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### Effect of Brain Injury on Demand of Alcohol

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Effect of Brain Injury on Demand of Alcohol

by

Whitney Michele Chaney

A thesis submitted to the School of Behavior Analysis of  
Florida Institute of Technology  
in partial fulfillment of the requirements  
for the degree of

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Applied Behavior Analysis and Organizational Behavior Management

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May, 2023

We the undersigned committee hereby approve the attached thesis,  
“Effect of Brain Injury on Demand of Alcohol”

by  
Whitney Michele Chaney

---

Kimberly N. Sloman, Ph.D., BCBA-D  
Associate Professor  
School of Behavior Analysis  
Major Advisor

---

Kaitlynn M. Gokey, Ph.D., BCBA-D  
Assistant Professor  
School of Behavior Analysis

---

Vida L. Tyc, Ph.D.  
Professor  
School of Psychology

---

Robert A. Taylor, Ph.D.  
Professor and Dean  
College of Psychology and Liberal Arts

# Abstract

Effect of Brain Injury on Demand of Alcohol

Author: Whitney Michele Chaney

Advisor: Kimberly Sloman, Ph.D., BCBA-D

Brain injury, or damage to the brain and/or surrounding structures, is listed by the CDC as the leading cause of disability and death in the United States. This kind of injury can result in symptoms that physical, cognitive, and behavioral functioning in those affected. Despite this, current literature reflects a significant deficiency in the understanding and management of behavioral symptoms, that present after the injury, in most neurorehabilitative treatments. This study aimed to investigate whether sustaining a brain injury can effect an individual's demand intensity for alcohol, if their demand was inelastic, and their probability for misuse of alcohol. To evaluate this, 50 participants (25 control, 25 injured) completed an alcohol use disorders identification test (AUDIT) and an alcohol purchase task (APT). Demand results were then analyzed using a modified exponential equation to measure the demand intensity,  $O_{max}$ ,  $P_{max}$ , and breakpoints. In addition to this, a statistical analysis was done using an unpaired t-test and a chi-square test on both the demand and AUDIT data collected. We concluded that the individuals who had sustained an injured had a higher intensity of demand that was inelastic to the changes in prices. They also demonstrated a higher  $O_{max}$ ,  $P_{max}$ , and breakpoint when compared to the control participants.

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# Chapter 1

## Effect of Brain Injury on Demand of Alcohol

A brain injury is a disability that comes with a list of symptoms; physical, psychological, and behavioral. Of the myriad of symptoms, increased impulsivity is often referenced as a common struggle for both the injured individual and those around them (Dixon et al., 2005). This increase can then result in maladaptive behaviors, like substance abuse. First, background information on what a brain injury is and how sustaining one can impact functioning is provided. This is followed by an explanation on how using behavior economic assessments can be used to operationally define and measure impulsivity. More specifically, this study focused on demand assessments of alcohol use in individuals with a history of brain injury to better understand the nature of impulse changes following injury and hopefully inform future intervention potential.

### Brain Injury

Brain injury is currently the most common cause of disability or mortality, in all populations, with there being approximately 1.7 million annually in the United States (Sabet et. al., 2021). Brain injuries can be the result of a disease or disorder, referred to as an acquired brain injury, or from a bump, blow, penetration, or jolt to the head, better known as a traumatic brain injury (TBI). These can then be classified into two categories; a localized brain injury (i.e., concussion) or a diffuse brain injury (i.e., diffused axonal damage from rapid acceleration/deceleration). The injury will often cause the individual to lose consciousness and results in injury to the cells of the brain and a disturbance in its ability to function properly. The impact of these traumas can also lead to increased intracranial pressure, damage to blood vessels, hydrocephalus (i.e., fluid retention in the brain), and/or damage to the central nervous system. Depending on the type of injury, there may be a risk of a secondary injury occurring as a result of the damaged tissue and cells due to disruptions to cerebrovascular blood flow or a compromised blood-brain barrier.

When providers are trying to determine the presence or magnitude of a brain injury following an incident, they will use a computerized tomography scan to quickly determine the type and location of the injury, as well as the Glasgow Coma Scale. The resulting score will correspond with the severity of the trauma (Table 1). A score of 13 to 15 would be categorized as a mild brain injury or concussion (Jain & Iverson, 2021). At this level, the loss of consciousness was likely brief, with the symptoms typically being minor (e.g., dazed, confused) and only lasting for a short time after the incident. With a Glasgow score of 9-12, the injury would be designated as a moderate. At this level, the individual would have been unconscious for a longer period of time and the symptoms can last for weeks. These symptoms would include confusion, impairments to cognitive and physical functioning, and some changes in behavior. Luckily, with moderate brain injuries, rehabilitation is likely to produce a successful return to normal functioning. Those with a severe brain injury, or with a score of 8 and under, are not as lucky. In these individuals, there is a high likelihood that they will require surgery to control the damage to the brain (e.g., ruptured blood vessels or bruising). Even with personalized physical and cognitive rehabilitation, individuals with severe brain injury are not likely to recover to a level of functioning they were at prior to the incident. It is at this level that individuals may struggle with persistent memory loss, permanent changes to their personality, or even the inability to continue taking care of themselves due to the damage to the executive functions and loss of self-control (2021). Other than the biological effects, there is also a mental and emotional impact that affect the injured and their families and/or caretakers.

## Behavioral Economics

The concept of behavioral economics was developed to aid in understanding what informs individual and group decision-making through behavioral science. To do this, behaviors that are associated with decision-making (i.e., selecting options when presented with choices) are assessed using economic principles (Reed et al., 2013). Traditionally, it is believed that individuals are in a constant state of assessing the consequences of each behavior based on what will yield the highest returns and then act accordingly. However, a behavior economic approach suggests this traditional stance does not take into account the

high probability of irrational behaviors or decisions being made when compared to what may be best for the individual. For instance, an individual may have a presentation due the next morning, but still chooses to go out for drinks rather than practice and prepare despite the negative impact this may have on performance.

Two methods of assessing this phenomenon are delay discounting and demand curves. In delay discounting, a researcher is able to determine an individual's preference for smaller, immediate or larger, delayed consequences in a generalized manner. In contrast, measuring for demand is able to measure the effect of a specific setting or commodity on the individual's decision-making. Both hold valuable information in their resulting data and, when applied together, can help to provide a more comprehensive view of human behavior.

## Delay Discounting

As behavior, impulsivity does not currently have a consistently recognized operational definition. However, to better gain an understanding of impulsive behaviors or decision-making processes, researchers have employed the use of delay discounting assessments as a method of gaining objective data on the mechanisms behind these behaviors. Delay discounting occurs when the value of a reward begins to decrease in relation to the amount of time it takes to receive. The methods for measuring this originated through studies observing nonhuman animals (Mazur, 1987). Mazur presented pigeons with a choice between two options: 2s of access to grain immediately or 6 s of access to grain after a delay. Depending on which the pigeons chose, the researcher would increase or decrease the length of the delay in the subsequent trial. This systematic process continued until the value in access became evenly split between the two options, this was aptly named the indifference point. The term, delay discounting, and the equation ( $V = A / (1 + kD)$ ) to describe response patterns proposed by Mazur is still in use today (Odum, 2011). In Mazur's hyperbolic equation, the indifference point (V) would be equal to the reward amount (A) and then divided by one over  $k$  multiplied by the delay (D). The  $k$  value is a free parameter that is meant to represent how greatly and quickly the delay affected the

value. This means that, when the  $k$  value is smaller than the effect of the delay is less and the effect is stronger if the  $k$  value is larger.

Another method used to interpret the same data is by calculating the area under the curve (AUC). To get this measurement the indifference points and delay amounts are first normalized and then equated to a range of 1 (no discounting) to 0. In this measurement, a larger AUC is indicative of lower rates of discounting and a smaller AUC of higher rates of discounting. These values can also be translated into more layman's terms by identifying the higher  $k$  value with an increased propensity for impulsive decision making.

It is also important to take into account the effect of the parameters within the delay discounting trials or sequences. Simple factors such as the direction of sequencing (i.e., ascending versus descending) or the delay duration progression of the choices can have an effect on the organism's rate of discounting. Robles and Vargas (2008) explored this in an experiment in which sixty-five participants were given a full length, 240-choice delay discounting assessment and then an abridged version that varied between an ascending or descending sequence order. The results showed that in the tests with a descending order, the  $k$  value and AUC was smaller and larger respectfully in comparison to the  $k$  value and AUC of the ascending group.

Rung and colleagues (2019) assessed the effect of three different delay durations on the individual's rate of discounting. These progressive durations included a standard delay, in which the duration between delays increased, a linear delay in which the duration remained the same, and an inverse delay, in which the duration decreased. The 125 participants each completed the three progressions and results showed that rate of discounting decreased after completing the inverse delay and, to a smaller degree, the linear progression. Additionally, this effect was only produced after being introduced to the alternative methods. Both these studies demonstrate how the order and rate in which the choices are presented can have an impact on the individual's degree of discounting and should be taken into consideration when designing the assessment.

Another factor that is often criticized is the use of hypothetical commodities instead of real-life consequences. Due to the intangible nature of hypothetical rewards, it is assumed that the validity of the data collected using them should be questioned. In 2002,

Johnson and Bickel determined whether the use of hypothetical values affected discounting outcomes. They recruited six participants who were then presented with an assessment with hypothetical choices. After the indifference point was reached, the researchers informed the participants that the choices would be primarily hypothetical, but that the choices would be designated for real money they would receive based on their selections. The primary finding from this study was that five of the six participants exhibited no difference in reporting between the hypothetical and real rewards.

Although hypothetical rewards have not been found to influence discounting, there are other factors that can affect the degree of discounting displayed by an individual. Age, reward magnitude, and social influence can play a role in decision making, as observed in the results of Bixter and Rogers (2019). They enlisted fifty young adult and fifty senior participants to perform a standard individual assessment using hypothetical monetary rewards and then a three-step evaluation in a two-person, same-age group team. The aim of the individual assessment was to evaluate each participant's rate of discounting and the effect reward magnitude had on discounting. Results showed that the young adult age group had a significantly steeper rate of discounting when compared with the senior group. However, the young adult group was more likely to discount smaller magnitude rewards than larger magnitude rewards. Next, researchers assessed the effects of social pressures on each participant's discounting during a three-step assessment. These data, when compared with the pre-assessment, showed that each teammate's selection was more similar to one another in the post assessment results. The researchers concluded that social influence may affect discounting.

Other studies have evaluated additional factors that may influence discounting including same or cross-commodity comparisons. For example, Moody et al. (2017) compared discounting rates when using alcohol versus monetary rewards in alcohol users. This was accomplished with sixty participants completing four discounting assessments; immediate access to alcohol versus delayed access to money, immediate access to alcohol versus delayed access to alcohol, immediate access to money versus delayed access to money, and immediate access to money versus delayed access to alcohol. Each of these assessments included five delay lengths that money would be delivered to. The results

showed that the same-commodity of alcohol was discounted at markedly higher rates compared to the same-commodity of monetary rewards. In addition, in the cross-commodity task comparison, the money now versus alcohol later task was identified as having a steeper rate of discounting compared to the alcohol now versus money now task. These findings illustrate how the degree of discounting can vary for a single individual depending on the specific nature of the reward presented. Expansion of this delay discounting research could help to reliably identify at-risk individuals before a dire dilemma develops and also could inform practitioners on the best treatment options for their clients and patients.

However, limitations of delay discounting paradigms with commodities other than money exist. For example, when conducting cross commodity analyses, it might be difficult to realistically equate a specific amount of money to the commodity (e.g., \$1000 vs. \$1000 worth of alcohol). Additionally, steep discounting patterns may not be predictive of actual abuse liability (MacKillop, 2016).

## Demand

The understanding that, as the monetary and/or response cost of commodities such as food or beverages increases, there will inevitably be a resulting decrease in the intake of that commodity, this is known as the Law of Demand (Reed et al., 2013). When the intake rates of the commodity are maintained while the cost continues to increase, the demand is considered inelastic. When intake rates decrease as the cost of the commodity increases, the demand has gained elasticity, The point at which the cost becomes so great that there is no intake is referred to as the breakpoint. Once the inelastic and elastic responses are graphed, the resulting curve is known as the individual's demand curve. A demand analysis is sensitive to environmental factors and may better predict potentially harmful or disruptive behaviors (MacKillop, 2016). Due to this, they are often used when measuring the value, motivation, and abuse liability of substance use while also helping to inform intervention decisions.

In most studies, a purchasing task will be specific to the commodity being observed. For example, in Ortelli and Martinelli (2021), the researchers presented a

hypothetical alcohol purchasing task (APT) that consisted of the participants self-reporting their projected alcohol consumption within a range of price points. Participants were informed that these decisions occurred in a relatively closed economy. That is, alcohol consumption had to be completed in a set time period and alcohol could not be accessed through any additional means. An alternative option for a non-alcohol beverage was also assessed to test whether the demand for alcohol would remain consistent. The researchers found that the resistance of demand to the change in price was fairly strong in the college-aged population of the study, but that the non-alcoholic alternative was able to bring the demand of alcohol down faster when introduced.

Hursh and Silberberg (2008) introduced a modified exponential equation to determine the indices of demand. The modified version of the equation allowed values of zero to be factored. To construct the equation, the amount of commodity intake at the price point is represented as  $Q$  with the price point being labeled as  $C$ . The intake levels that are documented at or near zero (i.e., no cost for the commodity) are designated as  $Q_0$  and is also indicated as the intensity of the demand. The range of intake based on the log units are represented as the parameter  $k$  and is determined by the highest value for the  $Q_0$ . Finally, the change in elasticity observed is represented by  $a$ . In addition to this, other indexes of demand such as the breakpoint,  $Omax$ , and  $Pmax$  can be derived from the data collected. The breakpoint, as described earlier, is the initial price point at which no commodity intake occurs. The  $Omax$  is obtained by multiplying the intake value by the cost to determine the maximum response output, with the  $Pmax$  being the specific price point at which the  $Omax$  occurs. This equation was used by Strickland and colleagues (2019) to assess alcohol demand of 223 participants. In this study, the participants were asked to provide an assessment of their alcohol and soda intake over the past month and then were given commodity purchase tasks for both, in which they were asked how much of each they would consume at a variety of price points. The finding showed that there was a strong positive correlation between the self-reported amounts and the direction of the demand relation. These results show the relationship between behavior pattern history and the degree of demand the individual exhibits for the commodity.

The validity of hypothetical versus actual commodity intake is often contested. Yet Amlung and colleagues (2012) provide evidence that the use of hypothetical commodities does not decrease the legitimacy of the data. The researchers recruited forty-one participants that were given an ATP that was expressly hypothetical, as well as one that explained that the indicated commodity would be real and given that day. The data demonstrated similar rates of responding between the hypothetical and real rewards. In the case of this study, all five demand indexes discussed earlier were assessed and showed high-magnitude results across the board, further supporting the use of hypothetical commodities in demand assessments.

What makes demand such an attractive addition when assessing impulsivity, as mentioned before, is that the measures taken with demand are more sensitive to changes in environmental variables. This makes it more reliable in gauging the efficiency of behavioral interventions on an individual's demand for a target commodity. This is illustrated in a cocaine study conducted by Yoon et al. (2021), in which demand data was taken for two groups; responders and non-responders, based on whether they were able to provide six consecutive negative urine tests. The data were collected prior to beginning treatment for baseline and then at two weeks and five weeks into treatment. The results showed that, while much lower in the responder group compared to the non-responder, there was a notable decrease in the cocaine demand in both responders and non-responders, with responders exhibiting a significantly lower demand by week five.

## Behavioral Economics and Brain Injury

A brain injury may affect a number of executive functions and self-regulatory processes that are damaged along with the physical structures of the brain. The specific topography of these symptoms is typically tied to the area of the brain that withstood the damage. When looking at an individual's degree of discounting (or impulsivity), the areas of the brain most commonly identified are the anterior cingulate cortex (ACC) and the orbitofrontal cortex (OFC). The ACC is strongly associated with emotional regulation and assessment, which if damaged, can impact an individual's ability to effectively control their emotional responses and impulses when aroused (Stevens et. al., 2011). This can lead



to rash decision making and a higher motivation for immediate gratification. The OFC, unlike ACC, have been directly associated with immediate decision making and the ability to determine the future consequences of those decisions (Li, et al., 2019).

With this in mind, high-risk behaviors like alcohol misuse can become a potential issue for individuals who have suffered a brain injury. By evaluating the self-reported pre- and post-injury alcohol intake of 170 participants with a history of brain injury, Pagulayan et al. (2016) determined long-term alcohol patterns at one month, six months, twelve months, and three to five years post-injury. A statistical analysis illustrated that the most significant increase in consumption appeared between one and six months, making it the ideal time for intervention. With alcohol being a relatively accessible and tangible reinforcer that also has the capacity to serve several behavioral functions, this increase was expected. Through access to social attention and/or escape from intrusive thoughts, memories, or pain, the misuse of alcohol is a risk for those suffering with the psychological and physical evidence of a traumatic event.

The purpose of the proposed study is to expand on the studies conducted by Ortelli & Martinetti's study (2021) targeting the impact of brain injury on alcohol demand. The specific aim is to determine whether there are higher demand rates of alcohol in individuals with a history of brain injury compared to healthy controls. It was hypothesized that alcohol would maintain a higher rate of demand in the injured population.

## Chapter 2 Methods

### Participants

Participants ( $N = 50$ ) were recruited through Amazon Mechanical Turk (MTurk), an online crowdsourcing platform. The participants were provided with a link to the Qualtrics site, where they were asked to review and initial an informed consent before moving on to the AUDIT and APT surveys. The brain injury group was made up of 25 participants, aged 25 or older ( 52% male, 76% Caucasian), that had sustained a brain injury during their life. The control group was made up of 25 participants, aged 25 or older (56% male, 72% Caucasian), that had never experienced a brain injury. Participants were excluded if they were abstaining from alcohol, had a past history of substance abuse, and/or a history of an impulsivity disorder. Once the survey was completed the individual was provided a code to submit into Amazon MTurk for response review. Participants that finished the survey in its entirety, and whose responses were reasonable and complete, were compensated \$2 upon review approval. Table 2 provides a summary of participant demographic characteristics. Of note, it was expected that participants would be disproportionately male and geriatric based on current brain injury statistics. However, in this study the ratio between male and female participants was negligible and over 80% of the injured population was over the age of 55. All participants were provided with an informed consent.

### Materials and Procedure

#### Alcohol Use Disorders Identification Test (AUDIT)

Developed by the World Health Organization (WHO), a ten-item, self-reported AUDIT questionnaire was provided prior to any additional tasks to assess the participant's current alcohol consumption and potential problematic drinking behaviors (Saunders et al, 1993). The resulting score ranges from 0 to 40, with 0 indicating that the individual

abstains from alcohol consumption. The range is then broken up into four zones that indicate the probability of misuse or abuse (see Table 3).

### Alcohol Purchase Task (APT)

A computerized behavior economic tool was used to assess the amount of alcohol consumption in response to rising purchasing costs. For this study, the participants were asked to choose how many units of a standard alcohol beverage (e.g., 12oz of beer, 5oz of wine, 1.5oz of liquor) they would purchase and consume at a variety of prices (\$0.00 [free], \$0.25, \$0.50, \$1.00, \$5.00, \$10.00, \$15.00, \$20.00, \$25.00, \$30.00, \$35.00, \$40.00, \$45.00, and \$50.00). The participants are asked to consider only their personal finances, that the alcohol being presented is what they prefer, that there would be no other sources for alcohol, and that all alcohol hypothetically purchased would be consumed that day. The instructions for this procedure are as originally outlined by Bruner and Johnson (2014). However, the price points were adjusted to account for the difference in the commodity being tested.

## Chapter 3

### Data Analysis

#### AUDIT Score

Each participant's AUDIT score was categorized according to the zones indicating risk of misuse. None of the participants were categorized as Zone 1, as this indicated abstinence from alcohol, which was one of the exclusion criteria. Participants whose AUDIT score was between 1 and 7 were categorized as a low risk (LA) for alcohol misuse and participants whose score was 8 and above were categorized as moderate/high risk (HA) for alcohol misuse. These categories were used to further analyze alcohol demand functions within and between groups.

#### Alcohol Demand

The data collected for the hypothetical alcohol consumption was first assessed for systematicity by determining whether the units of alcohol consumption at any given price point is at least 20% greater when compared to the following price point and units of alcohol consumption at the final price point is not at least 10% lower than at the starting price point. The second contingency would be exempt in the case of zero intake levels. The nonsystematic points were removed before data were inputted into the demand equation. The choice to use the criteria presented by Bruner and Johnson (2014) is due to the anticipated number of zero-responders projected. The more recent formula presented by Stein et al (2015) uses the log of consumption values, which cannot be defined when the consumption rate is 0. Data were analyzed by averaging units of alcohol consumption at each price point in the following ways. First, we averaged units of alcohol consumption within control and injured groups. Next, we averaged units of alcohol consumption according to AUDIT score category. Finally, we averaged units of alcohol consumption according to AUDIT score category and within control and injured groups. Once demand data were averaged, they were then assessed using the equation:

$$Q = Q_0 * 10^{k(e^{-aQ_0C} - 1)}$$

using the GraphPad Prism software. This produced the indices of demand for the mean consumption rates as a whole.

## Chapter 4 Results

### AUDIT Scores

The results from the AUDIT concluded a mean score of 3.96 (low risk) in the control group, indicating an overall low risk of alcohol abuse, and 5.16 (moderate risk) in the injured group, demonstrating a slightly higher risk of alcohol abuse following a brain injury. After conducting an unpaired t-test, it was concluded that this difference in reporting was not statistically significant ( $p = 0.295$ ).

### Demand

Table 4 illustrates the consumption means for the data collected on the brain injury population and the control population. As hypothesized, the injured population demonstrated a higher consumption mean throughout the APT survey, when compared with the control group, that maintained across all price points, as seen in the demand curve in Figure 1. This evidence also supports the assumption that the demand for alcohol in the injured population would be more inelastic than what is observed in the control population. When means for each price point were analyzed using Hursh & Silberberg's (2008) modified equation, the data indicated a higher intensity of demand ( $Q_0 = 5.4$ ) in the injured population, relative to the control ( $Q_0 = 4.5$ ). An additional t-test with Welch's correction was conducted to determine the statistical significance of this difference, but it concluded that it did not meet criteria ( $p = 0.5146$ ). The demand indices (Table 5) were analyzed using the Kaplan & Reed (2014) calculator and demonstrated notably higher values for measurements in the injured population as well. The highest response output ( $O_{max}$ ) displayed by the control population was 9.40 at a price of \$13.68 ( $P_{max}$ ), which is significantly lower than 10.9 responses at \$18.91 exhibited by the injured group. The participant breakpoints further supported that individuals in the injured population were more likely to maintain consumption despite a rise in price. This is especially evident when reviewing the participant breakpoint data in Figure 2, specifically the rate of breakpoint after 25\$, where 28% of the injured population were still reporting consumption, compared to only 12% of controls.

However, when conducting an a demand analysis on LA scores (1-7) compared to HA scores (8-15), the visual analysis showed that participants who scored in the HA score category displayed a noticeably higher intensity of demand ( $Q_0 = 7.4$ ) when compared to those in the LA score category ( $Q_0 = 4.0$ ) as depicted in Figure 3. An additional demand analysis was conducted to compare the LA scores versus HA scores between the control and injured groups. This analysis, displayed in Figure 4, illustrates a negligible difference in demand between the HA score, control group ( $Q_0 = 7.3$ ) compared to the HA score control ( $Q_0 = 7.2$ ). Interestingly, despite having a higher demand intensity, the HA score control group was found to be noticeably lower in both the  $P_{max}$  (9.1) and  $O_{max}$  (\$23.29) compared to the HA score injured group (11.5; \$29.10). The difference in demand intensity appeared more significant when comparing the LA score, injured group ( $Q_0 = 5.0$ ) against the LA score, control group ( $Q_0 = 3.5$ ). Similar to the HA score, in the LA score analysis showed a higher  $P_{max}$  (13.3) and  $O_{max}$  (\$23.29) compared to the LA control group (11.4; \$13.98). This suggests that, while higher AUDIT scores are indicative of high demand across both groups, a brain injury is more likely to present with a higher level of demand at both a LA score and a HA score.

## Chapter 5

### Discussion

The Centers for Disease Control and Prevention (CDC) estimated that in 2021, about 1.7 million individuals in the United States sustain a brain injury. Of those, 80,000 sustained permanent physical or cognitive disability. While research on brain injury has increased over the last few decades, expanding on the psychological and neurological challenges faced by those affected. However, brain injury has also been associated with an increase in maladaptive behaviors (e.g., substance abuse and aggression), this portion of the post-injury treatment has not been as thoroughly explored. Depending on the area of the brain affected and how severely it was damaged can result in changes to their personality or behaviors. When evaluating impulsivity, or decision making, this is particularly true for injuries to the ACC and the OFC. These areas of the brain affect how the individual regulates their emotions, which can result in emotionally charged decisions, and how they are able to recognize the potential consequences of their decisions. Due to the nature of these types of injuries, behavioral economic assessments like demand and delay discounting are especially effective in assessing fluctuations in the demand and discounting of commodities, like alcohol. Delay discounting is able to assess at which point the value of a reward (e.g., alcohol) begins to decrease, depending on the amount of time it takes to receive. Although this measurement does not assess for acute environmental variables, it provides an overview of the individual's decision making process. When done in conjunction with a demand assessment, which measures the intensity and change in the individual's demand of a commodity (e.g., alcohol), a more comprehensive understanding of how a brain injury influences an individual's decision making process.

The aim of this study was to determine whether sustaining a brain injury influenced an individual's demand for alcohol. As hypothesized, it was found that there were several socially significant differences in the demand and AUDIT data collected for the control and injured populations. Similar to what was seen in the Greek population used



in the Orтели & Martinetti (2021) study, a higher mean AUDIT score was observed in the injured population that coincided with higher rates of demand intensity. Visual analysis of demand curves show slight differences in demand between control and injured groups. These differences were more pronounced when data were analyzed between participants with high and low AUDIT scores both between and within groups. More specifically, participants who were injured with moderate/high AUDIT scores showed a higher demand for alcohol than participants who were not injured with moderate/high AUDIT scores. There is a social significance in these findings as injured participants appear more susceptible to impulsive behaviors, such as alcohol misuse, which affects the health and wellbeing of the individual and their caretakers. Due to the limited number of participants, these preliminary data were not statistically significant and additional participants are necessary to support these findings.

## Clinical Implications

From a behavior analytic perspective, operant behavior serves a purpose or function for all organisms. That is, behavior occurs because of the environmental consequences it produces. Alcohol consumption can be caused or maintained by a number of environmental consequences that occur from engaging in the behavior itself (i.e., automatic reinforcement) or through the behavior of others (social reinforcement). Two possible reinforcing functions of alcohol consumption are; the physiological effects of the drug or social attention from others. For example, the individual might drink because they like the feeling of alcohol or being drunk (automatic positive reinforcement) or it allows them to escape an aversive stimulus, like physical pain or negative emotions (automatic negative reinforcement). Alternatively, alcohol consumption may be reinforced by the behavior of others. Such is the case where individuals might drink alcohol due to the social attention associated with being at a bar and talking with others. This is an example of socially mediated positive reinforcement for alcohol consumption. Still, multiple or combined factors may maintain alcohol consumption. However, it is important to note that extensive research on the operant function behind drinking behaviors has not been conducted at the time of this article. Future research using a functional analysis (FA) to

objectively assess the motivating operations behind alcohol consumption can help to inform clinicians on why the behavior is occurring. This approach would provide information on the best intervention or what alternative behaviors would be the most appropriate for the patient, giving patients a recovery plan that is tailored to their needs.

Additionally, the findings from this study, along with future behavior economic research, can help identify an individual's potential inclination for discounting and heightened demand for commodities that can lead to additional high-risk behaviors such as, but not limited to; drug use, gambling, sexual promiscuity, stealing, and poor eating habits. By understanding the mechanisms that contribute to high risk behaviors following a brain injury, treatment providers can better prescribe strategies to reduce impulsivity and increase the quality of life of their patients and their caretakers. Future researchers can use demand assessments and delay discounting to evaluate which treatments and self-management interventions would be the most effective to promote healthy habits, with a goal of preventing the presentation of high-risk behaviors and mitigating the impact of the behaviors when they do present. In the study conducted by Pagulayan et al. (2016), the researchers determined that between the first and sixth month post-injury participants reported the highest rate of alcohol consumption. This indicates that within that time frame would be an ideal time for treatment providers to collect additional data on risk behaviors, like drinking alcohol. This will aid in identifying problematic behaviors before they become detrimental and for implementing preventative interventions to mitigate the risk of them presenting.

Yoon and his colleagues (2021), illustrate how evaluating demand can also be useful to determine how effective a treatment is in decreasing substance misuse behaviors. While their study was focused on the cocaine use, the researchers measured demand intensity and indices of participants with a cocaine use disorder (CUD) that were seeking treatment. The treatment used for that study was an abstinence focused contingency management intervention that provided high-magnitude reinforcement in the form of monetary compensation for negative urine screenings. Demand data was taken at baseline (prior to the introduction of the intervention) and then at two weeks and five weeks after intervention implementation. To differentiate treatment response between the participants,

those who were able to provide six successive urine samples, they were labeled as “responders” and those that were unable to meet this criteria were labeled as “non-responders”. The researchers were then able to compare the demand results from pre-and post-treatment and they found that, over the course of the treatment, there was a significant increase in reporting zero consumption across all price points, this was particularly true in the case of responding participants. These results indicated that the use of a contingency management intervention can reduce the demand for and consumption of cocaine. An expansion of this study with the brain injury population could help to inform clinicians on which interventions would be best for mitigating alcohol misuse.

## Limitations

When analyzing the sample populations, nearly all demographics were proportionate, the exception being ethnicity, with Caucasian making up 76% of the total population. It was assumed that there would be a higher prevalence of geriatric participants for the injured sample, however this was not the case. Due to the recruitment of participants through MTurk, there is a possibility that the geriatric demographic would be underrepresented in this study. That is, this population may be less likely to access online crowdsourcing platforms. The limited demographic pool resulted in limitations to the external validity and social significance of the results interpretation and it is suggested that future studies specifically assess the demand data of underrepresented demographics to help expand the understanding of the overall effect of brain injury on impulsivity. The final limiting result in the demographic data was the unexpectedly high (48%) female turnout in the injured population. While it is typically a benefit for there to be even distribution between the sexes, this is abnormal based on the most recent statistics released by the CDC (2019) that states women only make up approximately 26.5% of brain injury cases. This is likely the result of the small participant population size and indicates that the study population recruited for this study may not be an accurate representation of the overall brain injury population, which would also impact the external validity of the results. It is also important to note that, based on a study conducted by Gray and MacKillop (2014), responding in male participants resulted in a significant difference in demand intensity,

*Omax*, and elasticity when compared to female participants. Even when the researchers adjusted for the covariates, demand intensity in males was still reported to be significantly higher. With the unexpectedly higher number of female participants observed in this study, this could have impacted the demand data results presented.

The assessments used for this study were self-reported, a measurement method that is often seen as a limitation to the internal validity of results. This is based on the assumption that participants may not have the introspective skills needed to accurately report on their alcohol use. There is also a risk that there are biases in reporting that are the result of personal values and social perception. In addition to being self-reported, the survey's vignette provided a scenario that featured a bar setting. For individuals that do not find that type of environment reinforcing or who's drinking behavior is maintained by escape, this may have affected their responding in the APT.

Finally, this study did not account for other variables, such as location of the injury, multiple injuries, or the rehabilitative treatments received following the injury that could have influenced the results. While the survey did request information on participant's injury location and severity, post-injury treatments, and time since the injury, there was a negligible amount of feedback on these questions. As mentioned previously, the location of the injury, as well as the severity, can have a significant impact on the presentation and intensity of symptoms. Additional research would be needed to identify the impact of these variables and how they could affect the success of potential behavioral interventions.

In conclusion, this study has demonstrated that individuals who have sustained a brain injury report a higher rate of consumption of and demand for alcohol relative to those who have not experienced an injury. Future studies could expand on the current literature investigating the mechanics of impulsive, problematic behaviors following a brain injury and intervention plans focusing on preventative, rather than reactive, treatments.

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# Appendix

## Tables

**Table 1: Glasgow Coma Scale Breakdown**

<b><i>Mild</i></b>	<b><i>Moderate</i></b>	<b><i>Severe</i></b>
GCS 13 to 15	GCS 9 to 12	GCS $\leq$ 9
Memory loss lasting < 24 hours	Memory loss lasting from 24 hours to 7 days	Memory loss lasted > 7 days
Did not lose consciousness or was unconscious for < 30 minutes	Unconscious for > 30 minutes and up to 24 hours	Unconscious for > 24 hours

**Table 2: Participation Demographics**

	<b><i>Control</i></b> <i>N=25</i> <i>Prevalence %</i>	<b><i>Injured</i></b> <i>N=25</i> <i>Prevalence %</i>
<b>Sex</b>		
Male	56	52
Female	44	48
<b>Age</b>		
26-35	36	20
36-45	36	40
46-55	16	20
56-65	8	16
65+	4	4
<b>Ethnicity</b>		
Asian	8	12
Black	8	4
Caucasian	72	76
Hispanic	8	4
Other	4	4

<b>Employment</b>		
Full-Time	68	76
Part-Time	0	4
Self-Employed	28	16
Unemployed	4	4
<b>Household Income</b>		
> 15K	0	4
15-24K	4	4
25-49K	36	28
50-74K	32	32
75-99K	16	12
100-149K	8	12
150-199K	4	0
200K+	0	8
<b>Marital Status</b>		
Single	44	44
Married	48	48
Divorced	8	8

**Table 3: AUDIT Scoring**

<b>Score</b>	<b>Risk Level</b>
0	No risk; indicates abstinence
1-7	Low risk
8-12	Moderate risk
13+	High risk

**Table 4: Reported Consumption Means**

<i>Control</i> <i>N=25</i>		
<b>Price (\$)</b>	<b>M</b>	<b>SEM</b>
0	4.400	0.4203
0.25	4.320	0.4030
0.50	4.120	0.4055
0.75	4.040	0.4061
1.00	3.920	0.4200
5.00	2.324	0.2614
10.00	1.488	0.1716
15.00	0.840	0.1441
20.00	0.576	0.1214
25.00	0.432	0.1191
30.00	0.208	0.0597
35.00	0.172	0.0498
40.00	0.136	0.0360
45.00	0.136	0.0360
50.00	0.000	0.0000

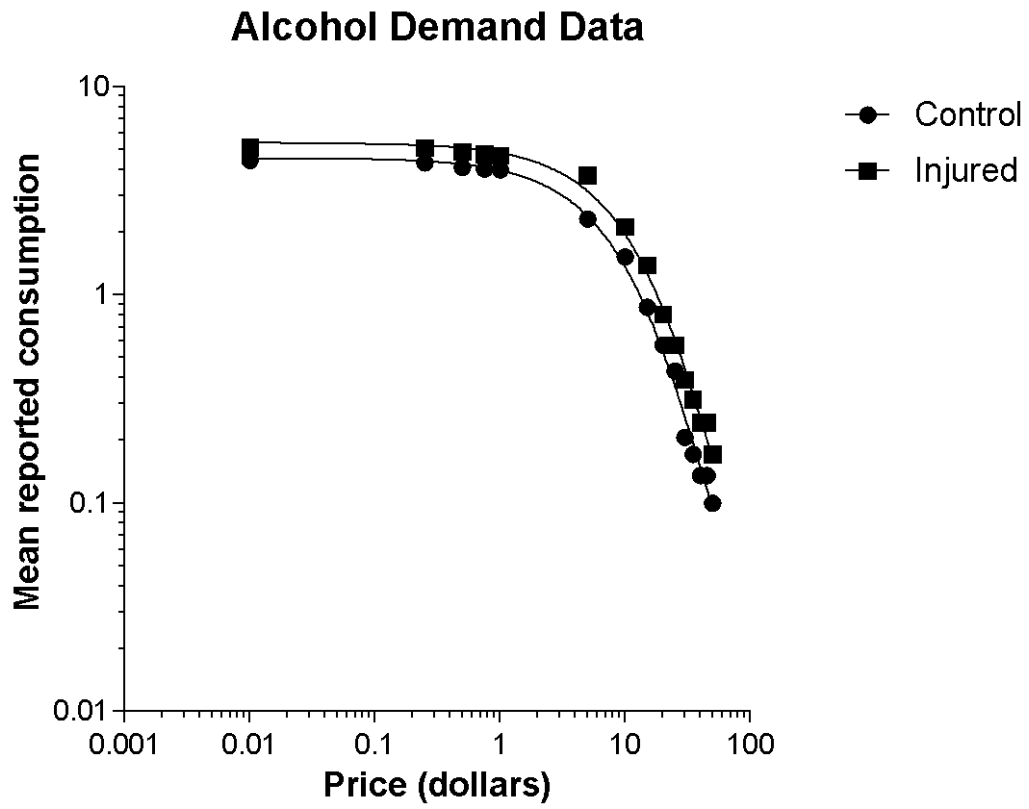
<i>Injured</i> <i>N=25</i>		
<b>Price (\$)</b>	<b>M</b>	<b>SEM</b>
0	5.12	0.4876
0.25	5.08	0.4930
0.50	4.88	0.5109
0.75	4.76	0.5205
1.00	4.68	0.5155
5.00	3.76	0.4736
10.00	2.136	0.3628
15.00	1.392	0.2990
20.00	0.808	0.1770
25.00	0.576	0.1214
30.00	0.392	0.1028
35.00	0.316	0.0785
40.00	0.244	0.0673
45.00	0.244	0.0673
50.00	0.172	0.0498

**Table 5: Summary of Group Level Exponential Demand Parameters**

	$a$	$K$	$Q_0$	$P_{max}$	$O_{max}$
<b>Control</b>	0.0054	2.4	4.5	9.5	13.68
<b>Injured</b>	0.0041	2.3	5.4	10.9	18.91

# Figures

Figure 1: Alcohol Demand by Group



**Figure 2: Participant Breakpoints**

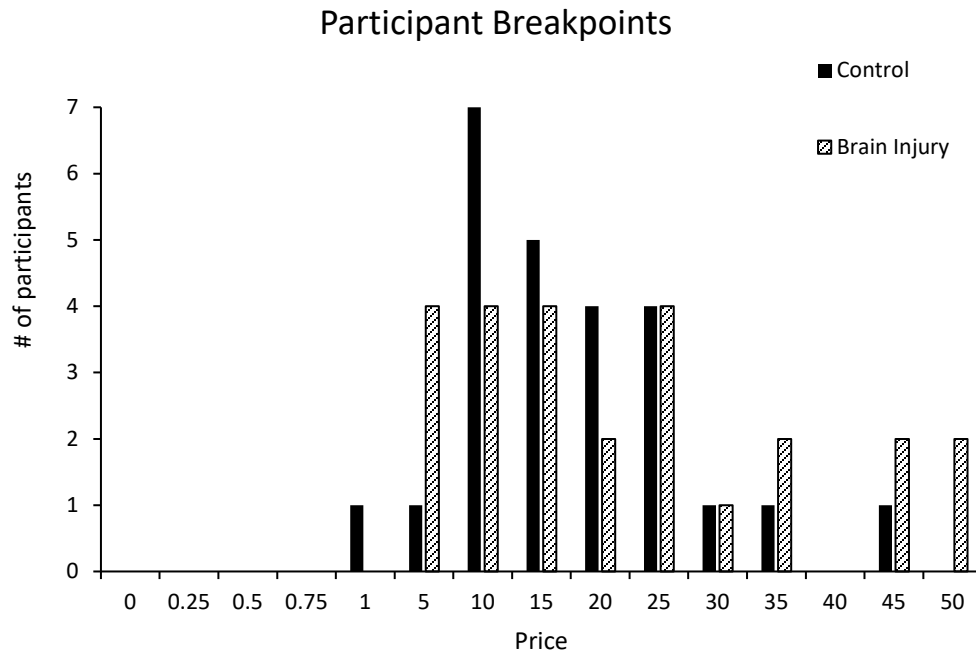


Figure 3: Alcohol Demand by AUDIT Score

### Alcohol Demand by Audit Score

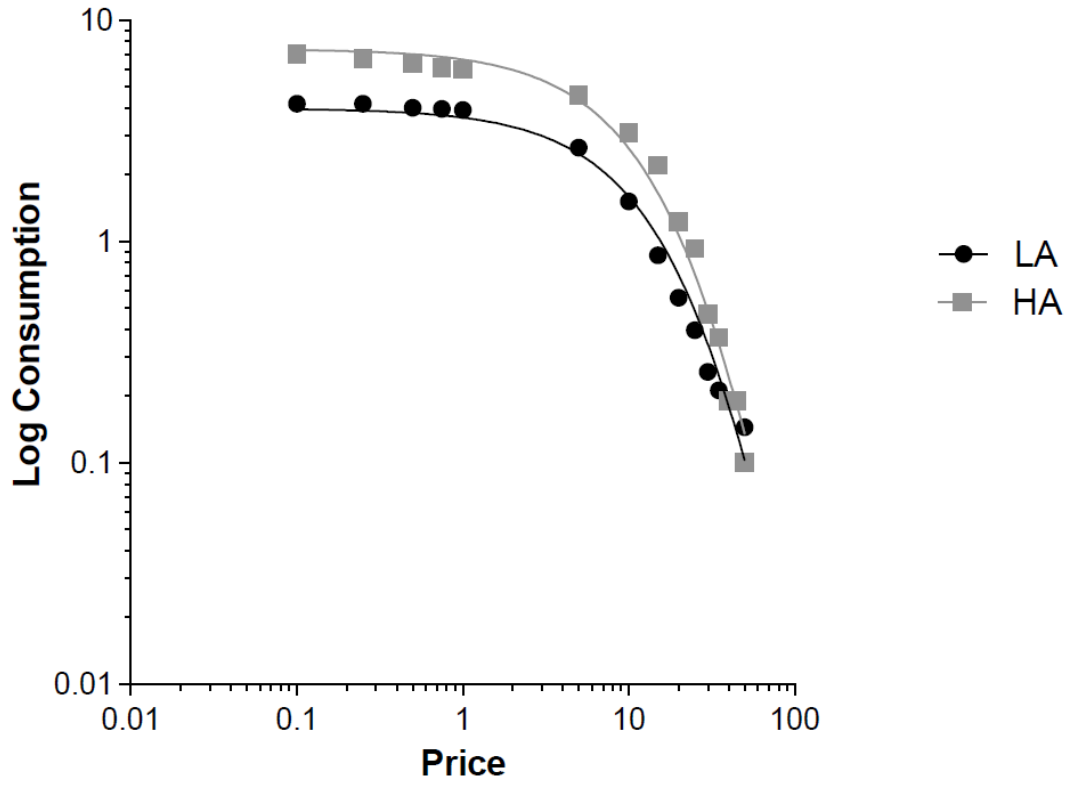


Figure 4: Alcohol Demand by Group and AUDIT Score

### Alcohol Demand by Group and Audit Score

