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Journal

Psychology of Addictive Behaviors, 37(1)

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Publication Date

2023-02-01

DOI

10.1037/adb0000888

Peer reviewed

Published in final edited form as:

Psychol Addict Behav. 2023 February ; 37(1): 144–155. doi:10.1037/adb0000888.

A Hypothetical Lottery Task to Assess Relative Resource Allocation towards Alcohol and Cannabis

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Abstract

Objective: Relative spending on substances (versus alternatives) is predictive of several substance use outcomes, but it can be challenging to assess. We examined a novel method of assessing relative resource allocation through use of a hypothetical lottery task wherein participants assume they collected $100,000 USD in lottery winnings, and were tasked with allocating their winnings across spending categories (e.g., savings, leisure, alcohol, cannabis, etc.). We hypothesized relative allocation of funds towards alcohol and cannabis would be positively associated with more use and problems of each substance.

Method: College students (N = 479; M_{age} = 19.9 [SD = 2.2]) reported on their substance use and problems, alcohol and cannabis demand, and the hypothetical lottery task.

Results: Relative resource allocation towards alcohol and cannabis on the lottery task positively correlated with alcohol and cannabis demand indices (intensity, breakpoint, O_{max}, and elasticity [negatively]), respectively. Using zero-inflated modeling, greater relative allocation towards alcohol positively related to alcohol use and problems in models that controlled for alcohol demand indices. For cannabis, relative resource allocation was also positively associated with cannabis use, but not problems, independently from alcohol demand indices.

Conclusions: Results provide initial support for the hypothetical lottery task as an indicator of relative resource allocation toward substances. Generally, these results extend previous behavioral

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Author Contributions: In the Contributor Roles Taxonomy (CRediT), N.M.G. was primarily responsible for the writing-original draft, writing-review and editing, methodology, and joint conceptualization of the ideas. D.N.J. was primarily responsible for the data curation, investigation, project administration, validation, writing-original draft, and writing-review and editing. J.G.M. was primarily responsible for writing-review and editing, and methodology. K.J.J. was responsible for the formal analysis, funding acquisition, investigation, methodology, resources, software, supervision, visualization, writing-original draft, writing-review and editing, and joint conceptualization of the ideas.

Disclosures: This research was presented at the Collaborative Perspectives on Addictions conference as a poster presentation in April 2022.

economic research demonstrating the utility of relative resource allocation as unique predictor of clinically relevant outcomes.

Introduction

Alcohol and cannabis are two of the most widely recreationally used substances, and although many people use these substances without experiencing social or health problems, unhealthy use of these substances is also associated with significant problems for the individual and for society (Haberstick et al., 2014; Johnston et al., 2022). Behavioral economic theory provides a framework to investigate and characterize substance use disorders (SUDs), in part by examining resource allocation of animals (including humans) under different reinforcement schedules (Baum & Rachlin, 1969; Rachlin & Laibson, 1997). Resulting behavioral theories of substance use suggest that understanding individuals' relative resource allocation towards substance-related (versus substance-free) rewards is critical to our understanding of SUDs (Vuchinich & Tucker, 1988). Thus, exploring novel ways of measuring and quantifying individuals' resource allocation related to substance use can help inform our understanding of factors affecting individuals' valuation of substances (e.g., Tucker et al., 2021). Understanding factors that affect the valuation of substances, in turn, can help in to identify potential prevention and intervention targets (Murphy et al., 2022).

Proposed as an advancement beyond previous reinforcement theories that emphasized strength of response rate maintained by a single reinforcer as an indicator of reinforcing efficacy, Howard Rachlin and colleagues' put forth the maximization theory in 1981, which established the importance of considering availability of other activities when considering relations between a reinforcer and individuals' responses over time. When applied to SUDs, Rachlin proposed that studying the patterns in how individuals distribute their resources (e.g., money) towards a particular reward (e.g., alcohol or cannabis use) *relative to other activities* might be indicative of individuals' preferences for that reward (Rachlin et al., 1981). Indeed, substantial behavioral economic research indicates that people with SUDs, including alcohol and cannabis use disorders, allocate considerable amounts of resources (e.g., time, money) towards purchasing substances, and that indices of relative resource allocation show meaningful associations with substance use severity (Bickel et al., 2014; Tucker et al., 2002; 2006).

The past 50 years of behavioral research has measured how much an individual values a reward (e.g., alcohol) using different methods. The most direct measures of the relative reward value of substances utilize human laboratory drug administrations (e.g., Bickel et al., 1991, Bickel and Madden, 1999). However, many practical and ethical limitations make conduct of such studies challenging, and prohibitive in many situations. Hypothetical tasks, where participants are instructed to imagine a particular scenario and asked to make certain decisions, present an alternative approach to operationalize indicators of reward value and relative behavioral allocation towards substances. In hypothetical purchases tasks, participants are usually asked to imagine a particular scenario (e.g., party), and asked how much of a commodity (e.g., alcohol, cannabis) they would buy/consume across escalating monetary prices. Money presents a common metric that is fungible and easily understood to measure, and compare, resource allocation across individuals. Indices resulting from purchase tasks have been shown to be valid – related to real-life behaviors – and reliable measures of demand, where responses on these purchase tasks (e.g., how much one spends on drinks) indicate the extent to which an individual (over)values a given substance. Indeed, demand as measured by alcohol purchase tasks have been related to several alcohol use outcomes, including drinking and driving (Teeters et al., 2014), alcohol use disorder symptomology (Bertholet et al., 2015), and response to treatment (Murphy et al., 2015). Demand indices from cannabis purchase tasks have also been related to cannabis use outcomes, such as driving after cannabis use (Patel & Amlung, 2019), cannabis dependence symptoms (Aston et al., 2015), and cannabis-related negative consequences (Minhas et al., 2021).

Hypothetical tasks present a time-efficient and controlled way to measure resource allocation, for instance to measure alcohol demand following exposure to a cue or to an alcohol intervention (e.g., Amlung et al., 2021; Murphy et al., 2015), while circumventing many of the ethical and practical limitations of drug administration studies. Hypothetical purchase tasks also show convergence with purchase tasks using actual rewards, although precise quantification of the strength of this association is not possible given practical/ethical limitations on the number of drinks that can be purchased and consumed in laboratory paradigms (Amlung et al., 2012; Amlung & MacKillop, 2015).

There are also direct measures of actual patterns of monetary allocation to alcohol versus other commodities. The ‘Alcohol-Savings Discretionary Expenditure’ (ASDE) index (Tucker et al., 2016), for example, is an interview-administered measure that quantifies spending patterns directed towards alcohol relative to expenditures towards savings over extended periods of time. Due to differences in time to receipt of each reward – that is, because alcohol rewards are experienced immediately and rewards from savings are experienced in the future – the ASDE index also captures another important construct affecting decision regarding resource allocation – delay discounting. Delay discounting is the subjective reduction in value of a reward with delay to its receipt (Ainslie, 1974, Loewenstein, 1988). Substantial evidence indicates that individuals with substance use disorders tend to discount delayed rewards to a greater extent than healthy controls (e.g., Amlung et al., 2016).

Tucker and colleagues (2002, 2006, 2008, 2009) grouped participants’ expenditures into obligatory (e.g., housing, food, taxes) and discretionary (e.g., entertainment, alcohol, elective savings) categories. Using expenditure across the time period of interest, the ASDE index was calculated as the proportion of discretionary expenditures spent on alcohol minus the proportion of discretionary expenditures put into savings. Higher ASDE value (i.e., higher proportions of money spent on alcohol relative to savings) is related to substance use outcomes, including recovery trajectories and intervention response (Tucker et al., 2006, 2009, 2016).

Relatedly, the ‘Relative Discretionary Expenditures on Alcohol’ (RDEA; Murphy et al., 2009) is a brief self-administered measure that asks individuals to report their past-month total discretionary income and their alcohol-related expenditures in estimate the proportion of total discretionary income allocated to alcohol. An initial study revealed associations between the RDEA and alcohol use and problems in multivariate models (Skidmore et al., 2014). Murphy et al (2015) randomized a sample of heavy drinking college students to receive different types of personalized feedback interventions or assessment only. Their study found that baseline alcohol demand and RDEA predicted increased alcohol use/problems at 1 and 6-month follow-ups, respectively (Murphy et al., 2015). Further, post-study interventions, reductions in RDEA from baseline to 1-month predicted reductions in drinking and alcohol-related problems at the 6-month follow-up. Research examining expenditure on other (non-alcohol) substances is limited. Worley and colleagues (2015) found that individuals who spent greater total amount and greater proportion of their income on drugs at baseline were more likely to use opioids during treatment. Relations between cannabis-related expenditure and cannabis use/related problems remain underexplored; the research thus far primarily focused on relations between cannabis use outcomes with cannabis demand and discounting (e.g., Aston et al., 2015; McIntyre-Wood et al., 2021; Strickland et al., 2017), thus highlighting a need for more examinations with other behavioral economic constructs.

Taken together, research indicates that relative spending on substances is related to substance use outcomes and may have clinical utility (e.g., predicting intervention outcomes). Evidence suggests differences observed in relative spending across individuals may be reflecting differences in the extent to which individuals (over)value a substance (Murphy and MacKillop, 2006; Tucker et al., 2002). Although measures of substance valuation based on actual expenditure patterns (e.g., ASDE, RDEA) are possible to obtain, there may also be utility in an approach that estimates resource allocation using a hypothetical task in a manner that might (1) allow for control of contextual factors on valuation of substances (by using a standardized scenario across all participants that may vary in real life, e.g., family circumstances) and (2) capture dynamic changes in preferences that might occur after an event that might be expected to change the relative value of a substance (e.g., a stressful life event or completing treatment).

Thus, the present study sought to investigate an alternative method of assessing relative resource allocation through use of a novel hypothetical lottery task wherein participants assume they collected $100,000 USD in lottery winnings, and were tasked with allocating their winnings across spending categories (e.g., food, savings, alcohol, cannabis, etc.). We hypothesized relative greater allocation of funds towards alcohol and cannabis in the context of this lottery task would be significantly associated with greater use and problems associated with each substance. In addition, we investigated relations between resource allocation towards substances on the lottery task and behavioral economic demand (i.e., using alcohol or cannabis purchase tasks).

The potential value of this new hypothetical lottery task comes in the brevity and standardization of hypothetical marketplace that directly places spending on substances *necessarily* at odds with spending on other commodities with the goal of revealing current preferences/valuation of substances. This task may be able to provide meaningful information on current resource allocation preferences even among individuals who might have actual recent expenditure patterns that were constrained by income or access to alcohol (e.g., young people), or that might not reflect their current preference structure (e.g., people who have recently completed treatment or experiences some other event that changed their relative strength of desire to consume alcohol). As such, this task may complement measures of actual recent expenditures on alcohol vs. other categories in predicting future rates of alcohol consumption.

Method

Participants and Procedure

Participants were undergraduate students who endorsed lifetime use of alcohol (99.6%) or cannabis (63.3%) recruited from a large southeastern public university. Data were collected online via a secure Internet-based survey system used to administer the questionnaire battery after participants provided informed consent. Participants were compensated with research credit. All study procedures were approved by the university's Institutional Review Board (IRB) prior to data collection. To aid in assessment of data quality, at the end of the questionnaire battery, participants were informed that the goal of this research was to help people struggling with mental health issues. They were asked if they believed that their data should be included and that their compensation would not be affected by their response. Participants who endorsed that their data should not be used ($n = 81$), that they were more than 85% distracted while taking the survey ($n = 7$), or individuals who chose to skip the lottery task in the questionnaire battery ($n = 35$) were excluded from analyses, leaving a total of 479 potential responses.

The final sample was a mean age of 19.9 years old ($SD = 2.2$ years) and was 78.2% female (20.0% male, 1.4% non-binary, and 0.4% prefer not to respond[1]). This group was 59% White, 22.4% Latino/Hispanic, 6.6% Black, 4.8% Asian, 6.4% Multiracial, and .8% other race. Information on family income was provided by 360 participants. Family income was measured on an ordinal scale ranging from less than $10,000 (3% of participants), $10,001 to $15,000 (1%), $15,001 to $25,000 (3%), $25,001 to $50,000 (11%), $50,001 to $75,000 (14%), $75,001 to $100,000 (15%), $100,000 to $150,000 (21%), $150,001 to $300,000 (20%), $300,001 to $500,000 (7%) to more than $500,000 (6%).

Furthermore, two sub-samples were selected for analyses concerning alcohol and cannabis use and problems corresponding to lifetime alcohol and cannabis users, respectively. These subsamples were selected due to the challenges in modeling demand curves for respondents with truly zero demand (i.e., never-users; see Stein et al., 2015). Similarly, valid allocation of resources towards substances on the lottery task would require some amount of exposure to the substance being bought. As such, this resulted in the alcohol analysis sample being $n = 452$ and the cannabis analysis sample being $n = 284$. Sample size was not determined by a priori power analysis; rather, data collection was determined to be finished upon the end of the Fall 2021 semester as the subject pool closed. There were additional measures collected in the current work; none of these have been published elsewhere, and none were

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[1]Due to the low number of non-binary participants and those who preferred not to respond, there was no variance in certain independent and dependent variables being analyzed, and as a result, gender had to be analytically examined as a dichotomous male-female variable.

examined in relation to the variables reported in the current manuscript. The analytic plan for the current work was not preregistered. We have reported how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

Measures

Alcohol Consumption.—The Daily Drinking Questionnaire (DDQ; Collins et al., 1985) was used to collect weekly alcohol consumption. Participants are asked to estimate their typical alcohol consumption on each day of the week over the period of the past month. Responses to each of the seven days are then summed to represent participants' average weekly alcohol consumption. The mean weekly alcohol consumption in the alcohol analysis sample was 7.2 drinks per week (SD = 7.7, min = 0, max = 40).

Cannabis Consumption.—Weekly cannabis consumption was collected using a modified version of the Daily Drinking Questionnaire (DDQ-C; Collins et al., 1985). Participants were asked how many times they typically smoked cannabis on each day of the week over the past month. They were instructed to quantify "smoke sessions" rather than individual inhalations of cannabis. Participants' average weekly cannabis consumption was represented as the sum of responses to each of the seven days with the mean of the cannabis analysis sample being 2.8 smoke sessions per week (SD = 5.5, min = 0, max = 32).

Alcohol Demand.—Several demand metrics were calculated from responses on the Alcohol Purchase Task (APT; Murphy & MacKillop, 2006) which asks participants to indicate the number of standard drinks they would consume in a hypothetical situation at 20 different price points ranging from free to $20.00 per drink. Formal modeling of economic demand (Hursh & Silberberg, 2008) corresponding to consumption across expenditures was conducted to derive four demand metrics using the 'beezdemand' *R* package (Kaplan, 2018). Alcohol demand metrics used in alcohol analyses for this study included Intensity (consumption when price is $0; M = 7.4 drinks, SD = 5.3), Breakpoint (price at which consumption ceases; M = 10.4 dollars, SD = 7.0), O_{max} (total maximum expenditure; M = 17.0 dollars, SD = 13.1), and Elasticity (rate of decrease in consumption as a function of price; M = .01, SD = .01). Elasticity was calculated using the exponentiated curve proposed by Koffarnus et al. (2015), using a k value of 4. Quality control was performed following the recommendations of Stein et al. (2015) to identify nonsystematic demand data. Specifically, cases exhibiting trend violations (i.e., responses where consumption did not decrease with price), bounce ratio (i.e., considerable price-to-price increases, calculated as number of these increases divided by total number of prices in the task, removing participants with a ratio ≥ 15%), and reversals (demand increasing again after being 0 at an earlier price) were removed prior to calculation of demand indices.

Cannabis Demand.—Separate demand metrics were also calculated using responses on the Marijuana Purchase Task (MPT; Aston et al., 2015). The MPT asks participants to indicate the number of grams of cannabis that they would purchase and consume in a week at 20 different price points ranging from free to $60.00 per gram. Demand metrics calculated for use in cannabis analyses corresponded to those derived from the APT and included Intensity (M = 7.5 grams, SD = 10.1), Breakpoint (M = 12.2 dollars, SD = 17.1), O_{max} (M =

28.8 dollars, *SD* = 56.2), and Elasticity (*M* = .3, *SD* = .8). The derivation of demand metrics followed the same process used for the APT.

Alcohol Problems.—Alcohol problems were quantified using sum scores on the Rutgers Alcohol Problem Index (RAPI; White & Labouvie, 1989). The RAPI is a 23-item self-report questionnaire that asks participants to indicate the number of times they experienced specific consequences of their drinking within the past year using a 4-point Likert scale ranging from 0, "None" to 3, "More than 5 Times". Items in the RAPI cover a range of domains, including social ("Had a fight, argument, or bad feeling with a friend") and occupational ("Went to work or school high or drunk"), as well as more general consequences related to drinking ("Neglected your responsibilities" and "Passed out or fainted suddenly"). Internal consistency in the present alcohol analysis sample was excellent (α = .91, ω = .92), and the mean score on the RAPI was 4.6 (*SD* = 6.8).

Cannabis Consequences.—A brief form version of the Marijuana Consequences Questionnaire (B-MACQ; Simons et al., 2012) was used to measure cannabis consequences. The B-MACQ is a 21 item self-report questionnaire asking participants to indicate if they had experienced a range of consequences related to their cannabis use over the past 6 months (i.e., "I have driven a car when I was high" and "When using marijuana, I have done impulsive things that I regretted later"). Responses to these items were dichotomous (0, "Yes" and 1, "No"), and scores were calculated as the sum of all items. The mean B-MACQ score was 5.6 (*SD* = 7.6) and internal consistency in the present cannabis analysis sample was notably high (α = .98, ω = .98).

Lottery Task.—The Lottery Task is a new self-report task that asks participants to allocate $100,000 to 20 different commodities according to their preference (see Table 1, Figure 1). To normalize lottery task responses that either exceeded a total of $100,000 or did not add all the way up to $100,000 (i.e., mathematical errors by participants), values spent on each commodity were standardized by dividing the item number by the sum of all items then multiplying the quotient by 100,000 for participants with a response for at least one commodity. As a result, item values represented the proportion of total money allocated to it. Commodities were categorized according to consumer expenditure surveys (U.S. Bureau of Labor Statistics, 2022), following from past work examining real spending in relation to risk for alcohol use (Tucker et al., 2002, 2009, 2016). There were five commodity categories in the lottery task considered as 'necessities': housing, transportation, healthcare, education (considering the age and setting of the sample), and food. There were six commodity categories considered as 'discretionary': substances, savings/investments, gambling, entertainment, charity, and apparel and services. From the lottery task, a 'Relative Discretionary Expenditures on Alcohol' index (i.e., lottery-RDEA) was derived, consistent with previous work (Murphy et al., 2009; Skidmore et al., 2014). Lottery-RDEA for alcohol was calculated as the quotient of resources allocated to alcohol divided by total discretionary spending. 'Relative Discretionary Expenditures on Cannabis' (lottery-RDEC) was calculated using the same method.

Data Analytic Plan

First, variable descriptive statistics were examined. As commonly observed in demand data, APT-Elasticity and MPT-Elasticity were highly kurtotic, along with both the Lottery-RDEA and Lottery-RDEC variables; thus, these variables were log transformed. Bivariate correlations and zero-inflated negative binomial models (ZINB) were used to investigate study hypotheses using the '*pscl*' package (Jackman, 2020) in R version 4.1 (R Core Team, 2021). Due to the nature of alcohol and cannabis use and problems among college students, there was a preponderance of zeroes in each dependent variable (alcohol use = 24.7%, cannabis use = 60.5%, alcohol problems = 31.6%, cannabis problems = 42.6%), leading to a zero-inflated distribution. Furthermore, use and problems of each substance followed a count distribution and the variance exceeded the mean (i.e., overdispersion), and based on model comparisons, a negative binomial distribution best modeled the distribution of scores.[2] ZINB models have two parts. In the first, the zero-inflation component, the model aims to predict "structural zeros" (i.e., excess zeros beyond what is expected based on the negative binomial distribution) in a logistic regression-like manner. Of note, a positive coefficient for an independent variable in this component of the model indicates higher levels of the predictor being associated with a greater likelihood of being a zero value on the dependent variable (i.e., opposite sign from what one might expect in a correlation between the two variables). In the second part of the ZINB model, the count component, the model aims to evaluate the degree to which an independent variable accounts for variance in the dependent variable, conditional on being a non-zero value on the dependent variable (i.e., the sign of coefficients would be the same as what one might expect in a correlation between the two variables).

First, bivariate correlations between lottery task and demand curve metrics were examined. Of note, due to the non-normal distribution of the lottery-RDEA and lottery-RDEC variables, Spearman correlation coefficients were used instead of Pearson correlation coefficients. Following this, ZINB models were conducted to evaluate the effect of lottery-RDEA and lottery-RDEC on alcohol and cannabis use and problems, respectively, while controlling for age and gender. Then, follow-up ZINB models that included the addition of the four demand metrics from the APT or MPT, respectively, were conducted to evaluate the degree to which any observed relation between lottery-RDEA and lottery-RDEC and alcohol or cannabis use and problems was unique above and beyond the related behavioral economic demand construct. All code and de-identified data used in the current work are available on the open science framework (OSF): https://osf.io/h2dwx/.

[2]Using the Akaike information criterion (AIC) and Bayesian information criterion (BIC), Vuong (1989) Z-tests can be utilized to compare the fit of zero-inflated poisson (ZIP), zero-inflated negative binomial (ZINB), and negative binomial hurdle (NBH) models. The Voung test indicated that in prediction of alcohol use, the ZINB model fit better than a negative binomial regression ($Z = 5.59$, $p < .001$), and also fit better than a ZIP ($Z = 8.06$, $p < .001$) and was equivalent to a NBH model ($Z = 1.38$, $p = .08$). In prediction of cannabis use, the ZINB model fit better than a negative binomial regression ($Z = 5.70$, $p < .001$), and also fit better than a ZIP ($Z = 4.95$, $p < .001$) or a NBH model ($Z = 2.85$, $p = .002$). In prediction of alcohol problems, the ZINB model fit better than a negative binomial regression ($Z = 1.98$, $p = .02$), and also fit better than a ZIP ($Z = 6.54$, $p < .001$) and was equivalent to a NBH model ($Z = 1.22$, $p = .11$). In prediction of cannabis problems, the ZINB model fit better than a negative binomial regression ($Z = 4.91$, $p < .001$), and also fit better than a ZIP ($Z = 9.27$, $p < .001$) and was equivalent to a NBH model ($Z = .98$, $p = .16$). As such, the ZINB was selected for all analyses.

Results

Lottery Task Descriptives

As observed in Table 1 and illustrated in Figure 1, participants allocated approximately an equal amount of resources between necessities and discretionary spending categories. Mean lottery-RDEA in the alcohol analysis sample was .010 (SD = .024) and in the cannabis analysis sample, mean lottery-RDEC was .011 (SD = .051), indicating individuals largely allocated resources away from substance use overall. Across all participants, the top necessities spending category was education ($15k), followed closely by housing ($12k). The top discretionary spending category was savings/investments ($33k). This is broadly consistent with consumer reports of how people spend actual lottery winnings in real life (Kaplan, 1987). Spearman's rank correlation was used to assess the relationships between family income and lottery-RDEA (r = .11, p =.04) and lottery-RDEC (r = −.13, p = .01).[3]

Associations with Behavioral Economic Demand

The lottery-RDEA was significantly positively correlated with alcohol demand intensity (r = .33), breakpoint (r = .26), and O_{max} (r = .29), and was negatively correlated with elasticity (r = −.29). The lottery-RDEC was significantly positively correlated with cannabis demand intensity (r = .49), breakpoint (r = .47), and O_{max} (r = .55), and negatively with elasticity (r = −.51).

Alcohol Use and Problems in the Alcohol Analysis Sample

Controlling for year in college and gender, the lottery-RDEA (see Table 2) showed a robust positive association with alcohol use in the ZINB model (zero-inflation component, b = −390.45, Z = −3.00, p = .003; count component, b = 6.83, Z = 3.88, p < .001). Similarly, in a ZINB model predicting alcohol problems, the lottery-RDEA (see Table 3) showed a positive association with alcohol problems, though was non-significant level in the zero-inflation component (zero-inflation component, b = −41.43, Z = −1.20, p = .23; count component, b = 11.09, Z = 3.07, p = .002). This set of results broadly suggest that individuals who allocated a lesser amount of discretionary spending on alcohol were more likely to have zero alcohol use or problems, and conditional on individuals exhibiting a non-zero amount of alcohol use or problems, greater allocation of discretionary spending on alcohol were more likely to be heavier drinkers and experienced more negative consequences.

Next, the four alcohol demand metrics were added to the model predicting alcohol use (see Table 2). Only one of the alcohol demand metrics were uniquely predictive in the zero-inflation component (APT-Intensity: b = −.22, Z = −2.74, p = .006; APT-Breakpoint: b = −.03, Z = −.91, p = .36; APT-O_{max}: b = −.04, Z = −1.15, p = .25; APT-Elasticity: b = −34.65, Z = −1.91, p = .06), and the lottery-RDEA was not a unique significant predictor (b = −510.19, Z = −1.66, p = .10). However, in the count component of the model, APT-Intensity (b = .06, Z = 6.16, p < .001) and the lottery-RDEA (b = 5.44, Z = 3.29, p = .001) both emerged as significant unique predictors, and the other three demand metrics

[3]Among participants with income data, associations with lottery categories were small, with correlations ranging from r = −.12 (with cannabis spending) to r = .12 (with alcohol).

were non-significant (APT-Breakpoint: b = .00, Z = .58, p = .56; APT-O_{max}: b = .00, Z = .87, p = .38; APT-Elasticity: b = 2.31, Z = .62, p = .53).

In the model predicting alcohol problems (see Table 3), only APT-Intensity (b = −.47, Z = −3.11, p = .002) was a significant predictor in the zero-inflation component, and the lottery-RDEA was not a unique predictor (b = −1.03, Z = −.06, p = .95) along with the rest of the demand metrics (APT-Breakpoint: b = −.06, Z = −.86, p = .39; APT-O_{max}: b = −.05, Z = −.72, p = .47; APT-Elasticity: b = −37.33, Z = −1.26, p = .21). However, in the count component of the model, both APT-Intensity (b = .05, Z = 3.21, p = .001) and the lottery-RDEA (b = 7.95, Z = 2.46, p = .01) were significant unique predictors, while the other demand metrics did not significantly predict alcohol problems (APT-Breakpoint: b = .00, Z = .23, p = .82; APT-O_{max}: b = .01, Z = 1.03, p = .30; APT-Elasticity: b = 7.85, Z = 1.32, p = .19). These results suggest that the lottery-RDEA is non-redundant with the alcohol demand construct, predicting above and beyond alcohol demand metrics in prediction of alcohol use and problems.

Cannabis Use and Problems in the Cannabis Analysis Sample

Controlling for year in college and gender, the lottery-RDEC (see Table 4) showed a positive association with cannabis use in the ZINB model (zero-inflation component, b = −4,200.19, Z = −2.54, p = .01; count component, b = 4.51, Z = 2.09, p = .04). Similarly, in a ZINB model predicting cannabis problems, the lottery-RDEC (see Table 5) showed a positive association with cannabis problems, although only in the zero-inflation component (zero-inflation component, b = −821.71, Z = −2.24, p = .02; count component, b = −1.13, Z = −.71, p = .48). This set of results suggest that individuals who allocated a lesser amount of discretionary spending on cannabis were more likely to have zero cannabis use or problems, and conditional on individuals exhibiting a non-zero amount of cannabis use or problems, greater allocation of discretionary spending on cannabis was associated with increased likelihood of using more cannabis, but not with experiencing more negative consequences.

Next, the four cannabis demand metrics were added to the model predicting cannabis use (see Table 4). Only one cannabis demand metrics was uniquely predictive in the zero-inflation component (MPT-Intensity: b = .14, Z = 1.81, p = .07; MPT-Breakpoint: b = −.00, Z = −.01, p = .99; MPT-O_{max}: b = −.12, Z = −2.33, p = .02; MPT-Elasticity: b = −.06, Z = −.16, p = .88), as well as the lottery-RDEC (b = −5,299, Z = −2.35, p = .02). In the count component of the model, none of the cannabis demand metrics were significant (MPT-Intensity: b = .02, Z = 1.49, p = .14; MPT-Breakpoint: b = .01, Z = 1.65, p = .10; MPT-O_{max}: b = .00, Z = 1.09, p = .27; MPT-Elasticity: b = −.38, Z = −1.21, p = .23), and the lottery-RDEC was also not a significant predictor (b = 4.33, Z = 1.58, p = .11).

In the model predicting cannabis problems (see Table 5), MPT-O_{max} (b = −.07, Z = −2.32, p = .02) was a significant predictor in the zero-inflation component, and the lottery-RDEC was not a unique predictor (b = −374.90, Z = −.1.46, p = .15) along with the other demand metrics (MPT-Intensity: b = −.02, Z = −.42, p = .67; MPT-Breakpoint: b = .02, Z = 1.23, p = .22; MPT-Elasticity: b = −.39, Z = −1.76, p = .07). In the count component of the model, only MPT-Elasticity (b = −.23, Z = −2.01, p = .04) and MPT-Breakpoint (b = −.02, Z = −2.81, p = .005) were significant predictors, and the RDEC (b = −1.44, Z = −.88,

p = .38) and the other demand metrics did not significantly predict cannabis problems (MPT-Intensity: b = .01, Z = .93, p = .35; MPT-O_{max}: b = .00, Z = .22, p = .83). These results suggest that the lottery-RDEC functions in at least a partially redundant manner with the cannabis demand construct, typically *not* predicting above and beyond cannabis demand metrics in prediction of cannabis use and problems.

Discussion

This study examined relations between hypothetical monetary resource allocation and substance use among college students. Results were generally consistent with our hypothesis, that higher allocation of resources towards alcohol and cannabis in the novel hypothetical lottery were related to greater use and problems associated with alcohol and cannabis, respectively. These results are in line with substantial previous behavioral economic research indicating that over(valuation) of substances are an important consideration in studying liabilities for, and maintenance of, SUDs. In relation to alcohol and cannabis demand, results indicate resource allocation as measured by the hypothetical lottery task are not redundant, indicating that relative resource allocation as measured by the lottery task may be capturing a distinct facet of valuation of substances (Rachlin et al., 1981; Rachlin and Laibson, 1997).

This is the first study to introduce and use this hypothetical lottery task. From their $100,000 USD, participants allocated a large amount towards necessities (i.e., education, housing), which is broadly consistent with past studies that show spending patterns of actual lottery winners (Kaplan, 1987), demonstrating the task's face validity. Participants allocated nearly a third of their monetary resources ($33k) towards savings and investments, which was the top discretionary category. Research quantifying how individuals' spend lottery winnings (termed as, unanticipated transitory positive income shock in the literature; Cheng et al., 2018) is limited. The lottery task presented here is not meant to address this question specifically, but it does provide a novel, brief approach to assessing the relative resource allocation to potential commodities (i.e., spending patterns from lottery winnings).

Regarding the findings of relative resource allocation in relation to alcohol, the lottery-RDEA index was a significant predictor of alcohol use and problems, after controlling for gender and year in college. Results with lottery-RDEA index are consistent with a robust line of work indicating that patterns of monetary allocation (e.g., ASDE index, which uses individuals' real financial records) are associated with alcohol use and recovery outcomes from alcohol use disorder (Tucker et al., 2002, 2009, 2016). The lottery task creates a closed economic system where everyone has the same amount of resources to allocate, allowing for examination of multicategory choice behavior and potentially reducing the impact of income differences on expenditure patterns. That said, there are very likely to be real-world factors outside of the closed economic system that affect responses. For example, college students who are on full scholarships may allocate fewer funds within this lottery task to pay for their education because they are actually experiencing lesser educational expenses outside of the lottery task. Moreover, current income differences, expectations about future income potential, and previous experience with saving money may all contribute to differences in how lottery winnings are allocated in a way that is unrelated to relative preference of drugs compared to other discretionary categories. Future studies may assess how participant income and financial circumstances may affect lottery winning allocations, as well as how such unanticipated transitory positive income (e.g., lottery winnings) affect the lives of participants and members of their social network (e.g., family, friends). Future studies may examine concordance between the ASDE index and indices from the lottery task, which may inform our understanding of relations between observed, real-life spending patterns examined in the ASDE and hypothetical spending decisions, which are made explicitly and all at once in the lottery task. Future studies should also determine if there are unique clinical correlates of the standard ASDE vs. the lottery-RDEA.

The lottery-RDEA also predicted alcohol use and problems above and beyond the conceptually-related construct of alcohol demand. While both demand for alcohol and relative resource allocation towards alcohol invoke valuation processes of alcohol and are correlated, they appear to be empirically distinct in potentially clinically-relevant ways (Murphy et al., 2015). Whereas demand curves provide indices of peak consumption, peak expenditures, and relative price sensitivity, they do not evaluate the value of the substance relative to a range of other activities as is the case with the lottery-RDEA. Past work has already established alcohol demand metrics derived from the alcohol purchase task to be predictive of intervention outcomes (Gex et al., 2022; Murphy et al., 2015); as such, future work may evaluate the prospective utility of relative resource allocation towards alcohol in the lottery task in intervention work.

Results with the lottery-RDEC index suggests similar patterns of relations may be present in cannabis as alcohol, which has been comparatively understudied. Specifically, we found that greater relative allocation of funds towards cannabis compared to other discretionary spending was associated with greater cannabis use and problems, controlling for gender and year in college. However, deviating from the findings for alcohol, the lottery-RDEC did not predict cannabis use or problems above and beyond cannabis demand. Moreover, while the lottery-RDEA was broadly predictive in both the zero-inflation and count components of models, the lottery-RDEC was more implicated in the zero-inflation than count components. This indicates that the lottery-RDEC was more sensitive to differentiating individuals with 0 (i.e., no) use or problems from those with any use or problems in a logistic-like fashion (“none versus some”), but not particularly sensitive to escalating use or problems, conditional on experiencing more than 0, whereas the lottery-RDEA was sensitive across both portions of these models. There are a number of reasons why these discrepancies may have been observed. First, the cannabis use variable was more zero-inflated than alcohol use variable. This may explain the tendency for the lottery-RDEC to be more strongly implicated in the zero-inflation component of models, and in heavier-using cannabis samples, the lottery-RDEC may be more sensitive in the count component of models. Further, cannabis use was measured by asking participants to report “smoke sessions” only, excluding other modes of cannabis consumption (e.g., edibles), which will be expanded in future studies. Secondly, the time frame for the alcohol versus cannabis problems measures differ; in the case of alcohol problems, the RAPI’s instructions specify past-year, and for cannabis problems, the B-MACQ’s instructions specified past-6-months. This may have additionally altered variability in each measure in comparison to one another. Lastly, the legality of cannabis versus alcohol may have also impacted responses on the lottery task.

Specifically, these data were collected in a U.S. state where cannabis is considered illicit for recreational use. As such, there is no regulatory processes for cannabis outlets (e.g., dispensaries); therefore, the pricing of and concentration of cannabis is much more variable in illicit markets. This makes estimation of pricing (and how much money buys how much cannabis) potentially difficult to compare across participants. As such, these findings should be compared to samples from U.S. states where cannabis is legal for recreational use, and may differ substantially.

Similar to research with the ASDE and RDEA, the present cross-sectional evidence showing lottery-RDEA and lottery-RDEC were related to alcohol and cannabis use and problems, respectively, provide initial support for the face validity and criterion-related concurrent validity of the lottery-task. Correlations between lottery-RDEA and indices derived from the alcohol purchase task, and correlations between lottery-RDEC and indices from the cannabis purchase task also provide initial evidence of the convergent validity of the task. Further, initial evidence is presented towards the incremental validity of the lottery task predicting alcohol use outcomes, above and beyond alcohol demand measured from alcohol purchase tasks. Evaluation of other psychometric dimensions of the lottery task are also needed to establish this new task as a research tool in the behavioral economic literature on addictive behaviors, including examination of the criterion-related predictive validity (i.e., lottery-RDEA/RDEC predicting future alcohol and cannabis use prospectively) and the discriminant validity of lottery task to assess the extent to which lottery-RDEA/RDEC are conceptually distinct from other constructs. The task's sensitivity to changes in the environment and scenario presented (e.g., lottery tasks using different winning amounts, with different populations), and relations with alcohol/cannabis use outcomes, are also needed to further establish the content and criterion validity of the task.

The chosen structure of the lottery task has some notable limitations. First, this lottery task solely uses hypothetical commodities. Past research supports some amount of concordance between purchase tasks that use hypothetical versus actual rewards (Amlung et al., 2021), but the relevant factors to manipulate in the hypothetical scenario that most affect responding are almost entirely empirically untested to this point. Another important factor for the lottery task is that some research indicates that individuals engage in different mental accounting when making decisions about money based on the source of money (e.g., lottery versus inheritance) may affect spending patterns (Chambers et al., 2017). The current study used a lottery as it is an easily relatable hypothetical scenario, but other pretenses may affect responding on the task. Importantly, the use of lottery winnings as a way to provide participants with a set amount of money to allocate to commodities introduces potential consequences and confounds. Although odds of lottery winnings are minimal, lottery purchasing is a fairly common behavior, with about half of the U.S. population reporting purchasing a state lottery in the past year (Auter, 2016). Individuals may have varying beliefs, attitudes towards anticipated consequences from lottery winnings, and experiences with lotteries, and gambling, in general, that may affect their responding on the lottery task, and should be systematically examined in future research. Future work could also examine resource allocation of other positive income flux based on other hypothetical scenarios (e.g., stimulus payments similar to those made during the COVID-19 pandemic).

The present study used $100,000 as the lottery winning amount because it is a reasonably large enough amount to allow for variability in resource allocation (i.e., allow for ample spending in both necessities and discretionary items) while not being too large of a lottery winning (e.g., $100 million) that might raise serious confounds (e.g., have serious taxation and inheritance implications, or change individuals lives in ways that may be difficult for many people to imagine). The degree to which lottery-RDEA/RDEC indices derived from hypothetical lottery tasks that use different lottery winning amounts (i.e., if participants were told they had won $10,000 vs $100 million) may vary, and should be evaluated in future studies. Other research also suggests spending patterns may differ based on how lottery winnings are delivered – lump sum payments vs monthly installments (Larsson, 2011). Future research may examine how patterns of spending may vary based on source of income (e.g., inheritance, work bonus, earned from employment) and method of delivery, and if these affect spending on substance and examine relations with substance use outcomes. Further, unlike alcohol/cannabis purchase tasks that limit the time to buy/consume the chosen substance to a specific time (e.g., how much would you buy/consume at a party, not allowing for stockpiling), this rendition of the lottery task did not specify a timeframe for expenditures. That is, participants were not directed to assume that this would be their only chance to make purchases, nor where they asked if they intended to use savings to buy more substances in the future, which should be explored in future studies. Finally, there is evidence that scarcity manipulations increase impulsive choice whereas thinking about positive future events (episodic future thinking) decreases impulsive responding in the moment and may reduce desire for substance use (Stein et al., 2021). Winning the lottery reflects a positive future-oriented outcome and thus could potentially attenuate relative preference for alcohol or other drugs.

This study relied on self-reports, which may have resulted in inflated associations observed between measures that were not completely free of shared-method variance, which can be investigated in future studies using different approaches (e.g., substance administration studies). Additionally, future studies should examine the test-retest reliability of the lottery task, to examine if an index calculated from multiple assessments of the lottery task captures a trait/construct of interest and utility in the study of human behavior, and to what extent relations are similar to or different from a one-time assessment of the task. Generalizability of findings are limited by nature of the study and can be examined using representative samples in future studies. The utility of this hypothetical lottery task with other populations (e.g., more severe substance use and problems) should also be examined in future research. Once validated among different populations, the lottery task presents a potentially versatile tool to measure indicators of several behaviors of interest to public health, including expenditure on other substances (e.g., tobacco) and other behaviors of public health import (e.g., gambling).

Future refinements of the task should seek to identify categories of spending that are most sensitive to environmental changes. Qualitative research may examine how participants interpret and perceive different categories, to better characterize the calculus behind their decisions. Substantial research supports the substitutability and complementary effects (Dolan et al., 2020; Subbaraman, 2016) within commodity spending and behavioral allocation; thus, identifying which other expense categories compete most with alcohol and cannabis may be a method to identify intervention targets. In conclusion, in this study, we used a new hypothetical lottery task to derive indicators of relative resource allocation towards alcohol and cannabis. The aforementioned limitations notwithstanding, the lottery-RDEA and RDEC indices provided potentially useful and unique information about resource allocation processes, and may be a useful new behavioral economic indicator of individuals' substance (over)valuation.

Acknowledgement:

Authors would like to thank the individuals who participated in this research and research assistants at Florida State University, in the Clinical Neuroscience Lab, who helped with conducting this research. We are also grateful for this special issue to show appreciation, honor, and extend the pioneering work of Dr. Howard Rachlin in advancing our understanding of human behavior.

Funding:

Funding for this research was supported by NIDA grant R36DA050049 (PI: Joyner) and NIAAA grant F31AA028751 (PI: Gebru). All funding sources had no other role in study design or manuscript preparation other than financial support of the PIs.

References

Ainslie GW (1974). Impulse control in pigeons. Journal of the Experimental Analysis of Behavior, 21(3), 485–489. 10.1901/jeab.1974.21-485 [PubMed: 16811760]

Amlung MT, Acker J, Stojek MK, Murphy JG, & MacKillop J (2012). Is talk "cheap"? An initial investigation of the equivalence of alcohol purchase task performance for hypothetical and actual rewards. Alcoholism, Clinical and Experimental Research, 36(4), 716–724. 10.1111/j.1530-0277.2011.01656.x [PubMed: 22017303]

Amlung M, Gray JC, & MacKillop J (2016). Delay discounting and addictive behavior: Review of the literature and identification of emerging priorities. In Addictions: A social psychological perspective (pp. 15–46). Routledge/Taylor & Francis Group.

Amlung M, & MacKillop J (2015). Further evidence of close correspondence for alcohol demand decision making for hypothetical and incentivized rewards. Behavioural Processes, 113, 187–191. 10.1016/j.beproc.2015.02.012 [PubMed: 25712039]

Amlung M, Marsden E, Murphy JG, & MacKillop J (2021). Contextual influences on alcohol demand: Behavioral and neural correlates of alcohol cue effects. Alcoholism: Clinical and Experimental Research, 240A–240A.

Aston ER, Metrik J, & MacKillop J (2015). Further Validation of a Marijuana Purchase Task. Drug and Alcohol Dependence, 152, 32–38. 10.1016/j.drugalcdep.2015.04.025 [PubMed: 26002377]

Auter Z (2016, July 22). About Half of Americans Play State Lotteries. Gallup.Com. https://news.gallup.com/poll/193874/half-americans-play-state-lotteries.aspx

Baum WM, & Rachlin HC (1969). Choice as Time Allocation1. Journal of the Experimental Analysis of Behavior, 12(6), 861–874. 10.1901/jeab.1969.12-861 [PubMed: 16811415]

Bertholet N, Murphy JG, Daeppen J-B, Gmel G, & Gaume J (2015). The alcohol purchase task in young men from the general population. Drug and Alcohol Dependence, 146, 39–44. 10.1016/j.drugalcdep.2014.10.024 [PubMed: 25468819]

Bickel WK, DeGrandpre RJ, Hughes JR, & Higgins ST (1991). Behavioral Economics of Drug Self-Administration. Ii. A Unit-Price Analysis of Cigarette Smoking. Journal of the Experimental Analysis of Behavior, 55(2), 145–154. 10.1901/jeab.1991.55-145 [PubMed: 2037824]

Bickel WK, Johnson MW, Koffarnus MN, MacKillop J, & Murphy JG (2014). The Behavioral Economics of Substance Use Disorders: Reinforcement Pathologies and Their Repair. Annual Review of Clinical Psychology, 10(1), 641–677. 10.1146/annurev-clinpsy-032813-153724

Bickel WK, & Madden GJ (1999). A comparison of measures of relative reinforcing efficacy and behavioral economics: Cigarettes and money in smokers. Behavioural Pharmacology, 10(6–7), 627–637. 10.1097/00008877-199908001-00023 [PubMed: 10780504]

Bureau of Labor Statistics. (2022). Consumer Expenditures Survey Glossary. https://www.bls.gov/cex/csxgloss.htm#otherx

Chambers V, Bland E, & Spencer M (2017). Does the source of a cash flow affect spending versus saving? Financial Services Review, 26(3), 291–313.

Cheng TC, Costa-Font J, & Powdthavee N (2018). Do You Have to Win It to Fix It? A Longitudinal Study of Lottery Winners and Their Health-Care Demand. American Journal of Health Economics, 4(1), 26–50. 10.1162/ajhe_a_00092 [PubMed: 29430486]

Collins RL, Parks GA, & Marlatt GA (1985). Social determinants of alcohol consumption: The effects of social interaction and model status on the self-administration of alcohol. Journal of Consulting and Clinical Psychology, 53(2), 189–200. 10.1037//0022-006x.53.2.189 [PubMed: 3998247]

Dolan SB, Spindle TR, Vandrey R, & Johnson MW (2020). Behavioral economic interactions between cannabis and alcohol purchasing: Associations with disordered use. Experimental and Clinical Psychopharmacology. 10.1037/pha0000397

Gebru N, Jones DN, Murphy JG, & Joyner KJ (2022, October 24). A Hypothetical Lottery Task to Assess Relative Resource Allocation towards Alcohol and Cannabis. Retrieved from osf.io/h2dwx

Gex KS, Acuff SF, Campbell KW, Mun EY, Dennhardt AA, Borsari B, Martens MP, & Murphy JG (2022). Change in alcohol demand following a brief intervention predicts change in alcohol use: A latent growth curve analysis. Alcoholism, Clinical and Experimental research, 46(8), 1525–1538. 10.1111/acer.14887 [PubMed: 35707989]

Haberstick BC, Young SE, Zeiger JS, Lessem JM, Hewitt JK, & Hopfer CJ (2014). Prevalence and correlates of alcohol and cannabis use disorders in the United States: Results from the national longitudinal study of adolescent health. Drug and Alcohol Dependence, 136, 158–161. 10.1016/j.drugalcdep.2013.11.022 [PubMed: 24440049]

Herrnstein RJ (1974). Formal properties of the matching law. Journal of the Experimental Analysis of Behavior, 21(1), 159–164. 10.1901/jeab.1974.21-159 [PubMed: 16811728]

Hursh SR, & Silberberg A (2008). Economic demand and essential value. Psychological Review, 115(1), 186–198. 10.1037/0033-295X.115.1.186 [PubMed: 18211190]

Jackman S (2020). pscl: Classes and Methods for R Developed in the Political Science Computational Laboratory. United States Studies Centre, University of Sydney, Sydney, New South Wales, Australia. R package version 1.5.5, https://github.com/atahk/pscl/.

Johnston LD, Miech RA, O'Malley PM, Bachman JG, Schulenberg JE, & Patrick ME (2022). Monitoring the Future national survey results on drug use, 1975–2021: Overview, key findings on adolescent drug use. Ann Arbor: Institute for Social Research, University of Michigan.

Kaplan HR (1987). Lottery winners: The myth and reality. Journal of Gambling Behavior, 3(3), 168–178. 10.1007/BF01367438

Kaplan B (2018). beezdemand: Behavioral Economic Easy Demand. R package version 0.1.0.

Koffarnus MN, Franck CT, Stein JS, & Bickel WK (2015). A modified exponential behavioral economic demand model to better describe consumption data. Experimental and Clinical Psychopharmacology, 23(6), 504–512. 10.1037/pha0000045 [PubMed: 26280591]

Larsson B (2011). Becoming a Winner But Staying the Same: Identities and Consumption of Lottery Winners. The American Journal of Economics and Sociology, 70(1), 187–209. 10.1111/j.1536-7150.2010.00768.x [PubMed: 21322898]

Loewenstein GF (1988). Frames of Mind in Intertemporal Choice. Management Science, 34(2), 200–214. 10.1287/mnsc.34.2.200

McDowell JJ (2021). Empirical Matching, Matching Theory, and an Evolutionary Theory of Behavior Dynamics in Clinical Application. Perspectives on Behavior Science, 44(4), 561–580. 10.1007/s40614-021-00296-w [PubMed: 35098025]

McIntyre-Wood C, Minhas M, Balodis I, Murphy JG, & MacKillop J (2021). A reinforcer pathology approach to cannabis misuse: Evaluation of independent and interactive roles of cannabis demand and delay discounting in a sample of community adults. Experimental and Clinical Psychopharmacology. 10.1037/pha0000485

Minhas M, Balodis I, Aston ER, Murphy JG, & MacKillop J (2021). Using an Optimized Marijuana Purchase Task to Examine Cannabis Demand in Relation to Cannabis Misuse in Heavy Drinking Emerging Adults. Journal of Studies on Alcohol and Drugs, 82(3), 351–361. 10.15288/jsad.2021.82.351 [PubMed: 34100703]

Murphy JG, Dennhardt AA, Yurasek AM, Skidmore JR, Martens MP, MacKillop J, & McDevitt-Murphy ME (2015). Behavioral economic predictors of brief alcohol intervention outcomes. Journal of Consulting and Clinical Psychology, 83(6), 1033–1043. 10.1037/ccp0000032 [PubMed: 26167945]

Murphy JG, Dennhardt AA, & Gex KS (2022). Individual Behavioral Interventions to Incentivize Sobriety and Enrich the Natural Environment with Appealing Alternatives to Drinking. In Tucker JA & Witkiewitz K (Eds.), Dynamic Pathways to Recovery from Alcohol Use Disorder: Meaning and Methods (pp. 179–199). Cambridge University Press. 10.1017/9781108976213.015

Murphy JG, & MacKillop J (2006). Relative reinforcing efficacy of alcohol among college student drinkers. Experimental and Clinical Psychopharmacology, 14(2), 219–227. 10.1037/1064-1297.14.2.219 [PubMed: 16756426]

Murphy JG, MacKillop J, Skidmore JR, & Pederson AA (2009). Reliability and validity of a demand curve measure of alcohol reinforcement. Experimental and Clinical Psychopharmacology, 17(6), 396–404. 10.1037/a0017684 [PubMed: 19968404]

Patel H, & Amlung M (2019). Elevated cannabis demand is associated with driving after cannabis use in a crowd-sourced sample of adults. Experimental and Clinical Psychopharmacology, 27(2), 109–114. 10.1037/pha0000240 [PubMed: 30475012]

Rachlin H, Battalio R, Kagel J, & Green L (1981). Maximization theory in behavioral psychology. Behavioral and Brain Sciences, 4(3), 371–388. 10.1017/S0140525X00009407

Rachlin H, & Laibson DI (1997). The matching law. Papers in Psychology and Economics. New York.

Simons JS, Dvorak RD, Merrill JE, & Read JP (2012). Dimensions and Severity of Marijuana Consequences: Development and Validation of the Marijuana Consequences Questionnaire (MACQ). Addictive Behaviors, 37(5), 613–621. 10.1016/j.addbeh.2012.01.008 [PubMed: 22305645]

Skidmore JR, Murphy JG, & Martens MP (2014). Behavioral economic measures of alcohol reward value as problem severity indicators in college students. Experimental and Clinical Psychopharmacology, 22(3), 198–210. 10.1037/a0036490 [PubMed: 24749779]

Stein JS, Craft WH, Paluch RA, Gatchalian KM, Greenawald MH, Quattrin T, Mastrandrea LD, Epstein LH, & Bickel WK (2021). Bleak present, bright future: II. Combined effects of episodic future thinking and scarcity on delay discounting in adults at risk for type 2 diabetes. Journal of behavioral medicine, 44(2), 222–230. 10.1007/s10865-020-00178-7 [PubMed: 32989616]

Stein JS, Koffarnus MN, Snider SE, Quisenberry AJ, & Bickel WK (2015). Identification and management of nonsystematic purchase task data: Toward best practice. Experimental and Clinical Psychopharmacology, 23(5), 377–386. 10.1037/pha0000020 [PubMed: 26147181]

Strickland JC, Lile JA, & Stoops WW (2017). Unique prediction of cannabis use severity and behaviors by delay discounting and behavioral economic demand. Behavioural Processes, 140, 33–40. 10.1016/j.beproc.2017.03.017 [PubMed: 28347716]

Subbaraman MS (2016). Substitution and Complementarity of Alcohol and Cannabis: A Review of the Literature. Substance Use & Misuse, 51(11), 1399–1414. 10.3109/10826084.2016.1170145 [PubMed: 27249324]

Teeters JB, Pickover AM, Dennhardt AA, Martens MP, & Murphy JG (2014). Elevated Alcohol Demand Is Associated with Driving After Drinking Among College Student Binge Drinkers. Alcoholism: Clinical and Experimental Research, 38(7), 2066–2072. 10.1111/acer.12448 [PubMed: 24948397]

Tucker JA, Cheong J, Chandler SD, Lambert BH, Kwok H, & Pietrzak B (2016). Behavioral economic indicators of drinking problem severity and initial outcomes among problem drinkers attempting natural recovery: A cross-sectional naturalistic study. Addiction, 111(11), 1956–1965. 10.1111/add.13492 [PubMed: 27318078]

Tucker JA, Foushee HR, & Black BC (2008). Behavioral economic analysis of natural resolution of drinking problems using IVR self-monitoring. Experimental and Clinical Psychopharmacology, 16(4), 332–340. 10.1037/a0012834 [PubMed: 18729688]

Tucker JA, Lindstrom K, Chandler SD, Bacon JP, & Cheong J (2021). Behavioral economic indicators of risky drinking among community-dwelling emerging adults. Psychology of Addictive Behaviors, 35(4), 415–423. 10.1037/adb0000686 [PubMed: 33630617]

Tucker JA, Roth DL, Vignolo MJ, & Westfall AO (2009). A behavioral economic reward index predicts drinking resolutions: Moderation revisited and compared with other outcomes. Journal of Consulting and Clinical Psychology, 77(2), 219–228. 10.1037/a0014968 [PubMed: 19309182]

Tucker JA, Vuchinich RE, Black BC, & Rippens PD (2006). Significance of a behavioral economic index of reward value in predicting drinking problem resolution. Journal of Consulting and Clinical Psychology, 74(2), 317–326. 10.1037/0022-006X.74.2.317 [PubMed: 16649876]

Tucker JA, Vuchinich RE, & Rippens PD (2002). Predicting natural resolution of alcohol-related problems: A prospective behavioral economic analysis. Experimental and Clinical Psychopharmacology, 10(3), 248–257. 10.1037/1064-1297.10.3.248 [PubMed: 12233985]

Vuchinich RE, & Tucker JA (1988). Contributions from behavioral theories of choice to an analysis of alcohol abuse. Journal of Abnormal Psychology, 97, 181–195. 10.1037/0021-843X.97.2.181 [PubMed: 3133403]

Vuong QH (1989). Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses. Econometrica, 57(2), 307–333. 10.2307/1912557

White HR, & Labouvie EW (1989). Towards the assessment of adolescent problem drinking. Journal of Studies on Alcohol, 50(1), 30–37. 10.15288/jsa.1989.50.30 [PubMed: 2927120]

Worley MJ, Shoptaw SJ, Bickel WK, & Ling W (2015). Using behavioral economics to predict opioid use during prescription opioid dependence treatment. Drug and Alcohol Dependence, 148, 62–68. 10.1016/j.drugalcdep.2014.12.018 [PubMed: 25622776]

Public health significance:

- This study investigated relative resource allocation (i.e., proportion of available money allocated) towards alcohol and cannabis versus other discretionary spending using a new, hypothetical lottery task.
- Relative amount of discretionary spending allocated to alcohol and cannabis was related to self-reported alcohol and cannabis use and problems, respectively, above and beyond measures of behavioral economic demand.
- Operationalizing relative resource allocation using this lottery task may help capture unique processes related to substance use and problems.

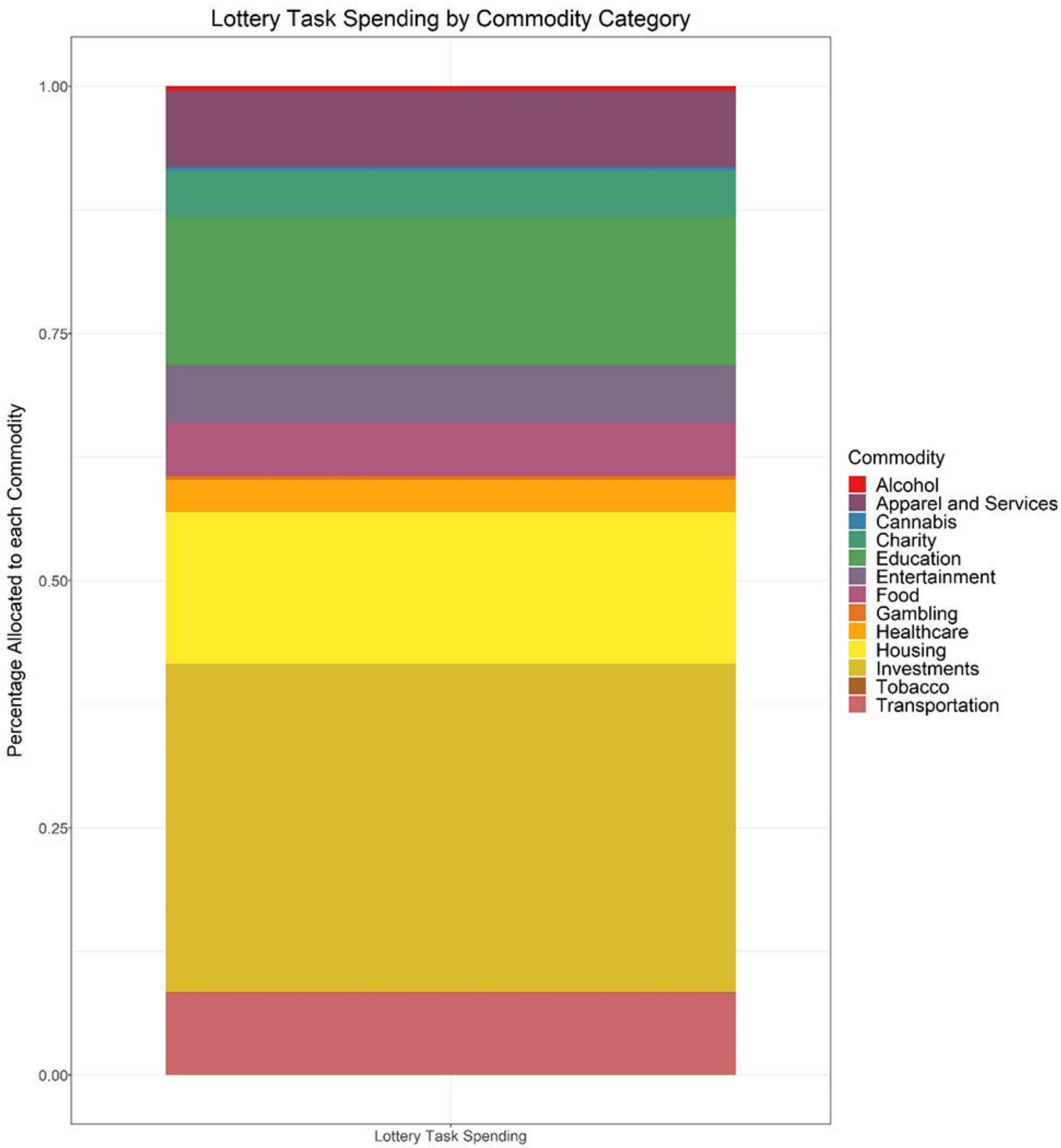

Figure 1. Visual Representation of Resource Allocation in the Lottery Task.

The order of colors follows the order of labels on the right of the figure. The vast majority of funds allocated in the lottery task are not directed towards substances.

Table 1

Means and Standard Deviations of Responses to Items on the Lottery Task in Units of Thousands

Variable	*M*	*SD*
Discretionary		
Substances		
Alcohol	.43	1.22
Marijuana	.33	2.40
Tobacco products (e.g., cigarettes, e-cigarettes/vaping)	.14	.90
Investment		
Savings and Investments	32.90	27.46
Gambling		
Gambling	.37	3.08
Entertainment		
Entertainment (e.g., movies, video games, computer games, new TV)	1.67	3.45
Pets	1.29	3.39
Hobbies	2.83	5.11
Charity		
Gifts to others and charity	4.68	9.13
Apparel and Services		
Clothing	4.18	8.60
Cell phone and internet	1.43	4.14
Beauty Products (e.g., salon or barbershop, makeovers)	1.13	2.58
Hired help (e.g., chef, housekeeper, etc.)	.82	3.50
Necessities		
Housing		
Housing (e.g., rent, mortgages)	12.54	15.14
Utility bills (e.g., electricity, water, sewage)	2.99	5.72
Transportation		
Transportation (e.g., buying/paying off a car, car maintenance)	8.23	11.71
Healthcare		
Healthcare costs (e.g., health insurance, buying prescriptions, dental and vision)	3.22	5.24
Education		
Education	15.20	18.65
Food		
Groceries	3.56	6.80
Restaurants	2.06	5.04

Note. Lottery Task Instructions: “Please imagine the following scenario: Congratulations! You have won the lottery! After going through the legal process of retrieving the money, you now have at your disposal $100,000 dollars in cash to spend however you would like. Please indicate the amount in dollars that you would spend engaging in the following activities. You may distribute as much or as little as you like, to as many or as few activities as you like, but please use all of the $100,000.” Numbers in table expressed in units of thousands.

Table 2

Main Effects for the Lottery-RDEA and APT-Demand Indices in Predicting Alcohol Use within Separate Zero-Inflated Negative Binomial (ZINB) Models

	Count Model				Zero-Inflation Model			
Lottery-RDEA Main Effect	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**
Year in College	−.01	.04	−.27	.79	−.07	.13	−.59	.56
Gender (female vs. male)	**.24**	**.12**	**2.07**	**.04**	**.64**	**.32**	**1.99**	**.047**
Lottery-RDEA	**6.83**	**1.76**	**3.88**	**<.001**	**−390.45**	**129.97**	**−3.00**	**.003**
Lottery-RDEA and APT-Demand Indices								
Year in College	−.03	.04	−.66	.51	.07	.15	.48	.63
Gender (female vs. male)	.01	.11	.07	.95	**1.33**	**.46**	**2.88**	**.004**
Lottery-RDEA	**5.44**	**1.66**	**3.29**	**.001**	−510.19	308.31	−1.66	.10
APT-Intensity	**.06**	**.01**	**6.16**	**<.001**	**−.22**	**.08**	**−2.74**	**.006**
APT-Breakpoint	.00	.01	.58	.56	−.03	.04	−.91	.36
APT-O_{max}	.00	.00	.87	.38	−.04	.04	−1.15	.25
APT-Elasticity	2.31	3.70	.62	.53	−34.65	18.14	−1.91	.06

Note. $N = 452$. Lottery-RDEA = Relative Discretionary Expenditures for Alcohol in the Lottery Task; APT = Alcohol Purchase Task; Unstd. = unstandardized. In the zero-inflation component of each model, the likelihood of the dependent variable having a ‘true zero’ value is being predicted. Significant ($p < .05$) regression coefficients, and their associated Z-values, are bolded.

Table 3

Main Effects for the Lottery-RDEA and APT-Demand Indices in Predicting Alcohol Problems within Separate Zero-Inflated Negative Binomial (ZINB) Models

	Count Model				Zero-Inflation Model			
Lottery-RDEA Main Effect	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**
Year in College	.09	.07	1.35	.18	2.31	1.39	1.66	.10
Gender (female vs. male)	−.21	.17	−1.25	.21	−9.64	66.09	−.15	.88
Lottery-RDEA	**11.09**	**3.61**	**3.07**	**.002**	−41.43	34.52	−1.20	.23
Lottery-RDEA and APT-Demand Indices								
Year in College	.03	.07	.40	.69	**.86**	**.38**	**2.25**	**.02**
Gender (female vs. male)	**−.44**	**.17**	**−2.68**	**.007**	−1.37	1.16	−1.18	.24
Lottery-RDEA	**7.95**	**3.24**	**2.46**	**.01**	−1.03	16.86	−.06	.95
APT-Intensity	**.05**	**.02**	**3.21**	**.001**	**−.47**	**.15**	**−3.12**	**.002**
APT-Breakpoint	.00	.01	.23	.82	−.06	.07	−.86	.39
APT-O_{max}	.01	.01	1.03	.30	−.05	.06	−.72	.47
APT-Elasticity	7.86	5.95	1.32	.19	−37.33	29.63	−1.26	.21

Note. $N = 452$. Lottery-RDEA = Relative Discretionary Expenditures for Alcohol in the Lottery Task; APT = Alcohol Purchase Task; Unstd. = unstandardized. In the zero-inflation component of each model, the likelihood of the dependent variable having a 'true zero' value is being predicted. Significant ($p < .05$) regression coefficients, and their associated Z-values, are bolded.

Table 4

Main Effects for the Lottery-RDEC and MPT-Demand Indices in Predicting Cannabis Use within Separate Zero-Inflated Negative Binomial (ZINB) Models

	Count Model				Zero-Inflation Model			
Lottery-RDEC Main Effect	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**
Year in College	.07	.09	.79	.43	−.28	.18	−1.57	.12
Gender (female vs. male)	−.22	.24	−.92	.36	−.21	.51	−.41	.68
Lottery-RDEC	**4.51**	**2.16**	**2.09**	**.04**	**−4,200.19**	**1,655.72**	**−2.54**	**.01**
Lottery-RDEC and MPT-Demand Indices								
Year in College	.10	.09	1.03	.30	−.35	.23	−1.51	.13
Gender (female vs. male)	−.23	.23	−.97	.33	.22	.73	.30	.77
Lottery-RDEC	4.53	2.33	1.94	.052	**−5,299.14**	**2,254.42**	**−2.35**	**.02**
MPT-Intensity	.02	.01	1.49	.14	.14	.08	1.81	.07
MPT-Breakpoint	.01	.01	1.65	.10	−.00	.02	−.01	.99
MPT-O_{max}	.00	.00	1.09	.27	**−.12**	**.05**	**−2.33**	**.02**
MPT-Elasticity	−.38	.31	−1.21	.23	−.06	.41	−.16	.88

Note. $N = 284$. Lottery-RDEC = Relative Discretionary Expenditures for Cannabis in the Lottery Task; MPT = Marijuana Purchase Task; Unstd. = unstandardized. In the zero-inflation component of each model, the likelihood of the dependent variable having a ‘true zero’ value is being predicted. Significant ($p < .05$) regression coefficients, and their associated Z-values, are bolded.

Table 5

Main Effects for the Lottery-RDEC and MPT-Demand Indices in Predicting Cannabis Problems within Separate Zero-Inflated Negative Binomial (ZINB) Models

	Count Model				Zero-Inflation Model			
Lottery-RDEC Main Effect	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**	**Unstd. B**	***SE B***	***Z*-value**	***p*-value**
Year in College	**.18**	**.07**	**2.44**	**.01**	.02	.14	.18	.86
Gender (female vs. male)	.02	.20	.13	.90	−.59	.40	−1.45	.15
Lottery-RDEC	−1.13	1.59	−.71	.48	**−821.71**	**366.18**	**−2.24**	**.02**
Lottery-RDEC and MPT-Demand Indices								
Year in College	**.21**	**.08**	**2.74**	**.006**	−.01	.16	−.03	.97
Gender (female vs. male)	−.00	.19	−.02	.99	−.29	.45	−.64	.52
Lottery-RDEC	−1.44	1.64	−.88	.38	−374.86	257.31	−1.46	.15
MPT-Intensity	.01	.01	.93	.35	−.02	.04	−.42	.67
MPT-Breakpoint	**−.02**	**.01**	**−2.81**	**.005**	.02	.02	1.23	.22
MPT-O_{max}	.00	.00	.22	.83	**−.07**	**.03**	**−2.32**	**.02**
MPT-Elasticity	**−.23**	**.12**	**−2.01**	**.04**	−.39	.22	−1.76	.08

Note. N = 284. Lottery-RDEC = Relative Discretionary Expenditures for Cannabis in the Lottery Task; MPT = Marijuana Purchase Task; Unstd. = unstandardized. In the zero-inflation component of each model, the likelihood of the dependent variable having a ‘true zero’ value is being predicted. Significant ($p < .05$) regression coefficients, and their associated Z-values, are bolded.