users and to test the current hypotheses on decision bias in cocaine addicts by analyzing the discounting data with the hyperbolic function. As noted earlier, there is robust evidence that cocaine users have a higher delay discounting rate (Bornovalova, et al., 2005; Heil, et al., 2006; K.N. Kirby & Petry, 2004); but there is little evidence they also have a lower probability discounting rate, despite some evidence that cocaine addicts have a propensity for risk-taking. The delay discounting performance among some substance users (other than cocaine users) has not been associated with impulsiveness, as measured by the Barrat Impulsivity Scale (Dom, et al., 2007; Matthew W. Johnson, et al., 2010); but the delay discounting performance among samples drawn from a normal population has been correlated with non-planning impulsiveness, as measured by the Barrat Impulsivity Scale. Previous studies also suggested binge eaters share with cocaine users a commonality of characteristics regarding impulsivity (Dawe & Loxton, 2004; Volkow & Wise, 2005). Thus, they are likely to share the decision bias measured by delay discounting rate, as observed in cocaine users. One study reported a significantly higher delay discounting rate in binge eaters when compared with obese women and normal controls; however, the observed difference likely was moderated by their education level (Davis, Patte, Curtis, & Reid, 2010).

Study 1 Method

The methods for this study were described previously in the general method section. In particular, the delay discounting rate (k.delay) and the probability discounting rate (k.probability) were calculated using the equation based on the following hyperbolic function in which V represents the subjective value of the delayed outcome, while d is the delay time for receipt of the outcome, and k is the discounting rate (Mazur, 1987):

$$V = \frac{A}{(1 + kd)}$$

Because the distributions of discounting rates were significantly different from a normal distribution, they were transformed using natural log for data analysis, as in previous studies (e.g. Matthew W. Johnson, et al., 2010).

Study 1 Result

Group difference on personality measures. Group differences for personality measures were analyzed using one-way multivariate analysis of variance (MANOVA) with significance set at the .01 level, with follow-up analyses of variance (ANOVA) tests. The results indicated that cocaine users scored significantly differently than matched controls on the omnibus measure of personality traits [Wilks's Λ = .57, $F(3, 69) = 17.2$, $p<.001$. $\eta2 = .43$] and particularly on externalizing of substance use ($F=43.41$, $p<.001$, $\eta2 = .38$) and non-planning ($F=29.75$, $p<.001$, $\eta2 = .30$). Binger eaters scored significantly higher than normal weight controls only on the externalizing of substance use [F(2, 52) = 5.2, p = .009. $\eta 2$ = .16], and were not significantly higher than over-weight controls on any of the subscales.

Group effect on discounting rates for cocaine addicts versus controls. To directly compare the delay discounting rate and probability discounting rate, the natural log transformed delay discounting rate and probability discounting rate were standardized based on the means of the control group. Because a Box's test of equality of covariance matrices suggests the observed covariance matrices of the discounting rates were not equal across groups, F(1, 73) = 7.96, *p* <.001, multivariate analysis of variance (MANOVA) , rather than the repeated measures-ANOVA, was used to test the group difference. The results of the MANOVA suggest there was a significant overall group difference on discounting rates, Wilks's Λ=.847, F(2, 72)=6.51, *p* = .003. $\eta 2$ = .153. Specifically, the cocaine users had significantly higher delay discounting rates than the controls, F (1, 73) = 13.08, *p* = .001, $\eta 2$ = .152. However, there was no significant group difference on probability discounting rate between cocaine users and controls, F (1, 73) = .878, *p* = .352, $\eta 2$ = .012. After controlling for ethnicity (Caucasian or non-Caucasian), the group difference on delay discounting rate continued to be significant, F (1, 72) = 7.30, p = .009, $\eta 2$ = .092. These results suggest the decision making bias in cocaine addicts is specific to decisions associated with delayed rewards.

Table 4.2 *The t Test Results of Group Difference (Cocaine VS Controls) in Delay Discounting at Each Time Scale*

Delay (days)	Group difference (cocaine-control)	t	*p* value*
1	-1.522	-3.811	<0.001
2	-1.767	-4.160	<0.001
30	-2.368	-3.445	<0.001
180	-2.458	-3.643	0.001
365	-1.581	-2.526	0.014

Note: *p*-values ascertained using a bootstrap method.

To further analyze the group difference at each time scale of delay discounting task, t tests with bootstrap resampling were used to compare group means of indifference points at each delay time (1, 2, 30, 180, 365). Because non-independent correlations were tested, Type I error rate was set at .01. As shown in Table 4.2, the cocaine group showed significantly lower indifference point at day 1, 2, 30, 180, but not at day 365. To illustrate the group difference on delay discounting rate, mean indifference points and confidence intervals were calculated with bootstrap resampling at each time scale and were fit with hyperbolic model (see Figure 4.1).

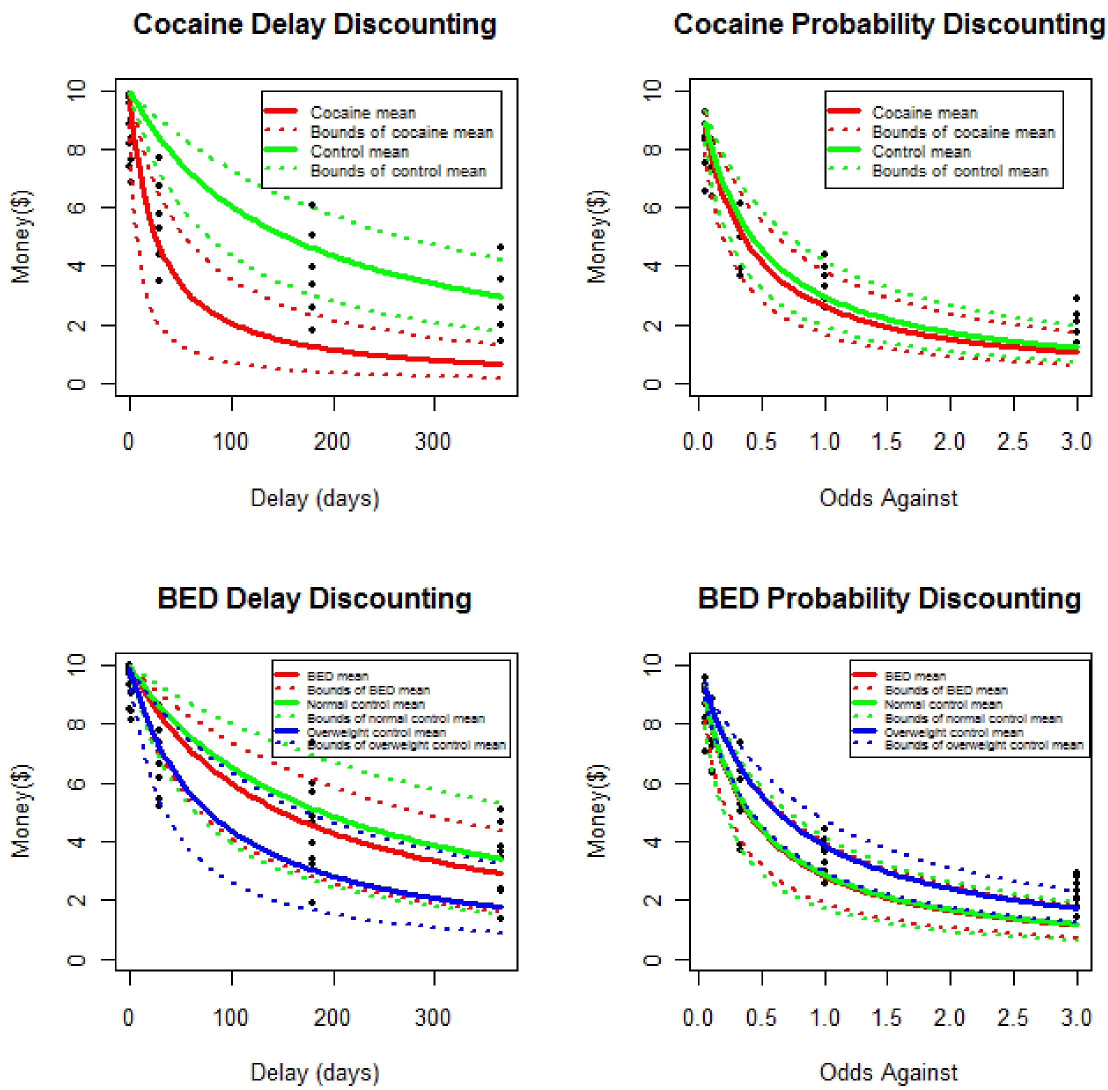


Figure 4.1. Mean discounting curves as described with hyperbolic model in cocaine addicts and binge eaters. The top set of graphs shows the mean discounting curves and confidence intervals in cocaine group (*n*=36) and matched controls (*n*=39). Top left figure shows the means (solid lines) and confidence intervals (dotted lines) for delay discounting curves in cocaine group (red) and controls (green). Top right figure shows mean discounting curves and confidence intervals for probability discounting curves in

cocaine users and controls. The bottom set of graphs shows data for binge eaters (red, *n*=20), normal-weight controls (green, *n*=16), and overweight controls (blue, *n*=19). Details are the same as in the top set of graphs.

As shown in Figure 4.1, the cocaine group showed a much steeper discounting on decisions associated with delay rewards (top left), but not on decisions associated with probabilistic rewards (top right), indicating the cocaine group was much more impatient and more likely to select small but immediate rewards than the controls.

Associations between delay discounting rate and self-report measures of impulsivity. Pearson's correlations were calculated to investigate the association between individual difference variables and discounting measures. Again, type I error rate was set at .01. Delay discounting rate was negatively and significantly correlated with Substance Use on the AES in the cocaine user group (r = -.48, n = 36, p = .003), but not in normal controls (r = 0.013, n = 39, p = .94). The difference between these correlations was statistically significant, Z = -2.22, p =.01. These findings indicated the cocaine users who had higher delay discounting rates also tended to have lower self-reported substance use problems, which is contradictory to the current hypothesis. The probability discounting rate was not significantly correlated with any personality subscales at the .01 level for either the cocaine group or the normal group.

Group effect on discounting rates for binge eaters versus controls. As shown in Figure 4.1 (bottom figures), Binger eaters did not show significantly higher or lower discounting curves than controls on delay rewards or probability rewards. A MANOVA was employed to analyze the group difference among binge eaters, normal-weight controls, and over-weight controls. No significant group effect was found, Wilks's Λ = .965, $F(4, 106) = .475$, $p = .754$. $\eta 2 = .018$.

Study 1 Discussion and Conclusions

Study 1 examined the specificity of decision making bias in cocaine dependence when the discounting data were analyzed using the hyperbolic function. Partially consistent with hypotheses, the results showed that cocaine users had significantly higher delay discounting rates than controls. However, inconsistent with hypotheses, they did not have significantly lower probabilistic discounting rates than controls. These findings indicate the decision making bias in cocaine addicts is specific to delayed rewards. That is, cocaine addicts are more impatient, but they are not necessarily higher risk takers.

Another finding from this study is that the decision making bias about delay rewards existed in cocaine users but not in binge eaters. These results indicate decision making bias is not a general feature of impulsivity, but rather is a specific bias of drug users.

The findings regarding the correlations between delay discounting rate and personality measures of impulsivity were not anticipated. Based on the results of Study 1, delay discounting rate in cocaine addicts was significantly and negatively correlated with the Substance Use factor (featuring, for example, marijuana problems and drug use) as assessed by the Adult Externalizing Scale. Given that cocaine-dependent participants did show a higher impulsive propensity on these factors than the controls, and the positive correlations between these factors and other personality measures of impulsivity, it is unlikely the significant and negative correlations between the externalizing factors and delay discounting rates were due to random responses.

Study 1 replicated the results of previous studies showing cocaine addicts tend to have higher delay discounting rates than controls. However, there was no significant group difference on probability discounting rate between cocaine addicts and controls. The delay discounting rate was positively and significantly correlated with the probability discounting rate in cocaine addicts (r = .445, n = 36, p = .007), but not in controls (r = .234, n = 39, p = .151). It is unclear whether the observed group difference on delay discounting rate in cocaine is due to the decision factor associated with reward valuation (value currency), which is probably common for both delay discounting and probability discounting, or the decision factor associated with time valuation, which is specific to delay discounting. Accordingly, Study 2 was conducted to answer this question.

Study 2: Decision Bias Described by the Saturating-Hyperbolic Function

Study 2 Introduction

The relationship between delay discounting and probability discounting in decision making has been investigated in a number of studies. There are some indications that delay discounting and probability discounting share certain commonalities. These commonalities include a similar conceptual framework and mathematical function (Green & Myerson, 2004). There is also a common neural system involved in both delay discounting and probability discounting (Peters & Büchel, 2009). However, there is also evidence that delay discounting and probability discounting involve at least some distinct processes. There are opposite magnitude effects on delay discounting and probability discounting in that a smaller reward magnitude leads to steeper delay discounting rate and shallower probability discounting rate (Du, Green, & Myerson, 2002; Green, Myerson, & Ostaszewski, 1999; Joel Myerson, 2003). Factor analyses indicate that delay discounting and probability discounting load on different factors (Estle, et al., 2007). Correlational studies indicate the delay discounting rate and probability discounting rate are either not significantly correlated (Olson, Hooper, Collins, & Luciana, 2007; Reynolds, Richards, Horn, & Karraker, 2004) or they are significantly and positively correlated (Estle, et al., 2007; Joel Myerson, Green, Scott Hanson, Holt, & Estle, 2003). These findings suggest there are common and distinct factors involved in delay discounting and probability discounting. However, the standard method of using the hyperbolic model to analyze discounting data does not allow for differentiation of the distinct factor from the common factor in delay discounting and probability discounting. On the other hand, a two-parameter model, such as the saturating-hyperbolic function, is more promising in this regard.

Study 2 Method

The methods for this study were described previously in the general method section. In particular, the discounting parameters were calculated using the following saturating-hyperbolic function, where A is the amount of the objective reward, and Q determines the amount with which the utility curve saturates, while d represents the delayed time in delay discounting or the odds against receiving the reward in probability discounting (Doya, 2008).

$$\frac{V}{A} = \frac{A}{(A+Q)} \times \frac{1}{(1+kd)}$$

This model generates discounting rates (k’.delay and k’.probability) and saturation indices (Q.delay and Q.probability).

Study 2 Result

Preliminary analyses. Delay discounting data from one control participant for the binge eating group did not fit the model. Probability discounting data from two cocaine addicts and one cocaine control did not fit the model. Therefore, their associated discounting parameters are shown as missing data.

Kolmogorov-Smirnova tests of normality were performed on all of the parameters. The distributions of discounting parameters from the saturating-hyperbolic model (k’.delay, k’.probability, Q.delay, and Q.probability) were significantly different from a normal distribution even after the log transformation. Thus, these parameters were further analyzed using non-parametric statistical methods.

Group difference in delay and probability discounting among cocaine addict sample. Mann-Whitney U tests showed the cocaine group had a significantly higher delay saturation index ($z = -2.317$, sig. = .02) and higher probability saturation index ($z = -2.244$, sig. = .025) than the controls. However, there was no significant group difference between the cocaine group and the control group for either delay discounting rate ($z = -1.62$, sig. = .106) or probability discounting rate ($z = -1.89$, sig. = .06). These results suggest the observed decision bias in cocaine addicts is more strongly associated with the decision factor related to value currency rather than with the decision factor related to time valuation. These findings are consistent with the t test results shown in Table 4.2 which indicated stronger group difference at the early time scales.

Because group difference was found in probability discounting between the cocaine group and the control group, t tests with bootstrap resampling were used to compare group means of indifference point at each probability scale (95%, 90%, 75%, 50%, 25%). Type I error rate was again set at .01. As shown in Table 4.3, the cocaine group showed significantly lower indifference point only at probability scale of 95%.

Table 4.3 *The t test Results of Group Difference (Cocaine VS Controls) in Probability Discounting at Each Time Scale*

Probability Scale	Group difference of Indifference Point	t	*p* value
95%	-1.352	-2.644	0.009
90%	-1.093	-1.936	0.054
75%	-0.143	-0.239	0.805
50%	0.381	0.715	0.453
25%	0.305	0.815	0.420

To illustrate the group difference on probability discounting rate, mean indifference points and confidence intervals were calculated with bootstrap resampling at each time scale and were fit with the saturating-hyperbolic model.

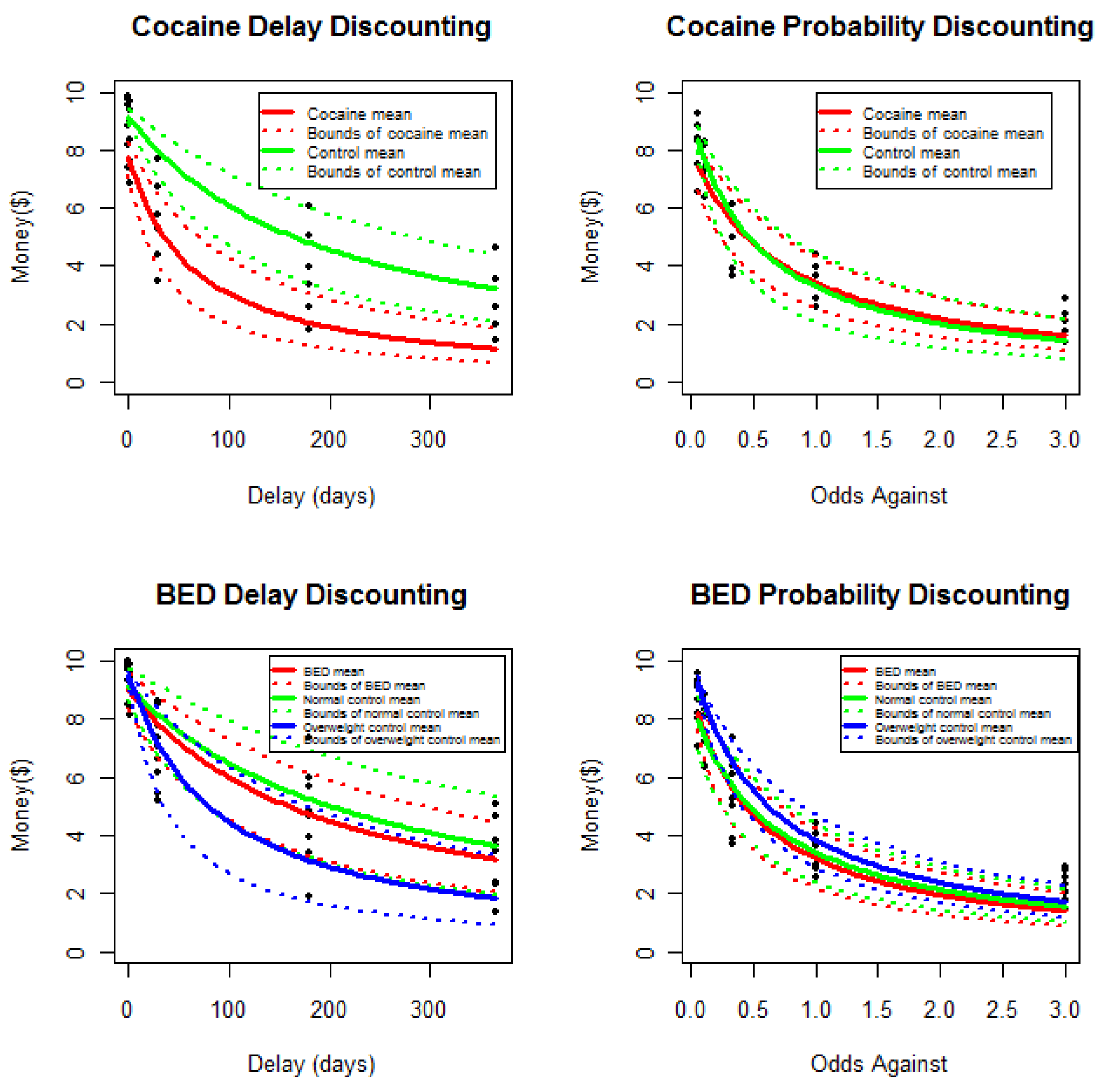


Figure 4.2. Mean discounting curves as described with saturating-hyperbolic model in cocaine-dependent (CD) adults and individuals with binge eating disorders (BED). The top set of graphs shows the mean discounting curves and confidence intervals in CDs (*n*=36) and matched controls (*n*=39). Top left figure shows the means (solid lines) and confidence intervals (dotted lines) for delay discounting curves in CDs (red) and controls (green). Top right figure shows mean discounting curves and confidence intervals for probability discounting curves in CDs and controls. The bottom set of graphs shows data

for binge eaters (red, *n*=20), normal-weight controls (green, *n*=16), and overweight controls (blue, *n*=19). Details are the same as in the top set of graphs.

As shown in Figure 4.2, when the discounting data were analyzed using the saturating-hyperbolic model, the cocaine group showed a much lower start point of discounting than the controls for decisions associated with delay rewards (top left); however, the slopes of the curves were similar. Thus, the two curves that represented the mean of the delay discounting curves appeared to be parallel. Similarly, the cocaine group also showed a lower start point of discounting than the controls for decisions associated with probability rewards (top right), but the curve was slightly flatter than for the controls.

Associations between discounting parameters and self-report measures of impulsivity. Spearman correlations were performed to investigate the associations between individual difference variables and discounting parameters. Because non-independent correlations were tested, type I error rate was set at .01. Neither the delay discounting rate nor probability discounting rate was significantly correlated with scores on any personality measures of impulsivity for either the cocaine group or the control group. The delay saturation index was not significantly correlated with scores on personality measures of impulsivity in the cocaine group, but it was positively and significantly correlated with substance use (r = .422, n = 37, p = .009), as measured by the AES, for controls. There were no significant correlations between the probability saturation index and scores on the personality measures for either the cocaine group or the control group.

Group effect on discounting rates among binge eaters. The group difference in discounting rates among binger eaters, normal controls, and over-weight controls was analyzed using Kruskal-Wallis tests. As shown in Figure 4.2 (bottom part), there were no significant between-group differences for binge eaters, normal controls, and overweight controls on delay discounting rate (x^2 =3.79, *df*=2, sig.=.15), probability discounting rate (x^2 =.033, *df*=2, sig.=.98), delay saturation index (x^2 =1.89, *df*=2, sig.=.39), or probability saturation index (x^2 =2.98, *df*=2, sig.=.23). Thus, binge eaters did not show significantly higher or lower decision bias on delay rewards or probability rewards compared to normal-weight or over-weight controls.

Study 2 Discussion and Conclusions

Study 2 investigated the specificity of decision making bias in cocaine addicts when the discounting data were analyzed using the saturating-hyperbolic function. Inconsistent with one hypothesis, the results showed the cocaine users did not have significantly higher delay discounting rates or lower probability discounting rates than controls. However, cocaine users showed significantly higher saturation indices on both delay discounting and probability discounting. The results indicated that the decision making bias in cocaine users is associated with a decision factor related to the value currency rather than a decision factor related to the time valuation or risk valuation.

Another finding from this study is that individuals from the normal population who have more disinhibition problems tended to have a higher delay saturation index. However, this correlation appeared to not be significant in the cocaine group. This finding is probably due to other factors that contribute to the severity of the disinhibition problems in cocaine users and also because the discounting parameters are less stable than the personality measures (Coffey, et al., 2003; Amy L. Odum & Baumann, 2010).

Consistent with the results in Study 1, the cocaine users did not share the decision bias with binge eaters, indicating this is a robust finding. One explanation is that the reinforcement effects of drugs have contributed to the decision making bias. In Heil et al.'s (2006) study of current cocaine users, abstinent cocaine users, and controls, the researchers found a non-significant group effect for delay discounting rates. Their results raise a question about whether the decision making bias is sensitive to drug use status.

Discussion and General Conclusions

The current studies investigated the specificity of decision making bias in cocaine users by analyzing the delay discounting data with both a hyperbolic function and a saturating-hyperbolic function. When the data were analyzed by the hyperbolic function, the cocaine users showed more bias than controls on decisions associated with delayed rewards, but not on decisions associated with probabilistic rewards. However, when the data were analyzed by the saturating-hyperbolic function, the cocaine addicts exhibited decision bias on decisions associated with both delayed rewards and probabilistic rewards. The decision bias in cocaine addicts was found to be specific to reward valuation or value currency rather than time valuation. One explanation is that the saturating-hyperbolic function described the discounting data more specifically and more accurately, allowing the differentiation between the reward valuation and time valuation in delay discounting. An alternative explanation is that saturation parameters are measured with more precision than are discounting parameters within the saturating-hyperbolic model. To this investigator's knowledge, there is no way to evaluate the goodness of fit for the different parameters in the model that are fit simultaneously. Although unlikely, it is theoretically possible that the appearance of a group difference is due to a general bias on these decision-making tasks combined with better measurement of the saturation parameters than the discounting parameters.

The findings about the correlations between discounting parameters and personality measures of impulsivity were not exactly anticipated. Some of the correlations, however, are consistent with those of previous studies. Specifically, the non-significant correlations between delay discounting rate and subscales on the Barrat Impulsivity Scale in both studies confirm the results of Coffey, Gudleski, Saladin, and Brady (2003) in which delay discounting rate was not correlated with BIS for either a cocaine group or control group, and the results of Reynolds et al. (2006) which showed a non-significant correlation between delay discounting rate and BIS in a normal sample. One explanation is that the personality trait of impulsivity contributes to the initiation of drug use, but it may not predict drug use or relapse when the effect of pharmacological change in the brain becomes more important (Kreek, Nielsen, Butelman, & LaForge, 2005).

This study has certain noteworthy limitations. First, although participants were selected using stringent inclusion and exclusion criteria, the statuses of cocaine dependence, binge eating disorder, and healthy controls were based on self-report information. Further, the cocaine users reportedly had an average of about 15 years of cocaine use. The negative correlations between externalizing characteristics and delay discounting rate obtained in the present research may not be generalizable to cocaine users with a shorter use history. Finally, the sample sizes of participants with binge eating disorder, over-weight controls, and normal-weight controls were relatively small, and only female participants were involved. Further study with larger and more heterogeneous samples are needed to replicate the findings from this study.

Chapter 5

A Personality Measure of Time Preference: Latent Trait Estimates Disentangling the Association Between Impulsivity and Impatient Financial Planning

Introduction

"Time preference" refers to the proclivity for immediate rewards or consequences over delayed rewards or consequences (Frederick, Loewenstein, & O'Donoghue, 2002). The concept of time preference was proposed by Böhm-Bawerk (1889) as a psychological characteristic of impatience in decision making. The term "preference" is meant to indicate a stable internal characteristic (Glimcher, Camerer, Fehr, & Poldrack, 2009). To measure this internal characteristic, early economists studied consumer behaviors and developed a mathematical structure of a decision making model. An experimental model of time preference was first introduced by Samuelson (1937). His discounted-utility model emphasizes a decision maker's time preference over consumption profiles and uses a single parameter—delay discounting rate—to represent all of the person's psychological concerns, such as uncertainty of human life, pleasure of receiving an immediate reward, and tendency to underestimate future wants (Frederick et al., 2002). This model soon became widely accepted due to its simplicity and elegance (Frederick et al., 2002). Based on the construct of time preference, economists have classified individuals using the delay discounting rate (Camerer, Loewenstein, & Prelec, 2005; Rustichini, 2009).

The delay discounting task is also often used in psychology research on impulsivity. Delay Discounting (DD) has been associated with a number of impulsive disorders, particularly in the area of substance abuse (e.g., Bornovalova, Daughters, Hernandez, Richards, & Lejuez, 2005; Heil, Johnson, Higgins, & Bickel, 2006; Odum, Madden, & Bickel, 2002; Yi, de la Piedad, & Bickel, 2006). Within the literature on substance abuse, cocaine addicts appeared to have higher delay discounting rates than other substance users (e.g., alcohol and heroin users; Bornovalova et al., 2005; Heil, Johnson, Higgins, & Bickel, 2006; Kirby & Petry, 2004). Therefore, there is a great deal of overlap between the economic literature on time preference and the psychology literature on impulsivity. However, it is still unclear as to how the construct of time preference in the economic literature is associated with the construct of impulsivity in the psychology literature.

Traditionally, impulsivity is also perceived as a personality trait, and it has been studied extensively using personality assessments. One widely use personality assessment for impulsivity is the Barratt Impulsiveness Scale (BIS) (Patton, Stanford, & Barratt, 1995). Studies on the relationship between impulsivity, as measured by the BIS, and the delay discounting rate have yielded inconsistent results. For example, delay discounting rate was observed to be positively and significantly correlated with Nonplanning on the BIS in a normal sample (BIS-11; de Wit, Flory, Acheson, McCloskey, & Manuck, 2007; Kirby & Finch, 2010; Mitchell, 1999). However, other studies indicated no significant correlations between delay discounting rate and subscales on the BIS-11 in samples obtained from the normal population (Reynolds, Ortengren, Richards, & de Wit, 2006), or in samples drawn from the impulsive population (Dom, De Wilde, Hulstijn, van Brink, & Sabbe, 2006; Johnson et al., 2010). One possible explanation for the discrepancy is the difference in measurement methods: the construct of time preference is measured by behavioral assessment (delay discounting task), while the construct of impulsivity is measured by a self-report personality assessment (BIS-11). Although the BIS-11 has high demonstrated reliability, the delay discounting measure is less stable than it would appear (Patton, Stanford, & Barratt, 1995; Glimcher, Camerer, Fehr, & Poldrack, 2009).

Thus, a reasonable step to explore the relationship between the construct of time preference and the construct of impulsivity would be to compare a reliable personality measure of time preference with responses to the BIS-11. To this author's best knowledge, however, there is no such measure that directly and reliably estimates time preference. In the literature on time preference, several factors have been used to explain the decision maker's time preference. Some of these factors are rational components of decision making, such as income and education; while some are irrational components, such as addictions and uncertainty (Becker & Mulligan, 1997). In a review by Frederick et al. (2002), the psychological component of time preference was determined by three specific constituent motives—spontaneous acts, the tendency to make plans and stick with them, and (lack of) the ability to inhibit one's automatic response. Similarly, Camerer et al. (2005) suggested a model of time preference that emphasizes the ability to think about the future, the types of situations that motivate people to be impatient, and the ability to inhibit behaviors that may lead to long-term consequences. Based on the literature, Drs MacDonald and Krueger in Department of Psychology and Dr. Rusticini in Department of Economy recently developed the Time Preference Scale to measure the individual difference of time preference. The purposes of the current study were to determine the psychometric properties of this scale, explore the association between time preference and impulsivity, and answer the following questions:

1) What are the item characteristics and item information of this measure, and what is the distribution of the latent trait of time preference in the current sample?

2) What are the convergent and divergent validity of the Time Preference Scale? It was hypothesized that the latent trait of time preference would be significantly correlated with delay discounting rate, but not with the probability discounting rate.

3) What is the concurrent validity of the Time Preference Scale, or to what extent does the Time Preference Scale differentiate normal samples from samples with addictive disorders? The hypothesis was that the latent trait in psychiatric groups (both cocaine addicts and binge eaters) would be significantly lower than that in the normal groups, and the latent trait of cocaine addicts group would be significantly lower than that of the binge eating disorder (BED) group.

4) What are the correlations between the latent trait of time preference, the delay discounting rate, and the personality measure of impulsivity, as measured by Barratt Impulsiveness Scale? The hypothesis was that the latent trait of time preference would be significantly correlated with both delay discounting rate and the Barratt Impulsiveness Scale, and the latent trait of time preference would predict delay discounting rate better than the Barratt Impulsiveness Scale.

Methods

Participants and Procedure

Participants in the current study were recruited either from undergraduate courses at the University of Minnesota or from the Twin Cities community through paper advertisement. A sample of 188 undergraduate students participated in the pilot study for the Time Preference Scale in which 19 candidate items (see Appendix E) were administered individually by research assistants in TRiCAM lab in Department of

Psychology. Based on the results of the pilot study, 9 items were selected as one dimension of the Time Preference Scale. Of the remaining items, 2 items were also closely correlated with the selected items, but they were removed due to high conceptual and contextual overlap.

Data for the final version of the Time Preference Scale were collected in three separate phases, which resulted in several non-overlapping samples of psychiatric adults, matched controls, and undergraduate students. Participants included 112 undergraduate students, 42 cocaine dependent adults (CD), 42 matched healthy controls for cocaine users, 28 adults with binge eating disorder (BED), and 40 controls for BEDs (including the overweight controls). All participants completed Delay Discounting task (measures temporal preference), and Probability Discounting Task (measures risk taking propensity), the Time Preference Scale, BIS, as well as other personality measures not discussed in the current study.

The total sample size was 264. All participants were between ages 18 and 46 years. The sample characteristics are shown in Table 5.1.

Table 5.1 *Sample Characteristics*

Characteristic	Group					
	Undergrad (19-item)	Undergrad (09-item)	CDs	CD Controls	BEDs	BED Controls
n	189	112	42	42	28	40

Age	22.98 (9.04)	20.12 (3.86)	38.48 (7.10)	38.44 (7.34)	32.18 (8.18)	30.35 (7.85)
Gender (% female)	66.1	66.3	21.43	21.43	92.86	100
Race (% Caucasian)	--	69.2	38.1	69.05	71.4	80.0
% Native American		0	7.1	2.4	3.6	0
% Native Hawaiian		0	2.4	0	0	0
% Asian		22.3	0	0	3.6	0
% African American		5.4	40.5	21.4	21.4	10.0
% Hispanic		0.9	4.8	4.8	0	2.5
% Other		4.5	7.0	2.4	0	2.5
Education (in years)	13.52 (2.14)	13.18 (1.36)	12.93(1.54)	14.05 (3.09)	15.43 (1.91)	14.46 (2.71)

Note. The 19-item version refers to the Time Preference Scale used in the pilot study. The 09-item version refers to the revised version of the Time Preference Scale used in the current study. CD refers to the cocaine dependent adults. BED refers to participants with binge eating disorder.

Measures

The time preference scale. The Time Preference Scale (TiPs) measures self-reported tendency to prefer immediate rewards compared to larger, long term rewards. The final version of TiPs consists of 9 items. Each item is rated on a scale, where 4 =

very true for me, 3 = somewhat true for me, 2 = somewhat false for me, and 1 = very false for me. Three of the 9 items (Item 3, 5, and 8) are reverse-scored, with higher scores indicating a lower delay discount tendency and more planning for the future.

Barratt impulsiveness scale (BIS-11; Patton, Stanford, & Barratt, 1995). The BIS-11 was used to measure personality traits of impulsiveness. This 30-item scale is composed of three factors: Attentional Impulsiveness, Motor Impulsiveness, and Nonplanning Impulsiveness.

The discounting measures (Richards, Zhang, & de Wit, 1999). The delay discounting task measured the subjective values after certain delays. It used a computerized random adjusting-amount procedure in which the smaller and immediate reward was adjusted until the value of the small reward was equal to the subjective value of the large and delayed reward (which meant an indifference point was reached). The task allowed participants to choose $10 after a delay (1, 2, 30, 180, or 365 days) or an immediate and smaller reward. For example, participants were offered the following choice: Would you rather have $5 now or $10 in 30 days? After the participant made a choice, the answer was used by the program to narrow the range of the immediate rewards for the subsequent questions. A series of questions were presented until an indifference point at a certain delay time was reached. In addition, the adjusting nature of the task was masked by mixing the delay discounting questions and probability discounting questions. Because there were 5 delay times, completing the task would lead to 5 indifference points which yielded a delay discounting rate (k.delay) through a hyperbolic function. A higher k.delay meant there was a steeper discounting function and a stronger preference for more immediate and smaller outcomes (or greater impatience).

The probability discounting task measured the subjective values with certain probability against receiving the reward. In the task, participants were asked to choose between $10 with a given probability (95%, 90%, 75%, 50%, 25%) and a smaller amount of guaranteed money. For example, one of the questions was “Would you rather take $5 for sure or $10 with a 50% chance?” Again, the smaller and assured reward was adjusted until an indifference point was reached for each probability level. The adjusted procedure was masked by mixing the probability questions with the delay questions. The 5 indifference points generated from the 5 probability levels were used to calculate a probability discounting rate (k.probability) using the hyperbolic function. A higher k.probability meant a steeper discounting function and stronger preference for more certain and smaller rewards (or higher risk aversion).

Data Analysis

Data for the Time Preference Scale obtained from the pilot study were used to evaluate the19 candidate items. Exploratory factor analyses showed the largest factor was composed of 9 items. Reliability analyses indicated these 9 items showed strong item-total correlations and an overall Cronbach’s alpha of .81, indicating good internal consistency. Data for the final version of Time Preference Scale were first analyzed to determine their unidimensionality.   A confirmatory factor analysis for one factor was conducted using Lisrel software.

The Graded Response Model (Samejima, 1969) was considered as an appropriate IRT model for the current study given that the ratings of each item assume an ordering of the levels. The model is a type of polytomous IRT model designed for ordinal variables. The model is defined as the following equation where β represents the person's ability, α represents the item discrimination, and λ represents the level boundaries. The ltm package for R was used for the current IRT analysis.

$$\pi_{kni} = \frac{\exp[\alpha_i(\beta_n - \lambda_{ik})]}{1 + \exp[\alpha_i(\beta_n - \lambda_{ik})]}$$

Results

Item Descriptive Statistics

As shown in Table 5.2, each item was completed by at least 259 participants. Because the total participants were 264, item missing rates were 2% or lower. A brief descriptive analysis showed no specific pattern in these missing data; thus the missing responses were included as a response type in the following analysis. The highest mean item score was for the first item—*I plan for my future*; while the lowest mean item score was the fourth item—*I spend a lot of time planning my financial future*.

Table 5.2 *Item Descriptive Statistics for the Time Preference Scale*

Item	*n*	*r*	*r*.cor	*r*.drop	mean	SD
Qti01	259	0.69	0.64	0.57	3.3	0.79
Qti02	261	0.75	0.71	0.66	3	0.92

Qti03	260	0.69	0.66	0.60	2.5	0.97
Qti04	262	0.70	0.66	0.57	2.4	0.93
Qti05	261	0.63	0.57	0.52	2.6	0.88
Qti06	259	0.78	0.75	0.69	2.9	0.91
Qti07	260	0.43	0.31	0.28	3.1	0.83
Qti08	259	0.52	0.44	0.39	2.8	0.99
Qti09	260	0.71	0.68	0.60	3.0	0.77

Unidimensionality

Cronbach's alpha was .83 for the Time Preference Scale, and it was higher than .80 for each item. The item-total correlations were between .32 (item 7--I*'d rather face a problem now than let it get any worse*) and .75 (item 6--*I'm very thoughtful about where my money goes*).

The confirmatory factor analysis for one factor model did not indicate a satisfactory fit of the data (CFI = 0.89, Standardized RMR = 0.089, RMSEA = 0.16). According to Hu and Bentler (1998), the parameter of standardized RMR (SRMR) is the most sensitive fit index for a small sample, and a cutoff value close to .08 for SRMR is considered a good fit. Table 5.3 shows that the estimates of the factor loadings ranged from .35 (item 7) to .77 (item 6), which is consistent with the pattern of item-total correlations.

Table 5.3 *Factor Loadings from One-Factor Confirmatory Factor Analysis for Items on Time Preference Scale*

Item	Loading	SD error	t statistic
Qti01	0.61	--	--
Qti02	0.71	0.09	8.35
Qti03	0.65	0.08	7.8
Qti04	0.63	0.08	7.63
Qti05	0.54	0.08	6.74
Qti06	0.77	0.09	8.79
Qti07	0.35	0.08	4.68
Qti08	0.47	0.08	6.05
Qti09	0.68	0.08	8.08

IRT Parameters

The item descriptive statistics suggested that the discrimination of each item may be quite different. To confirm this hypothesis, 2 models were compared to determine whether the model with the discrimination parameter fit better. The first model was set to estimate all parameters, including α (discrimination), β (ability), and λ (category threshold). An alternative model in which α was fixed was used to compare it with the first model. As shown in Table 5.4, all of the fit indices for the first model were lower than those for the alternative model, indicating that the first model fit better.

Table 5.4 *The Fit Index of the Original and Alternative Models*

Model	Log.Like	AIC	BIC

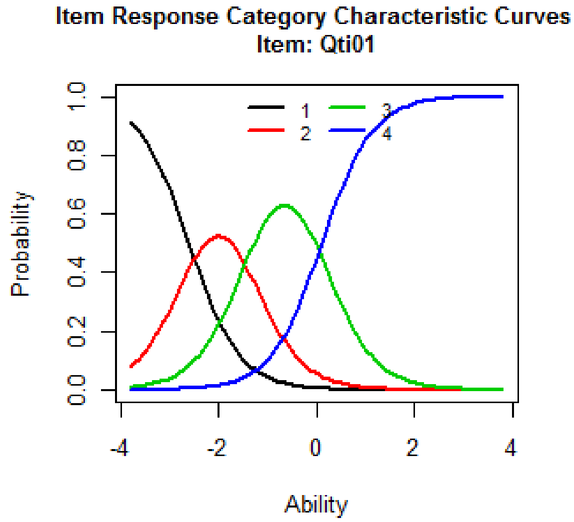
First	-2618.359	5308.718	5438.527
Alternative	-2658.47	5372.94	5473.903

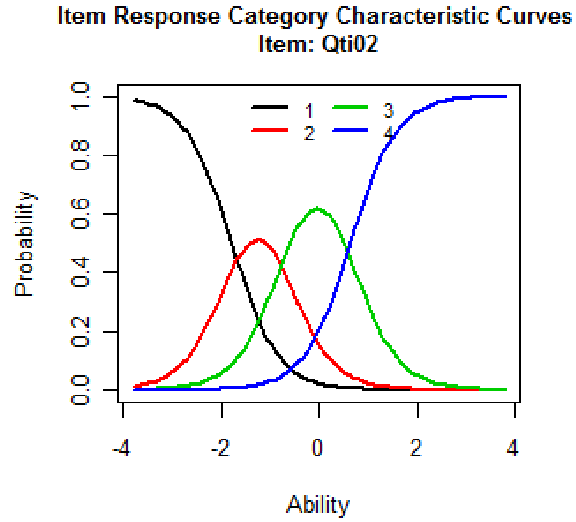
Table 5.5 presents the item discrimination and the category threshold estimates for all items. As shown in the table, thresholds 1, 2, and 3 were in order for each item, suggesting that the assumption of ordinal levels of responses is met. Further, the discriminations for all items seemed to be high, with the exception of item 7. In addition, item 7 has the lowest threshold. Thus, the rating 1 (very false for me) for item 7 (*I'd rather face a problem now than let it get any worse*) is too easy for most people to consider. In fact, Figure 5.1 suggests that people across the spectrum of the latent trait all have higher probability of endorsing higher ratings than "very false for me" on this item. Item characteristic curves for the other 8 items are also illustrated in Figure 5.1. The rating system for the 8 items appears to be functioning well because each category of each item had the highest probability of being chosen by people across the spectrum of the latent trait.

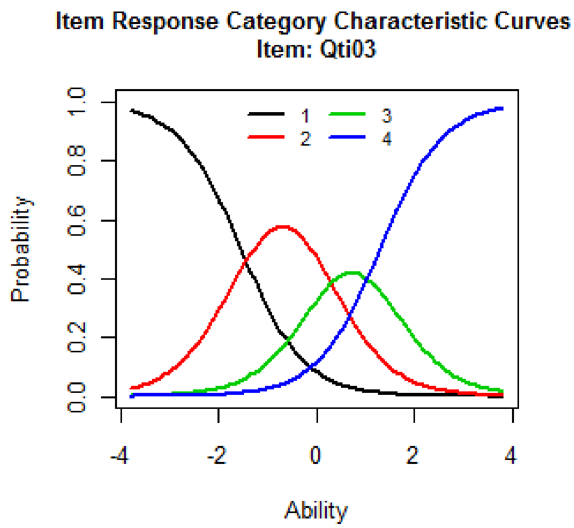
Table 5.5 *Item Parameters*

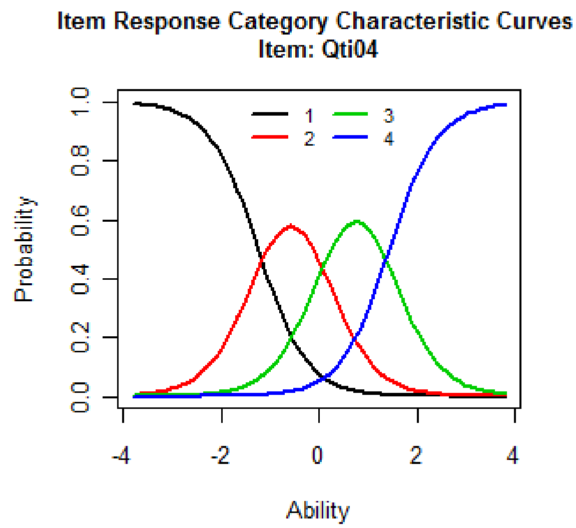
Item	Threshold 1	Threshold 2	Threshold 3	Discrimination
Qti01	-2.609	-1.422	0.113	1.959
Qti02	-1.795	-0.732	0.632	2.151
Qti03	-1.562	0.134	1.275	1.552
Qti04	-1.278	0.069	1.484	1.89
Qti05	-1.855	-0.101	1.614	1.429

Qti06	-1.685	-0.552	0.686	2.544
Qti07	-4.564	-2.184	0.714	0.716
Qti08	-2.482	-0.557	1.19	0.917
Qti09	-2.336	-1.147	0.725	2.064









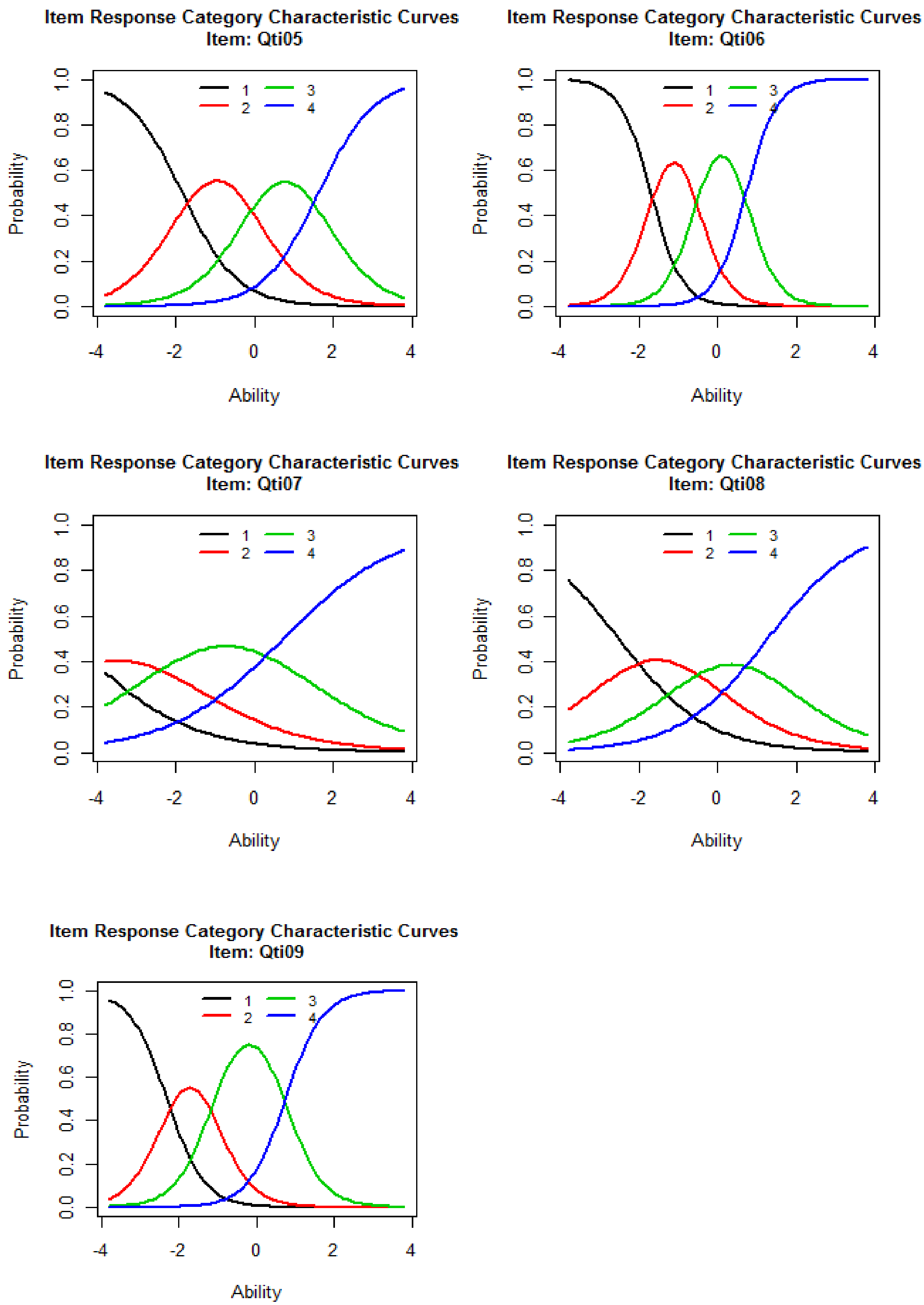


Figure 5.1 The item characteristic curves

Figure 5.2 shows the item information curves. Item 6 and item 2 provided peak information for the median level of the latent trait, while item 1 and item 9 provided more information for the lower level of the latent trait, and items 3, 4, and 5 provided more information on the higher level of the latent trait of time preference. However, item 7 and item 8 did not seem to provide additional information beyond the other 7 items.

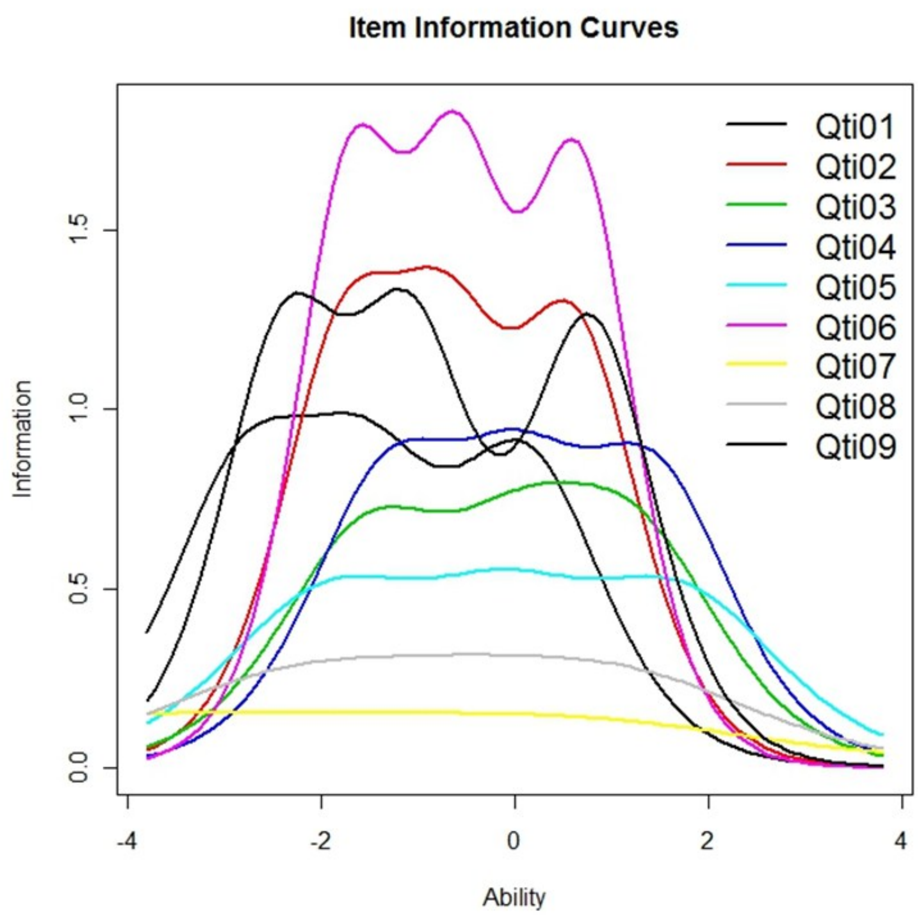


Figure 5.2 The item information curves

The estimated β ranged from -2.71 to 2.08. The distribution of the latent trait (time preference) was not significantly different from a normal distribution, as shown in Figure 5.3. (R. Yi, et al., 2006)

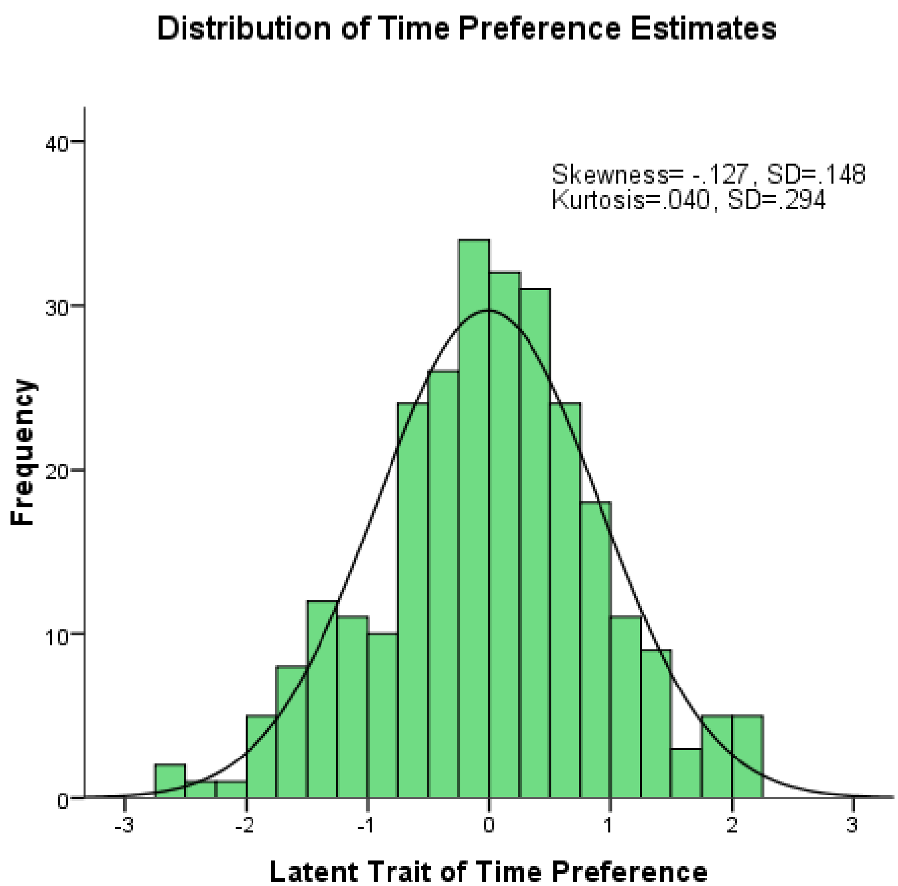


Figure 5.3 The distribution of latent trait

Validity Analyses

To explore the convergent validity and discriminant validity of the TiPs and to determine the correlation between the latent trait of time preference and the delay discounting rate, as measured by the Delay Discounting Task, Spearman's correlations were calculated on the latent trait, the delay discounting rate, and the probability discounting rate. The results suggested the latent trait of time preference was significantly correlated with delay discounting rate (r = -.200, n = 238, p = .002), but not with probability discounting rate (r = -.039, n = 218, p = .571). In addition, the latent trait of time preference was not significantly correlated with the delay saturation index (r < .001, n = 238, p = .996) or probability saturation index (r = -.022, n = 218, p = .745).

After the natural log transformation, the delay discounting rate was not significantly different from a normal distribution in the overall group (z = .713, n = 237, p = .689). The result of Pearson correlation suggest the latent trait of time preference was still significantly correlated with the delay discounting rate (r = -.164, n = 237, p = .01). After controlling for group membership (whether clinical group or not), the latent trait of time preference was still significantly correlated with the delay discounting rate (r = -.171, df = 200, p = .015). These results indicate the convergent validity and discriminant validity of the TiPs with laboratory decision-making measures are moderate and significant.

In addition, the Pearson correlation between time preference and non-planning was negative and significant (r = -.696, n = 194, p < .001); and the correlation between time preference and total score on the Barratt Impulsiveness Scale was also negative and significant (r = -.634, n = 194, p < .001). These results indicate the convergent validity of the TiPs with other measures of impulsivity is high and significant.

To explore the concurrent validity of the TiPs, an ANOVA was performed on the estimates of individual difference in time preference for the cocaine group, the BED group, and the matched control groups. The group effect was significant, $F(1, 148) = 26.92$, $p < .001$, $\eta^2 = .15$. As shown in Figure 5.4, the control groups had significantly higher scores on the latent trait of time preference, indicating the control groups generally plan more for the future. The ANOVA result showed that the study effect was also significant, $F(1, 148) = 7.45$, $p = .007$, $\eta^2 = .05$. As indicated in Figure 5.4, participants in the cocaine study had a lower mean of time preference score than participants in the BED study. The interaction between study and group was significant, $F(1, 148) = 9.01$, $p = .003$, $\eta^2 = .06$. The cocaine addicts had the lowest mean time preference estimates compared with the binge eaters and controls, with about 1 standard deviation below the overall mean.

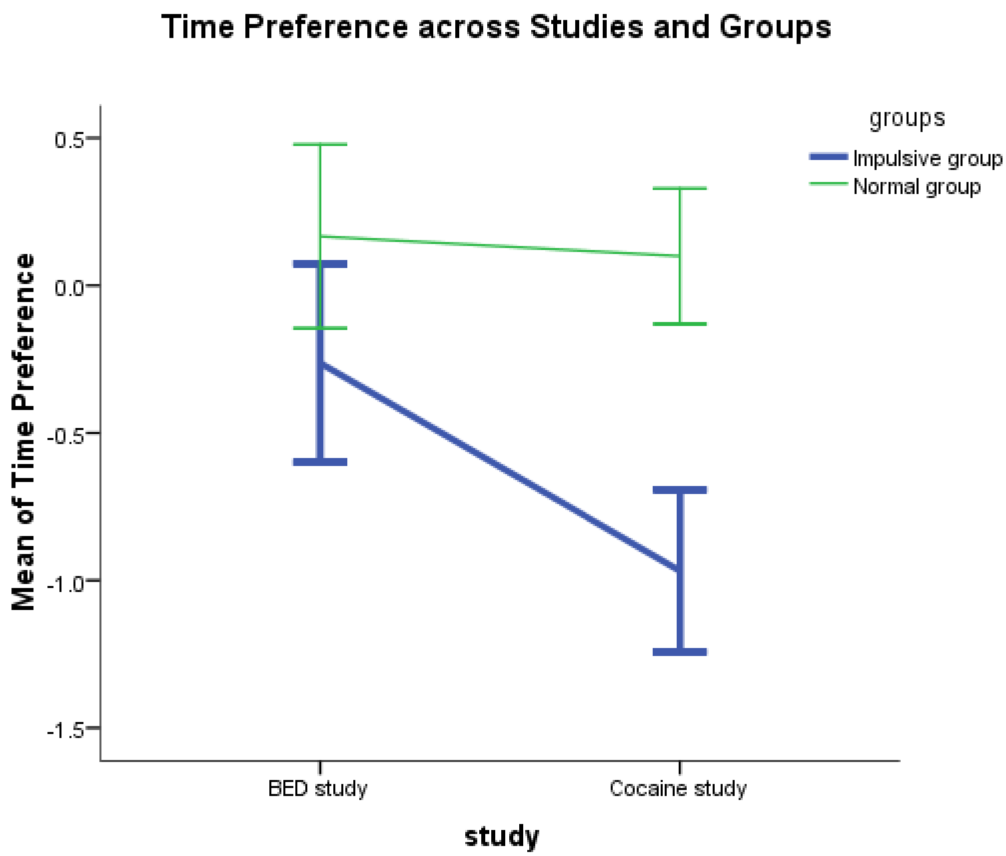


Figure 5.4 Time preference across studies and groups

Association between Impulsivity and Impatient Financial Planning

Pearson correlations were performed to compare how well the latent trait estimate of time preference and subscales of the BIS correlate with delay discounting rate within the normal samples and impulsive samples. Because non-independent correlations were tested, Type I error rate was set at .01. Within the normal samples, delay discounting rate was negatively correlated with time preference and the correlation was close to significant (r = -.142, n = 175, p = .06). The correlation between delay discounting rate and scores on the non-planning subscale of the BIS was positive and close to significant (r = .185, n = 175, p = .01). The correlation between the delay discounting rate and the total score of the BIS was not significant (r = .131, n = 175, p = .09).

Within the impulsive group, delay discounting rate was negatively correlated with time preference, and the correlation was significant at the .05 level (r= -.265, n = 62, p = .04). The correlation between delay discounting rate and scores on the non-planning subscale of the BIS was also significant at the .05 level (r = .282, n = 62, p = .03). The correlation between the delay discounting rate and the total score of the BIS was non-significant (r = .133, n = 62, p = .31). The correlation between time preference and non-planning was negative and significant (r = -.723, n = 70, p < .001); and the correlation between time preference and total score of the BIS was also negative and significant (r = -.647, n = 70, p < .001)

The magnitude of differences in correlations across the different samples (cocaine users, BED patients, their respective controls groups and undergraduates) were tested. There were no significant differences in correlations between delay discounting rate and time preference (z = .85, p = .40), non-planning subscale (z = -0.68, p = .50) or Barratt total (z = .01, p = .99).

Because there were no significant differences in correlations within impulsive groups and control groups, the correlations in the overall sample were calculated to maximize sensitivity. The Pearson correlation between delay discounting rate and time preference was negative and significant (r = -.164, n = 237, p = .01) , suggesting that people with a lower level of financial planning tend to discount more than people with a higher level of financial planning. The correlation between delay discounting rate and non-planning was positive and significant (r = .203, n = 237, p = .002); the correlation between delay discounting rate and the total score of the BIS was not significant (r = .125, n = 237, p = .06); the correlation between time preference and non-planning (r = -.735, n = 264, p < .001) and total score of the BIS (r = -.686, n = 264, p < .001) were both negative and significant. Comparison of these correlated correlations using Meng's test (Meng & Rosenthal, 1992) showed that the Non-Planning subscale, but not the TiPS, predicted the delay discounting rate better than the total score of the BIS (z=1.86, p=.03; z=.63, p=.74, respectively). The Non-planning subscale was no better at predicting delay discounting rates than was the TiPS (z=-.69, p=.24).

These correlation analyses suggest that the latent trait estimate of time preference is highly negatively correlated with the non-planning subscale as well as the overall score of the BIS. In addition, time preference appeared to predict the delay discounting rate better than scores on the Barratt Impulsiveness Scale in a broad, heterogeneous sample.

Discussion and Conclusions

Overall, the Time Preference Scale appears to provide items for both lower levels and higher levels of time preference. Item 4 and item 5 have the highest threshold 3, suggesting that it is relatively hard for people to actually spend more time to plan and to resist the temptation of spending money soon. Item 1 has the lowest threshold 3, suggesting that it is relatively easy for people to think about planning. The items generally have high discriminations, especially for the middle range of the latent trait. The discrimination (slope) parameter for item 6 is the highest. This finding indicates that whether people track their money best differentiates financial planning ability. Each rating category has been endorsed as each category has the highest possibility to be selected over the spectrum of the latent trait, with the exception of the lowest rating of item 7.

The current study showed that item 7 is potentially problematic. To explore the function of the scale without item 7, an IRT model was performed excluding item 7. The overall fit index indicated a better fit than the first model and the alternative model. However, the item parameters of the remaining 8 items were very similar to the parameters generated by the first model. The estimate of time preference without item 7 was very close to the estimate of time preference with item 7 (r = .998, n = 264, p < .001). See Appendix F for further information about the scale functioning after deleting item 7. Because the parameter estimations did not change much after deleting item 7, the item was retained.

The reliabilities and validities are good. Specifically, the internal consistencies for each item and for the overall scale were all higher than .8. The convergent validity is good, as the latent trait was significantly correlated with delay discounting rate. The divergent validity is also good, as the latent trait was not significantly correlated with probability discounting rate. The analysis of concurrent validity demonstrated the scale is able to differentiate the impulsive groups from normal groups and the cocaine group (more impulsive one) from the BED group (less impulsive one).

Analyses of the associations between the personality measure of time preference, delay discounting rate, and the personality measure of impulsivity suggest that people's financial planning ability is highly correlated with general planning and impulsivity overall. Further, financial planning ability predicts the delay discounting rate better than the overall score on the Barratt Impulsiveness Scale, but not the non-planning subscale. Therefore, the association between delay discounting rate and the personality measures of impulsivity is specific, but not necessarily limited to the domain of financial planning.

There are limitations of this study that suggest caution when drawing conclusions from the findings. First of all, confirmatory factor analysis suggested the 9 items of the Time Preference Scale fit the unidimensionality with satisfactory fit indexes. Although the results were not very robust, this investigator expects the assumption of unidimensionality will become more robust if a bigger sample is recruited. Second, the current study employed a two-step procedure to test concurrent validity in which a psychometric analysis was first conducted followed by a statistical analysis of group difference. Another way to analyze the group difference would be the use of an explanatory item response modeling (EIRM), which allows the psychometric analysis and the statistical analysis to occur within one step. Given that the test scores were highly reliable in the current study, it is estimated that there will be little difference between the results of the two-step analysis and the result of the EIRM analysis. However, further study with EIRM analysis may provide additional support for the validity of the Time Preference Scale.

Chapter 6.

Overall Conclusions and Future Directions

Impulsivity is a multi-dimensional construct associated with a range of psychological concerns. Scholars and researchers have investigated impulsivity through different paths, such as personality assessments and behavioral measures. In particular, the delay discounting paradigm as a measure of impulsive decision making has received considerable attention. Delay discounting is used in both animal and human studies with varying experimental procedures and data analysis models. Factors that influence delay discounting parameters include characteristics of the population, such as age, and procedures, such as reward domain, reward magnitude, etc.

Delay discounting can be described using different models that are based on different assumptions. The current literature indicates the exponential model describes empirical data well in economic studies when the risk associated with the delay duration is more constant and in human studies when rational strategies are emphasized. On the other hand, the hyperbolic model better describes the decision making processes of humans and animals when irrational components, such as emotions, are involved. A number of neural models have been proposed to explain the underlying mechanisms. Current studies have demonstrated the best fitting model can be varied due to the magnitude difference. Therefore, "the best fitting model" should be discussed within context. Furthermore, current studies have suggested the saturating-hyperbolic model fits empirical data better than the standard hyperbolic model when the reward magnitude is low ($10). The superiority of the saturating-hyperbolic model is more robust when clinical populations are involved. The results have indicated that models which allow for differentiation among different neural processes may provide better interpretation for studies on impulsivity, especially when clinical samples are involved.

Previous studies have suggested the delay discounting rate reliably differentiates drug users from controls with respect to propensity for impatience when the data are analyzed with the hyperbolic function. Current studies have replicated the result and indicate cocaine users tend to have higher delay discounting rate, but they are not different from matched controls with respect to probability discounting rate (which is used to measure risk taking propensity). However, when the data are analyzed with the saturating-hyperbolic function, results of current studies have suggested cocaine users do not differ from matched controls on the delay discounting rate. Rather, it is the saturation index that differentiates cocaine users from matched controls, indicating the observed decision making bias in cocaine users is specific to the decision factor associated with reward utility rather than the decision factor associated with time utility. In addition, this decision making bias is not associated with other impulsive disorders such as binge eating disorder, and thus it is likely a decision making preference specific to drug users.

Previous studies have yielded inconsistent conclusions regarding the association between delay discounting and personality measures of impulsivity. Most of these studies examined the correlation between delay discounting rate and scores on the Barrat Impulsiveness Scale. Current studies have also considered the Adult Externalizing Scale and the Time Preference Scale as well as other personality measures. The results showed the delay discounting rate across different reward magnitudes is positively and significantly correlated with the substance use factor of the Adult Externalizing Scale in normal samples when the sample size is relatively large. However, the non-planning impulsiveness subscale of the Barrat Impulsiveness Scale and the Time Preference Scale are significantly correlated with the delay discounting rate only when the reward magnitude is low ($10) and only when the sample size is large. These results indicate that the associations between delay discounting and personality measures of impulsivity are influenced by the task procedure of delay discounting and the types of personality measures administered. Comparison of the Time Preference Scale and the Barrat Impulsiveness Scale, as reported in Chapter 5, suggested the associations between delay discounting rate and the personality measures of impulsivity are specific to executive ability of planning, but are not necessarily limited to the domain of financial planning.

The finding that cocaine users have higher saturating indices instead of delay discounting rates than controls contrasts with previous assumptions that cocaine users have higher delay discounting rates. These results indicate that decision preference observed in cocaine users is due to strong physical needs or desires. Because the cocaine users who participated in the studies reported herein likely were in an advanced stage of the addiction (average years of use = 15), it is unclear whether conclusions regarding the group differences may also be valid for cocaine users who are in an early stage of use. Some authors have hypothesized that cocaine addiction involves a shifting from impulsivity to compulsivity (Belin, Mar, Dalley, Robbins, & Everitt, 2008; Koob & LeMoal, 2001). Therefore, one goal for future research will be to compare group differences between cocaine users who are in an early stage of addiction and controls to see if the group effect is the same. Furthermore, the saturating indices of cocaine users did not show significant association with the reward responding subscale of the Barrat Impulsiveness Scale in the current studies of cocaine users. The compulsivity hypothesis may also explain this result.

The findings in the current studies also raise a question that has not been systematically addressed: Is the saturating-hyperbolic model also superior to the hyperbolic model for probability discounting data under the same conditions as delay discounting? Previous studies have indicated that delay discounting and probability discounting follow the same mathematical model, which is the hyperbolic model. It is unknown whether this also is the case for the saturating-hyperbolic model. The studies reported herein suggest it fits the data well when reward magnitude is low and when applied to data from cocaine users. Given that there is scant literature about the saturating-hyperbolic model, future studies should reconsider the commonalities and differences between delay discounting and probability discounting when described by the saturating-hyperbolic model. Neural imaging studies on this model could examine whether the value utilities in delay discounting and probability discounting encode similarly regardless of the context of the task.

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Appendix A: Adult Externalizing Scale

Below are the 20 items of the Behavioral Inhibition System and Behavioral Approach System Scales as listed in Krueger et al. (2007). Each item is rated on a scale with 4 (very true for me), 3 (somewhat true for me), 2 (somewhat false for me), and 1 (very false for me). Item 16, 25, 26, 37, 50, 51, 55, and 56 are reverse scored.

1. I've made a fool of someone because it made me feel good.
2. I sometimes insult people on purpose to get a reaction from them.
3. I've told lies about someone else to make myself look better.
4. I have spread rumors about people who were competing with me.
5. I've hurt someone's feelings on purpose to get back at them.
6. I taunt people just to stir things up.
7. I have hit someone in the face or head in anger.
8. I have used a weapon against someone who insulted me.
9. One or more times in my life, I have beaten someone up for bothering me.
10. I have used a weapon to get something I wanted.
11. I have damaged someone's things because it was exciting.
12. I've broken something belonging to someone else to get back at them.
13. I have destroyed property just for kicks.
14. I have damaged someone's property because I was angry with them.
15. How other people feel is important to me
16. I don't care much if what I do hurts others.
17. I am sensitive to the feelings of others.
18. I get unfairly blamed for things.

19. I get blamed for things that I don't do.
20. People use me.
21. People often abuse my trust.
22. My drinking led to problems at home.
23. At times I kept drinking alcohol even though it caused problems with family or friends.
24. I've lost control of my alcohol use.
25. I'm not a drinker.
26. I don't drink.
27. At times, marijuana has been more important to me than work, friends, or school.
28. My marijuana use has led to problems at home, work, or school.
29. I've spent big parts of my day using marijuana.
30. I've spent more money on marijuana than I should have.
31. I've kept using marijuana even though it caused problems with my memory or health.
32. I've bought items used for smoking marijuana.
33. I have bought marijuana.
34. I have snuck marijuana or hash into a public event.
35. I have tried smoking marijuana.
36. I've smoked marijuana at parties.
37. I've never used marijuana in my life.
38. I've gotten high using marijuana.
39. I have rolled a marijuana joint.

40. I've used marijuana when it might be hazardous, like while driving a car.

41. I've smoked marijuana before going to work or school.

42. I have used more drugs for longer than I meant to.

43. My drug use has caused problems with my family.

44. I've had legal problems because of my drug use.

45. I gave up things I used to enjoy because of drugs.

46. At some point in my life, I needed more drugs to get the same effect.

47. I've broken the law to get money for drugs.

48. My drug use led to problems at work or school.

49. I've taken an illegal drug that gave me a rush and made me more awake.

50. I've never taken illegal drugs.

51. I have never bought drugs.

52. I tried an illegal drug at a party.

53. I've used drugs when it might be hazardous, like while driving a car.

54. I have taken a drug like LSD or magic mushrooms.

55. I've never used street drugs.

56. I've never had any desire to try an illegal drug.

57. I have broken into someone's home and taken things.

58. I have stolen something out of a vehicle.

59. I have stolen something worth more than $10.

60. I have broken into a house, school, or other building.

61. I have robbed someone.

62. I have conned people to get money from them.

63. I have lied to avoid paying back loans.

64. I have lied to get someone to sleep with me.

65. I have talked a stranger into giving me money.

66. I have borrowed money with no thought of paying it back.

67. I have lied on a job application.

68. I rarely lie.

69. I don't lie very much.

70. I've failed to make payments on a loan.

71. I've missed a rent or mortgage payment.

72. I have failed to show up to court when I was supposed to.

73. I've asked someone to help bail me out of debt.

74. I have failed to pay a traffic fine.

75. I've quit a job without giving two weeks notice.

76. I have run up big debts that I had trouble paying.

77. I have missed work without bothering to call in.

78. I've been fired from more than one job.

79. I keep appointments I make.

80. People think of me as dependable.

81. I've had legal problems because I couldn't resist my impulses.

82. I have been in trouble with the law for something I did on impulse.

83. My impulsive decisions have caused problems with loved ones.

84. I get in trouble for not considering the consequences of my actions.

85. My lack of self-control gets me in trouble.

86. Many problems in my life are caused by doing things without thinking.

87. I don't think about the outcomes of my decisions enough.

88. I think about things before I do them.

89. I plan before I act.

90. I have a hard time waiting patiently for things I want.

91. When I want something, I want it right now.

92. I hate waiting to get things that I want.

93. Many people consider me a rule breaker.

94. I often disobey rules.

95. I have a habit of breaking rules.

96. I often get in trouble for breaking rules.

97. I often get bored quickly and lose interest.

98. I get bored easily.

99. I like risky activities.

100. I do lots of things just to get a thrill.

Appendix B: Barratt Impulsiveness Scale

Below are the 30 items of the Barratt Impulsiveness Scale as listed in Patton et al. (1995). Each item is rated on a scale with 4 (very true for me), 3 (somewhat true for me), 2 (somewhat false for me), and 1 (very false for me). Scoring on items 1, 7, 8, 9, 10, 12, 13, 15, 20, 29, 30 is reversed.

1. I plan tasks carefully (non-planning impulsiveness).
2. I do things without thinking.
3. I make-up my mind quickly.
4. I am happy-go-lucky.
5. I don't "pay attention."
6. I have "racing" thoughts.
7. I plan trips well ahead of time (non-planning impulsiveness).
8. I am self controlled (non-planning impulsiveness).
9. I concentrate easily.
10. I save regularly (non-planning impulsiveness).
11. I "squirm" at plays or lectures.
12. I am a careful thinker (non-planning impulsiveness).
13. I plan for job security (non-planning impulsiveness).
14. I say things without thinking (non-planning impulsiveness).
15. I like to think about complex problems (non-planning impulsiveness).
16. I change jobs.
17. I act "on impulse."
18. I get easily bored when solving thought problems (non-planning impulsiveness).

19. I act on the spur of the moment.

20. I am a steady thinker.

21. I change residences.

22. I buy things on impulse.

23. I can only think about one thing at a time.

24. I change hobbies.

25. I spend or charge more than I earn.

26. I often have extraneous thoughts when thinking.

27. I am more interested in the present than the future (non-planning impulsiveness).

28. I am restless at the theater or lectures.

29. I like puzzles (non-planning impulsiveness).

30. I am future oriented.

Appendix C: Behavioral Inhibition System and Behavioral Approach System Scales

Below are the 20 items of the Behavioral Inhibition System and Behavioral Approach System Scales as listed in Carver and White (1994). Each is rated on a scale with 4 (very true for me), 3 (somewhat true for me), 2 (somewhat false for me), and 1 (very false for me). Items 1 and 18 are reverse scored.

1. Even if something bad is about to happen to me, I rarely experience fear or nervousness.
2. I go out of my way to get things I want.
3. When I'm doing well at something I love to keep at it.
4. I'm always willing to try something new if I think it will be fun.
5. When I get something I want, I feel excited and energized.
6. Criticism or scolding hurts me quite a bit.
7. When I want something I usually go all-out to get it.
8. I will often do things for no other reason than that they might be fun.
9. If I see a chance to get something I want I move on it right away.
10. I feel pretty worried or upset when I think or know somebody is angry at me.
11. When I see an opportunity for something I like I get excited right away.
12. I often act on the spur of the moment.
13. If I think something unpleasant is going to happen I usually get pretty "worked up."
14. When good things happen to me, it affects me strongly.
15. I feel worried when I think I have done poorly at something important.
16. I crave excitement and new sensations.

17. When I go after something I use a "no holds barred" approach.

18. I have very few fears compared to my friends.

19. It would excite me to win a contest.

20. I worry about making mistakes.

Appendix D: Time Preference Scale

Below are the 9 items of the Time Preference Scale recently developed by MacDonald, Rusticini and Krueger. Each is rated on a scale with 4 (very true for me), 3 (somewhat true for me), 2 (somewhat false for me), and 1 (very false for me). Items 3, 5, and 8 are reverse scored.

1. I plan for my future.
2. It's important to me to save money from every paycheck.
3. I spend money freely.
4. I spend a lot of time planning my financial future.
5. I'd rather enjoy my money now than spend my savings when I'm older.
6. I'm very thoughtful about where my money goes.
7. I'd rather face a problem now than let it get any worse.
8. I frequently buy things impulsively.
9. When I make a decision today, I have my future in mind.

Appendix E Item Descriptive Statistics for 19-item Version

A total of 19 items were designed to elicit subjects' self-report trait-like tendencies to select immediate rewards compared to larger, long term rewards. Each item (except item 1) is rated on a scale with 4 = very true for me, 3 = somewhat true for me, 2 = somewhat false for me, and 1 =very false for me. Items 2, 3, 4, 5, 6, 7, 8, 10, 12, 14, 15 are reverse scored. Of the 19 items, 9 items were selected based on the factor analysis and item analysis.

Candidate items	Selected items	Content	*n*	*r*	*r*.correct	*r*.drop	mean	SD
1		Over the course of my life I'd rather A) be young and rich then old and poor (R), or B) have just enough money to get by throughout my life.	188	0.014	-0.103	-0.097	2.5	1.12
2		Compared to most people I know, I plan more for the future	189	0.606	0.596	0.499	2.2	0.78
3		I save more money for the future than most people I know	189	0.626	0.617	0.548	2.6	0.8
4		It's worth taking classes and earning less when you are young so as to get a good job later	189	0.164	0.078	0.024	1.6	0.65
5		Education would be a good investment for me because it would increase my future	189	0.128	0.026	-0.014	1.5	0.62

		earnings potential						
6	**Qti01**	**I plan for my future.**	**189**	**0.628**	**0.618**	**0.53**	**1.7**	**0.64**
7	**Qti09**	**When I make a decision today, I have my future in mind.**	**189**	**0.577**	**0.559**	**0.469**	**2.1**	**0.65**
8		An egg today is worth a chicken tomorrow	189	0.333	0.264	0.204	2	0.67
9		The important thing is what I have today, not tomorrow.	189	0.301	0.222	0.179	2.6	0.81
10	**Qti02**	**It's important to me to save money from every paycheck**	**188**	**0.627**	**0.621**	**0.533**	**2.1**	**0.75**
11	**Qti03**	**I spend money freely**	**189**	**0.58**	**0.567**	**0.499**	**2.4**	**0.76**
12	**Qti04**	**I spend a lot of time planning my financial future**	**189**	**0.581**	**0.572**	**0.469**	**2.6**	**0.68**
13	**Qti05**	**I'd rather enjoy my money now than spend my savings when I'm older**	**189**	**0.633**	**0.626**	**0.549**	**2.3**	**0.7**
14	**Qti06**	**I'm very thoughtful about where my money goes.**	**188**	**0.712**	**0.726**	**0.657**	**2.1**	**0.68**
15	**Qti07**	**I'd rather face a problem now than let it get any worse**	**188**	**0.405**	**0.343**	**0.278**	**1.8**	**0.64**
16		I have committed to do things that I later regret	189	0.251	0.165	0.138	2.5	0.69
17		I live for the moment	189	0.286	0.214	0.184	2.8	0.67
18	**Qti08**	**I frequently buy things impulsively**	**189**	**0.522**	**0.499**	**0.447**	**2.3**	**0.78**

19	When I don’t have enough money to get something I need, I use my credit card to buy it.	189	0.309	0.235	0.208	1.9	0.89

Appendix F: Item Analyses for the Time Preference Scale without Item 7

Item Descriptive Statistics

Item	*n*	*r*	*r*.cor	*r*.drop	mean	SD
Qti01	259	0.67	0.62	0.54	3.3	0.79
Qti02	261	0.74	0.7	0.65	3	0.92
Qti03	260	0.72	0.68	0.63	2.5	0.97
Qti04	262	0.7	0.65	0.58	2.4	0.93
Qti05	261	0.67	0.59	0.55	2.6	0.88
Qti06	259	0.78	0.74	0.69	2.9	0.91
Qti08	259	0.55	0.46	0.41	2.8	0.99
Qti09	260	0.71	0.66	0.59	3	0.77

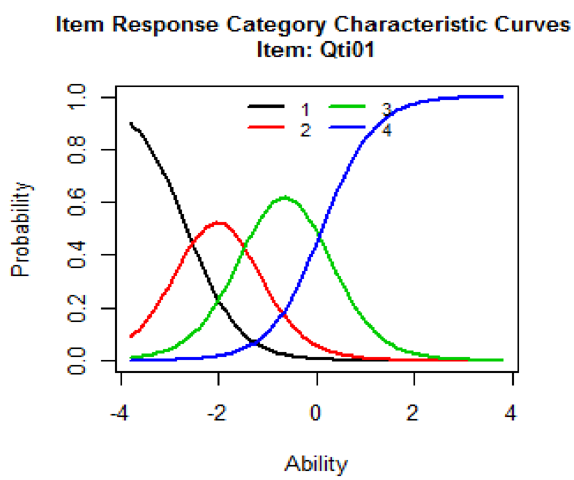
The Fit Index of Models

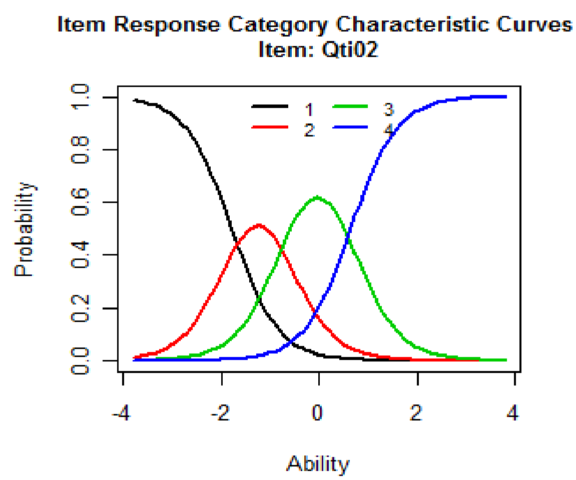
Model	Log.Like	AIC	BIC
First	-2618.359	5308.718	5438.527
Alternative	-2658.47	5372.94	5473.903
Without item 7	-2257.218	4578.437	4692.988

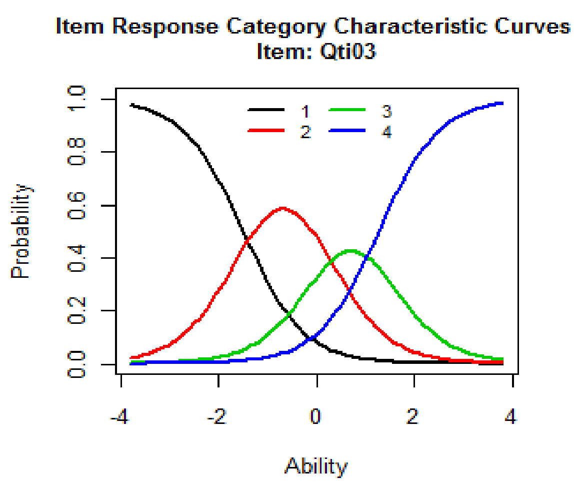
The Item Parameters

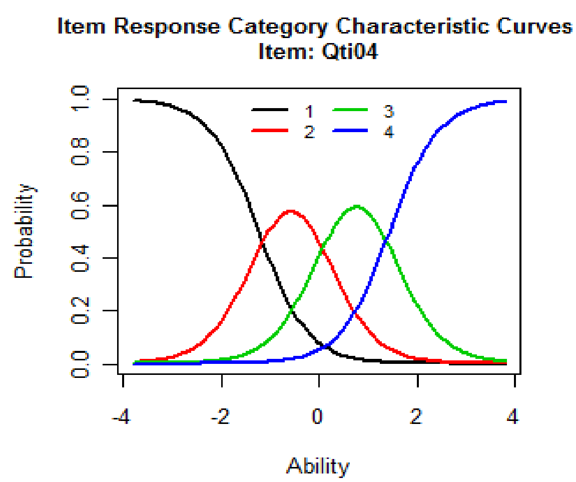
Item	Threshold 1	Threshold 2	Threshold 3	Discrimination

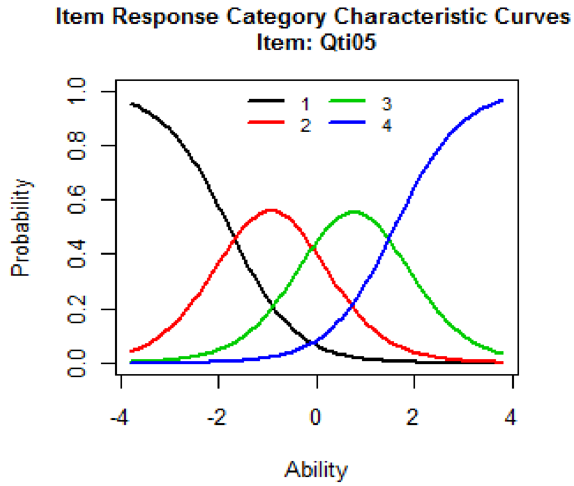
Qti01	-2.64	-1.411	0.122	1.879
Qti02	-1.779	-0.714	0.646	2.116
Qti03	-1.493	0.152	1.273	1.625
Qti04	-1.229	0.079	1.437	2.004
Qti05	-1.787	-0.08	1.604	1.483
Qti06	-1.685	-0.52	0.724	2.548
Qti08	-2.436	-0.547	1.237	0.917
Qti09	-2.334	-1.122	0.757	2.027

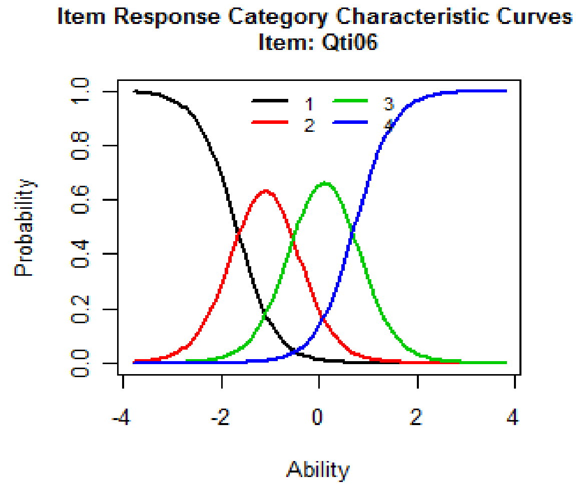


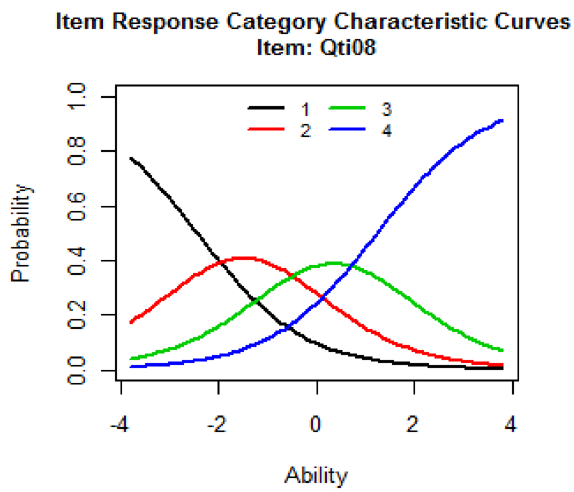


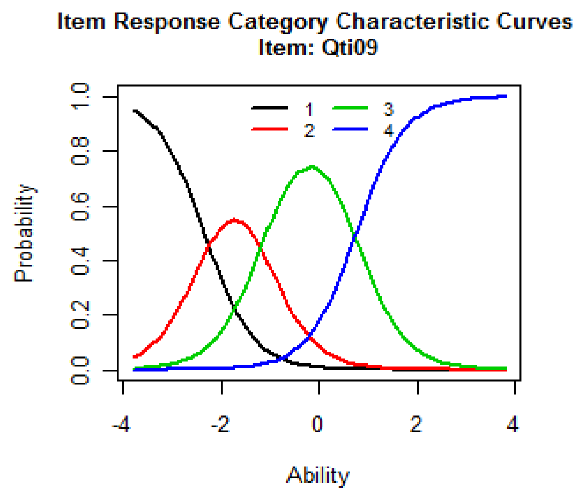




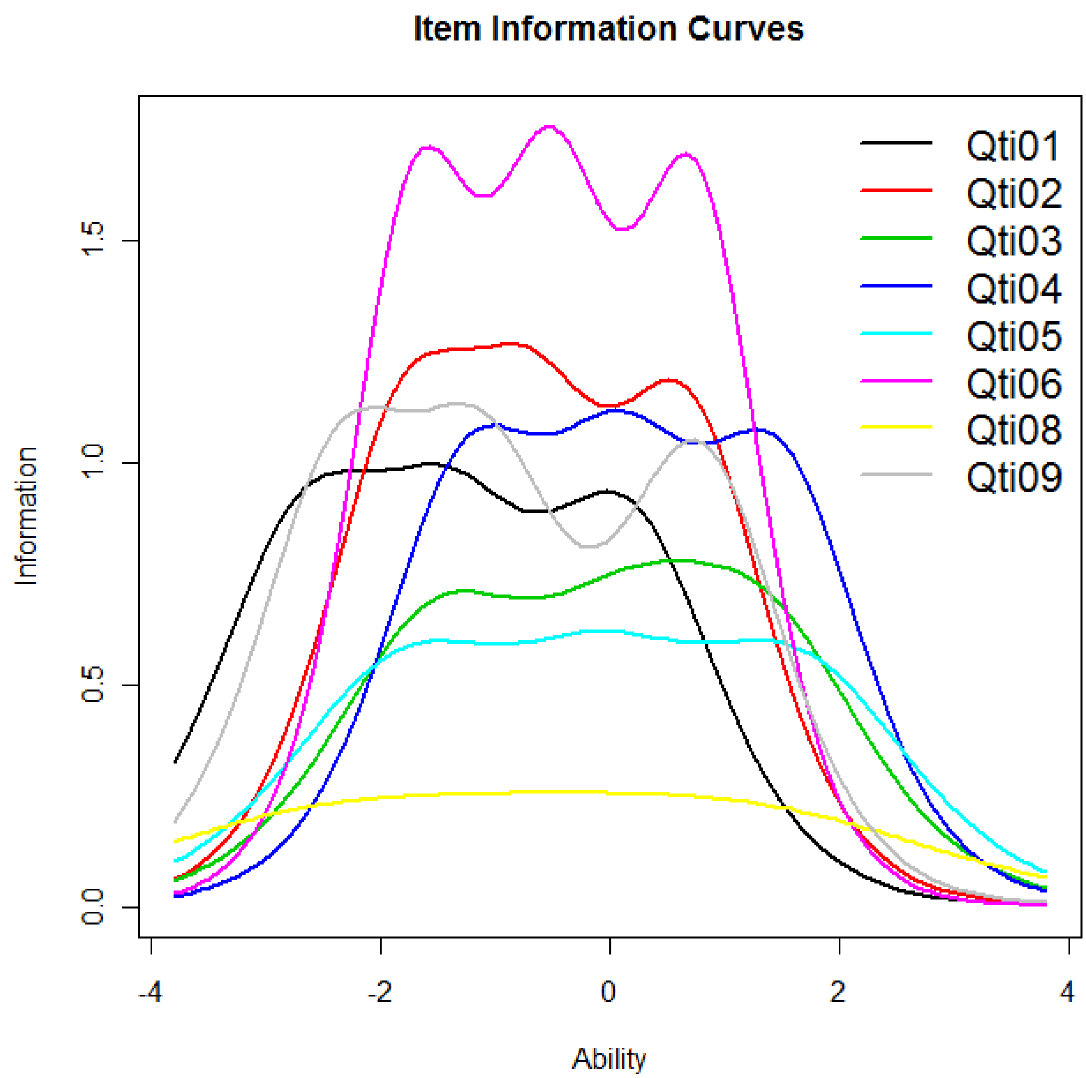




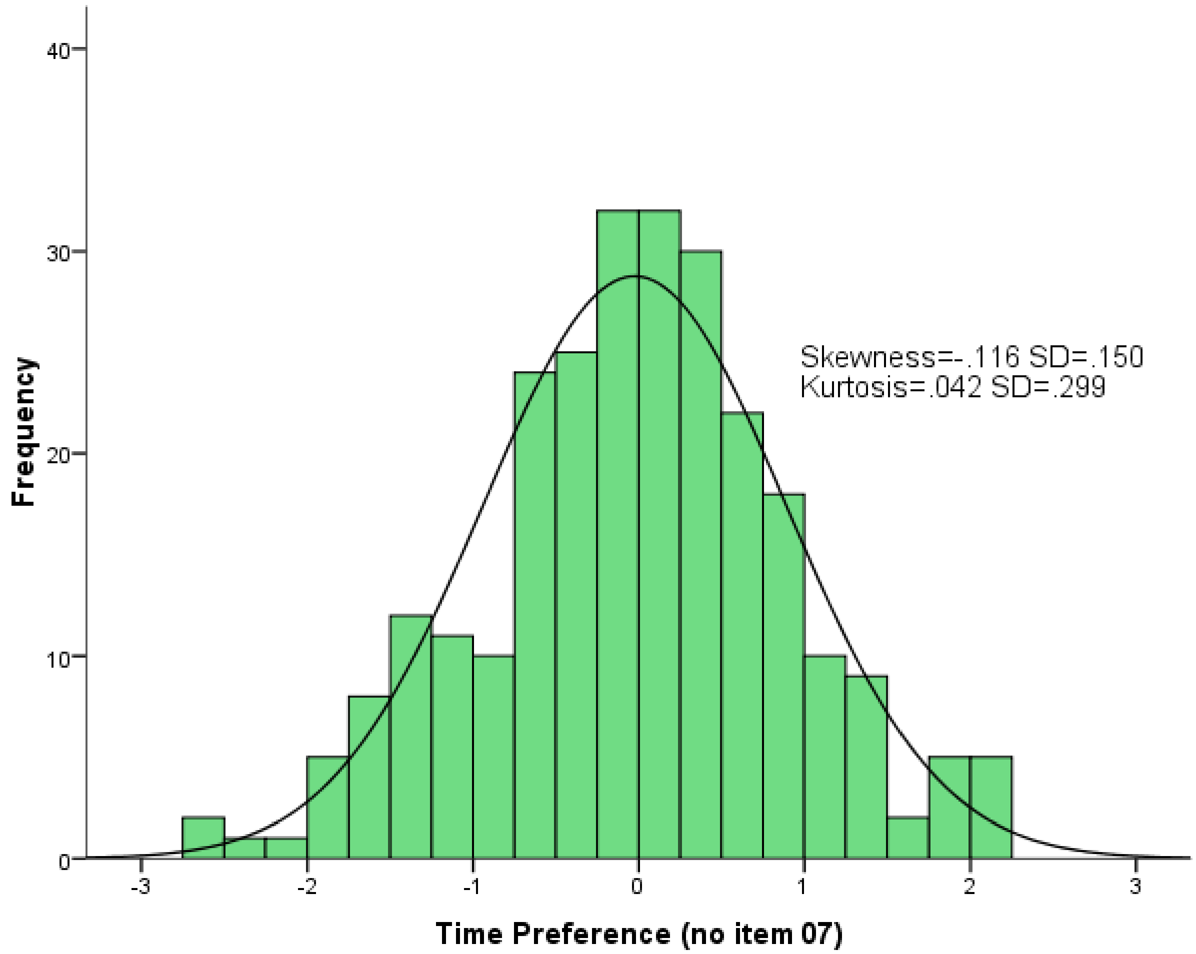




Item Characteristic Curves



The Item Information Curve



The Distribution of Latent Trait