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SLOT MACHINE USE AS A MEASURE OF DECISION-MAKING IN SUBSTANCE USE DISORDERS

Theodore David Krmpotich

Bachelor of Science, Regis University, 2010

A Master's Thesis

Submitted to the Graduate Faculty

of the

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In partial fulfillment of the requirements

for the degree of

Masters of Arts

Grand Forks, North Dakota

May

This thesis submitted by Theodore Krmpotich in partial fulfillment of the requirements for the Degree of Master of Arts from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

Jeffrey Weatherly, PhD

Dmitri Poltavski, PhD

Alison Looby, PhD

This thesis (or dissertation) is being submitted by the appointed advisory committee as having met all of the requirements of the School of Graduate Studies at the University of North Dakota and is hereby approved.

Wayne Swisher

Dean of the School of Graduate Studies

Date

PERMISSION

Title	Slot Machine Use as a Measure of Decision-Making in Substance Use Disorders
Department	Psychology
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Theodore Krmpotich 4/14/16

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ABSTRACT

Many of the decision-making tasks involve gambling and gambling paradigms and therefore it is important to understand how gambling relates to decision-making, especially in individuals who use substances. The goal of this study was to investigate how individuals with SUD will perform on a slot machine and relate the slot-machine performance to current lab measures of decision-making. Individuals with and without substance use disorders gambled on a slot machine and completed other decision-making tasks (e.g., IGT, BART, delay discounting). Rewards were manipulated in terms of magnitude (real monetary payout verses no payout) for two reasons. Gambling performance was compared to three common lab measures of decision-making (i.e., IGT, BART, & delay discounting). In addition, measures of substance use and gambling motivation were obtained to relate the slot-machine paradigm to meaningful reasons for engaging in addictive behaviors. There were four main findings in this study. First, all participants tended to bet more tokens per trial on the slot machine when there was no monetary compensation compared to if there was. Second, no group or magnitude differences were found on any of the decision-making tasks (i.e., IGT, BART, and delay discounting). Third, the slot machine and all the decision-making task seems to be relatively independent from each other. Fourth, performance on the slot machine and the decision-making tasks was able to predict using alcohol for positive reinforcement, in particular, for social situations and enhancing positive feelings and experiences. It is important that future research investigates decision making 1) uses multiple measures of

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decision making to access potentially different aspect of decision-making and 2) flesh out the differences between these tasks and find out what these tasks are able to detect.

CHAPTER I INTRODUCTION

Decision-Making in Substance Use Disorders

Individuals with substance use disorders (SUD) tend to make poor decisions (Bechara, 2003). For example, individuals with SUD repeatedly take drugs despite longterm negative consequences. Decision-making was not always thought to be important in studying addiction (Bechara, 2003), but research is increasingly suggesting that decisionmaking is a crucial construct for understanding the mechanism involved in addictive behavior (Bechara, 2003; Bechara et al., 2001; Lejuez, Aklin, Zvolensky, & Pedulla, 2003; Lejuez et al., 2003). A plethora of research has suggested that individuals with SUD perform poorly compared to controls on decision-making tasks, often failing to learn to adjust their choices over time (Bechara, 2003; Leeman & Potenza, 2012). Three commonly used tasks in the substance use literature are the Iowa Gambling Task (IGT), the Balloon Analogue Risk Task (BART), and delay discounting (Bechara, Damasio, Damasio, & Anderson, 1994; Kirby & Maraković, 1996; Lejuez et al., 2002). All of these tasks tap different aspects of decision-making and play a crucial role in how the decision-making process is understood in SUD. Many of the tasks noted above investigate decision-making under risky and ambiguous circumstances. The deficits seen in SUD come in circumstances where there is not a clear "right" decision. Some decisions will yield reward now and others later, or they will be able to help the individual avoid a potential consequence.

Decision-making is still poorly understood in SUD, and the results of studies are often conflicting (Leeman & Potenza, 2012). Some studies find that individuals with SUD perform worse on measures of decision-making and other studies find no differences between SUD participants and controls (See Leeman & Potenza, 2012, for a partial review). Many reasons could be accounting for these discrepancies. For example, decision-making is often measured with tasks that involve gambling paradigms (Bechara, Tranel, Damasio, & Damasio, 1996; Lejuez et al., 2002). Using gambling paradigms to measure decision-making may be problematic as many individuals with SUD may also have comorbid gambling problems (Petry, Stinson, & Grant, 2005). This potential confound makes it difficult to untangle the role gambling plays in decision-making for individuals with SUD. Little research has investigated substance users performance when gambling, such as a on a slot machine. Researching performance on a slot machine may be very relevant, as poor performance could indicate that gambling behavior plays a substantial role in decision-making in SUD. Gambling performance could also be related to measures of decision-making to see how similar or different these tasks are and used to try and predict outcome measure, such as substance-use severity. Comparing gambling to commonly used measures of decision-making may shed some light on if these constructs are related and if so how. The goal of this study was to investigate how individuals with SUD would perform on a slot machine and relate the slot-machine performance to current lab measures of decision-making.

Gambling and Decision-Making Paradigms

Slot Machines

Many decision-making tasks used in research are based on real-world gambling paradigms. Gambling is often defined as giving up something in the hopes of gaining something with greater value (American Psychiatric Association, 2013). When gambling, an individual is faced with making decisions under risk, uncertainty, and ambiguity. Gambling is similar to many decision-making paradigms in research; however, unlike these tasks, in real-world gambling these choices are often for real money and can carry very severe consequences. Due to a plethora of research showing the similarities between gambling and substance use, pathological gambling has been reclassified as an addictive disorder in the DSM-5 (American Psychiatric Association, 2013). Pathological gambling was also renamed gambling disorder in the DSM-5. The term gambling disorder will be used in this paper to reflect this update. Individuals with gambling disorder show similar decision-making deficits and other behaviors similar to substance users (Leeman & Potenza, 2012). Both disorders are characterized by tolerance, withdrawal, repeated attempts to stop, and continued engagement despite longterm negative consequences (American Psychiatric Association, 2013). The spectrum of shared clinical and biological features has led to the reclassification of pathological gambling from a disorder of impulse-control to a behavioral addiction in the DSM-5. In addition, SUD and pathological gambling are highly comorbid (Petry, Stinson, & Grant, 2005). Compared to controls, individuals with pathological gambling are five to seven times more likely to have alcohol, nicotine, or substance dependence (Petry et al., 2005).

Despite the immense amount of similarities between gambling disorder and SUD, there has been little empirical research on gambling. Not investigating gambling behaviors could be a potential confounding factor when using these gambling-paradigms

as a measure of decision-making in substance users. Precautions should be taken to fully understand the individuals' gambling history in order to accurately judge the performance on these tasks.

Previous research has compared individuals' performance on slot machines. Many studies have attempted to find reasons why people may gamble more or less (Chóliz, 2010; Coates & Blaszczynski, n.d.; Dixon, Harrigan, Sandhu, Collins, & Fugelsang, 2010; Dixon, MacLaren, Jarick, Fugelsang, & Harrigan, in press; Dixon, Nastally, Jackson, & Habib, 2009; Weatherly, McDougall, & Gillis, 2006; Weatherly, Thompson, Hodny, & Meier, 2009). For example, one factor that affects gambling is the payback percentage, which is the rate of payoff for the game. A 97% playback percentage would mean that for every dollar the slot machine takes in it will dispense, on average, 97 cents back. Gillis, McDonald, and Weatherly (2008) found that increasing the payback percentage can increase the frequency of betting while playing on a simulated slot machine. However, to see this effect, the difference in playback percentage had to be quite large (105% versus 85%). In contrast, Haw (2008) was not able to detect that participants could tell a meaningful change between different payout schedules unless the participant received a lot of reinforcement.

Very little research has investigated the effects of drugs and alcohol on slot machine performance. Whitton and Weatherly (2009) investigated performance on both a simulated slot machine and video poker amongst American Indians and non-American Indians after alcohol consumption. They found a weak interaction between ethnicity and alcohol on the number of credits bet but failed to find a significant simple effect. The sample size in this study was quite low (i.e., 12 in each group) and a larger sample size

could have led to more robust results. Also, the study attempted to investigate how alcohol intoxication would affect performance on a slot machine and they did not investigate whether or not having problematic alcoholic use affected performance.

The Iowa Gambling Task (IGT)

The Iowa Gambling Task (IGT) is one of, if not the most, widely used assessment for decision-making in both research (Bechara, Damasio, Damasio, & Anderson, 1994; Bechara, Tranel, Damasio, & Damasio, 1996; Brevers, Bechara, Cleeremans, & Noël, 2013), and, more recently, clinical use (Buelow & Suhr, 2009; Lin, Song, Chen, Lee, & Chiu, 2013). In the IGT, an individual must select a card from one of four decks (Deck A, B, C, or D). Every time that the individual selects a card, he/she will win some amount of hypothetical money as well as possibly receive some sort of monetary punishment. The overall goal of the task is to win as much money as possible. The rewards for each deck remain the same, but the punishers will vary among the different cards in each deck, ranging from the loss of no money to losing a very large amount of money. Each deck has a different payout schedule. In Decks A and C, the losses are of small magnitude, but very frequent, and in Decks B and D the losses are infrequent, but of a much larger magnitude. If the individual continuously selects cards from deck C or D, over time he/she will win hypothetical money, which is in contrast to if the individual continuously chooses from deck A or B, in which case he/she will lose money over time.

The individual gets to choose 100 cards, and starts the game with a hypothetical \$2000. In order to maximize the amount of money won on the task, the individual must learn, over time, to select cards from the decks with better payout schedules or "good" decks (i.e., C & D), and stop selecting cards from the decks with poorer payout schedules

or "bad" decks (i.e., A & B). Many individuals with certain disorders, such as SUD, fail to learn to adjust their choices over time and will continue to select cards from the "bad" decks despite losing hypothetical money over time (Bechara et al., 2001).

The IGT has been shown to be sensitive to at least 13 different disorders, including addictive disorders such as SUD and gambling disorders (Lin et al., 2013). However, many variations and different ways of administering the task has made the research and clinical utility of the task difficult to ascertain (Fernie & Tunney, 2006). For example, Fernie and Tunney (2006) found that altering the task instructions by adding a hint about reinforcer types improved performance. Also important to note is the "Deck B Phenomenon" where even "normal decision-makers" often prefer to select cards from deck B, which over time results in a net loss and must be taken into consideration when interpreting the task (Lin et al., 2013). Despite these limitations, the IGT has remained a staple task when measuring decision-making and has many useful applications (Buelow & Suhr, 2009).

There are many reasons why using the IGT is useful for investigating decisionmaking, especially in individuals with SUD. The complex nature of the task makes it difficult to learn the payout schedules for each of the decks. The result of this complex payout schedule is that the individual needs to make risky choices under ambiguous circumstances. Making choices under ambiguous situations has been shown to mimic real world decision-making (Platt & Huettel, 2008), which greatly improves the utility of the IGT (Bechara et al., 1994). The IGT has helped flesh out making decisions under different circumstances (Brevers et al., 2013). For example, the IGT has helped demonstrate that ambiguity is particularly important in decision-making in addiction

(Brevers et al., 2012). Brevers et al. (2012) found that poor decision-making in problem gambling was related to tasks of ambiguity (i.e., IGT), but not decision-making under only risky circumstances (i.e., coin-flipping task). This result suggests that different aspects of decision-making need to be taken into consideration when investigating different addictive disorders.

Studies like the one by Brevers et al. (2012) show the importance of using the IGT in addiction because deficits in decision-making under ambiguity are particularly salient in this population. The IGT has also been useful for assessing for individual differences in decision-making (Harman, 2011; Suhr & Tsanadis, 2007). For example, Harmon (2011) showed that individuals with little interest in thinking performed worse on the IGT than those with a greater interest in thinking as measured by a Need-for-Cognition scale (Cacioppo, Petty, & Feng Kao, 1984). Suhr and Tsnadis (2007) found that poor performance on the IGT was related to elevated fun-seeking personality using the Behavioral Inhibition/Activation Scales (Carver & White, 1994). Finally, the IGT is widely used and well known, making it useful to compare results across many different studies. All of these studies help demonstrate the utility of the IGT in investigating decision-making.

Failure to learn to adjust choices over time on the IGT has become a hallmark sign of problems with ventral medial prefrontal cortex, or what will be referred to in this paper as orbitofrontal cortex (OFC; Fellows, 2007). Bechara et al. (1994) created the IGT to help assess for OFC damage by mimicking real-world decision-making. They found that individuals with OFC damage performed poorly compared to controls and failed to learn to adjust their choices over time (Bechara et al., 1994; Bechara et al.,

1996). This finding became important for individuals with SUD because metabolic abnormalities had been seen in the OFC in individuals with SUD, but this abnormality was largely overlooked in terms of addiction at first (Bechara, 2003). Later, Bechara's group found individuals with OFC damage showed similar behaviors to individuals with SUD, such as having poor insight (being unaware of the problem) and choosing immediate rewards while ignoring any potential consequences (Bechara, 2003). Bechara used the IGT to compare individuals with SUD, controls, and individuals with OFC damage (Bechara et al., 2001). They found that substance users performed poorly compared to controls and that twice as many individuals with SUD compared to controls (61% versus 32.5%) showed deficits similar to individuals with OFC damage (Bechara et al., 2001). Performance on the task also directly correlated with aspects of substance use (i.e., abstinence, years of abuse, relapses, and the ability to hold meaningful employment; Bechara et al., 2001). These studies from Bechara's lab started to show several important things: the OFC plays a crucial role in role in decision-making, deficits seen in the IGT can be directly related to substance use, and that investigating decision-making is crucial for understanding addiction.

The Balloon Analogue Risk Task (BART)

Another important task that has helped researchers understand decision-making is the Balloon Analogue Risk Task (BART; Lejuez et al., 2002). In the original task, individuals are serially presented with 90 balloons. The individual decides whether he/she will pump air into the balloon or not. Every time that he/she decides to pump air into the balloon, he/she collects a small amount of money (usually 1 or 5 cents per pump). However, at some point the balloon will pop. If the balloon pops, then the

individual loses all of the money that he/she earned on that balloon. Instead of deciding to pump more air into the balloon, the individual can choose to collect all of the money earned for that balloon, and then proceed to the next balloon. In this way, the individual must try to learn how much air he/she can pump each balloon up with before the balloon pops, so as to maximize gain. The goal of the task is to make as much money as possible.

There are three different colors of balloons. Orange balloons pop, on average, after eight pumps, yellow balloons after 16 pumps, and blue balloons pop after 64 pumps. For the first part of the task, the colored balloons are presented in a random order. In the second half, the individual is presented with 15 orange balloons, then 15 yellow balloons, and finally 15 blue balloons, in that order. A later version of this task discarded the colored balloons. Instead only 30 balloons are presented with an average threshold of 64 pumps before they pop. The task is analyzed by taking the average number of pumps from all the balloons that did not pop (Lejuez et al., 2002). This dependent variable excludes the balloons that pop because it is not known how much further the person would have pumped up the balloon if he/she had been able to. Other variables that can be investigated include the total number of balloons popped, money earned and the interpump interval (how fast the individual was pumping up the balloons; Lejuez et al., 2002).

The BART, alongside the IGT, is another way to measure decision-making under risky and ambiguous circumstances. Lejeuz et al. (2003) showed that the task can differentiate smokers from non-smokers. In fact, using a logistic regression, they showed that the BART can differentiate smokers and non-smokers better than the IGT. The task has also been used in children, generally showing greater risk-taking in adolescents with substance use or conduct problems than controls (Crowley, et al., 2010; Crowley, et al.,

2006; Lejuez, et al., 2003). In addition, BART has shown adequate validity as a measure of risk-taking using genetic markers (Hopko et al., 2006) as well as good temporal stability (r_{tt} >0.70; White, Lejuez, & de Wit, 2008).

Unfortunately, overall results have varied using the BART. The BART may not be incredibly sensitive to decision-making deficits in all substance-using populations, though in general, substance users will pump more air into each balloon than controls indicating higher risk taking (Leeman & Potenza, 2012). The discrepancies in the research could be due to the many different versions of this task and different substance using populations tested. For example, Crowley et al. (2006) found that adolescent boys with substance-use problems took greater risks on the BART compared to controls, but this finding was not replicated using the same version of the task in adults with substance-use problems (Thompson et al., 2012). In some versions of the task, the individual may get paid one or five cents per pump of air into the balloon. This difference in payment could be very significant as magnitude of reward and punisher has been shown to be sensitive in substance users (Thompson et al., 2012). Future research will need to investigate whether factors, such as the magnitude of the reward, are contributing to the mixed results. In addition, many researchers have created alternative versions of the task that have proven useful. Crowley et al. (2010) modified the task for the fMRI environment. He coined this new task the Colorado Balloon Task, which has been shown to be sensitive to substance use and gender differences (Crowley et al., 2010). Alterations of the task, can be useful in certain populations, but make it more difficult to ascertain why some studies show that the BART is able to differentiate substance users and controls and other studies are not.

In general, the BART can be a useful additional task that looks at decisionmaking. Unlike the IGT, the amount of risk changes over time on the BART. It is very unlikely that the balloon will pop after just one pump of air. However, every time additional air is added to the balloon, the risk is increased that the balloon is going to pop, making it so that each decision to further pump up the balloon is more risky than the last. The individual must learn how much risk is appropriate to take in order to maximize their profits. As mentioned before, individuals with SUD have more difficulty with decisions in ambiguous situations than only risky ones (Brevers et al., 2012). The BART offers a unique combination of both risk (how much air can the individual get into the balloon before it pops) and ambiguity (it is completely unknown when the balloon will pop). Unlike the IGT, an individual is also rewarded for taking greater risk on the task than individuals who are risk averse. Previous research has shown that people, in general, are risk averse (Kahneman & Tversky, 1979; Thaler, Tversky, Kahneman, & Schwartz, 1997). So having a task that rewards making risky decision-making can be useful, because making risky decisions is not always a bad thing. For example, people with power (such as business executives) or people who are seeking power tend to make riskier decisions than those who do not (Anderson & Galinsky, 2006; Ronay & von Hippel, 2010). Ronay and van Hippel (2010) used the BART to show that men equate making riskier decisions with gaining power. They found that males with higher testosterone showed greater risk-taking when primed with low power, and when primed with high power, higher testosterone males took fewer risks (Ronay & von Hippel, 2010). It is interesting to note that making very risky decisions can be advantageous for some people (e.g., businesspeople), but quite detrimental to others (e.g., individuals with SUD).

Results from all of these studies help show that the BART helps assess a slightly different aspect of decision-making that still seems to be important when looking at addiction (Lejuez, et al., 2003).

Delay Discounting

"Discounting" is the concept that delaying a consequence, or decreasing the probability of its occurrence, decreases its effect on behavior. Discounting is an important construct because it can have a direct effect on reward processing and decisionmaking. One measure of discounting, temporal discounting, investigates how individuals value long-term rewards in favor of short-term rewards (Kirby & Maraković, 1996). In general, research has shown that individuals with SUD devalue long-term rewards in favor of short-term rewards to a much greater extent than controls (Andrade & Petry, 2012; Businelle et al., 2010; Kollins, 2003; Petry, 2001).

In general, for temporal-discounting tasks, an individual will be presented with two options and has to choose one of them. Usually these options are monetary, but they do not have to be (e.g., cigarettes or medical treatment; Weatherly, Terrell, & Derenne, 2010; Weatherly & Terrell, 2010). For the purpose of describing the task, monetary values will be used. The individual is presented with two options. The first option will be a lower amount of money and the individual can choose to immediately take this amount of money. The second choice will be a higher amount of money, though the individual would have to wait some amount of time before collecting the money. For example, an individual may be asked if he/she would prefer \$5 now or \$100 dollars in two weeks. The amount of money and the timeframe can be manipulated in this example.

In theory, as the length of time increases the person will be more and more likely to take the immediate reward rather than wait. For example, an individual would be more likely to select to wait two weeks for the \$100 than if he/she had to wait 10 years. Alternatively, the closer the monetary values reach each other the more likely the individual would be to select the immediate reward. For example, an individual would be more likely to select that he/she wants \$90 now rather than wait two weeks for \$100 than if he/she was offered \$5 now verses \$100 in two weeks. By repeatedly asking an individual such questions, one can find a hypothetical amount where he/she is no longer willing to wait for the delayed reward and chart this number over several delay periods (1 week, 2 weeks, 1 year, 5 years, etc.).

The way the task has been outlined above is only one example of how discounting information can be collected. The individual chooses either the immediate or delayed reward. Fill-in-the-blank and multiple-choice methods have also been developed and shown to be valid (Weatherly & Derenne, 2011). In these methods, the individual simply chooses at what point he/she will no longer wait for the money (either by writing it in or selecting from a list of preselected answers). Some individuals will discount faster than others; that is, he/she devalues the long-term reward in favor of what he/she can immediately have.

There are two main methods for analyzing the delay-discounting data. First, the rate of change over time can be observed. This rate-of-change can be modeled using a hyperbolic function or an exponential one (Kirby & Maraković, 1995). In general, hyperbolic has been shown to fit the data better than the exponential curve, but both

methods tend to underestimate the rate of discounting (Bickel & Marsch, 2001; Kirby & Maraković, 1995). Below is the standard hyperbolic equation used to model the data:

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

In this equation, (V) is the individual's current subjective value of the delayed reward, (A) is the amount of the delayed reward, (D) is the time delay to the reward, and (k) is an individual constant representing the rate of devaluation of the reward. The constant in the equation (k) can then be compared across individuals. The higher the value of k, then the more rapidly an individual devalues rewards as they become increasingly delayed.

This analysis assumes that the data fit a hyperbolic curve, though this assumption is not necessarily true. It makes little sense to try and fit non-hyperbolic data to this function. Johnson and Bickel (2008) devised a method for removing data that violated this assumption. In their method, they were able to identify individuals with erratic response patterns where k would over- or underestimate the devaluation of the reward. The data from these individuals were then excluded from the analysis. Johnson and Bickel's criteria sometimes removed a substantial portion of the data, which is problematic. It can be argued why or why not it is important to remove nonsystematic data, but this argument becomes difficult, almost meaningless, when data from a third of the participants are removed from the data pool, and limits the interpretability of the remaining findings.

An alternative method for analyzing discounting data is to calculate the Area Under the Curve (AUC; Myerson, Green, & Warusawitharana, 2001). In this method, the data do not need to fit a hyperbolic curve, though the method is vaguer about the rate of discounting (Myerson et al., 2001). To calculate AUC, the data are normalized and

plotted on XY axes. X is the delayed value and Y is the subjective value. Both these numbers are normalized by turning them into proportions so the delay (x) is expressed as a proportion of the maximum delay, and the subjective value (y) is divided by the actual, delayed amount. Once these points are plotted on the XY axes, a line is drawn to connect each point as well as a vertical line from each point to the X axis. These lines create several trapezoids under the curve. The area of each trapezoid is found by using the following formula:

$$A_{Trap} = (x_2 - x_1)[(y_1 + y_2)/2)]$$

In this equation, x_1 and x_2 are the delays, and y_1 and y_2 are the subjective values of the delays. The area of each trapezoid is added up to get the total AUC. This method gives a value between 0 (steepest discounting) and 1 (no discounting), therefore a higher AUC would mean less discounting. There are several benefits to this technique over hyperbolic k. The method does not assume a function for the rate of discounting and can handle skewed data better than previous methods developed (Myerson et al., 2001).

Many studies report that individuals with SUD will devalue long-term rewards at a faster rate than controls (Andrade & Petry, 2012; Businelle et al., 2010; Kirby, Petry, & Bickel, 1999; Kollins, 2003; Petry, 2001; Thompson et al., 2012). For example, Kirby, Petry, and Bickel (1999) found that heroin addicts discounted at a steeper rate compared to controls. However, not all future studies could replicate this finding (Leeman & Potenza, 2012). These inconsistent results may reflect differences in delay-discounting tasks and analyses (Reynolds, 2006). Many previous studies, for example, compared groups by fitting hyperbolic curves to estimate discounting rates and end up excluding a large portion of participants. A particularly interesting finding is that individuals who

have both gambling and substance-use problems tend to discount at a steeper rate than if they only have an SUD or gambling problem (Andrade & Petry, 2012; Petry, 2001). This finding suggests that both disorders have an additive effect on discounting and that individuals who are comorbid with both disorders may be particularly prone to poor decision-making.

Although delay discounting is another measure of decision-making, it is unique compared to the IGT and BART. Unlike the IGT and BART, delay discounting is not investigating decision-making in ambiguous or risky situations. There is little ambiguity in this task, as both the amount of the reward and the delay period is explicitly laid out for the individual. The mixed findings on this task are interesting and raise the question of whether individuals with SUD are poor at decision making in general or only in ambiguous circumstances (Brevers et al., 2012). Also, delay discounting is not based on any sort of gambling paradigm (though is still considered gambling by the definition presented earlier), which will be discussed further below. It is important to note that this task measures decision-making in a very different way from the IGT and BART. Future research is important to flesh out what populations of SUD and under what circumstances differences in delay discounting are seen. Regardless of the limitations, this task has been widely used. A search on PubMed using the terms "addiction" and "delay discounting" in December 2013 revealed over 70 empirically based studies published since 2007 showing some relationship between discounting and addiction. The task has been sensitive to many substance-use populations and results can be compared alongside many other studies making this task particularly useful when looking at decision-making in individuals with SUD.

Effects of Other Constructs on Decision-Making

Poor decision-making in substance users is also related to personality traits such as impulsivity, risk-taking, and behavioral approach (i.e., the willingness to approach potential rewards). A vast literature has shown that drug and alcohol addictions are associated with impulsivity (Leeman & Potenza, 2012; Lejuez et al., 2010). One measure of impulsivity, temporal discounting, has shown that individuals with SUD devalue longterm rewards in favor of short-term rewards to a much greater extent than controls (Andrade & Petry, 2012; Ledgerwood, Alessi, Phoenix, & Petry, 2009; Leeman & Potenza, 2012; Petry, 2001). Individuals with SUD also take greater risks than controls (Lejuez, Aklin, Zvolensky, et al., 2003; Rogers et al., 1999). Impulsivity and risk-taking, together, have been shown to increase the probability of initial drug experimentation over either construct alone (Dayan, Bernard, Olliac, Mailhes, & Kermarrec, 2010; Lejuez et al., 2010; Poulos, Le, & Parker, 1995). Substance users also tend to have a greater propensity for behavioral approach, which is the willingness to approach rewards, than controls (Franken & Muris, 2006; Krmpotich et al., 2013; Simons, Dvorak, & Lau-Barraco, 2009; Van Toor et al., 2011; Wardell, Read, Colder, & Merrill, 2012). Suhr and Tsnadis (2007) found that poor decision-making was related to variables such as behavioral approach, in particular fun-seeking.

In addition to personality traits, the type of drug used may also play a role in decision-making deficits. Many individuals in the substance-use literature are polysubstance users, making it difficult to determine what effect particular drugs have on variables like decision-making. However, there is some evidence to suggest that not all substances have the same effect on decision-making (Gonzalez, Bechara, & Martin,

2007). In particular, alcohol and psychostimulants (e.g., methamphetamine, cocaine, crack, etc.) seem to have the most robust effects on decision-making, although this deficit in decision-making seems particularly pronounced with psychostimulants (Gonzalez et al., 2007). Gonzalez et al. (2007) compared a group of alcohol users, methamphetamine users, and controls on the IGT and found that performance in both patient groups were lower than controls, but methamphetamine users performed even more poorly than alcohol users.

Reward Contingencies

Different reward contingencies may be processed by different areas of the brain (Elliott, Dolan, & Frith, 2000). For example, lateral and medial OFC may play different roles in decision-making (Elliott et al., 2000). In general, medial OFC seems to be more strongly implemented in motivation, uncertainty, valuation, and effort (Tanabe et al., 2013), whereas lateral OFC seems to be more involved with processing aversive outcomes or suppressing unrewarding responses (Elliott et al., 2000; Seymour et al., 2005). For reward contingencies, the brain processes magnitude and frequency of rewards/punishers differently. Lateral OFC seems to be more involved in the frequency of rewards. For example, Strenziock et al. (2010) found that decreased grey-matter volume in the lateral OFC was more associated with adolescent boys who frequently watch violent television shows and movies compared to boys with greater medial OFC volume. Medial OFC works in conjunction with the striatum (particularly ventral) to process the magnitude of rewards (Diekhof, Kaps, Falkai, & Gruber, 2012). Changes in medial OFC seem to be more robust in SUD than lateral OFC. Structurally, there is reduced volume in the medial OFC in substance users using volume-based, and cortical

thickness, measures (Kühn, Schubert, & Gallinat, 2010; Tanabe et al., 2009, 2013). Functionally, there is also less activity in the medial OFC of stimulant dependent individuals compared to controls (Tanabe et al., 2007). Substance-dependent individuals have also been shown to be worse than controls at avoiding cards with high magnitude loss during a modified version of the IGT (Thompson et al., 2012). Together, these findings suggest that there may be problems for individuals with SUD when processing the magnitude of rewards/punishers, as opposed to frequency.

One of the criticisms of the IGT has been how many contingences are manipulated at once. For example, each time a card is chosen, the individual simultaneous receives both a reward and a punisher. Having multiple contingencies simultaneously makes it difficult to differentiate the processes underlining rewards and punishers using the IGT. The IGT is sensitive to showing that substance users have a deficit, but it had been very difficult to untangle what is causing these differences using this task. Computational modeling has been one approach to help untangle these differences in decision-making. The basis for these models are from machine-learning paradigms (Watkins & Dayan, 1992). In the model by Watkins and Dayan, a mathematical equation is used to represent the quality of learning (Q-Learning) and attempts to identify factors that could be attributing to why some people learn more efficiently than others.

Stout et al. (2004) used a similar model looking at expectancy valence – in other words, internal factors that may affect learning. They found that using a computational model on the IGT showed that poor performance in cocaine users is related to a hyposensitivity to loss and an erratic response pattern that may be driven by high levels

of impulsivity (Stout et al., 2004). Computational modeling has also shown that individuals with SUD have altered predictive-error (Tanabe et al., 2013). Prediction error is the difference between what one expects from an action and what actually happens. Tanabe et al. (2013) showed that SUD had a dampened prediction error signal in the medial OFC and the ventral striatum while performing a modified version of the IGT. Together, these studies help illustrate how important it is to look into the mechanisms that are problematic for individuals with SUD for decision-making. It is crucial for future research to continue looking at decision-making in ways to help untangle these intricate differences.

Addiction and Decision-Making

Many studies have shown that individuals with SUD have deficits in decisionmaking. This same trend is seen in individuals with gambling disorder, that is these individuals show similar decision-making deficits on the IGT, BART, and delay discounting (Leeman & Potenza, 2012). Another proposed disorder of addiction for the DSM-6 is Internet-Gaming Disorder (American Psychiatric Association, 2013). Research has shown that individuals who excessively game (in this case, World of Warcraft) also show deficits on the IGT compared to controls, suggesting impaired decision-making (Pawlikowski & Brand, 2011). Even individuals with some eating disorders show deficits in decision-making that are very similar to addiction (Frank et al., 2012). Frank et al. (2012), showed deficits in prediction error signal in individuals with anorexia nervosa and obesity, similar to what is seen in addiction (Tanabe et al., 2013). In fact, explaining eating disorders using a model of addiction is getting more and more popular in the field of addiction (Volkow & Wise, 2005) though not everyone agrees

with this decision (Wilson, 2010). All of these studies show that addiction, in of itself, has an adverse effect on decision-making. Especially because additive effects on delay discounting have been shown with substance use and gambling (Andrade & Petry, 2012; Petry, 2001), it may be very important to focus on all aspects of addiction when investigating decision-making. This idea is especially crucial with substance use and gambling with the many similarities between these disorders (Leeman & Potenza, 2012).

Motivation for Substance Use and Gambling

Individuals with addiction continue to use drugs or gamble despite long-term consequences (Bechara, 2003), highlighting the importance of researching why individuals maintain these behaviors. One explanation for gambling and substance use motivation, is that drug use and gambling can be maintained through positive reinforcement (e.g., feeling more excited) or negative reinforcement (e.g., feeling less stressed or anxious). Using substances for negative reinforcement has been shown to be a predictor from initial drug use to addiction (Gerevich & Bácskai, 1996). Individuals with SUD have been shown to have deficits in negative reinforcement learning, and are unable to learn as well how to avoid negative outcomes compared to controls (Thompson et al., 2012). Together, these results suggest that negative reinforcement learning is an important construct in the maintenance and motivation for substance use. Similarly, individuals who gamble for negative reinforcement were much more likely to have gambling problems (Weatherly & Miller, 2013). These findings suggest that the motivation for drug use may also play a critical role in gambling and decision-making behavior.

Alcohol Use Functional Assessment (AFA)

Using substances for negative reinforcement has been shown to be a predictor from initial drug use to addiction (Gerevich & Bácskai, 1996), and individuals with addiction have been shown to be less sensitive to negative-reinforcement learning compared to controls (Thompson et al., 2012). A preliminary scale, the Alcohol Use Function Assessment (AFA), has been designed to assess positive and negative reinforcement contingencies for engaging in substance use. The 24-item AFA has two subscales: one about substance use for positive reinforcement and one for negative reinforcement. This scale has been validated (Krmpotich, unpublished data) showing good construct, divergent, and convergent validity. The AFA offers a way to investigate the relationship between alcohol use motivation and decision-making. A similar scale, the Substance Use Functional Assessment has been validated and used to shown that negative reinforcement mediates negative affect and addiction severity (Krmpotich et al., unpublished data).

The Drinking Motives Questionnaire - Revised

Cooper (1994) originally developed the Drinking Motives Questionnaire to assess for reasons why adolescents engage in alcohol consumption. The questionnaire was based on a four factor model originally proposed by Cox and Klinger (1988). Her analysis supported the model proposed by Cox and Klinger and the scale was validated across gender, race, and age (Cooper, 1994). The four factors assessed for both internal and external reasons for drinking as well as positive and negative reinforcement: Social (drinking to obtain positive social rewards; external positive reinforcement), Coping (drinking to reduce or regulate negative emotions; internal negative reinforcement), Enhancement (drinking to enhance positive mood or well-being, internal positive reinforcement) and Conformity (drinking to avoid social censure or rejection; external

negative reinforcement). Later research suggested that a 5-factor model may also explain the data (Grant et al., 2007), but the 4-factor model will be retained in this study for easy evaluation of positive and negative reinforcement.

Gambling Functional Assessment – Revised

Dixon and Johnson (2007) developed the Gambling Functional Assessment (GFA). The task looks at motivations for why people gamble, and was composed of 22 items. Later the task was updated (Gambling Functional Assessment – Revised; Weatherly, Miller, Montes, & Rost, 2012). A factor analysis also revealed 2 main factors, and 8 questions loaded on each factor. The authors' interpreted these two factors as gambling for positive motivation and gambling for negative motivation or escape. This 16-item scale measures why people engage in gambling, focusing on this idea of gambling for positive reinforcement as opposed to negative reinforcement (Weatherly et al., 2012). Weatherly and Miller (2013) went on to show that gambling as an escape was more heavily related to developing problems with gambling.

South Oaks Gambling Screen (SOGS)

Lesieur and Blume (1987) developed the South Oaks Gambling Task (SOGS) as a quick measure to screen for individuals who may be experiencing problems from gambling based on *DSM-3* criteria. The SOGS, in and of itself, is not a diagnostic tool, but can be useful in identifying individuals who may have a gambling disorder. The SOGS is an 16-item questionnaire and one of the most widely used diagnostic screens for pathological gambling (Stinchfield, 2002). The SOGS can accurately detect individuals who truly do have problems with gambling, though the SOGS also has a high false-positive rate among the general population (Stinchfield, 2002). This tool has been used

to identify substance users with gambling problems in previous research (Tanabe et al., 2007).

Current Study

Many of the decision-making tasks involve gambling and gambling paradigms and therefore it is important to understand how gambling relates to decision-making, especially in individuals who use substances. To date, little research has investigated substance users' performance on actual gambling tasks such as a slot machine. One way to assess the role of gambling is to compare an actual measure of gambling (slot-machine performance) to measures of decision-making (i.e., IGT, BART, & delay discounting). Finding out how substance users gamble compared to controls could offer valuable insight into how gambling is related to decision-making for substance users.

The goal of this study was to investigate how individuals with SUD will perform on a slot machine and relate the slot-machine performance to current lab measures of decision-making. Individuals with and without substance use disorders gambled on a slot machine and completed other decision-making tasks (e.g., IGT, BART, delay discounting). The recruited individuals had substance use problems with alcohol, as alcohol and psychostimulants have been shown to be particularly pronounced with decision-making deficits (Gonzalez et al., 2007). Alcohol use disorders are also common in a college-student population.

Rewards were manipulated in terms of magnitude (real monetary payout verses no payout) for two reasons. First, the magnitude of reward and punishment has been shown to be robust in this population (Thompson et al., 2012). Second, having real

monetary payout on the decision-making paradigms and slot machine may increase the ecological validity of the task and be easier to relate them to real-world decision-making (Fernie & Tunney, 2006). Gambling performance was compared to three common lab measures of decision-making (i.e., IGT, BART, & delay discounting). In addition, measures of substance use and gambling motivation were obtained to relate the slot-machine paradigm to meaningful reasons for engaging in addictive behaviors.

There were three primary hypothesizes. First, individuals with alcohol-use symptoms would gamble more and for higher stakes at the slot machines than controls, especially when real monetary (high magnitude) stakes were involved. Second, performance on the slot machine would be related to other tasks of decision-making. Finally, poor performance on all decision-making tasks (slot machine, IGT, BART, & delay discounting) would relate to using substances and gambling as an escape and not for maintain a positive state.

CHAPTER II METHOD

Participants

Seven-hundred fifty-one participants were recruited from the undergraduate psychology program at the University of North Dakota. These participants received course credit for completing a screening survey (detailed below). From the pool of 751 initial participants, 40 (5%) participants were recruited to take part in main portion of the study (detailed below). These participants received both additional course credit as well as monetary compensation. The number of participants needed for the study was calculated using G-Power v3.1. The calculation was based on a power of 0.80 using a small effect size (Cohen's F = 0.15). Participants were selected to take part in the main part of study if they met inclusion criteria for one of the following groups: Alcohol Use Symptoms (AUS) or controls. Participants in the AUS group self-reported at least two symptoms of an Alcohol Use Disorder, in the last year, as defined in the DSM-V. These individuals may not actually be diagnosed with an Alcohol Use Disorder by a clinician, but are reporting some potentially maladaptive symptoms. Self-reported symptoms in the last year from other substance use disorders, including tobacco use disorder, were not exclusionary. Individuals in the control group did not self-report any symptoms from any substance use disorder in the last year. Caffeine use was not assessed, as the DSM-V does not recognize caffeine-use disorder. All participants who scored a 5 or higher on the SOGS, were excluded due to the possibility of Gambling Disorder. Seventeen

individuals were recruited for the AUS group and 23 individuals were recruited for the control group. The study was approved the Institutional Review Board (IRB) at the University of North Dakota.

Materials

Slot Machine

As a measure of gambling, participants gambled on an IGT S2000 Red, White, and Blue slot machine. The machine had a playback percentage of 97%. In other words, for every dollar the slot machine took in it dispensed, on average, 97 cents back. The machine accepted tokens worth \$0.05, and participants could bet 1-3 tokens on each spin. Participants started each condition with 50 tokens (\$2.50). The conditioned ended when one of three requirements was met: the participant decided to stop, 10 minutes had elapsed, or the participant ran out of tokens. Instructions for the task are presented in Appendix A. Three dependent variables of interest were measured - the number of trials played, the total number of tokens bet, and the amount bet on average each trial. The number of trials and the number of coins bet were recorded by the internal control board on the slot machine as well as hand tallied by one of the researchers, whom was observing the participant. The number of bets per trial was calculated by dividing the total number of coins bet by the total number of trials.

Iowa Gambling Task (IGT)

As a measure of decision-making, participants completed this computerized card game in which the participant selects a card from one of four decks (Bechara et al., 2003). Every time that the participant selects a card, he/she either wins some amount of

hypothetical money, or intermittently loses some money. The monetary gain for each deck remained the same but the monetary loss varied among the different cards in each deck, ranging from the participant losing no hypothetical money to the participant losing a very large amount of hypothetical money. Each deck had a different payout schedule. In Decks A and C, the losses were of small magnitude, but very frequent, and in Decks B and D the losses were infrequent but of a much larger magnitude. The participant must learn over time to select cards from the decks with better payout schedules (C and D) and stop selecting cards from the "bad" decks A and B. The participant had to select 100 cards from the decks over the course of the game. The dependent variable was the total number of plays on good decks minus the number of cards selected on the bad decks (Bechara et al., 2003). The IGT has been shown to have very good construct validity (Buelow & Suhr, 2009).

Balloon Analogue Risk Task (BART)

For a second measure of decision-making, participants completed this computerized task (Lejuez et al. 2002) in which they earned hypothetical money by incrementally increasing the size of a balloon. In this task, participants were presented with 30 balloons. The participant decided whether he/she wanted to pump air into the balloon or not. Every time the participant decided to pump air into the balloon, he/she collected a small amount of money (i.e., one cent per pump). However, at some point the balloon would pop. If the balloon popped, the participant lost all of the money that the/she earned on that balloon. On average, each balloon popped after 64 pumps. Each trial required a decision between increasing earnings versus "collecting" money already earned. The dependent variable was the average number of pumps, excluding balloons that popped (Lejuez et al. 2002). The BART has shown adequate validity as a measure of risk-taking using genetic markers (Hopko et al., 2006) as well as good temporal stability (r_{tt} >0.70; White, Lejuez, & de Wit, 2008).

Delay Discounting

As a third measure of decision-making, participants completed a computerized discounting task in which they made decisions to collect a hypothetical reward at some time in the future or a lesser amount now. Two different rewards were used: money (\$1000) and alcohol (100 bottles of preferred liquor or wine). There were seven delay periods (1 day, 1 week, 1 month, 6 months, 1 year, 5 years, & 10 years). The multiple-choice method was used to collect the responses (Weatherly & Derenne, 2011). To assess the rate of discounting of delayed reward, we used two approaches: (1) estimating the discounting rate from the hyperbolic equation: V = A/(1 + kD) and (2) computing AUC for each participant's response trajectory. Both these methods were calculated with and without applying the criteria by Johnson and Bickel (2008) for removing non-systematic data.

Alcohol Use Functional Assessment (AFA)

A preliminary scale, the AFA, has been designed to assess positive and negative reinforcement contingencies for engaging in substance use. This 24-item scale attempts to measure why people engage in substance use. Questions are answered on a scale ranging from 1 (Not at all) to 7 (All the time). The AFA has two subscales: one about substance use for positive reinforcement (11 items) and one for negative reinforcement (13 items). Responses for both subscales are summed. Dependent variables were the total scores on the positive and negative subscales. This scale has been validated

(Krmpotich, unpublished data) showing good construct, divergent, and convergent validity. The AFA offers a way to investigate the relationship between alcohol use motivation and decision-making. This scale is presented in Appendix B.

The Drinking Motives Questionnaire - Revised

The Drinking Motives Questionnaire assessed for reasons why adolescents engage in alcohol consumption (Cooper, 1994). There are four subscales: Social (drinking to obtain positive social rewards; external positive reinforcement), Coping (drinking to reduce or regulate negative emotions; internal negative reinforcement), Enhancement (drinking to enhance positive mood or well-being, internal positive reinforcement) and Conformity (drinking to avoid social censure or rejection; external negative reinforcement). The scale consists of 20 items that are rated on a 5-point Likertlike scale (almost never to almost always). Five items load onto each of the four factors. The scale has shown good construct validity for both the 4 factor model (Cooper at al., 1994; Kuntsche et al., 2008) and the five factor model (Grant et al., 2007).

Gambling Functional Assessment – Revised (GFA-R)

This 16-item scale measures why people engage in gambling (Weatherly et al., 2012). Questions are answered on a scale ranging from 0 (Never) to 6 (Always). The GFA-R has two subscales: one about gambling for positive reinforcement (8 items) and one for negative reinforcement (8 items). Responses for both 8-item subscales are summed. Dependent variables were the total scores on the positive and negative subscales. This scale has been validated (Weatherly, Dymond, Samuels, Austin, & Terrell, 2014) and has been shown to have good reliability (α ranges from 0.69 to 0.95, r_{tt}

ranges from 0.40 to 0.74; Weatherly et al., 2012) and construct validity (Weatherly et al., 2011).

South Oaks Gambling Screen (SOGS)

The SOGS is an 16-item questionnaire and the most widely used diagnostic screen for pathological gambling (Lesieur & Blume, 1987). This 16-item questionnaire assesses problems with gambling and a score of 3 or higher likely indicates that the individual has problems from gambling. This measure has been shown to have good reliability (α ranges from 0.69 to 0.86) and validity, though there is a high false-positive rate (Stinchfield, 2002).

Procedure

All participants were provided written and informed consent as approved by the University of North Dakota's Institutional Review Board. An initial, large group of participants complete a screening process through the use of SONA, an online department system for research participation. This screening contained a demographics questionnaire, questions about drug use, a delay-discounting paradigm, the AFA, the GFA-R, and the SOGS. Those who qualified for the study (met criteria for the AUS or control group as outlined above) was then recruited to play on a slot machine and complete the IGT and BART. All three of these tasks were completed twice. Magnitude of the reward was be manipulated by offering conditions with real monetary payout and without. The order of the trials was counterbalanced across participants via a balanced Latin square method. For the slot machine, each condition lasted until one of the following criteria was met: 10 minutes passed, the participant decided to quit, or the participant ran out of tokens. The monetary payment was calculated as follows: for the

IGT, the total amount of money at the end of the task was divided by 1000; for BART and the slot machine the participant collected whatever amount of money that he/she earned on the task. Participation took approximately 1 hour.

Design

This study was a 2x2 mixed-design quasi experiment. The pseudo independent variable was the presence of alcohol use disorders symptoms from the DSM-5. This variable had two levels: AUS (at least 2 symptoms) and control (no symptoms). The main dependent variables were measures of decision-making (slot machine, BART, IGT, & delay discounting). These variables had two levels varying the magnitude of the reward (no monetary compensation vs. monetary compensation). Other variables of interest included motivation for substance use and gambling (AFA, DMQR, & GFA-R). Dependent variables were inspected for homogeneity of variance and normal distribution. All analyses were conducted using SPSS 21.

Hypothesis Analysis

The primary hypothesis was that individuals with AUS would gamble more and for higher stakes at the slot machines than controls, especially when real monetary (high magnitude) stakes are involved. To test this hypothesis, three 2x2 mixed-model ANOVA were run, one for each of the dependent variables (the number of trials played, the total amount bet, and the average amount bet on each trial). The pseudo independent variable would be the presence of AUS (two levels, control and AUS). The dependent variables would have two levels varying the magnitude of the reward (no monetary compensation vs. monetary compensation).

The second hypothesis was that performance on the slot machine will relate to other tasks of decision-making. This hypothesis was assessed in several different ways: mixed model ANOVAs, correlations, and a Cluster Analysis.

First, 2x2 mixed-model ANOVAs for IGT and BART, set up as previously described for the slot machine, were run. The dependent variable for IGT was the total number of plays on good decks minus the number of cards selected on the bad decks (Good minus Bad), and the average number of pumps, excluding balloons that popped (Pump minus Pop) for the BART. For delay discounting, the same analysis was run except the within-subject factor was the object being delayed (money verses alcohol). There are two dependent variables for delay discounting (i.e., hyperbolic *k* and AUC). Johnson and Bickel's (2008) algorithm for nonsystematic data was not applied because, with these criteria in place, 65% of the data would be eliminated. For hyperbolic *k*, skewness and kurtosis suggested that the data were highly non-normally distributed. For this reason, the analysis used only used AUC. These ANOVAS were run to get a sense of how this group of participants were performing on decision-making tasks.

Second, the main dependent variables on all of the tasks were correlated with each other as well as the measure of gambling (i.e., slot machine) to see how similar these tasks are at explaining the variance seen in the data. The following dependent variables were used: slot machine (average number of tokens bet per trial), IGT (Good minus Bad), BART (Pump minus Pop), delay discounting (AUC for monetary discounting). Only data from the no-monetary condition were used because this method is the typical administration of these tasks. The following correlations were run: slot machine and IGT, slot machine and BART, slot machine and delay discounting, IGT and BART, IGT

and delay discounting, and BART and delay discounting. A Bonferonni correction for alpha suggested that alpha needed to be adjusted from 0.05 to 0.008 (.05/6) to correct for the increased possibility of a Type I error. A Pearson's *r* was used for normally distributed data and Spearman's rho for non-normally distributed data.

Third, a Cluster Analysis was run to see which tasks participants performed the most similar on. A Custer Analysis groups a set of objects in such a way that objects in the same cluster are more similar to each other than to those in other clusters (Kaufman and Rousseeuw 1990). These groups of objects are typically cases, or participants in psychological research; however these objects can be other things such different diseases, laboratory tests, training methods, behavioral patterns, factors of human performance, organizations, school courses, languages, and test items to name a few (Anderberg, 2014). Cluster analysis can also be used to determine structure of the data in a similar manner to factor analysis (Punj and Stewart, 1983). Cluster analysis can be used to look at cases or objects as well as attributes of these objects (dependent variables, this is accomplished by reversing the data matrix; Romesburg, 2004). This is especially useful in finding redundant data (Anderberg, 2014). In other words, a cluster analysis can be useful to see which decision-making are similar (i.e., that they are measuring the same thing – being redundant with each other). A factor analysis was not chosen, as the sampling adequacy was considered to be "miserable" (KMO = .59) and the data did not appear to be appropriately correlated for factor analysis (Bartlett's Test of Sphericity, p =(0.43). The same four dependent variables that were used for the correlations were used in the cluster analysis: used slot machine (average number of tokens bet per trial), IGT (Good minus Bad), BART (Pump minus Pop), delay discounting (AUC for monetary

discounting). An Agglomerate Hierarchical Cluster procedure was used to group together using a between-linkage grouping to combine four objects: slot machine, IGT, BART and delay discounting. This procedure is appropriate to use when all measures are continuous variables. This procedure meant that the four tasks each started out as separate cluster and, at each stage of the analysis, the two clusters that were the closest in distance (measured using squared Euclidian distance) were combined into one cluster. This process repeated combing two more clusters at each stage until there was only one cluster left. The analysis is recommended to stop when the distance between clusters that are being combined increases by a much larger amount that previous stages.

To assess for the final hypothesis, multiple regressions were run to see if performance on the IGT, BART, and slot machine could predict reasons for using alcohol or gambling. This direction for the regression was chosen to investigate if any of these measures are able to predict reasons for why people may be using drugs or alcohol. This question is useful to answer since it will help determine what the utility of these tasks are and if these tasks are assessing motivating states that have been associated with problematic drinking or gambling. Tasks were investigated separately in the monetary condition and the non-monetary condition to see if the magnitude of the effect would play a role, as the magnitude of the reward has been shown to be an important factor in decision-making deficits seen in SUD (Thompson et al., 2011). All multiple regressions were run using a bias corrected accelerated (BCa) bootstrapping procedure with 5000 iterations because some of the data were not normally distributed. The BCa method for bootstrapping is one way to help use nonsystematic data in a regression analysis (Carpenter and Bithell, 2000). Data transformations were not used due to the

transformed data still not being normally distributed. Regression models were only run using data from individuals in the AUS group because the control group had a very restricted range of data on these measures. Regressions were run separately for the monetary and non-monetary conditions. Collinearity measures were checked to see if there were any issues with multi-collinearity between the measures of decision making that could interfere with the validity of the regression model. VIF needed to be less than 10, and tolerance needed to be greater than 0.2. Multi-collinearity was not an issue in any of the models. The following dependent variables were used: DMQ-R Social Subscale, DMQ-R Coping Subscale, DMQ-R Enhancement Subscale, DMQ-R Conformity scale, AFA Positive Reinforcement Subscale, AFA Negative Reinforcement Subscale, GFA-R Positive Reinforcement Subscale, and the GFA-R Negative Reinforcement Subscale. This analysis consisted of a total of 16 regression models. A Bonferonni correction for alpha suggested that alpha needed to be adjusted from 0.05 to 0.003 (0.05/16) to correct for the increased possibility of a Type I error.

CHAPTER III RESULTS

Demographics

All demographic data are presented in Table 1. There were no differences between the number of men and women in each group ($\chi^2 = 0.40$, p = 0.53). There were no differences in age between the groups (t(38) = 1.02, p = 0.32). Control participants (M = 3.48, SD = 0.35) reported a higher GPA on average than AUS participants (M =3.08, SD = 0.60; t(34) = 2.47, p = 0.04).

Alcohol and Substance Use

Some controls reported drug or alcohol use (i.e., more than five times in their life). Eleven (48%) controls reported drinking alcohol, one (4%) reported using cannabis, one (4%) reported using tobacco, and one (4%) reported using prescription stimulants (i.e., not as prescribed). All controls denied any DSM-V symptoms from any drug or alcohol use disorder. No control participants reported that they thought their alcohol or drug use was a problem.

All AUS participants reported some drug or alcohol use (i.e., more than five times in their life). All AUS participants reported drinking alcohol, six (35%) reported using cannabis, four (24%) reported using tobacco, and one (6%) reported using sedatives. Ten (59%) AUS participants rated that they had the most problems from their alcohol use, four (24%) denied any drug was more problematic than another, and three (18%) reported having the most problems from a drug other than alcohol. All AUS participants reported that they used alcohol at least once a month, and over half (53%) reported that they use alcohol at least once a week. On average, AUS participants reported 3.29 (SD = 1.65) DSM-V alcohol use symptoms, and 4.18 (SD = 2.83) DSM-5 symptoms from all drugs categories combined. Five (29%) AUS participants reported that they thought their alcohol or drug use was a problem.

Decision-Making Tasks

Data for the slot machine task, IGT and BART are presented in Figure 1. Data for delay discount tasks are presented in Figure 2.

Slot Machine: Number of Trials

Skewness and kurtosis values suggested that the data could be considered normally distributed. There was homogeneity of variance between the groups (Box's M = 4.97, F(3, 115051) = 1.56, p = 0.20). There was no main effect of group (F(1, 38) =0.34, p = 0.56; $\eta^2 = 0.01$; power = 0.09). There was no main effect of magnitude (F(1, 38) =1.00; p = 0.32; $\eta^2 = 0.03$; power = 0.16). There was no significant interaction between group and magnitude (F(1, 38) = 0.06, p = 0.81; $\eta^2 < 0.01$; power = 0.06).

Slot Machine: Number of Coins Bet

Skewness and kurtosis values suggested that the data could be considered normally distributed. There was homogeneity of variance between the groups (Box's M = 2.86, F(3, 115051) = 0.90, p = 0.44). There was no main effect of group (F(1, 38) =1.16, p = 0.29; $\eta^2 = 0.03$; power = 0.18. There was no main effect of magnitude (F(1, 38)) = 2.10; p = 0.16; $\eta^2 = 0.05$; power = 0.29). There was no significant interaction between group and magnitude (F(1, 38) = 0.004, p = 0.95; $\eta^2 < 0.001$; power = 0.05).

Slot Machine: Bet per Trial

Skewness and kurtosis values suggested that the data could be considered normally distributed. There was homogeneity of variance between the groups (Box's M = 2.87, F(3, 115051) = 0.09, p = 0.97). There was no main effect of group (F(1, 38) =0.38, p = 0.54; $\eta^2 = 0.01$; power = 0.09). There was a trend for a main effect of magnitude (F(1, 38) = 3.51; p = 0.07; $\eta^2 = 0.09$; power = 0.45). Participants tended to bet more per trial if there was no monetary compensation (M = 1.62, SE = 0.06) compared to if they received the amount of money that they had won or accumulated (M = 1.52, SD =0.06). There was no significant interaction between group and magnitude (F(1, 38) =0.31, p = 0.58; $\eta^2 < 0.01$; power = 0.08).

Iowa Gambling Task (IGT)

Skewness and kurtosis values suggested that the data could be considered normally distributed. There was heterogeneity of variance between the groups (Box's M = 9.52, F(3, 115051) = 2.99, p = 0.03), increasing the potential for a Type I error. There was no main effect of group (F(1, 38) = 1.28, p = 0.27; $\eta^2 = 0.03$; power = 0.20). There was no main effect of magnitude (F(1, 38) = 0.11, p = 0.75; $\eta^2 < 0.01$; power = 0.06). There was no significant interaction between group and magnitude (F(1, 38) = 0.33, p = 0.57; $\eta^2 = 0.01$; power = 0.09).

Balloon Analogue Risk Task (BART)

Skewness and kurtosis values suggested that the data could be considered normally distributed. There was heterogeneity of variance between the groups (Box's M = 13.09, F(3, 115051) = 4.11, p = 0.006), increasing the potential for a Type I error. There was no main effect of group (F(1, 38) = 1.41, p = 0.24; $\eta^2 = 0.04$; power = 0.21). There was no a main effect of magnitude (F(1, 38) = 0.92; p = 0.34; $\eta^2 = 0.02$; power = 0.16). There was no significant interaction between group and magnitude (F(1, 38) = 1.54, p = 0.22; $\eta^2 = 0.04$; power = 0.23).

Delay Discounting

Eight participants were excluded from the analysis for not completing the task leaving a total of 16 Controls and 16 AUS participants. For AUC, skewness and kurtosis values suggested that the data could be considered normally distributed. There was homogeneity of variance between the groups (Box's M =0.27, F(3, 162000) = 0.80, p =0.97). There was no main effect of group ($F(1, 30) = 0.004, p = 0.95; \eta^2 < 0.001;$ power = 0.05). There was no difference between discounting between alcohol and money ($F(1, 30) = 1.03; p = 0.32; \eta^2 = 0.03;$ power = 0.17). There was no significant interaction between group and magnitude ($F(1, 30) = 0.38, p = 0.54; \eta^2 = 0.01;$ power = 0.09).

Cluster Analysis

The Cluster Analysis started with four separate clusters: Monetary delay discounting (AUC), slot machine (Control Bets per Trial), BART (Pump minus Pop), and IGT (Good minus Bad). In the first stage of the analysis slot machine and delay discounting were combined into a single cluster. For stage 2, the coefficient jump was large suggesting that the analysis should end here (54.12 – 71.51 compared to stage 3, 71.51 -77.50). The analysis stopped with three clusters left (AUC & slot machine, BART, IGT). This result suggests the only significant overlap was between the slot

machine task and delay discounting. The correlation matrix for all the decision-making tasks is presented in Table 2. The proximity matrix is presented in Table 3. The icicle plot is presented in Figure 3. The dendrogram is presented in Figure 4.

Relationship to Motivation and Reinforcement Contingences

Multiple regressions were run to see if performance on the IGT, BART, and slot machine could predict motivation and reinforcement contingences for using alcohol or gambling.

Social

The decision-making tasks were able to predict using alcohol for social reasons in the monetary condition (R2 = 0.69, p = 0.001) but not in the nonmonetary condition (R2 = 0.15, p = 0.53). In the monetary condition, both BART (β = 0.52, p = 0.04) and the slot machine (β = 0.68, p = 0.01) were able to significantly predict the DMQR Social subscale. There was a trend for IGT being a significant predictor (β = 0.35, p = 0.09).

Enhancement

The decision-making tasks were able to predict using alcohol for enhancement in the monetary condition (R2 = 0.58, p = 0.002) but not in the nonmonetary condition (R2 = 0.16, p = 0.50). In the monetary condition, only the slot machine (β = 0.83, p = 0.003) was able to significantly predict the DMQR Enhancement subscale. IGT (β = 0.10, p = 0.55) and BART (β = 0.15, p = 0.38) were not significant predictors of using alcohol for enhancement.

Conformity

There was a trend for decision-making tasks predicting using alcohol for

conditioning reasons in the monetary condition (R2 = 0.49, p = 0.03) but not in the nonmonetary condition (R2 = 0.13, p = 0.61). In the monetary condition, the slot machine (β = 0.81, p = 0.02) significantly predicted DMQR conformity subscale. There was a trend for BART (β = 0.48, p = 0.11) predicting DMQR Conformity. IGT (β = -0.31, p = 0.27) was not a significant predictor of using alcohol for conformity.

Other Regressions

No other regressions were significant. Decision-making tasks were unable to predict positive reinforcement maintaining gambling in the monetary (R2 = 0.23, p = 0.31) and nonmonetary conditions (R2 = 0.14, p = 0.58), negative reinforcement maintaining gambling in the monetary (R2 = 0.05, p = 0.88) and nonmonetary conditions (R2 = 0.01, p = 0.99), positive reinforcement maintaining alcohol use in the monetary (R2 = 0.26, p = 0.25) and nonmonetary conditions (R2 = 0.12, p = 0.63), negative reinforcement maintaining alcohol use in the monetary (R2 = 0.26, p = 0.25) and nonmonetary conditions (R2 = 0.12, p = 0.63), negative reinforcement maintaining alcohol use in the monetary (R2 = 0.19, p = 0.41) and nonmonetary conditions (R2 = 0.07, p = 0.82), and using alcohol for coping in the in the monetary (R2 = 0.23, p = 0.33) and nonmonetary conditions (R2 = 0.11, p = 0.67).

CHAPTER IV DISCUSSION

Study Goals and Main Findings

Overall, this study was completed to examine the relationship between gambling and decision-making tasks in alcohol users. There were three main goals for this study. The first goal was to investigate if individuals with AUS would gamble more and for higher stakes at the slot machine than controls, especially when real monetary (high magnitude) stakes were involved. The second goal was to compare performance on a slot machine to decision-making tasks (i.e., IGT, BART, & delay discounting). The third goal was to investigate if poor performance on decision-making tasks (i.e., slot machine, IGT, & BART) was related to using substances and gambling as an escape. The data failed to support any of the hypotheses. However, several important results were found. First, all participants tended to bet more tokens per trial on the slot machine when there was no monetary compensation compared to when there was actual compensation. Second, no group or magnitude differences were found on any of the decision-making tasks (i.e., IGT, BART, & delay discounting). Effect size and power suggested that this finding was not a Type II error and that there does not seem to be any group or magnitude differences on these tasks in this sample. Third, the slot machine and all the decisionmaking tasks seem to be relatively independent from each other. These tasks seem to measure different aspects of decision-making and, surprisingly, do not have a lot of overlap in explaining variance in the data or participant performance. Fourth,

performance on the slot machine and the decision-making tasks was able to predict using alcohol for positive reinforcement, in particular, for social situations and enhancing positive feelings and experiences.

Slot-Machine Performance

For the slot machine, there were a couple of possible main effects of magnitude. Though nothing reached statistical significance, power and effect sizes did not always suggest that retaining the null was ideal. There was a medium effect size for an effect of magnitude on the slot machine, which suggested that with more participants a result may be detected. Effect sizes also suggested that the number of tokens bet may become significant with the addition of more participants. If so, participants tended to bet more if there was no monetary compensation (M = 66.14, SE = 6.03) compared to if they received the amount of money that they had left or accumulated (M = 58.31, SE = 5.36). Altogether, these results would suggest that participants across both groups tended to bet

This result was opposite of what was hypothesized, which was that alcohol users would bet more in the high-magnitude condition. Despite that the results did not line up with the hypothesis, there is some empirical support that shows that, in general, individuals are more conservative when receiving monetary payment on tasks (Weatherly & Meier, 2007). Weatherly and Meier (2007) found that participants played the same number of hands (i.e., number of trials) in a video poker task regardless of whether or not the credits had monetary value. In contrast, they also found that these participants tended to bet a smaller amount if the credits had monetary value. In other words, the number of

trials was not affected by the monetary value of the token, however the amount bet on each trial was affected. This result suggests that the frequency of play (number of trials) is not as affected by monetary value as the amount bet (magnitude) and is an important finding because there is some research suggesting that problems with reward magnitude are especially prevalent in individuals with SUD (Thompson et al., 2012). It is important for future studies to take into account that the actual monetary value of what is being bet may play a role in how everyone performs on tasks involving betting real or hypothetical money.

Research has found, in general, that participants are more conservative if gambling with their own money (Weatherly & Brandt, 2004; Weatherly et al., 2006; Weather & Meier, 2007). The present results extend these findings to suggest that individuals with AUS are also more conservative with their own money despite that, in general, these individuals are willing to take greater risk in high-magnitude conditions (Thompson et al., 2011). Previous results on gambling paradigms may be an overestimation of real-world gambling in alcohol users because these participants usually only receive hypothetical money in the studies. It is important to note that when using gambling and decision-making tasks in research, performance can be altered depending on if the participant is making decisions about real money or not. This discrepancy is also an important factor to take into consideration when using decision-making tools to assess for difficulties in decision-making. The present results extend this previous finding to suggest that monetary payment will affect substance users and controls equally though, so it is probably not an important contributing factor to group differences seen in decision-making tasks between substance users and controls. Future researchers

should try to extend these results by running a more powerful study to check and see if these results truly do hold with the addition of more participants. It will also be useful to test if these results are similar in other addictive disorders (e.g., gambling disorder, internet gaming disorder, ect.).

No other results were significant for the slot-machine task. Power was low for all these analyses, suggesting the possibility of Type II errors. However, the effect sizes are also small. Overall, this trend suggests that even with enough power to detect the effect, the difference is not overall that meaningful. These results suggest that a gambling paradigm (i.e., slot machine) may not be ideal for determining differences between alcohol users and controls and therefore, this task would not be an ideal tool to use diagnostically. Based on the data, the number of coins bet per trial appeared to be the most robust measure on the slot-machine task. Power and effect sizes suggested that this measure will be the most likely measure to differentiate any possible group or magnitude effects. However, more empirical data would need to be collected to determine if gambling could differentiate AUS participants from controls. It could be that the effect was not noteworthy of detection because this addiction is not that severe of an alcohol use group. Although individuals reported DSM-5 symptoms of alcohol use, they were not necessarily diagnosed with any disorders. Results could be different when investigating more severe alcohol use problems and disorders in which differences could be more meaningful and easily detected. Researchers would not necessarily expect differences to be readily observable in a group with relatively minor alcohol use problems (i.e., not actually needing a diagnosis or treatment at this time).

Differences on other Decision-Making Tasks

There were no significant group or magnitude differences found on the IGT, BART, or delay discounting. For all these analyses, power was low, suggesting the possibility of a Type II error. In addition, the effect sizes were small suggesting that this is not a meaningful difference even if one were detected. These results are noteworthy for a couple of reasons. First, all three tasks were poor at differentiating between AUS participants and controls. Although poor decision-making is commonly observed in substances users (Bechara et al., 2003), this deficit is not an actual diagnostic criteria for substance use disorders. In other words, although studying decision-making is important for substance use disorders, decision-making tasks may not be ideal to differentiate substance users from controls. In addition, as noted above, it could be that this particular group of AUS participants is not severe enough to be able to detect meaning differences in. Although many studies have found group differences on these decision-making tasks, others have not. It is important for future researchers to discover why these differences are not always observed. Second, there does not seem to be any significant different between using hypothetical money and using real money on these tasks. As discussed previously, some research has found that individuals are more conservative in betting their own money on gambling tasks (Weatherly & Brandt, 2004; Weatherly et al., 2006; Weatherly & Meier, 2007). These results do not suggest that this observation is the case for these decision-making tasks. This finding does help generalize these tasks to real world decision-making as monetary payment may not change the behavior on these tasks. However, monetary payment was small on these tasks (e.g, 1 cent for 1 pump on BART). Real-world decision-making for individuals with SUDs often involves much higher risks

than a small amount of money (i.e., decisions that involve 1-cent increments). Poor decisions in this population can result in extreme long-term consequences such as time in prison, losing their children, or financial hardship. These decision-making tasks may still be highly underestimating the risk involved in problematic decision-making that is typically observed in individuals with SUDs. Future research will need to investigate this more. Despite this limitation, research has demonstrated that the IGT is comparable to real-world decision-making (Bechara, 2003).

Relationship among Decision-Making Tasks

Overall, these results do not suggest strong overlap between the slot machine, IGT, BART, and delay discounting. There were no significant correlations among any of these tasks, suggesting that these tasks are measuring different constructs. In addition, a cluster analysis revealed that none of the tasks are closely related. The closest observed relationship was between the slot machine and delay discounting. These tasks may be more related because they are both less ambiguous paradigms compare to the BART and IGT. Although the BART and IGT also involve gambling, these tasks are more complex – often involving choices under ambiguity and risk. In the IGT, the individual does not know what they are potentially risking before the game starts, and the payout and punishments remain vague throughout the game. Similarly, in the BART, the individual does not know when the balloons will pop, and although each press of the balloon gets riskier over time, it is completely unknown when the balloon will actually pop. This point is in contrast to the slot machine and delay discounting, which contain information that removes some ambiguity. In delay discounting, the individual knows the exact time

of the delay and the individual simply selects how much he/she is willing to give up to prevent that delay from happening. On the slot machine, an exact payout schedule is provide to the individual and the individual has control over how much he/she would bet and when they were going to stop (unlike the IGT where the participant must play exactly 100 trials). It could be that the IGT and BART involve more ambiguity which is why the slot machine and delay discounting were less related them. Had the cluster analysis continued, the next cluster would have combined IGT and BART offering further evidence that these tasks are more similar than delay discounting and the slot machine. This finding relates to previous research which has shown that individuals with both gambling and substance use disorders perform more poorly than individuals with just substance use disorders (Andrade & Petry, 2012). This effect was not seen for BART, and only seen using delay discounting (Andrade & Petry, 2012) and a computational model on a modified version of the IGT (in which some ambiguity was removed from the game; Krmpotich et al., 2015). Together, these results suggest that discounting may hold more similarity and be more important in gambling that BART or the IGT.

Overall, despite this potential relationship between the slot machine and delay discounting, the data suggest that all of these tasks are relatively independent including the three decision-making tasks. It will be important for future research to flesh out different aspects of decision-making and discover which aspects each of these tasks are measuring, and how to optimally utilize these tasks both in research and clinically. In addition, although gambling is involved in the tasks, these results do not suggest that gambling is a primary component (as these tasks tended to be unrelated to actual

gambling, i.e., the slot machine). Future research will need to tease apart the exact role gambling has in these decision-making tasks.

Relationship to Motivation and Reinforcement Contingencies

Previous research has shown that gambling or using drugs to escape a negative state is far more predictive of severe gambling or substance use problems than gambling or drinking for a positive state (Baker, 2004). Contrary to the hypothesis, gambling on the slot machine and performance on the decision-making tasks were not related to using alcohol or gambling to escape a negative state. The data on the slot machine, IGT and BART were unable to predict either the coping scale on the DMQR or the negative reinforcement scale on the AFA. Both of these questionnaires are measures of using drugs or alcohol as an escape. However, the data on these tasks were able to predict using alcohol for positive reinforcement in certain states. These results showed that poorer performance on the decision-making tasks predicted increased endorsement of using alcohol for social situations and enhancing positive feelings and experiences. In addition, a trend was found for these tasks predicting conforming to social pressure, which is a form of external negative reinforcement. Due to low power, this result must be interpreted with caution and could be a Type I error as it did not meet the alpha adjusted cutoff. Future research will need to reinvestigate if these tasks can predict drinking to conform to social pressure.

Decision-making processes may differ under positive and negative states. For example, Fernández-Serrano et al. (2011) was able to get different results on the IGT by manipulating the affective state of cocaine addicted individuals before they took the task.

In general, decision-making tasks are phrased in a very positive way, which could be why they are relating to more positive constructs (i.e., you have the chance the win money as opposed to you need to win this task to afford your rent this month). Different results might be obtained if these tasks were presented in a context where an individual needs to cope or avoid negative states. Future research will need to investigate if changing the context behind the decision-making can help create tasks that are more predictive of real-world outcomes. For example, Weatherly, Derenne, and Terrell (2011) found that the rate of discounting changed depending on whether or not the person had "won" money or if they were "owed" money. Together, these studies also suggest that the context of the decision-making task can alter performance and this idea will have to be further explored in future research. This alteration could also improve the clinical utility of the tasks. It would be especially helpful for clinicians to able to measure decision-making in a way that relates to constructs that are involved in problematic substance use behavior as opposed to motivations that have not been shown to be as problematic.

One reason that research shows conflicting results on these decision-making tasks may be that these are measures of decision-making in a positive state. These tasks may be predicting decision-making skills involved in trying to enhance a positive state rather than avoiding negative affective states (i.e., playing the IGT to feel better after fighting with a friend). Therefore, these tasks are not necessarily measuring the problematic decision-making that tends to lead individuals to use alcohol as a coping mechanism or to avoid feeling negative affective states. Creating and validating tasks that measure this aspect of decision-making may hold more clinical utility and may be a stronger predictor of problematic substance use behavior.

In addition, these results were only found using data from the monetary condition. If the decision-making tasks were completed only using hypothetical money there was no positive prediction of drinking alcohol for social situations or enhancing positive feelings and experiences. This finding may be related to the level of risk. As the situation becomes more risky (involves real money), researchers may be able to detect the influences of that decision-making process better investigating decision-making in situations with little to no risk. It is important to note, that the normal administration of these tasks was not able to predict any motivation for alcohol use. Finally, gambling on the slot machine was the most powerful (and in some cases) the only significant predictor. This result highlights the similarity of gambling and drinking for positive reinforcement and suggests a strong underlying mechanism between these two disorders.

Finally, these tasks were unable to predict gambling for positive or negative reinforcement. Future research will need to investigate why there is evidence of a relationship between gambling motivation and decision-making on gambling paradigms. It is possible that because this group of individuals reported few, if any gambling symptoms, that the effect was not meaningful enough to detect.

Limitations

There were several limitations to this study. First, power was low. Higher power is needed to ascertain which of these effects are empirically supported and which are not. The data in this study suggested the validity of some of the results, however many of these results are not strongly supported in this study due to low power. Despite this fact, several precautions were taken to abet the validity of the results. The use of effect sizes

helps ascertain which results were plausible given additional power and which ones were not. Second, only individuals with symptoms of an alcohol use disorder were recruited in this study. Marked distress or impairment was not assessed for in these participants. In other words, no formal diagnosis was given to any of these individuals, which weakens the generalizability to individuals with actual diagnosed alcohol or other substance use disorders. Despite this weakness, symptoms count is how the DSM-V measures diagnostic severity in alcohol and other substance use disorders so it worth studying further. Third, individuals were not excluded based on meeting symptoms for other substance use disorders. This inclusion criterion can impact the generalizability to previous research that only investigates pure alcohol use disorders. It becomes difficult to discern if symptoms of an alcohol use disorder caused these effects or if other drugs played a role. Despite this limitation, many substance users abuse multiple substances and substance use and gambling disorders are highly comorbid. Not investigating alcohol use in isolation may be helpful when trying to address comorbidity problems. Fourth, our study was too underpowered to look at sex, which has been shown to also decision-making performance on some tasks (Powell & Ansic, D., 1997; van den Bos et al., 2013). Future research will need to continue to take into account that individuals with SUDs tend to perform differently on decision-making task depending on sex. Fifth, the variance in the data that could have been accounted by participants in the control group was not removed. This could be problematic if drug use in general affects performance on decision-making tasks and not just maladaptive addictive behaviors. Future studies will need to parse this question out. Sixth, cluster analysis is not typically used to group dependent variables together. In general, in psychological research, factor analysis is

used for this purpose. Our data did not appear to be appropriate for factor analysis and although cluster analysis can be an alternative there is potential concern due to the difficult of this analysis not being related to prior research. In addition, some research has suggested there may be assumptions and mathematical constricts that have not fully been investigated when using cluster analysis in this fashion (Anderberg, 2014) which limits the interpretability of these results. Seventh, investigating if motivation for alcohol, drug, and gambling use could predict performance on the decision-making tasks could also be a useful analysis to see how motivation related to decision-making and how this can influence the process. Future research will need to investigate this topic more. Finally, the study's magnitude manipulation was not robust. Although receiving real monetary compensation is something most studies do not do, the difference between no money and a few dollars may not be that meaningful.

Strengths

Despite the previously mentioned limitations, there are strengths to this study as well. First, this study took gambling behaviors into account when looking at decisionmaking tasks. Participants were actively screened out if they had any problematic gambling behavior. This exclusion criterion is important when trying to flesh out the similarities and differences between substance use and gambling disorders. Researchers need to be very clear which of these behaviors are and not problematic for the participants. Second, this study investigated how gambling may be similar or different to decision-making paradigms. Because many decision-making tasks involve gambling and are based on gambling paradigms it is important to investigate the role of gambling in

decision-making. Third, this study investigated some of the relationships between gambling and substance use behaviors. This relationship is important for future research as these disorders are so highly comorbid and are both considered addictive behaviors (American Psychological Association, 2013). Fourth, this study investigated how similar decision-making task are to actual gambling paradigms. These results showed that there is not a lot of overlap with all of these decision-making tasks suggesting that there is a lot of utility to using different decision-making tasks. In addition, a gambling paradigm was the strongest potential predictor of group and magnitude differences in the study and the most powerful predictor of using alcohol as a social, conforming, and enhancement motivation. Fifth, this study took monetary rewards into account. Most research involving decision-making tasks involves using hypothetical money, which can decrease the ecological validity of these studies overall. These results suggested that, in terms of finding group difference between controls and AUS participants, monetary payment is not an important factor. However, receiving actual monetary payment did have a direct influence if the decision-making tasks were able to predict using alcohol for positive reinforcement, suggesting that monetary compensation is an important consideration when developing future studies. Finally, this study was able to help address the clinical utility of decision-making tasks by relating these tasks to both functional assessment and assessments of alcohol motivation. Functional and motivational assessments (i.e., AFA, GFA-R, & DMQR) are useful both as a research tool and therapeutically. These instruments provide insight into whether individuals are using substances or gambling to avoid negative affective states, and if so could suggest that these individuals are at higher risk for more symptoms of addiction. These assessments can also help identify

behavioral contingencies that are noteworthy for intervention. Contingency based therapies have been shown to especially help for substance use disorders (Carroll & Onken, 2014; Dutra et al., 2008; Lussier et al., 2006; Prendergast et al, 2006).

Conclusion

There were four main findings in this study. First, all participants tended to bet more tokens per trial on the slot machine when there was no monetary compensation compared to if there was. Second, no group or magnitude differences were found on any of the decision-making tasks (i.e., IGT, BART, and delay discounting). Effect size and power suggested that this result was not a type 2 error and that there does not seem to be any group or magnitude differences on these tasks in this population. Third, the slot machine and all the decision-making task seems to be relatively independent from each other. These tasks seem to measure different aspect of decision-making and, surprisingly, do not have a lot of overlap in explaining variance in the data or similar participant performance. Fourth, performance on the slot machine and the decisionmaking tasks was able to predict using alcohol for positive reinforcement, in particular, for social situations and enhancing positive feelings and experiences.

It is important that future research investigates decision making 1) uses multiple measures of decision making to access potentially different aspect of decision-making and 2) flesh out the differences between these tasks and find out what these tasks are able to detect. Currently the IGT is considered a clinical measure of decision-making so it will be important for future research to detect exactly what aspects of decision-making this test assesses for and what problems it may be able to detect. Because research is spilt

on if this task can consistently find differences between substance users and controls this is a very important issue. Our results suggests that these tasks may be better at detecting decision-making in regard to positive reinforcement, that is drinking socially, and drinking to enhance pleasurable experiences. These constructs are not as related to problematic substance use as much as using drugs or alcohol for coping or for escaping negative states. Other decision-making task may need to be used or developed that tap into decision-making in this mental state to better assess for more clinically relevant decision-making difficulties. This could help improve the clinical utility of decision making measures and may offer more consistent results in studies in the future that look at decision-making in substance use disorders.

APPENDICES

Appendix A.

MONETARY CONDITION

You are about to be given a chance to play a slot machine, the same as those found in actual casinos. You have been staked with 50 credits to bet. Each credit is worth \$0.05. In other words, if you choose to play, you have \$2.50 to gamble. At the end of the session, you will be paid in cash for the total number of credits you have accumulated or have remaining. It should be your goal to end the session with as many credits as you can. How you accomplish that is up to you. You can bet anywhere from 1 to 3 credits per play and you may quit playing at any time. The session will end when (a) you decide to quit, (b) 10 minutes have elapsed, or (c) you reach 0 credits. Be sure to cash out after each win. Do you have any questions?

NO MONEY CONDITION

You are about to be given a chance to play a slot machine, the same as those found in actual casinos. You have been staked with 50 credits to bet. Each credit is worth \$0.05. In other words, if you choose to play, you have \$2.50 to gamble. It should be your goal to end the session with as many credits as you can. How you accomplish that is up to you. You can bet anywhere from 1 to 3 credits per play and you may quit playing at any time. The session will end when (a) you decide to quit, (b) 10 minutes have elapsed, or (c) you reach 0 credits. Be sure to cash out after each win. Do you have any questions?

Appendix B.

ALCOHOL USE FUNCTIONAL ASSESSMENT

Using this 7-point scale, please circle the number that best represents the extent to which each statement applies to your alcohol use.

 1
 2
 3
 4
 5
 6

 7
 7
 Neutral

 Strongly
 Neutral

 Strongly
 Agree

- 1. I take alcohol when I feel anxious.
- 2. I take alcohol to feel confident.
- 3. I take alcohol to feel good about myself.
- 4. I take alcohol when I feel sad.
- 5. I take alcohol to feel joyful.
- 6. I take alcohol to enjoy social activities more.
- 7. I take alcohol when I am faced with difficult tasks.
- 8. I take alcohol to feel more alive.
- 9. I take alcohol to fit in with others.
- 10. I take alcohol when I feel bad about myself.
- 11. I take alcohol when I feel afraid or scared.
- 12. I take alcohol to feel euphoric.
- 13. I take alcohol when I feel upset.
- 14. I take alcohol when I feel guilty or remorseful.
- 15. I take alcohol when I feel angry.
- 16. I take alcohol to feel positive.
- 17. I take alcohol when I feel nervous.
- 18. I take alcohol when I am having problems with friends.
- 19. I take alcohol when I am having problems.
- 20. I take alcohol when I feel tense
- 21. I take alcohol when I am with friends who are also drinking.
- 22. I take alcohol to get a "high".
- 23. I take alcohol to feel a rush or feeling excitement.
- 24. I take alcohol when I am having problems with my relationships.

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	Controls		AUS		Significance
	M	SD	M	SD	p
Demographics					
Sex	6M/17F		6M/11F		0.53
Age	19.35	2.37	20.06	1.92	0.32
GPA	3.48*	0.35	3.08	0.60	0.03
Addiction					
AUS	0	0	3.29	1.65	< 0.001
SUS	0	0	4.18	2.83	< 0.001
SOGS	0.30	0.56	0.65	1.06	0.19
AFA					
Positive	17.04	12.05	46.06	23.64	< 0.001
Negative	13.48	1.88	33.06	31.30	0.02
GFA-R					
Positive	17.52	10.91	25.53	14.42	0.05
Negative	11.18	9.74	5.13	6.32	0.43
DMQR					
SOC	4.82	4.50	18.47	9.35	< 0.001
COP	2.64	4.22	11.23	6.09	< 0.001
ENH	2.32	3.86	15.64	6.78	< 0.001
CON	6.00	2.78	10.59	5.42	< 0.01

Table 1. Demographic and Questionnaire Data

*Only 20 out the 24 controls reported their GPA

Table 2. Correlation Matrix

	Slot Machine	IGT	BART	DD Money
Slot Machine		-0.32	0.00	0.25
IGT			-0.04	0.08
BART				-0.10
DD Money				
	IGT	BART	DD Money	
Slot Machine	-0.32	0.00	0.25	
IGT		-0.04	0.08	
BART			-0.10	

Table 3. Proximity Matrix

	Slot Machine	IGT	BART	DD Money
Slot Machine		90.54	74.73	54.12
IGT			71.51	66.01
BART				78.71
DD Money				

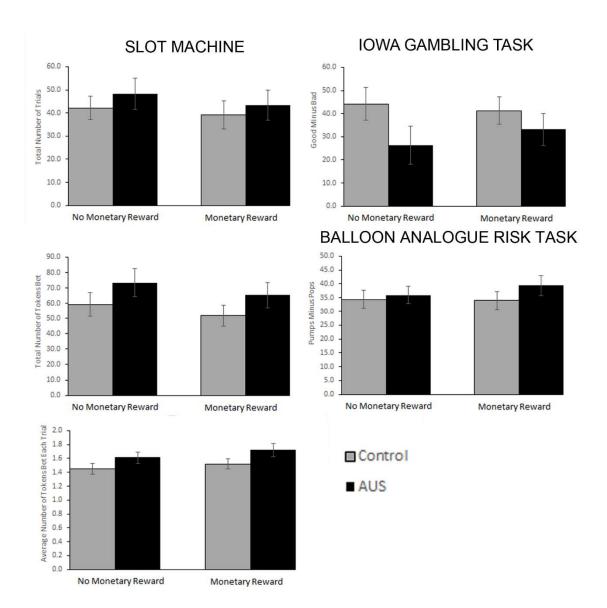
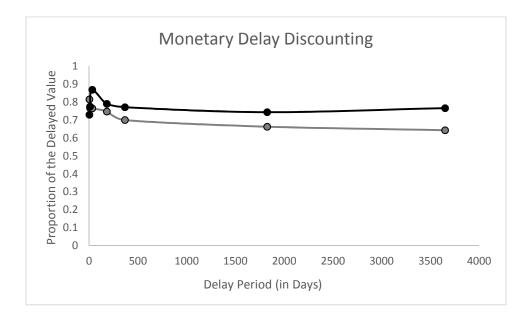


Figure 1. Performance on the slot machine and decision-making tasks.



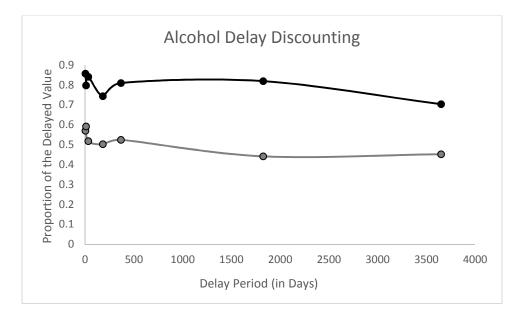


Figure 2. Delay discounting data where the controls are in grey and AUS are in black.

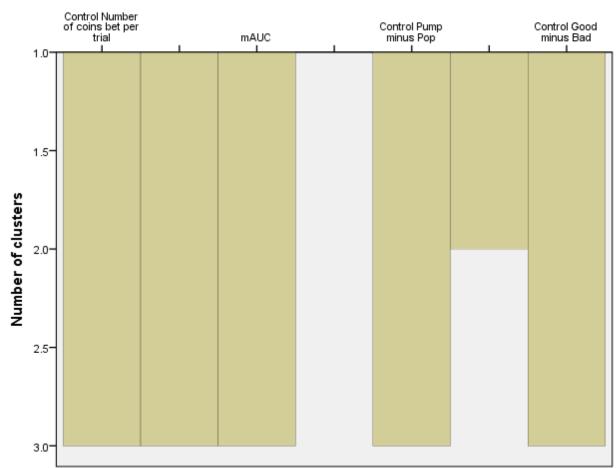
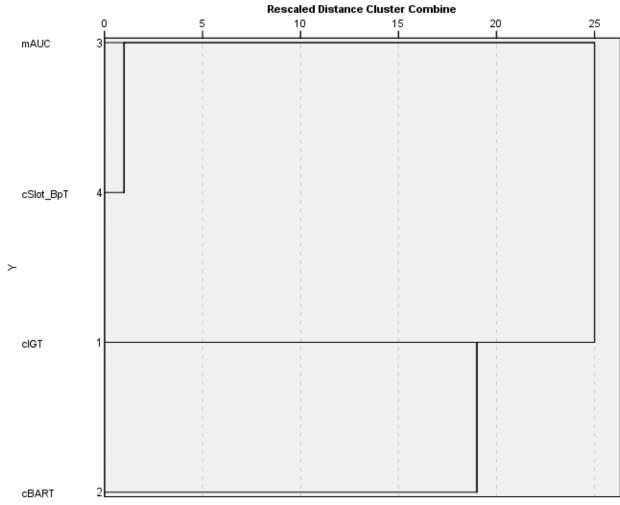


Figure 3.The Icicle Plot is a visualization of the conglomeration schedule. Each of the four tasks has a column marked at the top of the figure (slot machine, IGT, BART, & delay discounting). There are columns between each task to represent linkage. A vertical bar descends from each of the columns that mark the four tasks to the bottom of the graph. The first two tasks that are linked together (slot machine & delay discounting has a bar between them that descends the furthest of the remaining columns. This shows that these are the first two clusters that merge with each other. The next set of clusters that join (BART and IGT) have a bar that descends halfway down the graph. This shows that these are next two clusters to merge. Finally, the last two clusters (AUC and Slot with IGT and BART) has no bar descending between the columns. In other words, the further the bar descends between two task columns means, the more similar those tasks are to each other.

Case



Dendrogram using Average Linkage (Between Groups)

Figure 4. The dendrogram is another way to visualize how the clusters merge together. On the Y axis. There are four rows that represent the four tasks. On the X axis is the relative distance in space between the clusters when they merge. The further away from the left side of the graph means the tasks are more similar. The graph is read from left to right with each new cluster being linked. Further distances mean those clusters where further apart when they were ultimately linked together.