Delay Discounting of Monetary Outcomes by Detained Male Adolescents and College Students

by

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Abstract

The main purpose of this study was to compare delay discounting of hypothetical monetary outcomes by adolescents adjudicated of illegal behavior to that of college students in order to lay a foundation for future discounting work with adjudicated adolescents. It is important to note that we conducted this work during the COVID-19 pandemic, which influenced the methodology due to constraints. We administered a hypothetical monetary delay-discounting task to three groups: (1) adjudicated adolescent males, (2) college student males, and (3) college student females. Using a least squares nonlinear regression, we then fit the following models to each data set both individually and at the group level: (a) exponential, (b) hyperbolic, and (c) hyperboloid. Thereafter, we determined the best fitting model for individual data sets and group data using the Information-Theoretic approach. Results showed that the hyperboloid model was the best fitting model for mean data across all groups. There was variability in the best fitting model for individual data within all groups. We also found that members of Group 1 discounted delayed monetary outcomes more steeply than members of Groups 2 and 3, which showed no differences. Overall, results showed that delay discounting by adjudicated adolescents is a research area worthy of future attention. Findings from this study will inform future work on delay discounting by justice-involved youth and may help to inform treatment of this population in the future.

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Chapter 1

Literature Review

Applied Behavior Analysis

Applied behavior analysis (ABA) is a branch of psychology in which behavior analysts use the scientific method to assess and treat socially significant behavior (Baer et al., 1968). More specifically, researchers and clinicians who practice ABA describe, predict, and test effects of independent variables on a behavior of interest. Both in research and clinical work, practicing ABA involves the objective measurement of behaviors that are meaningful to the broader scientific community, the direct recipient of the services, society at large, and many times all three.

The formalization of ABA as a line of research and clinical practice was substantiated by the establishment of the *Journal of Applied Behavior Analysis* in 1968 (Northup et al., 1993). As such, the field of ABA has over a 50-year history from which to draw evidence for both research questions and clinical programming. Research on behavior analytic techniques has provided evidence for a variety of effective interventions for both skill deficits (e.g., academic skills), and behavioral excesses (e.g., problem behavior). One area in which ABA has a rich literature and a recent growing interest is that of behavioral economics.

Behavioral economics is a sub-field of ABA in which researchers model human choice making in regards to a variety of decisions relevant to public policy (Reed et al., 2013). Some of these decision areas include choices regarding substance use, cigarette smoking, healthy food choices, gambling, and indoor tanning. One underlying assumption of behavioral economics is that humans sometimes make irrational choices. Irrational choice refers to the propensity to make decisions that do not necessarily maximize long-term benefit. One specific concept of behavioral economics that is particularly relevant to the irrationality of human choice making is that of delay discounting.

Delay Discounting

Delay discounting refers to a phenomenon in which the value of a reward changes as a function of the delay to its receipt (Madden & Johnson, 2010). More specifically, rewards lose increasingly more value the longer an individual must wait for them. Researchers have given delay discounting high levels of attention for decades in part due to its presence in a variety of real-life, everyday situations and choices (Weatherly, 2014). For example, we face a delay-discounting scenario every time we choose a food item to eat. The option to consume a tasty but unhealthy food item (e.g., cheeseburger and fries) is always present. These tasty yet unhealthy options are associated with immediate reinforcement in the form of a flavorful, edible item. Conversely, we may also choose a less traditionally tasty but healthy food item (e.g., green salad with light dressing and grilled salmon). The healthy choice delivers delayed reinforcement in the form of better long-term health indices (e.g., lower blood pressure). These long-term health indices are associated with the larger payoff of a longer life when compared to the smaller but immediate payoff associated with a tasty meal. The delay-discounting scenario (i.e., smaller sooner reward or larger later reward) is present across both small daily choices and larger less frequent choices.

Consider a financially stable college student who would like to pursue a career in psychology. They can choose to volunteer their time in a psychology lab earning valuable experience that will serve them well during the graduate school application process or they can take a job that pays but is unrelated to their future goals. The unrelated job delivers more immediate reinforcement in the form of a regular paycheck for extra spending money but may not serve them as well during the graduate school application process, which may be a year into the future. This college student is facing a delay-discounting scenario. They can choose the smaller, sooner reward (i.e., the job that pays but is unrelated to future goals) or the larger, later reward (i.e., the non-paying but related job). When someone discounts delays at high rates (i.e., tends to choose the smaller, sooner reward), we say that they are a steep discounter. Steep discounting is synonymous with high rates of discounting. The ubiquitous nature of delay discounting is one reason that the phenomenon has received a high level of research attention.

Not only is the delay-discounting scenario present in an abundance of common decisions, steep delay discounting is related to a variety of problematic behaviors (Tangney et al., 2004). Bickel et al. (2012) stated that delay discounting is a "trans-disease" process, meaning that the process is prevalent across a variety of disorders, which thereby causes advances in one disorder to be relevant to other disorders. Some problematic behaviors related to steep delay discounting include lower grades (Kirby et al., 2005), antisocial personality disorder (Petry, 2002), disordered eating (Rasmussen et al., 2010; Weller et al., 2008), gambling (Alessi & Petry, 2003; Petry & Madden, 2010; Reynolds, 2006), cigarette and cannabis relapse (Krishnan-Sarin et al. 2007; Sheffer et al., 2012, 2014; Stanger et al., 2012), risky sexual behavior (Collado et al. 2017), and criminal behavior (Daugherty & Brase, 2010; Lee et al., 2017; Mishra & Lalumiere, 2017).

In addition to being associated with a variety of problematic behaviors and characteristics, delay discounting may also be of interest to researchers because it remains relatively stable across time and commodities (Odum, 2011). Said differently, if an individual shows steep discounting in relation to one commodity (e.g., food) they are likely to show steep discounting in relation to other commodities (e.g., money). Results of analyses that show similar discounting across commodities and time have led to the assertion that delay discounting has trait-like qualities (Odum et al., 2020). Research showing a change in delay discounting due to contextual variables like environment, or satiation and deprivation provides evidence that delay discounting is subject to state-like changes as well (Odum et al., 2020).

A state variable is a variable that affects responding over a relatively short duration whereas a trait variable is in comparison a more stable and long-lasting characteristic (Odum, 2011). It is important to note that a trait variable does not necessarily mean responding in the same way all the time. Rather, a trait variable shows "relative endurance" and "response consistency" (Odum, 2011) but is susceptible to some degree of contextual influence. Although both state and trait variables can affect responding, the longevity of trait variables, especially problematic ones that are trans-disease, may be of particular interest to those aiming to reduce problematic behaviors. If a practitioner can eliminate or decrease a problematic trait with an intervention, it is less likely that the trait will continue to influence responding across the client's life. Therefore, targeting problematic traits for intervention may produce large, collateral improvements in the quality of a client's life (Odum et al., 2020).

Although there is a vast literature base on delay discounting in laboratory settings, many of these research studies focus on the process of discounting itself, rather than the treatment of discounting delayed rewards. However, given the potential problems that are associated with steep discounting and the nature of the variable as a trait, it may behoove clinicians to consider discounting rates (i.e., *k values*) as dependent measures for change. Reed et al. (2013) called for the application of behavioral economics to therapeutic settings. As an example, it may be possible for clinicians to identify clients who are at risk of problematic behavior via delay-discounting tasks. Said differently, clinicians may administer delay-discounting tasks to identify clients who are steep discounters. Steep discounters may be at risk for the problematic behaviors previously mentioned such as gambling, over-eating, or drug use. If a clinician targets self-control as a behavior for treatment, large collateral changes in problem behavior may be seen across diverse topographies and functions, as well as contexts, producing a more efficient treatment model. However, it is important to note that self-control and impulsivity are multi-faceted and not entirely accounted for by delay discounting (for a more in depth review of these differences and the argument for separating them, see Paglieri, 2016).

When targeting delay discounting for change, clinicians and researchers must consider several factors that have been shown to influence discounting (e.g., Weatherly, 2014). These factors include the type of measurement tool used (e.g., Smith & Hantula, 2008), the commodity and magnitudes being assessed (e.g., Terrell et al., 2014), the participant's age and gender (e.g., Green et al., 1994; Harman et al., 2020; Kirby & Marakovic, 1996), and whether a clinical population is participating (e.g., Dixon et al., 2003). Finally, when analyzing data, the researcher or clinician must determine which analytic method is the best fit for their data (Newland, 2019).

Measurement Tools

In a seminal study, Rachlin et al. (1991) presented a series of hypothetical choices of monetary amounts across different delays or probabilities to a group of 80 college students. More specifically, Rachlin et al. presented a series of choices between a varied immediate amount from $1 to $1000 and a fixed amount of $1000 at several different delays presented one at a time. For example, the first delay tested was 1 month. Therefore, the first choice was between $1 now and $1000 in a month. The next choice was $5 now or $1000 in a month, then $10 now or $1000 in a month, and so on. Researchers presented 30 different immediate amounts across seven different delays presented once in ascending order and once in descending order for a total of 420 choices.

Rachlin et al. then fit hyperbolic and exponential discounting models (discussed later) to the data and found that the hyperbolic function was a better fit, which was consistent with previous research with non-human animals, showing generality to human participants.

The purpose of the task used by Rachlin et al. (1991) was to determine the point at which the subjective amount of the delayed choice equaled the amount of the immediate reward. Researchers now refer to this as an indifference point (Reed et al., 2013), which describes the point at which the perceived value of the reward with a delay subjectively equals the value of the reward with no delay. In other words, an indifference point is the point at which the subject is indifferent between the immediate and delayed amounts. For example, we would expect a participant to choose the delayed amount when presented with a choice between $1 now or $1000 in a week. A choice of $1000 in a week suggests that the participant perceives $1000 with a week's delay as more valuable than $1 with no delay. Several choices later, the participant may need to decide if they prefer $980 now or $1000 in a week. Assume the participant still prefers the delayed amount. The next choice would be $990 now or $1000 in a week. At this point, assume the participant switches responding to the immediate amount suggesting that the subjective value of the delayed amount is somewhere between $980 and $990, or approximately $985. Said differently, $1000 in a week is subjectively worth $985 now to our hypothetical participant. Determining the subjective value of a delayed reward may allow for predictions about socially relevant choice making behavior.

Since the seminal study by Rachlin et al. (1991), many other researchers have used a similar binary choice procedure to study a variety of delay-discounting phenomena across a variety of populations (e.g., Acuff et al., 2018). For example, Odum et al. (2002) used a similar procedure to evaluate delay-discounting rates of delayed health outcomes across current cigarette smokers, ex-smokers, and never smokers. Although the procedure developed by Rachlin et al. is highly accepted in research with over 1400 citations reported by Google Scholar as of February 2021, there are some limitations, particularly the length of time needed to conduct 420 choices, which may lead to participant fatigue during the task.

To address these limitations, several researchers have evaluated the utility of shorter delay-discounting tasks. One of the first modifications to the Rachlin et al. (1991) procedure was the development of an adjusting amounts procedure (Richards et al., 1999). An adjusting amounts procedure uses a software program to collect data and the software program adjusts the amount of the immediate alternative reward on the basis of the participants' previous answers. The adjusting amounts procedure is a quicker way to determine indifference points. The average amount of time to generate 15 indifference points is 15 min for a participant who is responding consistently (Epstein et al., 2003). Although the adjusting amounts procedure is experimentally valid and much shorter in duration, an adjusting amounts procedure requires a specific software program and expertise in programming, which may not be available in all settings.

Since the development of the adjusting amounts procedure, researchers have developed even briefer tasks that do not necessarily require the use of advanced technology. Two of these tasks are the 27-item monetary choice questionnaire (MCQ) developed by Kirby et al. (1999) and a 5-item adjusting delay task developed by Koffarnus and Bickel (2014). The 27-item MCQ has a high level of validity when compared to adjusting amounts procedures (e.g., Epstein et al., 2003) and thus, can be used in clinical settings with confidence in the predicted discounting rates. The 5-item task has not been validated to the same extent, possibly because of the more recent publication date. Although these briefer tasks can be used to estimate an individual's discounting rate in 5 min or less, the tasks assume a hyperbolic discounting function and thus, the tasks are limited insofar as to which experimental questions they can address. Further, these tasks would only be appropriate to use with a population that has previously shown hyperbolic discounting of rewards. However, if research has not yet evaluated whether a specific population discounts rewards hyperbolically, the brief formats that assume hyperbolic discounting may not be appropriate, or are limited at the least.

Generality across Commodities

Although many delay-discounting tasks involve a series of choices regarding monetary amounts, many questions regarding impulsivity do not necessarily involve money. For example, researchers have implemented delay-discounting tasks across a variety of commodities including controlled substances, sexual behavior, and food (Hendrickson & Rasmussen, 2013; Hendrickson et al., 2015). Generally speaking, researchers comparing monetary discounting rates to directly consumable commodity discounting rates find that discounting rates of the latter are steeper (Bickel et al., 2011). Holt et al. (2016) referred to the difference in discounting rates across commodities as the domain effect. Researchers have posed several hypotheses as to why the discrepancy in discounting rates across commodities exists.

One explanation for differences in discounting across commodities is that many frequently tested non-money commodities (e.g., food, controlled substances) are immediately consumable. Additionally, money is liquid and fungible, meaning that it can be exchanged for many items, even itself, and thus, maintains its value over time. Generally, subjects discount directly consumable commodities more steeply than money and steep discounting of one commodity may predict steep discounting of other commodities (Friedel et al., 2014; Giordano et al., 2002; Odum, 2011). In the same way that researchers have focused on the correlation of discounting across commodities, researchers have also questioned the correlation of discounting across real and hypothetical outcomes.

Hypothetical versus Real Outcomes

Delay-discounting tasks with humans typically present a series of choices with hypothetical outcomes. Hypothetical outcomes offer some obvious advantages over real outcomes. The first advantage is that some commodities may be impossible or unethical to deliver (e.g., monetary rewards up to $1000, some duration of sexual interaction, legal outcomes). The second advantage is that the delays being studied (e.g., up to several years) would pose significant barriers to this type of research. Additionally, evaluating delay discounting and using discounting rates as a measure for change in a clinical population may necessitate the use of hypothetical over real outcomes. As such, it is important to consider the support for the use of hypothetical outcomes as some researchers have questioned the generality to choices using real outcomes (Critchfield & Kollins, 2001). To address the potential limitation of hypothetical outcomes, several researchers have designed specific studies to evaluate the extent to which choices for hypothetical outcomes correlate with choices for real outcomes.

Johnson and Bickel (2002) examined the correlation of monetary delay discounting across hypothetical and probabilistic real rewards within six participants. In the hypothetical reward condition, researchers told participants that they would not actually be delivering any of the monetary amounts. In the probabilistic real reward condition, researchers told participants that they would select one outcome at random and they would give the participant the specified amount after the specified delay. Results indicated that there was no systematic difference between real and hypothetical conditions for five of six participants. The one participant that did show a systematic difference in discounting consistently discounted hypothetical rewards more steeply than probabilistically real rewards. Although Johnson and Bickel provided a first attempt at evaluating the concordance between choices for real and hypothetical outcomes, the small sample size was a noted limitation.

Since Johnson and Bickel's (2002) study, many other researchers have designed studies to compare hypothetical and real rewards. Madden et al. (2003) showed that there were no differences in monetary discounting rates obtained from the real reward and hypothetical reward conditions in 20 college students. Madden et al. (2004) replicated these with a larger sample size (i.e., 40 participants) and evaluated both within and between subject results. In addition to the discounting of hypothetical monetary outcomes, several researchers have evaluated discounting of different hypothetical outcomes such as cigarettes and food (Green & Lawyer, 2014; Robertson & Rasmussen, 2018). Overall, mixed results suggest that there may be some specificity regarding the correlation of potentially real and hypothetical outcomes across commodities. Said differently, results of research using non-monetary commodities (e.g., cigarettes, food) has been mixed, with some studies showing slight differences when comparing real and hypothetical outcomes of these non-monetary commodities.

Taken together, results suggest that hypothetical reward outcomes may be a viable proxy for real outcomes when real reward choices are not feasible, especially for monetary discounting. However, researchers should exercise caution when interpreting results of commodities that have not yet been evaluated. In addition to task features, researchers should be aware that certain participant characteristics, such as age and gender, might affect delay discounting as well.

Influence of Age and Gender

There is solid evidence that impulsivity shows age-related changes, with declines into adulthood (Romer, 2010). Said differently, children and adolescents engage in more impulsive behavior than adults do. As such, delay discounting should be steeper in children and adolescents than in adults. Green et al. (1994) evaluated delay discounting across three age groups; children (sixth grade aged), young adults (college aged), and older adults (enrolled in an aging and development program). Results indicated that all age groups discounted delayed rewards and that children showed the steepest discounting rates, young adults showed the next steepest discounting rates, and older adults showed the least steep discounting rates. These results are consistent with the hypothesis that delay discounting decreases with age and suggest that younger individuals may be more susceptible to steep discounting of delayed rewards. As a follow up, Green et al. (1996) conducted a study with upper income young adults, upper income older adults, and lower income older adults and found that generally, discounting rates decreased with both age and income.

Steinberg et al. (2009) recruited a sample of 935 participants across varying age groups and found that 10- to 13-year-old participants discounted delays more steeply than 14- and 15-year-olds, who discounted delays more steeply than participants aged 16 and older. Overall, there were no significant changes in discounting rates after the age of 16. Further, there were no differences in discounting by gender in any age group. Steinberg et al. suggested that the ages between 13 and 16 may be a particularly crucial time in developing skills needed for orientation to larger, delayed rewards.

In regards to gender differences in delay discounting, Kirby and Marakovic (1996) found a reliable difference in discounting rates between different male and female undergraduate students, with males discounting probabilistic monetary rewards more steeply than females, on average. However, there were individual differences within their data. By contrast, Harman et al. (2020) found no differences in the discounting of hypothetical monetary outcomes by college students across genders. Similarly, Olson et al. (2007) found no difference in delay discounting of probabilistic monetary outcomes by participants ages nine through 23, and Lahav et al. (2015) found no gender differences in the discounting of 150 Israeli teenagers using a hypothetical fill in the blank task. Weafer et al. (2015) found no gender differences in delay discounting of adult alcohol-users ages 18 through 30, although they did find gender differences in a go no-go task. It is also noteworthy that many delay-discounting studies do not evaluate gender differences despite both males and females in their samples (e.g., Jarmolowicz et al., 2020; Scheithauer et al., 2020). Overall, the literature appears to be mixed on whether there are gender differences in delay discounting rates so researchers should attend to this potential variable of influence.

The results of research on the influence of age and gender on delay discounting shows that younger individuals discount rewards more steeply than older individuals and that sometimes, males discount delays more steeply than females. More specifically, results of Steinberg et al. (2009) and Lahav et al. (2015) showed that delayed rewards may impact individuals under the age of 16 to a greater degree than those 16 and older. Further, a number of studies have shown no differences in delay discounting by gender, but overall, there are mixed results on this particular topic. The line of research on age and delay discounting provides support for treatments designed to increase self-control and decrease discounting in adolescents. In summary, researchers examining delay discounting in adolescent populations should consider the effects of age and possibly gender on discounting rates.

Discounting in Clinical Populations

Previous research has shown that differences by clinical population may influence delay-discounting data (e.g., Dixon et al., 2003; Morrison et al., 2019). Said differently, populations recruited from college student samples or adults with no clinical diagnoses may behave very differently on discounting tasks when compared to populations with a clinical diagnosis (e.g., attention-deficit/hyperactivity disorder; Barkley et al., 2001; Rosch et al., 2018) or other documented challenges (e.g., history of criminal behavior, cigarette smokers). When determining which discounting task to utilize and how many participants need to be recruited, researchers should consider these differences.

Dixon et al. (2003) conducted a study comparing delay discounting of hypothetical monetary outcomes by pathological gamblers to non-gamblers. The data produced by the pathological gamblers were noticeably more variable than the non-gamblers' data. More participants in the pathological gamblers group showed nonsystematic discounting of delays. These differences influenced the adoption of less stringent exclusionary criteria and yet researchers still excluded a higher percentage of data sets in the pathological gamblers group than in the control group. Of the systematic data sets remaining after exclusion, the pathological gamblers group showed steeper discounting than the non-gamblers group, overall. This study showed one example of clinical populations producing data that are more variable and steeper than non-clinical populations.

Morrison et al. (2019) evaluated the effects of Acceptance and Commitment Therapy (ACT) on delay discounting, among several other factors, in a community sample of adults seeking therapy. Results showed that there was no effect of ACT on delay discounting which was divergent from previous research. Morrison et al. note that this could potentially be due to their participant inclusion criteria, which was designed to increase the clinical severity of the sample. For example, 73% of the sample reported struggling with one or more target behaviors for six or more years. Although Morrison et al. did not specifically include a comparison sample, it provides another example of clinical populations producing data that are divergent from what has been found in non-clinical populations through the comparison of their results to those of previously published studies.

There are additional examples of higher rates of discounting in clinical populations over controls. Kirby et al. (1999) showed heroin users exhibit higher discounting rates than non-drug using controls and Friedel et al. (2014) found that cigarette smokers discount money, food, and entertainment more steeply than non-smokers. In summary, it is important for researchers working with clinical populations to consider the individual differences that may be present in their population. Further, it is important for researchers working with novel clinical populations, such as adjudicated adolescents, to expect to lay some foundational work in identifying the best experimental methods for their specific population.

Dependent Variables

In order to make meaningful conclusions about delay discounting in a population, researchers must first determine which dependent variable they will evaluate. There are two options for dependent variables when evaluating delay discounting: (a) area under the curve (AUC), and (b) *k* values or discounting rates. Myerson et al. (2001) proposed the theoretically neutral measure, AUC. Contrary to discounting rates in which researchers fit a mathematical model to obtained data, Myerson et al. proposed that simply measuring the area under the discounting curve produced by obtained indifference points would provide a more parsimonious measure of delay discounting. Myerson et al. named this measure AUC and many researchers have used this measure to quantify delay discounting (e.g., Friedel et al., 2014; Lawyer & Schoepflin, 2013; Moody et al., 2017). When interpreting AUC, steeper discounting (higher impulsivity) is associated with a smaller AUC (closer to 0) and shallow discounting (less impulsivity) is associated with a larger AUC (closer to 1). In addition to being free from underlying assumptions, Myerson et al. state that AUC measures are typically normally distributed, allowing for the use of parametric statistical tests, which is in contrast to *k* values (discussed below), which are typically highly skewed.

Although there are some advantages of AUC, the method is not without limitations (Borges et al., 2016; Mitchell et al., 2015; Myerson et al., 2011; Yoon et al., 2017). First, although Myerson et al. (2001) stated that AUC values should be normally distributed, they sometimes are not (e.g., Friedel et al., 2014; Yoon et al., 2017). Because AUC often requires normalization, researchers cannot always generalize results across studies without adjusting for variations in the ranges of the independent variable(s). Second, AUC is not a particularly sensitive analytic methodology. As one example, it is possible that two differently shaped discounting curves will produce the same AUC value, which creates difficulty in interpreting the effect of delay on subjective value (Mitchell et al., 2015). Third, and most pertinent to the current study, AUC does not address questions of model fitting. Although this final point is one of the perceived strengths of AUC, it is also a reason not to use AUC as a primary dependent measure when conducting a study of model fitting.

Another possible dependent variable in delay discounting studies is a *k* value, which represents the discounting rate that is derived from the best fitting model. A multitude of delay-discounting research supports the use of *k* values as a dependent variable (Madden & Bickel, 2010). Several researchers have compared *k* values and AUC as dependent measures (Mitchell et al., 2015; Yoon et al., 2017). This line of research has shown that AUC is nonlinearly related to *k* values, which implies that the two measures may not always yield the same results, particularly when the data describe especially steep or shallow discounting. Ultimately, experts in this area propose that researchers use *k* values alone or in combination with AUC. Taken together, although the theoretical neutrality of AUC may be useful in some situations, it is not appropriate to use as the only data analysis tool and further, may not be necessary for all experimental questions.

Mathematical Modeling

Mathematical modeling is a process by which mathematical concepts and language are used to describe phenomena (Neufeld, 2015). Mathematical modeling can be useful in making predictions about behavior in a variety of situations. The field of economics uses mathematical modeling to predict consumer choice behavior under a variety of different situations, mostly relating to product price and availability variations (Rachlin, 2006). The field of behavioral economics has adopted mathematical modeling as well (e.g., Gilroy et al., 2019). Researchers have fit several mathematical models to delay-discounting data including exponential, hyperbolic, and hyperboloid models (Doyle et al., 2011; McKerchar et al., 2009).

An exponential model is one in which the decay rate is proportional to the magnitude. Classic economics, accounting, and finance all assume an exponential model as this maximizes monetary payout (Doyle et al., 2011). The following equation describes an exponential model of delay discounting:

$$V = Ae^{-kd}$$

where V is the discounted value of the future reward, A is the reward amount, d is the delay until reward receipt, k is the discounting rate, and e is the base of the natural logarithm.

The exponential model assumes preferences that remain constant across time and that are independent of reward amount (McKerchar et al., 2009). Humans and non-human animals often times depart from a constant preference across time and thus, their choice making behavior does not typically follow the exponential discounting model. Otherwise stated, the exponential model is often times not the best model for human and non-human delay-discounting data. Instead, the hyperbolic discounting function has proven to be a better fit (Green & Myerson, 1996).

Hyperbolic discounting describes a situation in which rewards are discounted more steeply at short delays and less steeply at longer delays than with exponential discounting and is expressed with the following equation:

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

where the parameters are the same as the exponential equation. Mazur (1987) found that the hyperbolic equation fit the data of pigeons' discounting of food rewards better than the exponential model. Similarly, Jones and Rachlin (2006) found that the hyperbolic equation fit the social discounting data of over 300 human participants. The field of psychology has long since used the hyperbolic equation for human decision making as it assumes a preference shift; a phenomenon in which individuals change their original choice as time passes which is well-documented in research with human participants (e.g., Giordano et al., 2002; Green & Myerson, 1996; Scheres et al., 2006; Yi et al., 2020). This is in contrast to the exponential function, which does not account for preference shift unless *A* changes with reinforcer magnitude.

Rachlin (1989) proposed raising the denominator of the hyperbolic function to a power resulting in the following hyperboloid equation:

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

where the parameters are the same as in the hyperbolic model above with the addition of a free parameter, *s*. Raising the denominator to a power causes the curve to flatten out as *d* increases (Myerson & Green, 1995). Although researchers have shown that the hyperboloid model fits data well in many cases (Myerson & Green, 1995), it is unclear whether the extra free parameter is necessary in all situations (e.g., Green et al., 1994; Mitchell et al., 2015).

Although a large body of research has shown that both the hyperboloid and the hyperbolic functions fit discounting data better than the exponential function (e.g., Green et al., 1997; Jones & Rachlin, 2006; Mitchell et al., 2015), researchers are still testing additional mathematical models and variations that may better describe obtained discounting data (McKerchar et al., 2009; Mitchell et al., 2015). When evaluating which model fits discounting data best, researchers may choose from several data analysis methods.

Data Analysis

Researchers should first determine whether their data are systematic and, thereafter, only include those data in the analysis. Johnson and Bickel (2008) described a method for determining systematic data and proposed that data should be deemed unsystematic when one or both of the following criteria are met:

> (1) if any indifference point (starting with the second delay) was greater than the preceding indifference point by a magnitude greater than 20% of the larger later reward;
>
> (2) if the last indifference point was not less than the first indifference point by at least a magnitude equal to 10% of the larger later reward. (p. 267)

Johnson and Bickel explain that criterion 1 violations suggest that the subjective value of a reward increases with the delay and criterion 2 violations suggest that delays do not affect subjective reward values. This approach to determining systematic data has been accepted by several delay-discounting researchers (e.g., Morrison et al., 2019; Peters & Buchel, 2010).

Although the Johnson and Bickel (2008) criteria have been adopted by a large number of researchers, it is important to consider that certain clinical populations may show higher percentages of unsystematic data. Dixon et al. (2003) used exclusionary criteria that were less stringent when working with discounting data obtained from pathological gamblers. The authors noted that there were many departures from a theoretically consistent delay-discounting pattern. As such, they considered a participant's data inconsistent with delay discounting if:

(1) the indifference points did not decrease at least twice across successive delay values and,

(2) the indifference points increased more than once across successive delay values.

In their participant pool of 20 pathological gamblers, experimenters excluded 9 data sets due to the aforementioned criteria. Dixon et al. excluded 45% of their clinical data, which is in contrast to their control sample of which they excluded only 5% of data sets. The latter, smaller excluded percentage is more in line with the majority of discounting research, which typically shows exclusion percentages of less than 10% of obtained data (e.g., Koffarnus & Bickel, 2014; Stein et al., 2016). It is important to consider adopting participant-specific exclusionary criteria when working with clinical populations.

Once a researcher has excluded non-systematic data, there are several methods by which to evaluate model fitting. One popular method is to run a least squares regression for each model and use the R^2 of the regression lines to make the determination. Johnson and Bickel (2008) pointed out several issues with the R^2 method, particularly when using R^2 to determine whether obtained data is systematic. First, the regression used in delay-discounting data is nonlinear. Johnson and Bickel state that the sum of squares error (SSE) for the mean, of which R^2 is found upon, in a nonlinear regression does not actually represent the highest possible SSE for the model. Thus, the R^2 for nonlinear regression is somewhat ambiguous and may not represent the best method to analyze delay-discounting data. Further, Johnson and Bickel found a positive correlation between the *k* values and R^2 of several published delay-discounting data sets, suggesting that R^2 may be biased towards high rates of discounting and that it may not be the best measure to determine the model of best fit.

One popular approach in delay discounting research is to test multiple models for a given data set to determine the best fit. It is important to note that this can only be done once a dependent variable (e.g., AUC, *k* value) has been chosen and the dependent variable should remain constant across candidate models. Newland (2019) proposed using the Information Theoretic (I-T) approach to model selection for delay discounting data to avoid some of the problems that come along with null hypothesis testing. The I-T approach has been used by various researchers for decades for model selection purposes (Burnham & Anderson, 1998), and is well suited for model fitting questions in delay discounting research as well. Newland notes several advantages of the I-T approach. The first advantage is that the I-T approach tells the investigator what the probability of the test hypothesis is given the data set, as opposed to the probability of the data set given the null hypothesis. The second advantage is that the I-T approach, based on the Akaike Information Criterion (AIC), encourages the investigator to test many different hypotheses. To demonstrate the I-T approach, Newland generated 10,000 Monte Carlo simulation delay-discounting data sets and used the I-T approach to evaluate which model out of eight was the best fit. Results showed that the I-T approach accurately identified the model that was the true fit for the data and that increasing the sample size increased the accuracy of identifying the best fitting model. Delay-discounting researchers who aim to identify the best fitting model for their data set should consider the I-T approach.

Impulsive Behavior in Adolescents with Illegal Behavior

Reynolds and McCrae (2018) defined criminal behavior as any deviant, unacceptable, and unlawful actions. The National Center for Juvenile Justice reported that the United States legal system handled 744,500 juvenile delinquency cases in 2018 (Sickmund et al., 2020). The four major classifications of criminal behavior include drug, property, public order, and personal offenses (National Center for Juvenile Justice, 2019). Illegal sexual behavior is a subset of personal offenses that has taken on specific interest in research as evidenced by academic journals such as *Sexual Abuse* and *Journal of Sexual Abuse*. Researchers have asked questions related to better assessment and prediction of individuals who are likely to offend both sexually and non-sexually (e.g., Seto & Lalumiere, 2010; Walt & Jason, 2017). One factor that research has linked to criminal behavior is self-control (Reynolds & McCrea, 2018); however, many studies use self-reported scales of impulsivity. Research on the correlation between self-reported scales of impulsivity and delay-discounting tasks are somewhat mixed (Olson et al., 2007), which suggests that more research on behavioral models of impulsivity with justice involved individuals is necessary.

Wilson and Daly (2006) compared discounting rates between a group of detained adolescent offenders and a control sample recruited from various local high schools and results showed that there were no significant differences in *k* values between the groups. However, there are some limitations of the methodology employed by Wilson and Daly. First, it appears that the researchers used a discounting task that assumes a hyperbolic function, which in turn estimates *k* values, rather than apply a model fitting procedure to calculate *k*. This procedure is limited because there is no prior research to show that detained adolescents discount hyperbolically and as such, the *k* values in their study are rough estimates at best. Second, their offender group consisted of both males and females with mean ages of 15.8 and 14.8 respectively and their control group consisted of both males and females with mean ages of 16.0 and 16.2 respectively. Although these ages are similar, results by Steinberg et al. (2009) suggest that ages between 14 and 16 may be particularly formative years in building sensitivity to delayed outcomes. The age ranges of the samples in this study are on the cusp of the age range that may still show age effects on delay discounting. As such, the results by Wilson and Daly must be interpreted with caution and more research on delay discounting in adjudicated adolescents is needed before making firm conclusions.

As a step towards evaluating the link between self-control and illegal sexual behavior, Vazsonyi and Crosswhite (2004) evaluated the relation between childhood victimizations (e.g., physical abuse, emotional neglect) and substance use (a characteristic that is related to steep discounting rates; Athamneh et al., 2019) on aggression during a sexual offense among a sample of adolescents with illegal sexual behavior. Results showed a significant effect of poly-victimization (multiple childhood trauma experiences) on sexual aggression, rather than an effect of any one particular type of individual trauma experience. Further, results showed that poly-victimization was also positively related to increased likelihood of substance use, which has been linked to steep discounting, prior to the sexual offense. Although the study did not specifically evaluate impulsive behavior in the sample, authors suggest that researchers should pursue analyses of other factors that may contribute to increased severity of sexual offending, specifically noting impulsivity.

Vazsonyi et al. (2017) conducted a meta-analysis of 99 studies examining the link between self-control and criminal behavior. Vazsonyi et al. found a correlation between lowered self-control and increased criminal behavior with weaker effect sizes in studies with male participants, older adults, and studies that used self-report impulsivity scales as their primary measure. More specifically, results also showed (a) stronger associations between low self-control and general deviance and physical violence and (b) weaker associations with the delinquent behaviors of substance abuse and academic or organizational dishonesty. Overall, results of their meta-analysis were consistent with previous meta-analyses on the link between self-control and crime (see Pratt & Cullen, 2000). Specifically, results showed that there is a relationship between low self-control and criminal behavior, and the strength of the association may be offense specific.

Reynolds and McCrea (2017) argued that in some environments, it may be advantageous for an individual to engage in highly impulsive behavior. The argument made by Reynolds and McCrea may be particularly relevant to individuals with a criminal background, who often come from unpredictable environments (Bickel & Marsch, 2001; Green et al., 1994; Wilson & Daly, 2006). Some of the environmental qualities identified by Reynolds and McCrea that may create a situation in which impulsivity is favored include high mortality rates, unpredictability in resources (e.g., food and water), and high levels of ongoing violence.

Although it appears that self-control may be negatively related to illegal behavior in adolescents, there is little directed research on the topic. A study by Kahn et al. (2015) found that delay discounting was a mediator between the development of risky sexual behavior and parent-adolescent relationship quality for low self-control adolescents. Although Kahn et al. provide some support for the further evaluation of delay discounting, the authors did not study delay discounting specifically nor did they attempt any model fitting. Another study conducted by Lee et al. (2017), showed a bi-directional relationship between delay discounting rates and self-reported criminal behavior by college undergraduate students. Both of these studies used the 27-item MCQ (Kirby et al., 1999), which assumes hyperbolic discounting. Although this measure may have been acceptable for their research questions, a PubMed search of the keywords "delay discounting" (or "temporal discounting"), "illegal" (or "crim*", or "delinq*"), and "adolescen*" conducted on February 8, 2021 returned zero relevant results, suggesting that there is limited research on the delay discounting of adolescents with illegal behavior. Given the plethora of research suggesting that delay discounting is related to poor outcomes including criminal behavior (e.g., Mishra & Lalumiere, 2017), directed research on the topic is warranted.

Chapter 2

Experiment

COVID-19 Pandemic Influence

The originally proposed dissertation included a sequence of four experiments, all with adjudicated adolescent male participants. The experiments would have included collecting delay discounting data using hypothetical monetary and sexual outcomes, and conducting model fitting analyses and comparisons of *k* values across the different commodities. I also proposed evaluating the effects of a mindfulness-based group therapy model on *k* values across these two commodities. Soon after we collected hypothetical monetary data with 41 adjudicated adolescents, the state went into lockdown and the juvenile correctional facility no longer allowed entry to non-essential staff. After evaluating the obtained data and finding a higher than usual percentage of unsystematic data (described in detail below), I decided to accrue a college student comparison sample at the suggestions of Dr. Newland and Dr. Podlesnik. The data originally collected from the adjudicated adolescents and the newly collected college student comparison sample provides the foundation for the approved modifications to my dissertation as described below.

Methods

Purpose

The purpose of this experiment was to evaluate monetary delay discounting in a sample of adolescents with a history of illegal behavior by evaluating the fit of three mathematical delay-discounting models using a least squares nonlinear regression and I-T approach for model selection. The models I tested were:

(a) exponential, $V = Ae^{-kd}$

(b) hyperbolic, $V = A / (1 + kd)$

(c) hyperboloid, $V = A / ((1 + kd)^s)$

I compared the results of our Group 1 clinical sample composed of adjudicated adolescent males to Group 2, which was composed of male college students and Group 3, which was composed of female college students. I also calculated AUC values at the individual level to support meta-analysis efforts of delay discounting researchers and to provide an additional dependent variable for analysis. I tested the following two hypotheses in this study:

1. The hyperbolic model will be the best fit for individual data for the majority of all individual participants as well as group data for all groups.
2. Group 1 participants will show steeper discounting than participants from groups 2 and 3.

As additional post-hoc analyses, I also investigated the following:

3. Whether the AUC values were different across groups.
4. Whether the distribution of indifference points was different across groups.

Participants

For Group 1, I recruited 41 adolescents from a residential treatment facility that served adolescent males who had been adjudicated for illegal behavior. The residential facility divided residents into three different groups depending on their general category of offenses: sexual offenses, general delinquency, or controlled substances. Participants ranged in age from 14 to 21. Participants were not excluded based on IQ or psychological diagnoses. Participants would have been excluded if they were less than four months away from being released or if they had been documented illiterate (neither of these instances occurred). Participants were excluded if they failed to respond to a series of eight pre-requisite questions accurately (see Appendix). I designed the questions to ensure the participants could discriminate between larger versus smaller amounts and sooner versus later delays. One participant was excluded due to answering all questions incorrectly on the pre-requisite questions. The remaining 40 participants answered all questions correctly.

Prior to commencement of the study, I met with the legal guardian and the treatment team of the facility to explain the study. I then asked the members of the treatment team to identify any adolescents that fit the criteria above for consideration in the study. Additionally, I visited each dorm, explained the study to the students in the dorm as a group, and answered any questions. Thereafter, I approached students who had expressed interest in participation one by one to review the assent form. Specifically, I explained the purpose of the study and that participation was voluntary. I explained that the participant could drop out at any time and clarified that the adolescent could initially agree to participate and later decide to stop. I explained that participation in the study was separate from treatment and research participation did not affect the court-ordered treatment that adolescents received at the facility or their release dates. I explained these parameters in language that was understandable to the specific adolescent. Once I collected signatures from all participants, I delivered the assent forms to the legal guardian to approve each adolescent's choice to participate. The legal guardian signed the forms and returned them to me for storage.

For Groups 2 and 3, 171 students (26 males and 145 females) were recruited from an online system through the university. To keep the sample sizes similar across groups, all male data sets were used and 26 of the 145 female data sets were selected using a random number generator. Participants were students in undergraduate psychology courses at the University. Participants received 1 hour of extra credit in exchange for study participation. The University's Human Subjects Institutional Review Board approved the survey before data collection began.

Setting

All sessions with adjudicated adolescents were conducted in a quiet room or area that was in each respective dorm so that students did not need to travel around the facility campus to participate. The room or areas contained one square table, four chairs, and two laptop computers on opposite sides of the table so that participants sitting at a laptop could not see the screen of the other laptop. Two researchers (one research assistant and myself) were present and sat on opposite sides of the table without laptops. The researchers monitored the participants to ensure they stayed on task. If the participants asked questions about the task, the researchers responded vaguely and re-directed back to the task. For example, some participants asked "why are they asking these questions" and the researchers would say "to evaluate how youth like you make decisions which may help inform better treatment in the future" (this information was in the assent form). If the participants tried to speak to the researchers about a topic not related to the task, the researchers told the participants that they could talk after they finished.

For college students, I used an online survey administered via Qualtrics™. Due to the pandemic, data were collected remotely and asynchronously so the setting in which participants completed the task was most likely variable across participants but unknown. Although the setting and software system differed across groups, the logistical ease and the ongoing pandemic necessitated the change. This will be noted as a potential limitation when interpreting results.

Electronic Data Collection System and Response Measurement

Researchers assigned each participant a code number. For Group 1, researchers collected discounting data using E-Prime3 software on a laptop computer and labeled the data file with the participant code. I presented participants with a total of 420 questions regarding hypothetical monetary outcomes (e.g., “would you prefer $100 now or $1000 in one month?”) via E-Prime3. The specific monetary amounts and delays and order of presentation were identical to the procedure described by Rachlin et al. (1991). More specifically, questions included a choice between one immediately available amount (i.e., $1,000, $990, $980, $960, $940, $920, $900, $850, $800, $750, $700, $650, $600, $550, $500, $450, $400, $350, $300, $250, $200, $150, $100, $80, $60, $40, $20, $10, $5, or $1) and $1000 at a variable delay (i.e., 1 month, 6 months, 1 year, 5 years, 10 years, 25 years, and 50 years). In other words, each choice included one immediately available amount that varied across trials, but with a constant delay (i.e., no delay), and one constant amount ($1,000) with a delay that varied across trials. All possible combinations of amounts and delays were presented once in ascending order and once in descending order for 420 total choices. The location of the immediate and delayed choice varied across trials. The duration of each session with each participant was approximately 30 min. After participants completed the task, I collected participant’s ages and offense categories through a centralized system database on the facility campus.

For Groups 2 and 3, I collected data using the electronic, online system Qualtrics™. The task was composed of questions identical to and presented in the same order as those presented to Group 1. In addition to collecting data on choice behavior on the monetary discounting task, I also asked college student participants to self-report age and gender using fill-in-the-blank modalities. Groups 2 and 3 completed the task in an average of 34 min and 48 min, respectively.

Data Analysis

I first calculated indifference points similarly to the method described by Dixon et al. (2003). Specifically, I took the average of the first immediate amount that was selected on the ascending cycle and the last immediate amount that was selected on the descending cycle for each of the seven delays. For example in the one month delay, if the first immediate amount that the participant chose on the ascending cycle was $950 and the last immediate amount that the participant chose on the descending cycle was $900, I averaged those selections for an indifference point of $925 at the one-month delay. If the participant always chose the delayed amount, even when the amounts were equal (i.e., Do you prefer $1000 today or $1000 in a month), I did not enter an indifference point for that delay. If the participant always selected the smaller sooner, I entered an indifference point of the smallest presented value, $1.

I subsequently examined indifference points for systematic responders first as outlined by Johnson and Bickel (2008) and next as outlined by Dixon et al. (2003). After visually evaluating the data, I determined that both exclusion criteria were too stringent and not appropriate for the unique patterns I observed in the data obtained from adjudicated adolescents. As such, we (Dr. Newland and I) created semi-novel exclusion criteria that were more appropriate for our data as outlined below:

1. If, starting on the second delay, an indifference point was greater than the preceding indifference point by more than 20% of the delayed amount, or greater than $200 in the current study (Johnson & Bickel).
2. If indifference points increased more than once across successive decreasing delay values (Dixon et al.).
3. If the final indifference point was greater than or equal to the first indifference point.

We adopted criterion 1 from Johnson and Bickel, criterion 2 from Dixon et al., and added criterion 3. Criterion 1 allowed for minor increases in indifference points but controlled the extent to which those increases occurred. Criterion 2 further controlled for excess variability in a data set and ensured the overall pattern of indifference points reflected choices consistent with discounting delays. We included criterion 3 based on patterns present in our data as well as the theoretical possibility of a situation in which the final indifference point could be greater than the first, but not necessarily greater than the preceding indifference point by over 20% of the delayed amount. For each data set, I considered all three criteria and excluded a data set if it met at least one of the aforementioned criteria.

Based on the above criteria, 24 of 40 data sets from Group 1, three of 26 data sets from Group 2, and five of 26 data sets from Group 3 were excluded. After excluding all of the data sets that met at least one of the above criteria, I calculated mean and median indifference points for each group. The median indifference points from Group 1 met exclusionary criteria based on criterion 2 above but those based on the mean did not. Neither median nor mean indifference points for the remaining groups met exclusionary criteria. As such, I used the mean indifference points for group analyses across all groups for consistency.

Next, I ran a least squares nonlinear regression using the solver tool in Excel™ set to 10,000 iterations for each individual data set and mean indifference points for each group. The number of data points in each regression was the same, seven, but the data points for the group analyses were obtained by averaging the indifference points across all individuals in that group. The regression used the following models:

(a) exponential, $V = Ae^{-kd}$

(b) hyperbolic, $V = A / (1 + kd)$

(c) hyperboloid, $V = A / ((1 + kd)^s)$

I included the exponential model as researchers have given a large amount of attention to this model due to its relation to economics (Doyle et al., 2011). I included the hyperbolic model as this has been a well-researched model for both human and non-human delay-discounting research (Mazur, 1987). I included the hyperboloid model as some researchers have shown that it may be a better fit than the hyperbolic, with the addition of another free parameter, *s* (Myerson & Green, 1995; Rachlin, 1989). In all models, I constrained free parameters to positive numbers based on previous research (Reed et al., 2012).

After running the least squares nonlinear regression for each of the aforementioned models, I analyzed which model was the best fit using the I-T approach for both individual and group data. Specifically, I first calculated the log likelihood from the residual sum of squares, and thereafter calculated the AIC corrected for small samples (AICc). I then calculated the delta AICc, AICc weight, and the evidence ratio. According to Burnham et al. (2011), the delta AICc is critical for ranking models, the AICc weight describes the probability that the model is the best in the candidate set, and the evidence ratio describes the strength of the evidence for one model being the best in the candidate set. All calculations were conducted in Excel using the formulas described by Newland (2019) and Burnham and Anderson (1998).

Finally, I calculated AUC for each participant individually and for each group by finding the area of each trapezoid created by each indifference point. Specifically, I followed the Excel™ tutorial described by Reed et al. (2012). The equation for the AUC estimate is

$$\text{AUC} = \sum (x_2 - x_1) [(y_1 + y_2)/2]$$

Where x_1 and x_2 are successive delay values, and y_1 and y_2 are the indifference points that correspond to those delays. A lower AUC represents steeper discounting and a higher AUC represents less steep discounting. As such, AUC should be negatively correlated with hyperbolic *k* values in that higher *k* values should correspond to lower AUC values and lower *k* values should correspond to higher AUC values. It is important to note that the *k* values in the hyperboloid model cannot be used as an independent index of discounting because they are dependent on the value of *s* (Friedel et al., 2014; McKerchar et al., 2010). For remaining inferential statistical analyses (e.g., Kruskal-Wallis tests, correlations), I used IBM SPSS Statistics 25.

Results

Table 1 shows age, criminal offense category, and indifference points for the participants in Group 1 with 24 data sets out of 40 excluded. Table 2 shows age and indifference points for the participants in Group 2 with three of 24 data sets excluded. Table 3 shows age and indifference points for the participants in Group 3 with five of 26 data sets excluded. Interestingly, two data sets from Group 3 were excluded due to indifference points remaining at $1000 across delays, which suggests no sensitivity to delay. No other group showed a data set of this nature. The mean age in years of participants was 17.5, 19.5, and 19.6 for Groups 1, 2, and 3, respectively. Members of Groups 2 and 3 did not report any genders other than male and female.

Tables 4, 5, and 6 show a summary of the *k* and *s* values for each model with the best fit as identified by the I-T approach bolded, the corresponding R^2, AICc weight for the best model, and the AUC for each individual participant in Groups 1, 2, and 3, respectively. For Group 1, Table 4 shows the exponential was the best fit for six of 16 participants with the AICc weight above .9 for all six participants. An AICc weight above .9 suggests there is a high probability that the model is the best in the candidate set. The hyperbolic was the best fit for five participants with an AICc weight over .9 for two of those participants. The hyperboloid was the best fit for five participants plus the group mean indifference points, with an AICc weight above .9 for two of those participants and the mean. It is notable that in general, the R^2 values were quite high even though the AICc weight could vary considerably.

For Group 2, Table 5 shows the exponential was the best fitting model for eight of 23 participants and the AICc weight was above .9 for three of those data sets. The hyperbolic was the best fitting model for 11 participants and the AICc weight was above .9 for seven of those data sets. Finally, the hyperboloid was the best fitting model for four participants plus the group mean indifference points and the AICc weight was above .9 for two of those data sets as well as the mean. Similarly to Group 1, the R^2 values in Group 2 show a similar pattern in relation to AICc weight.

For Group 3, Table 6 shows the exponential was the best fitting model for seven of 21 participants and the AICc weight was above .9 for zero of those data sets. The hyperbolic was the best fitting model for 10 participants and the AICc weight was above .9 for two of those data sets. Finally, the hyperboloid was the best fitting model for four participants plus the group mean indifference points and the AICc weight was above .9 for one of those data sets as well as the mean. Similarly to Groups 1 and 2, the R^2 values in Group 3 show a similar pattern in relation to AICc weight.

Tables 7, 8, and 9 show the I-T approach with the AICc for the group level data for Groups 1, 2, and 3, respectively. In contrast to individual results, for which no model was consistently the best, with the grouped data, Tables 7, 8, and 9 show strong evidence that the hyperboloid model was the best fit followed by the hyperbolic and exponential. For all three groups, using group-wise data, the hyperboloid was the best fit with an AICc weight ranging from 0.956 to 0.993. The AICc weights suggest there is very good evidence for the hyperboloid being the best fit in the candidate set for all groups.

Figures 1, 2, and 3 show three exemplars each of the nonlinear regression of all three models for individual data for Groups 1, 2, and 3, respectively. I chose the representative data set for each model based on which data set had the highest AICc weight for that model. All figures show the subjective value in dollars on the y-axis and the delay in months on the x-axis. The black squares represent the obtained indifference points, the green solid data path represents the exponential model, the blue dashed data path represents the hyperbolic model, and the red dotted data path represents the hyperboloid model.

For Group 1, the left panel of Figure 1 shows the data set for P-12. The exponential model was the best fit with an AICc weight of 0.996. The middle panel shows the data set for P-41 and the hyperbolic model was the best fit with an AICc weight of 0.942. The right panel shows the data set for P-09 and the hyperboloid model was the best fit with an AICc weight of 0.971. Overall, visual analysis is consistent with the results of the I-T approach to model selection for these representative data sets. For P-12 and P-41 (left and middle panels), the indifference points follow a steep curve, suggesting a high rate of delay discounting. Comparatively, the indifference points produced by P-09 (right panel) are less steep and follow the hyperboloid model well. This illustrates what the exponent for the hyperboloid model does: when it is less than 1.0 (as it was), this dampens the impact of delay over a hyperbolic curve, which is a hyperboloid with an exponent of 1.0.

For Group 2, Figure 2 is structured similarly to Figure 1. The left panel of Figure 2 shows data from P-52 and the exponential model was the best fit with an AICc weight of 0.984. For P-52, the hyperboloid and exponential models follow a similar curve. The tendency of the I-T approach to select the simplest yet best fit may explain why the exponential model was selected as the best fit in this and similar data sets. The middle panel shows data from P-46 and the hyperbolic model was the best fit with an AICc weight of 0.967. Finally, the right panel shows data from P-57 and the hyperboloid model was the best fit with an AICc weight of 0.960. Overall, visual analysis is consistent with the results of the I-T approach to model selection. P-46 shows the steepest discounting out of the three representative data sets from Group 2.

For Group 3, Figure 3 is structured similarly to Figure 1. The left panel of Figure 3 shows the data set for P-84 and the exponential model was the best fit with an AICc weight of 0.842. For P-84, the hyperboloid and exponential models follow a similar curve. The middle panel shows the data set for P-75 and the hyperbolic model was the best fit with an AICc weight of 0.963. Finally, the right panel shows the data set for P-71 and the hyperboloid model was the best fit with an AICc weight of 0.910. Overall, visual analysis is consistent with the results of the I-T approach to model selection. P-71 shows the steepest discounting out of the three representative data sets from Group 3.

Figure 4 shows the nonlinear regression for mean indifference points for Group 1 (left panel), Group 2 (middle panel), and Group 3 (right panel). The hyperboloid was the best fitting model for all three groups and visual analysis is consistent with the I-T approach results. The AICc weight for the hyperboloid model was 0.956, 0.993, and 0.993 for Groups 1, 2, and 3, respectively, as shown in Tables 7, 8, and 9, indicating that the hyperboloid model is likely the best model in the candidate set for mean indifference points across all groups. Group 1 shows the steepest discounting curve, and Groups 2 and 3 appear to be of similar steepness.

Figure 5 shows the distribution of best fitting model *k* and *s* values for participants by group. Overall, the y-axis represents the distribution of the specified parameter, and the x-axis represents the group. Black circles represent individual participants and the black lines represent group mean data for the hyperboloid parameters as based on the group mean indifference points. I present group mean data for the hyperboloid model parameters only because the hyperboloid model was identified as the best fitting model for all groups. For *k*, members of Group 1 show larger values across all three models. For group mean data on the hyperboloid *k* (third panel), Group 1 shows the highest value at 4.7 and Group 2 and 3 are of similar values at 0.3 and 0.5 respectively. The hyperboloid *s* values (fourth panel) show less variation in distribution across groups for individual and group mean data.

Figure 6 shows the distribution of AUC values on the y-axis across groups on the x-axis. Black circles represent individual participants and the black lines represent group mean data based on the group mean indifference points. At the individual level, AUC values show a more even distribution for Groups 2 and 3 when compared to Group 1 with the majority of AUC values falling below 0.1. For group mean AUC values, Group 1 shows the smallest value at 0.13 and Groups 2 and 3 are similar at 0.30 and 0.32, respectively.

Figure 7 shows the distribution of individual and group mean AICc weights for the best fitting model across groups. The AICc weight value is on the y-axis and the group is on the x-axis. Black circles represent the exponential model, grey squares represent the hyperbolic model, white triangles represent the hyperboloid model and black bars represent the group mean best fitting model, which was the hyperboloid for all groups. This figure shows that the majority of AICc weights for the best fitting model from Group 1 individual participants are above 0.9 and are never lower than 0.6. The AICc weights from Groups 2 and 3 individual participants are more widely distributed, but are never lower than 0.4. Lower AICc weights for Groups 1 and 2 tend to be from the hyperbolic model, however there are some higher values for the hyperbolic as well for both groups. The model distribution for Group 3 appears more even for the hyperbolic model with a clustering of exponential model data points between 0.6 and 0.7. The group mean AICc weights for the hyperboloid model are all above 0.9.

Figure 8 shows the data used in the independent samples Kruskal-Wallis test of AUC values across groups. A Kruskal-Wallis test was used because both the AUC values and the log transformed AUC values violated the assumptions of normality. More specifically, Groups 1 and 3 violated normality with a long left tail. When log transformed, Group 2 violated normality with a long left tail. As such, a non-parametric test was used. There was a statistically significant difference among the three groups in terms of AUC values, $H(2) = 12.44$, $p = .002$, $\eta^2 = 0.18$. More specifically, Group 1 ($M = 0.13$, $SD = 0.23$, $n = 16$) was significantly different from Group 2 ($M = .30$, $SD = 0.20$, $n = 23$), $H(1) = -18.16$, $p = .006$, $d = 0.72$, and from Group 3 ($M = .32$, $SD = 0.29$, $n = 21$), $H(1) = -17.78$, $p = .004$, $d = 0.68$. Groups 2 and 3 were not significantly different from each other, $H(1) = .38$, $p = 1.000$, $d = 0.07$. The bracket above the figure represents significant differences across Groups 1 and 2 and Groups 1 and 3 and no significant difference across Groups 2 and 3. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Figure 9 shows the data used in the independent samples Kruskal-Wallis test of indifference points across groups. A Kruskal-Wallis test was used as the indifference points violated the assumptions of normality similarly to that which was described above. There was a statistically significant difference among the three groups in terms of indifference points, $H(2) = 55.51$, $p = .000$, $\eta^2 = 0.13$. More specifically, Group 1 ($M = 237.60$, $SD = 322.02$, $n = 110$) was significantly different from Group 2 ($M = 497.26$, $SD = 352.58$, $n = 158$), $H(1) = -98.03$, $p = .000$, $d = 0.76$ and from Group 3 ($M = 500.02$, $SD = 369.67$, $n = 146$), $H(1) = -99.99$, $p = .000$, d

= 0.75. Groups 2 and 3 were not significantly different from each other, $H(1) = -1.95$, $p = 1.000$, $d = 00$. The bracket above the figure represents significant differences across Groups 1 and 2 and Groups 1 and 3 and no significant difference across Groups 2 and 3. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Discussion

In summary, a nonlinear regression was used to evaluate the fit of three different models to both individual and group monetary delay discounting data by a sample of adjudicated adolescents and a sample of college males and college females for comparison. The I-T approach was used to determine which model was the best fit for each individual data set and group mean data. Additional analyses to evaluate differences in both AUC and indifference points between groups were also included.

Overall, several important findings from this study contribute to the delay discounting literature at large and will help build a foundation for future studies on delay discounting by adjudicated adolescents. The main finding was that for all group mean data, the hyperboloid was the best fitting model in the candidate set; however, there was individual variability within all groups. Despite clear evidence that the hyperboloid was the best for group data, even across very different groups, the best model varied across individuals. This result is in contrast to Hypothesis 1 in which I hypothesized that the hyperbolic model would be the best fit for all groups and most individual data sets.

The second main finding is that participants of Group 1 showed steeper discounting as evidenced by visual analysis of indifference points and model fits. This finding is also supported by participants of Group 1 producing indifference points and AUC values that were significantly lower than those produced by participants of Groups 2 and 3. This finding supports Hypothesis 2 and is consistent with delay discounting research focused on clinical samples such as controlled substance users (Petry, 2002), pathological gamblers (Dixon et al., 2003), and those with certain clinical mental health diagnoses (Wilson et al., 2011).

These results have several implications when taken together with the existing literature on delay discounting. The first implication is that when researchers are interested in looking at aggregated group data, the hyperboloid model may be a better option than exponential or hyperbolic models according to the I-T approach. This implication is made stronger by the finding in the current study that the hyperboloid model was the best fit for group data across three very different groups. This finding is in line with those of other researchers who have shown that hyperboloid functions are superior to exponential and hyperbolic functions for delay discounting data (e.g., McKerchar et al., 2009, 2010; Mitchell et al., 2015; Sargisson & Schoner, 2020). However, much of the published discounting research focuses on aggregated group data and the present analysis revealed considerable variability in what constituted the best fitting model at the individual level. As such, more focus should be directed towards reporting delay discounting at the individual level to evaluate how and why individual differences occur.

It is possible that some level of variability at the individual level occurred due to each individual's history with monetary choices. It may be that participants of Group 1 had little experience in making monetary decisions, as many have been in residential facilities for extended durations. They may also be more likely to have come from low socioeconomic backgrounds. In contrast, it is possible that a larger number of participants from Groups 2 and 3 have more experience with monetary choices and possibly come from higher socioeconomic backgrounds. In addition to exerting potential influences on which model is the best fit, an individual's history with monetary choices may also influence the extent to which they discount delayed monetary outcomes.

The second implication derives from the novel nature of the population of interest and the topic area. This study is the first of its kind to evaluate delay discounting by adjudicated adolescents using model fitting and the I-T approach. The results of the current study show that adjudicated adolescents may be susceptible to steeper discounting, which is in line with other studies showing steeper discounting in clinical versus non-clinical populations (e.g., Dixon et al., 2003; Petry, 2002; Rosch et al., 2018; Wilson et al, 2011). These findings provide support for targeting changes in delay discounting as a dependent variable for adjudicated adolescents, which could lead to large collateral changes in other areas of an individual's behavior (Odum et al., 2020).

On the subject of steeper discounting, a discussion of *k* and *s* values is warranted. In regards to interpretation of the exponents in discounting equations, *k* is the discounting rate and *s* is the nonlinear scaling of amount and time (McKerchar et al., 2010). When *s* is 1.0, the equation is the same as the hyperbolic. When *s* is less than 1.0, the subjective value of a reward decreases more steeply than the hyperbolic equation would have predicted when the delay values are low but then decreases less steeply when delay values are high. Figure 4 shows a visual example of this phenomenon in each panel. As a verbal example, McKerchar et al. stated that according to the hyperboloid equation, the perceived difference in wait duration from 1 to 2 months is much more than that from 12 to 13 months when *s* is less than 1.0. In reference to our data, when the hyperboloid equation was identified as the best fit for individual data sets, *s* was less than 1.0 in all but one instance (P-13 at a value of 4.27). Further, *s* was always less than 1.0 and similar in value for group data across all groups. Generally, regardless of the model, *k* values were larger for participants of Group 1 than Groups 2 and 3. Additionally, the *k* value of the group mean data was larger for Group 1 than Groups 2 and 3, suggesting a steeper rate of discounting by participants in Group 1.

Results of the I-T approach at the individual level showed that there was a higher incidence of AICc weights above 0.9 for Group 1 (see Figure 7). One possible interpretation of this may be that models generated from steeper discounting data may vary more and as such, a higher incidence of AICc weights above 0.9 were identified for Group 1. It may be that models generated from steeper discounting data are more discriminable and thus, lead to a larger delta AICc and in turn, higher AICc weights. For example, see P-84's data set in Figure 3. The exponential and hyperboloid model follow very similar curves and are close to overlap. Because they are both so similar, they may be of almost equal goodness of fits. The I-T approach favors simpler models by adding a penalty term for additional parameters in a model. As such, the exponential was identified as the best fit over the hyperboloid. However, the closeness in the two models may be partially responsible for the AICc weight being below 0.9. This would also mean that for Groups 2 and 3, there may have been multiple models in the candidate set that described the data well, which might lead to smaller AICc weights. It is also possible that variability in indifference points could be responsible for the difficulty in distinguishing the best model at the individual level but not the group level.

In relation to AICc weights below 0.9, Friedel et al. (2014) evaluated delay discounting by smokers and non-smokers for money, alcohol, entertainment, and food and used the I-T approach to model selection. They compared the hyperbolic to the hyperboloid model and, although they did not report a complete I-T table, they similarly did not find large differences between AIC values for any commodity or any group. Their largest delta AIC was less than 2.0

which suggests that the secondary model may not be distinguishable from the primary model and would most likely have produced an AIC weight less than .9 for the primary model. These results are consistent with many of the individual results found in the current study, especially those from Groups 2 and 3. It is important to note that the AIC values reported by Friedel et al. were at the group level. Our group level analysis showed AICc weights above 0.9 for all group-level data. It is the individual level where models are difficult to distinguish.

The results of McKerchar et al. (2010) provide additional support for the suggestion that multiple models were good fits for our individual data sets that did not have an AICc weight above 0.9. They evaluated differences in *s* values in two different hyperboloid models: one in which the entire denominator was raised to a power (the model I evaluated) and one in which only the independent variable, delay, was raised to a power. Overall, results showed *s* significantly differed from 1.0 in less than 50% of cases and less than 35% of cases, respectively. As a reminder, when *s* is 1.0, it is the hyperbolic equation. Taken together, this finding supports the notion that AICc weights of less than 0.9 in the current study suggests that multiple models were acceptable fits and no one model was substantially better than any others in the candidate set.

Although not a central hypothesis of the current study, it is also notable that no gender difference appeared in AUC values or indifference points from Groups 2 and 3. As both groups consisted of college students with a similar mean age (19.5 and 19.6), and were selected from the same population, we can consider the fact that the main difference between these two groups was gender. This finding adds to a mixed literature of gender effects in delay discounting indices, but does not clarify it. Several articles show no gender differences in delay discounting of monetary outcomes, including studies focused on younger and adolescent populations (hypothetical outcomes: Harman et al., 2020; Lahav et al., 2015; Steinberg et al., 2009; Weafer et al., 2015; probabilistic outcomes: Olson et al., 2007). In contrast, several researchers have found gender differences in delay discounting (hypothetical outcomes: Blessington & Hayashi, 2020; Sweeney et al., 2020; Yankelevitz et al., 2012; probabilistic outcomes: Kirby & Marakovic, 1996). However, many studies that do show gender differences evaluate commodities other than money (e.g., sexual outcomes as in Sweeney et al., smartphone use as in Blessington & Hayashi). In summary, the literature appears to be mixed on the topic of gender's influence on delay discounting and the results of the current study add to this literature.

An important element of the current study that contrasts with the literature is that 24 of 40 participants or 65% of our adjudicated adolescent participants' data sets met exclusionary criteria; a large percentage when compared to other published studies. For example 5 out of 111, or 4%, of undergraduate participants were excluded by Koffarnus and Bickel (2014), 2 out of 54, or 3%, of adult smoker participants were excluded by Stein et al. (2016), and 11 out of 66, or 16%, of adults interested in weight loss recruited through Amazon Mechanical Turk were excluded by Sze et al. (2017). The large excluded percentage in our adjudicated adolescents group is in contrast to the college student groups with only 11% and 19% excluded from the college male and female groups, respectively. Dixon et al. (2003) excluded a similarly large percentage of their gambling population (45%) when compared to their control population (5%). The current results are more similar to those of Dixon et al. who found a larger percentage of unsystematic data in their clinical population but not in their control population.

The large percentage of excluded participants is interesting for several reasons. First, although previous research has validated the type of task I used with other populations (e.g., Acuff et al., 2018; Odum, 2002), none of these studies reported as high of a percentage of excluded data sets. As this is the first study evaluating delay discounting with adjudicated adolescents, there is no other research to serve as a complete comparison but some possible reasons can be offered. A meta-analysis of delay discounting in children by Staubitz et al. (2018) found that researchers typically use smaller monetary amounts and shorter delays with children, whose mean age was 13 years. Further, a paper by Steinberg et al. (2009) suggested that there may not be significant differences in discounting after age 16 years. As the population in Group 1 of the current study was a mean age of 17.5 years, there was no substantial literature to suggest the task I chose would not be appropriate. It is plausible that the delays (up to 50 years) or monetary amounts (up to $1,000) used were not specific enough for this population. This suggests that conducting parametric analyses evaluating different delays and monetary amounts to identify durations and amounts that are more population appropriate are warranted. It may also be that a different task method such as fill-in-the-blank (Chapman, 1996; Lahav et al., 2015) is more appropriate for adjudicated adolescents.

The major limitations of this research were created by the COVID-19 pandemic and were not possible to anticipate when designing the study. These limitations include the inability to continue the originally proposed methods as the facility denied entry for non-essential staff and was not technologically equipped for remote research. However, the adapted study will provide a foundation for future research on delay discounting in adjudicated adolescents.

An additional limitation that has been discussed above is the small sample size in Group 1. I collected data for 40 participants in this group but excluded a larger number of unsystematic data sets than originally anticipated from the numbers reported in the literature. Shortly after I completed the initial data analysis and saw that our sample size would be smaller than originally anticipated, COVID-19 precautions were already in place, preventing us from additional data collection with members of Group 1. Future research should consider recruiting a sample size that will sufficiently power an analysis of the difference between AUC and even *k* and *s* (if applicable) values. A power analysis suggests that a minimum sample size of 56 total participants would sufficiently power such an analysis with an effect size of 0.8. This is a worthy area of future research as there is mixed literature as to the interchangeability of AUC and *k* values as dependent variables for delay discounting research (Friedel et al. 2004; Mitchell et al., 2015; Myerson et al., 2001; Yoon et al., 2007). As adjudicated adolescents are a new population of focus for delay discounting research, it will be important to lay the groundwork of evaluating dependent variables of interest for this novel population.

A limitation that should be considered is that our adjudicated adolescent sample was a mean of two years younger than our college student samples and, although it wasn't examined directly, likely came from a different socioeconomic background than college students at a residential campus. However, results of previous research suggest there may not be significant age differences in delay discounting after age 16 (Steinberg et al., 2009). As our Group 1 sample was too small to evaluate within-group age differences, future work should evaluate potential age differences in delay discounting by adjudicated adolescents with a larger sample size. Further, future research should recruit a same age comparison sample when evaluating delay discounting with adjudicated adolescents.

Another limitation is that of location differences between and possibly within groups. Specifically, members of Group 1 completed the task in a very different location than members of Groups 2 and 3. Further, the location in which members of Groups 2 and 3 completed the task was unknown to the researchers but most likely varied by participant since it was completed online. However, it is probable that any major issues resulting from these variable locations would have been identified by evaluating the data for systematic responders. A limited line of research has shown that discounting rates may vary as a function of location for some clinical populations. Dixon et al. (2006) found that gamblers discounted delays more steeply when completing a discounting task in an off-track betting facility than in another community location not related to gambling. Dixon et al. did not evaluate this effect in a control group so it is unclear as to whether non-clinical subjects would show this effect. As there is only one published study showing this effect with only 20 participants, the generality of this effect to other participants is limited. Future research should consider evaluating the effect of environmental changes related to the commodity being evaluated in adjudicated adolescents.

Another possible limitation is that a different computer program was used for data collection for Group 1 than was used for Groups 2 and 3. Although a different computer software program was used, the task was identical in almost every way (e.g., question presentation order, one question per screen). Further, there is support for correlation of discounting rates across paper and computer formats (Smith & Hantula, 2008) which is arguably more discriminable than two different software programs. As such, it is probable that the computer software program did not affect discounting rates to a substantial degree.

Future research should continue with the pre-pandemic research proposal and begin with a parametric analysis of appropriate delays and monetary amounts for adjudicated adolescents (the Auburn University Institutional Review Board has already approved this modification). Thereafter, researchers should evaluate the validity of different task types with adjudicated adolescents to identify the briefest format while maintaining task validity. Specifically, researchers should compare results of a binary choice procedure, a fill-in-the-blank procedure, and possibly even the abbreviated task described by Kirby et al. (1999). Further, the results of the current study suggest that it may prove fruitful for researchers to develop an abbreviated task similar to the Kirby et al. task but with a hyperboloid assumption of discounting. More specifically, the Kirby et al. task assumes hyperbolic discounting (i.e., an *s* value of 1.0) but the results of the current study suggest that the hyperboloid (i.e., an *s* value less than 1.0) may be a better fit in some cases.

Hereafter, researchers should evaluate delay discounting by adjudicated adolescents across different commodities, specifically those related to their offenses (e.g., sexual outcomes, controlled substances). Lastly, researchers should evaluate how delay discounting across different commodities is affected by different treatment packages. The first treatment package to evaluate, which was part of the initial proposal, is a mindfulness-based group therapy program. Specifically, the mindfulness-based group therapy program would use behavioral skills training to teach adolescents to engage in several different mindfulness activities (e.g., mindful coloring, mindful breathing techniques) across three 1-hr sessions. Thereafter, researchers can evaluate different treatment types, dosages, and delivery modalities to identify the best treatment for adjudicated adolescents at the individual and group level. Results of this line of research could equip adolescents with a history of delinquent behavior to make choices that consider all possible outcomes, and maximize their long-term benefit.

In regards to treatment for delay discounting, there are a variety of methods that have been shown to decrease discounting rates such as framing techniques, and exposure to nature (see Rung & Madden, 2018 for a meta-analysis). Researchers should evaluate of a variety of these treatments while also taking participant choice into consideration. Fostering autonomy should be a primary consideration in ABA therapy for ethical reasons and may be particularly important in the current population (Martin et al., 2006). Youth in state custody may experience a high degree of staff-led activities and a low opportunity to exercise choice. Making healthy choices is an important life skill and adolescents in residential facilities may be missing valuable opportunities to practice this behavior. As such, treatment choice should be a focus in future research on the topic. For example, researchers could evaluate both effectiveness and preference for treatments rooted in mindfulness, episodic future thinking, delay fading, and framing techniques.

Researchers should also evaluate how treatments aimed to produce responding to larger later consequences, such as creating and maintaining exercise regimens, healthy eating plans, or financial literacy programs, affect delay discounting. Black and Rosen (2011) found that a money management-based substance use treatment decreased delay discounting in adults with a history of controlled substance use. Further, cocaine use decreased as a result of treatment, showing generalization of decreased discounting to a socially relevant behavior that occurred outside of the laboratory. Black and Rosen suggested that regular review of future rewards may have increased the salience of these delayed rewards and, in turn, increased their perceived likelihood and value. Researchers should consider conducting similar types of research on the effects of treatments that increase the salience of future rewards on delay discounting and generalized behavioral choices.

Regarding data analysis, future research should consider the high percentage of data sets that were excluded due to patterns inconsistent with delay discounting. As previously mentioned, one direction to address this issue should be the evaluation of tasks specific to our unique population. Another alternative and interesting option would be to analyze the existing data set without exclusions using a multilevel analysis of choice data (Young, 2018). Analyzing the choice data directly as opposed to converting it to indifference points allows the researcher to include all data sets unless there were procedural errors that led to an incomplete data set (e.g., participant fell asleep, technology failures). Further, a multilevel analysis of choice data allows the researcher to evaluate the effects of magnitude and delay independently. Future researchers should consider this methodology, especially when working with clinical populations who may produce higher instances of unsystematic data.

In summary, this study evaluated delay discounting of hypothetical monetary outcomes in adjudicated adolescents and compared those results to two groups of college students. We found that the hyperboloid model fit well for all three groups at the group level but that there was considerable variability at the individual level in all three groups. We found that adjudicated adolescents produced more instances of nonsystematic data, suggesting they generally were more likely to make choices in an inconsistent fashion as they progressed through the task, than were college students. We also found that adjudicated adolescents discounted delays relating to hypothetical monetary outcomes more steeply than our two college student groups. There were no difference in discounting between the two college student groups. Overall, this experiment will serve as a foundation to guide future research on delay discounting in adjudicated adolescents.

Table 1

Adjudicated Adolescents Group Demographics and Indifference Points

Participant Number	Age	Offense	Indifference Points by Delay in Months						
			1	6	12	60	120	300	600
9	15	SO	825	600	550	325	450	250	175
12	17	SO	600	20	7.5	15	10	3	1
13	18	SO	40	1	1	1	1	1	1
15	18	GD	900	1000	895	750	725	700	675
16	17	GD	1000	965	800	725	700	700	700
23	19	GD	1000	1	1	1	1	1	1
25	18	GD	985	1	1	1	1	1	1
26	19	GD	50	70	1	1	1	1	1
27	16	GD	500	22.5	20.5	40	40	40	40
31	17	GD	90	1	1	1	1	1	1
32	18	GD	572.5	502.5	502.5	490.5	50.5	10.5	25
33	17	GD	950	400	225	100	100	60	60
40	18	CS	500	425	300	200	125	60	70
41	18	CS	550	275.5	1	1	1	1	1
42	18	CS	500	1	1	3		10.5	
43	18	CS	525	495.5	3	1	1	1	1
Mean	17.5	N/A	599.2	298.8	206.9	165.9	147.1	115	116
Excluded Participants									
4	20	SO	285	250	325	500	70	55	100
5	16	SO	1000	1000		40	500	1	1
6	16	SO	95	10.5	20.5	1	20.5	1	1
7	16	SO	80	100.5	325	80	1	1	1
8	16	SO	850	1	500	730	750	1000	1000
10	18	SO	115	165	80	80	115	1	1
11	18	SO			7.5	10.5	5	490.5	490.5
14	18	GD	475	1	150.5	5.5	495	250	125
17	17	GD	450	375	350	200	250	100	125
18	17	GD	230	5.5		5	125.5	127.5	620
19	19	GD	740	675	185	550	600	600	575
20	18	GD	N/A	N/A	N/A	N/A	N/A	N/A	N/A
21	17	GD	530	245	70	525	430	520	450.5
22	17	GD	535	790	890	1	3	1	1
24	19	GD	400	450	450	500	400	375	475
28	17	GD	1000	805	980	920	40	302.5	
29	18	GD	177.5	12.5	225	1	1	400.5	1
30	16	GD	1000	22.5	425.5	400.5	1	1	1
34	16	SO	600	300	90	180	600	800	775

35	17	GD	3	460.5	1	1	1	1	1
36	18	GD	1000	1000	990	995	990	1000	990
37	18	GD	100	7.5	3	5	5	5	227.5
38	17	GD	240	5.5	3	1	1	1	490.5
39	17	GD	500	350	175	400	475	425	375
44	16	GD	275.5	275.5	125.5	20.5	42.5	375.5	200

Note. SO = sexual offense; GD = general delinquency; CS = controlled substance.

Table 2

College Male Group Demographics and Indifference Points

		Indifference Points by Delay in Months						
Participant Number	Age	1	6	12	60	120	300	600
45	18	600	425	225	150	105	20	1
46	25	462.5	230	1	1	1	1	1
47	19	1000	850	550	150	100	60	5
49	22	1000	1000	900	900	800	725	625
50	19	900	800	725	200	100	50	60
51	18	625	475	400	150	150	325	100
52	21	980	960	920	650	450	80	60
53	18	1000	850	800	800	800	600	450
54	18	1000	1000	1000	1000	500	125	60
55	18	930	575	475	625	500	205	200
56	22	1000	800	700	400	250	140	80
57	18	1000	700	600	500	500	300	300
58	20	960	930	950	900	800	600	50.5
59	21	980	940	900	600	400	300	250
61	18		1000	825	750	500	225	150
62	19	1000	250	100	40	40	20.5	40
63	19	800	500	200	200	325	275	250
64	19	750	200	100	10	15	1	1
66	21	1000	990	500	500	300	200	50.5
67	19	990	900	900			550	275
68	19	1000	900	750	500	500	500	500
69	19	1000	990	980	960	940	550	250
70	19	800	500	550	225	200	100	20
Mean	19.5	899	728.9	610.9	464.1	376.2	258.8	164.3
Excluded Participants								
48	20	920	960	800	850	900		
60	18	550	250	400	225	250	150	125
65	18	980	100	200	250	250	150	150

Table 3

College Female Group Demographics and Indifference Points

		Indifference Points by Delay in Months						
Participant Number	Age	1	6	12	60	120	300	600
71	21	400	325	375	150	175	90	20
73	19	830	650	250	90	1	1	1
74	19	1000	675	375	175	150	175	90
75	18	850	500	400	100	50	85	
76	19	870	327.5	260	200	175	70	50
77	20	1000	1000	1000	1000	1000	1000	500
78	26	950	500	550	3	1	1	1
79	20	990	600	500	500	325	375	1
82	18	1000	850	550	525	310	450	265
83	21	1000	1000	1000	995	980	980	375
84	18	1000	980	980	900	900	100	60
85	19	1000	1000	980	980	940	900	100
86	21	1000	900	750	350	200	100	20
88	19	1000	1000	990	970	980	950	910
89	19	900	850	900	525	525	450	250
90	18	325	600	600	350	125	60	3
91	19	1000	250	250	100	20	10	1
92	21	1000	800	750	500	500	100	100
93	19	1000	770	500	535	520	375	327.5
94	18	725	400	200	150	150	100	80
96	20	1000	500	450	300	100	20	5
Mean	19.6	890.8	698.9	608	454.9	401.4	318.6	166
Excluded Participants								
72	21	1000	390	95	190	52.5	20.5	155
80	18	420	750	350	635	30	5	1
81	18	1000	1000	1000	1000	1000		1000
87	18	1000	1000	1000		1000	1000	
95	18	305	850	550	550	700	250	1

Table 4

Group 1 Model Comparison

Participant Number	Exponential *k*	Hyperbolic *k*	Hyperboloid *k*	Hyperboloid *s*	R^2	AICc weight	AUC
9	0.0158	0.0408	**1.3713**	**0.2188**	0.927	0.971	0.2974
12	**0.5267**	0.9507	0.0306	17.5267	0.997	0.996	0.0083
13	40.2359	24.7767	**1.1212**	**4.2771**	0.999	0.943	0.0012
15	0.0009	0.0013	**0.1699**	**0.0939**	0.935	0.962	0.7156
16	0.0219	0.0013	**0.6320**	**0.0714**	0.858	0.940	0.7101
23	**0.2922**	0.4740	0.0024	120.1366	0.947	0.911	0.0060
25	**0.2964**	0.4836	0.0014	200.5346	0.949	0.918	0.0059
26	2.9957	**15.5081**	1072.5643	0.4058	0.373	0.701	0.0019
27	**0.6903**	1.2190	0.0877	8.2637	0.994	0.955	0.0412
31	**2.4079**	10.5594	1.3427	2.8252	1	0.978	0.0014
32	0.0781	**0.1054**	2.8535	0.2741	0.648	0.753	0.0948
33	0.1340	**0.2094**	0.2114	0.9933	0.963	0.646	0.0865
40	0.1495	0.3353	**7.6044**	**0.2790**	0.9240	0.962	0.1044
41	0.3482	**0.7567**	0.6752	1.0713	0.931	0.942	0.0063
42	**0.6983**	1.2818	0.0193	36.4556	0.998	0.993	0.0070
43	0.1966	**0.5246**	1.0659	0.6940	0.738	0.707	0.0082
Mean	0.1966	0.4468	**4.7486**	**0.3274**	0.954	0.956	0.1342

Note. Bolded coefficients represent the best fitting model. AICc = Akaike information criterion corrected for small samples; AUC = area under the curve.

Table 5

Group 2 Model Comparison

Participant Number	Exponential *k*	Hyperbolic *k*	Hyperboloid *k*	Hyperboloid *s*	R^2	AICc weight	AUC
45	0.1572	0.3222	**1.8077**	**0.4339**	0.953	0.525	0.0598
46	0.6845	**1.0574**	1.2510	0.9068	0.925	0.967	0.0054
47	0.0373	**0.0586**	0.0254	1.8585	0.986	0.565	0.0963
49	0.0009	**0.0012**	0.0183	0.1820	0.9210	0.524	0.7419
50	**0.0269**	0.0463	0.0179	1.993	0.997	0.496	0.1175
51	0.1060	0.1730	**5.2166**	**0.2405**	0.812	0.626	0.2240
52	**0.0070**	0.0118	0.0002	35.0164	0.995	0.984	0.2506
53	0.0015	**0.0023**	0.1703	0.1278	0.882	0.659	0.6333
54	**0.0047**	0.0071	0.0001	45.1424	0.941	0.883	0.3142
55	0.0070	**0.01584**	1.2792	0.1929	0.660	0.444	0.3195
56	0.0150	**0.0281**	0.0565	0.6673	0.992	0.525	0.2058
57	0.0064	0.0131	**0.5768**	**0.2040**	0.9430	0.960	0.3784
58	**0.0024**	0.0035	1.95E-05	126.3877	0.919	0.888	0.5497
59	0.0058	**0.0097**	0.0262	0.5498	0.979	0.669	0.3705
61	0.0051	**0.0087**	0.0056	1.3476	0.965	0.507	0.3413
62	**0.1890**	0.3069	0.0003	517.2000	0.971	0.905	0.0416
63	0.1282	**0.1783**	3.5524	0.2337	0.780	0.490	0.2731
64	**0.2597**	0.4867	0.1008	3.1846	0.994	0.567	0.0146
66	0.0118	**0.0234**	0.0705	0.5484	0.876	0.827	0.2342
67	**0.0289**	0.0353	0.0765	0.5776	0.885	0.498	0.3425
68	0.0025	0.0059	**0.3576**	**0.1602**	0.906	0.933	0.5170
69	**0.0018**	0.0025	8.20E-05	23.2664	0.956	0.905	0.6151
70	0.0677	**0.0944**	0.4997	0.4230	0.944	0.636	0.1386
Mean	0.0106	0.0216	**0.3357**	**0.2859**	0.983	0.993	0.3003

Note. Bolded coefficients represent the best fitting model. AICc = Akaike information criterion corrected for small samples; AUC = area under the curve.

Table 6

Group 3 Model Comparison

Participant Number	Exponential *k*	Hyperbolic *k*	Hyperboloid *k*	Hyperboloid *s*	R^2	AICc Weight	AUC
71	0.194	0.618	**31.443**	**0.229**	0.802	0.910	0.1114
73	**0.096**	0.152	0.046	2.468	0.968	0.663	0.0303
74	0.070	**0.090**	0.207	0.588	0.953	0.879	0.1663
75	0.093	**0.148**	0.211	0.802	0.991	0.963	0.0798
76	0.150	**0.232**	0.716	0.509	0.930	0.812	0.1126
77	**0.001**	0.001	0.000	135.336	0.727	0.605	0.8742
78	**0.070**	0.118	0.026	3.098	0.671	0.671	0.0352
79	0.012	**0.032**	0.525	0.280	0.738	0.649	0.2932
82	0.008	0.015	**0.353**	**0.234**	0.880	0.551	0.3930
83	**0.001**	0.001	0.000	105.468	0.742	0.635	0.8305
84	**0.004**	0.005	0.000	93.021	0.897	0.842	0.3741
85	**0.002**	0.002	0.000	2543.669	0.764	0.699	0.7195
86	0.016	**0.029**	0.018	1.389	0.998	0.859	0.1635
88	0.000	**0.000**	0.008	0.046	0.947	0.536	0.9495
89	0.004	**0.008**	0.072	0.310	0.924	0.662	0.4475
90	0.047	**0.087**	28.544	0.181	0.474	0.641	0.1154
91	**0.160**	0.254	0.087	2.263	0.934	0.541	0.0358
92	0.008	**0.016**	0.036	0.638	0.939	0.840	0.2561
93	0.005	0.011	**0.788**	**0.175**	0.874	0.855	0.4186
94	0.159	0.288	**1.540**	**0.418**	0.962	0.640	0.1197
96	0.068	**0.093**	0.188	0.650	0.935	0.929	0.0883
Mean	0.010	0.020	**0.523**	**0.244**	0.973	0.993	0.3284

Note. Bolded coefficients represent the best fitting model. AICc = Akaike information criterion corrected for small samples; AUC = area under the curve.

Table 7

AICc table for Group 1 Mean Indifference Points

Model Name	RSS	K	Log-Lik	AICc	△AICc	Evidence Ratio	AICc weight	RSQ	Model Rank
Hyperboloid	8505.986	3	-26.036	66.073	0	1	0.956	0.954	1
Hyperbolic	68968.650	2	-32.723	72.447	6.373	0.041	0.039	0.992	2
Exponential	136013.637	2	-35.100	77.201	11.127	0.003	0.003	0.986	3

Note. RSS = residual sum of squares; K = number of parameters; Log-Lik = log likelihood; AICc = Akaike information criterion corrected for small samples; RSQ = R squared.

Table 8

AICc table for Group 2 Mean Indifference Points

Model Name	RSS	K	Log-Lik	AICc	△AICc	Evidence Ratio	AICc weight	RSQ	Model Rank
Hyperboloid	6996.379	3	-25.353	64.705	0	1	0.993	0.983	1
Hyperbolic	99027.211	2	-33.989	74.979	10.273	0.005	0.034	0.959	2
Exponential	211840.263	2	-36.651	80.302	15.596	0.000	0.000	0.926	3

Note. RSS = residual sum of squares; K = number of parameters; Log-Lik = log likelihood; AICc = Akaike information criterion corrected for small samples; RSQ = R squared.

Table 9

AICc table for Group 3 Mean Indifference Points

Model Name	RSS	K	Log-Lik	AICc	△AICc	Evidence Ratio	AICc weight	RSQ	Model Rank
Hyperboloid	9604.801	3	-26.462	66.924	0	1	0.993	0.973	1
Hyperbolic	135360.430	2	-35.083	77.167	12.461	0.001	0.011	0.931	2
Exponential	264414.985	2	-37.427	81.854	17.148	0.000	0.000	0.888	3

Note. RSS = residual sum of squares; K = number of parameters; Log-Lik = log likelihood; AICc = Akaike information criterion corrected for small samples; RSQ = R squared.

Figure 1

Least Squares Regression for Representative Individual Indifference Points for Group 1

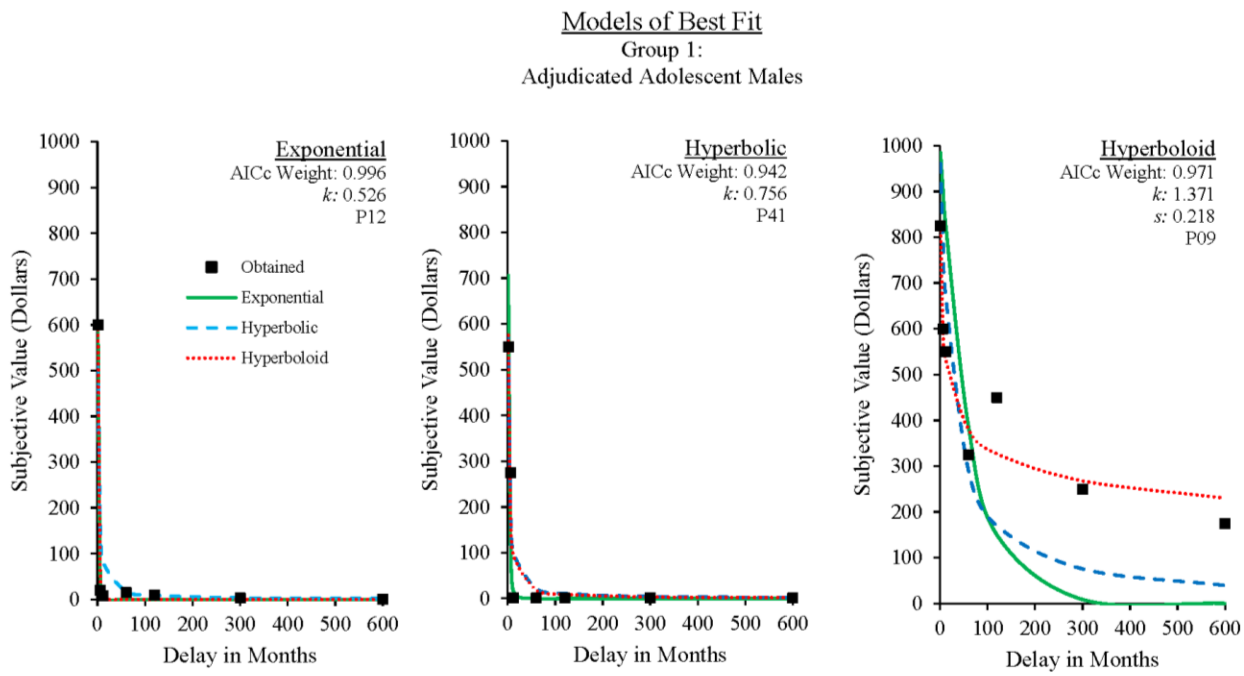


Figure 2

Least Squares Regression for Representative Individual Indifference Points for Group 2

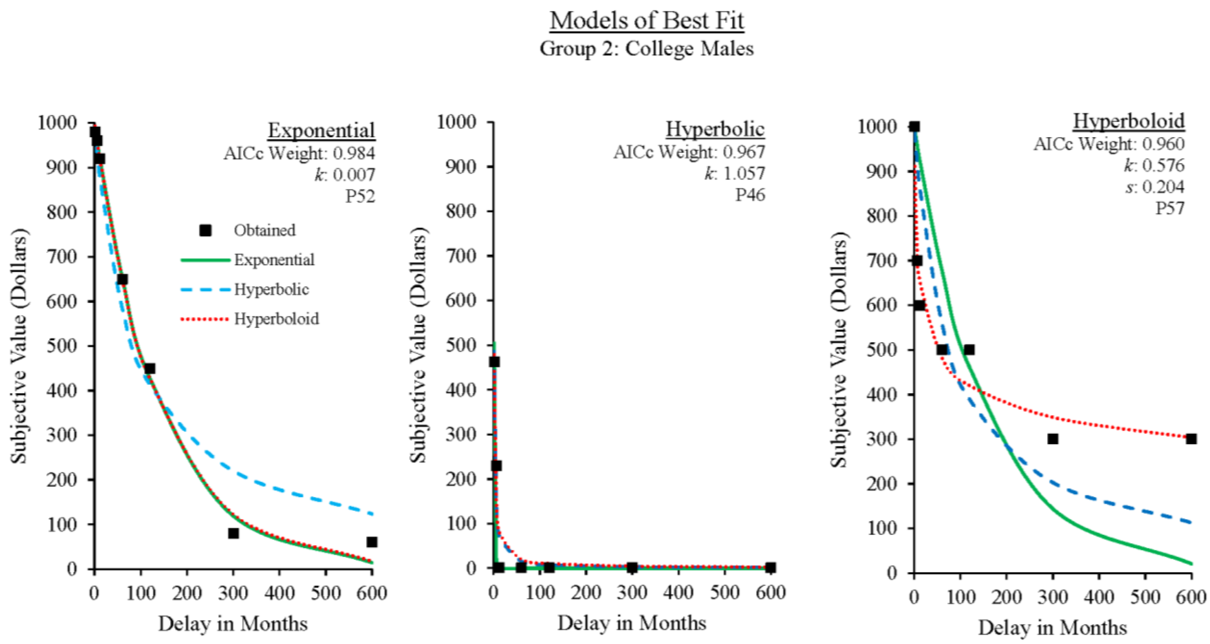


Figure 3

Least Squares Regression for Representative Individual Indifference Points for Group 3

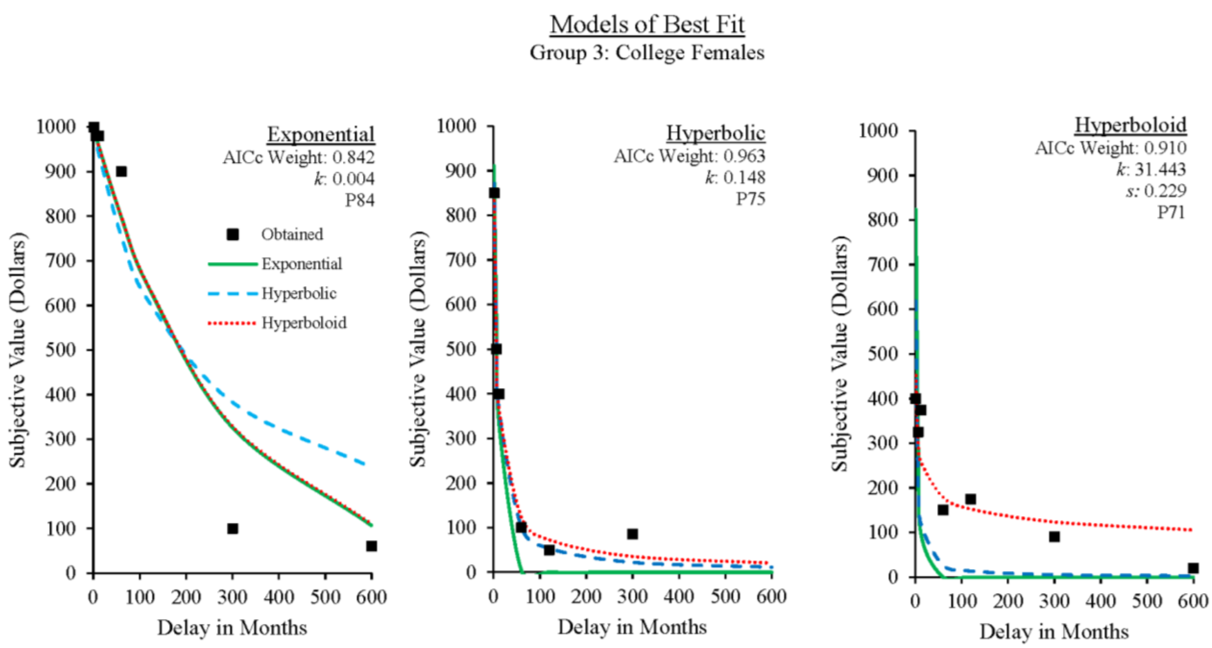


Figure 4

Least Squares Regression for Group Level Indifference Points across Groups

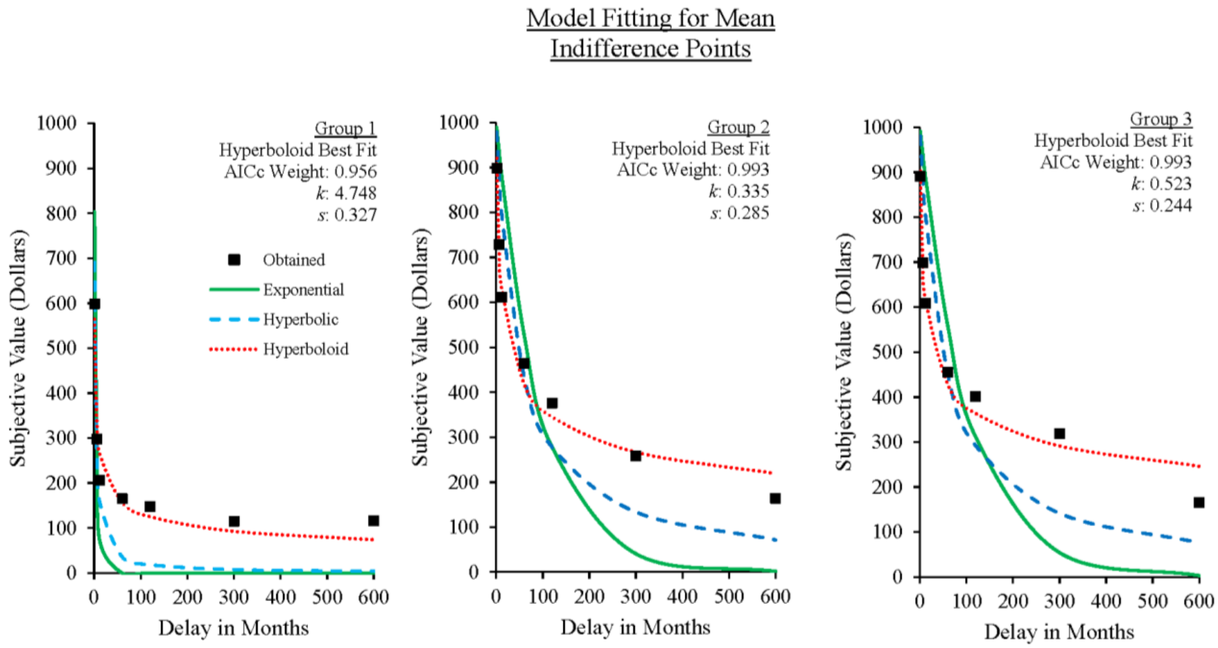


Figure 5

K and S Distributions for Best Fitting Model

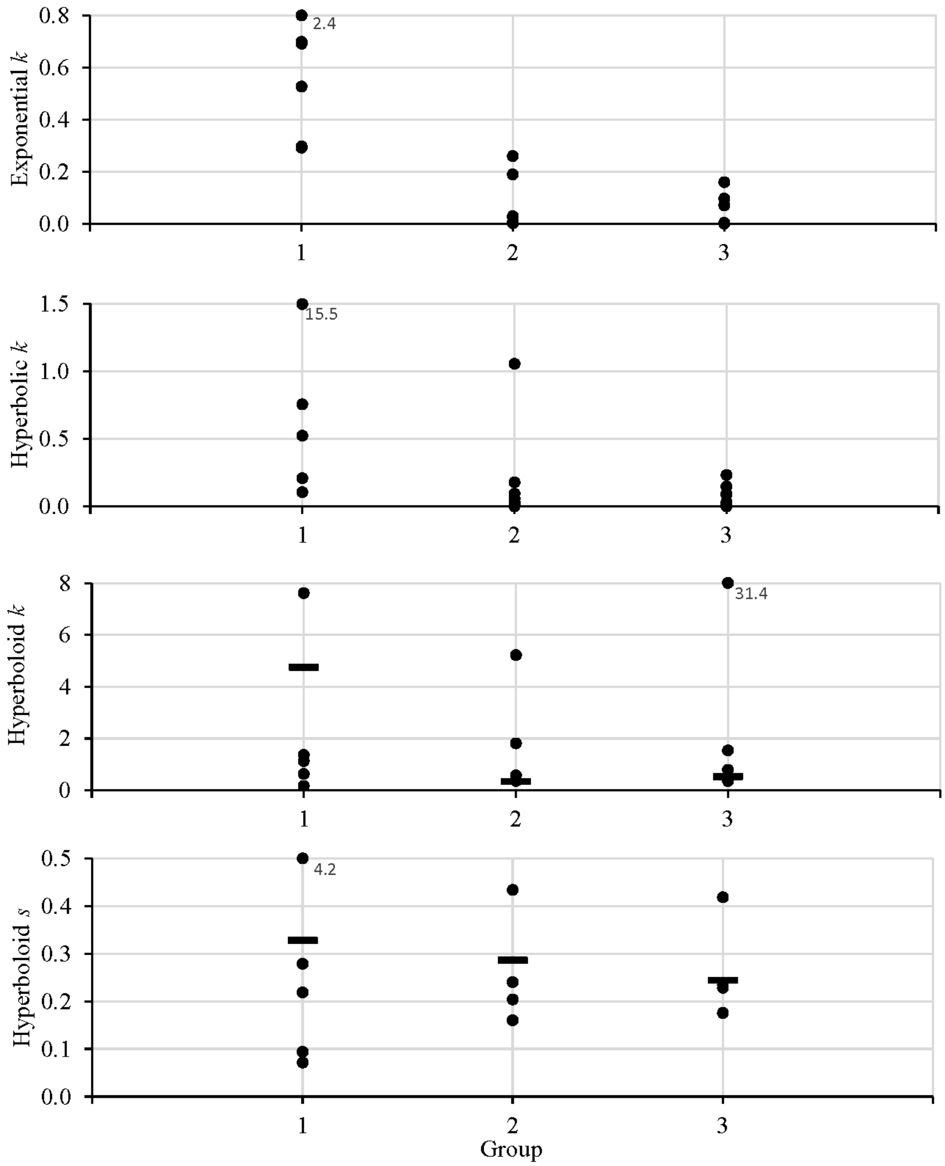


Figure 6

Area Under the Curve Distributions

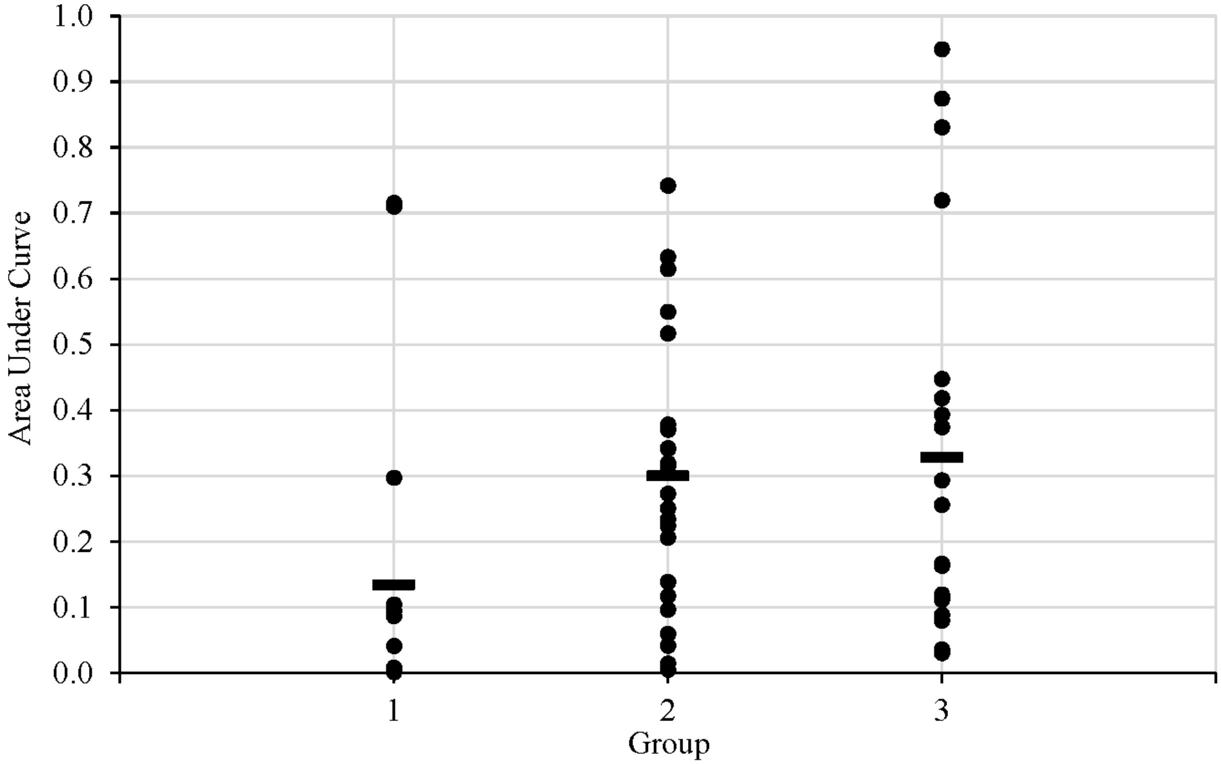


Figure 7

AICc Weights Distribution by Model across Group

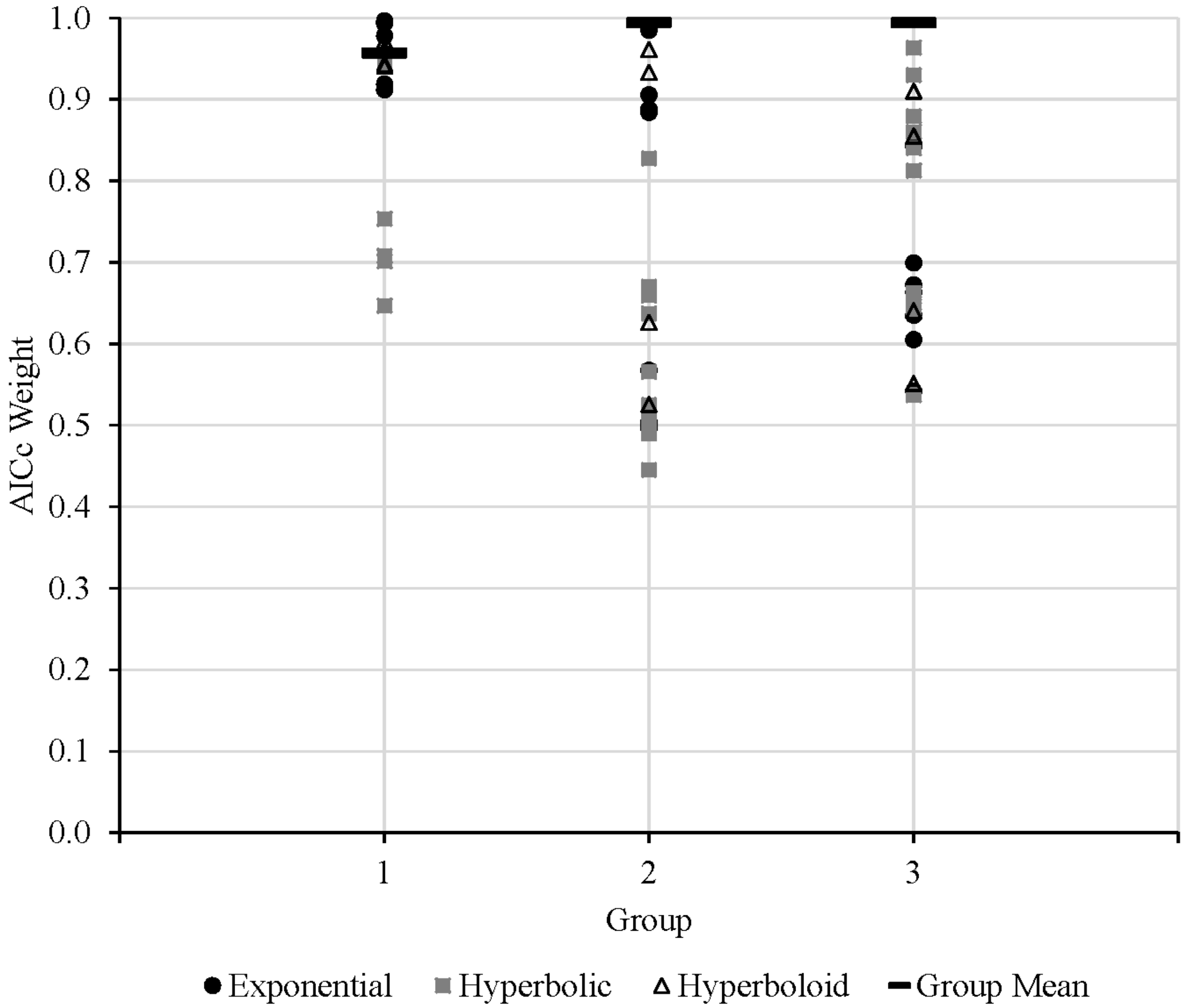
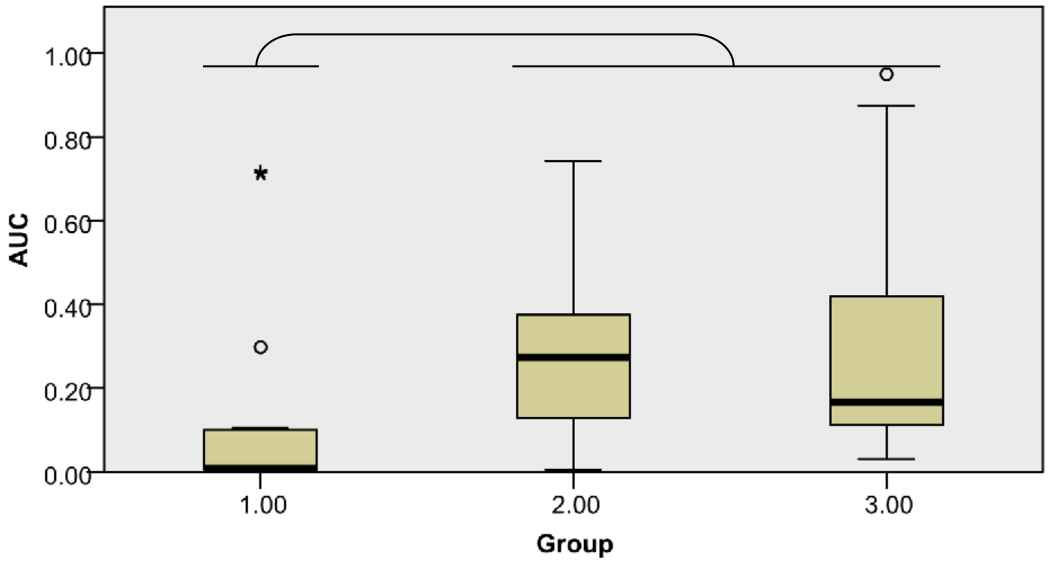


Figure 8

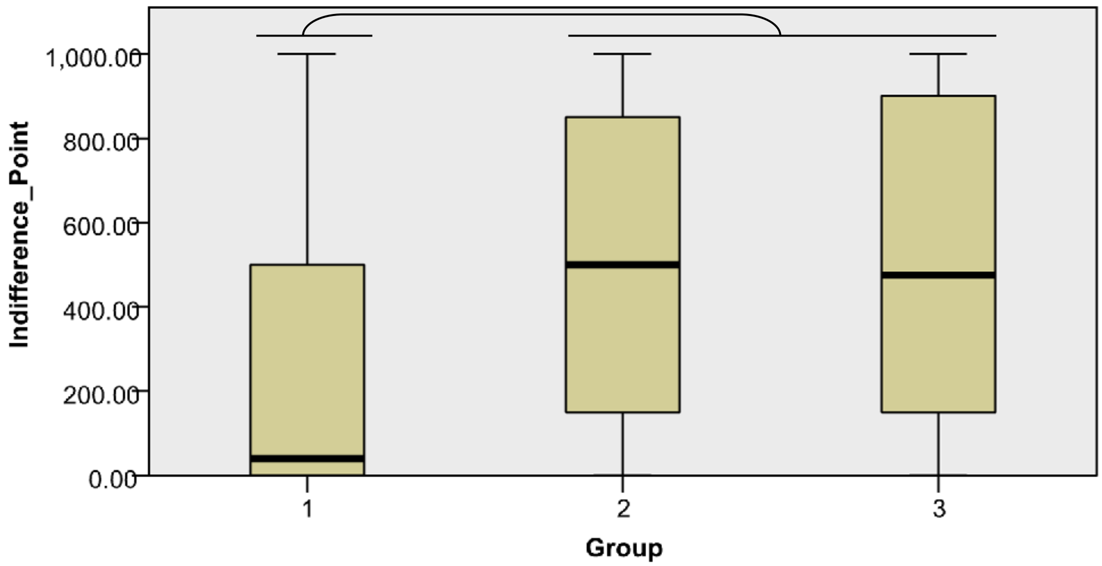
Independent Samples Kruskal-Wallis Test of Area Under the Curve across Groups



Note. Group 1 represents adjudicated adolescents, Group 2 represents college males, and Group 3 represents college females. Group 1 was statistically significant from Groups 2 and 3. Bracket represents significant differences amongst groups.

Figure 9

Independent Samples Kruskal-Wallis Test of Indifference Points across Groups



Note. Group 1 represents adjudicated adolescents, Group 2 represents college males, and Group 3 represents college females. Group 1 was statistically significant from Groups 2 and 3. Bracket represents significant differences amongst groups.

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Appendix

Magnitude and Delay Assessment

Participant code: ___________________________

For each question, circle the option that is largest or the option that is soonest.

- For the next four questions, circle the largest option

    1. $1000 today or $10 today
    2. $50 today or $500 today
    3. 10 min today or 1 min today
    4. 1 min today or 9 min today

- For the next four questions, circle the soonest option

    5. $1000 in 50 years or $1000 today
    6. $1000 today or $1000 in one month
    7. 10 min today or 10 min in one day
    8. 10 min in 365 days or 10 min today