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Authors
Campbell, Kevin W
Voss, Andrew T
Acuff, Samuel F
et al.

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Statistically Derived Patterns of Behavioral Economic Risk among Heavy Drinking College Students: A Latent Profile Analysis

Kevin W. Campbell[1], **Andrew T. Voss**[1], **Samuel F. Acuff**[1], **Kinsey Pebley**[1], **Kristoffer S. Berlin**[1], **Matthew P. Martens**[2], **Brian Borsari**[3,4], **Ashley A. Dennhardt**[1], **James G. Murphy**[1]

[1]The University of Memphis

[2]The University of Missouri

[3]Mental Health Service San Francisco VA Health Care System

[4]Department of Psychiatry, University of California – San Francisco

Abstract

High levels of three behavioral economic indices (delay discounting, alcohol demand, and proportionate substance-related reinforcement) are consistently associated with greater alcohol misuse and alcohol-related problems. However, it is unclear whether and how these variables jointly increase risk for alcohol-related outcomes among college students who engage in heavy episodic drinking (HED; 4/5+ drinks for women/men, respectively). The current study used a person-centered approach to identify similar patterns of behavioral economic domains among heavy drinking college students and to investigate the relationship between these empirically derived classes and alcohol-related outcomes. A sample of 393 college students (60.8% female, 78.9% White/Caucasian) reporting at least 2 heavy drinking episodes in the previous month completed measures of alcohol use and problems, demographics, delay discounting, and alcohol reward value (alcohol demand and proportionate substance-related reinforcement). Latent profile analyses revealed that a three-class solution provided the best fit to the data: a *low reward value, high discounting* class (LRHD; $n = 53$), a *moderate reward value, low discounting* class (MRLD; $n = 214$), and a *high reward value, high discounting* class (HRHD; $n = 126$). Members of the HRHD class reported significantly greater alcohol consumption, past-month HED episodes, alcohol-related problems, and AUD symptoms than those in the MRLD and LRHD classes. Results suggest that there are three constellations of behavioral economic processes, and that, consistent with the reinforcer pathology model, students who overvalue alcohol-related reward and discount the future more steeply are at the greatest risk for alcohol misuse and alcohol-related problems.

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Keywords

substance use; alcohol; behavioral economics

Despite slight decreases in heavy episodic drinking (HED) in recent years, 37.4% of college-aged individuals still report engaging in past-month HED (Hingson, Zha, & Smyth, 2017). HED is associated with alcohol-related consequences such as driving while intoxicated, fights, assaults, and medical/legal issues (Hingson, Zha, & White, 2017). These consequences contribute to the substantial public health and economic burden of college student alcohol misuse in the United States (Sacks, Gonzales, Bouchery, Tomedi, & Brewer, 2015). Thus, it is important to understand the mechanisms underlying college students' decision to consume alcohol at such high levels despite incurring the associated personal costs.

Behavioral Economic Reinforcer Pathology Model of Alcohol and Drug Misuse

Behavioral economics (BE) combines microeconomic concepts and behavioral psychology to explain the environmental factors and internal processes that contribute to the excessive preference for substance use relative to other available reinforcers (Bickel, Snider, Quisenberry, & Stein, 2017). According to BE theory, substance misuse is a *reinforcer pathology*, characterized by the joint effects of two reinforcement processes: (a) a tendency to devalue delayed outcomes in favor of immediate rewards (delay discounting), and (b) persistent overvaluation of alcohol or drugs, which may result from deficits in the availability of environmental reward (Joyner et al., 2016). The distinct BE components associated with the reinforcer pathology model, including delay discounting and elevated alcohol/drug reward value, have been implicated in the progression of substance use and the development of substance-use disorders and other maladaptive health behaviors (Bickel, Johnson, Koffarnus, MacKillop, & Murphy, 2014; Lemley, Kaplan, Reed, Darden, & Jarmolowicz, 2016; MacKillop, 2016). In addition to the risk conferred by individual reinforcement processes, recursive interactions between delay discounting and elevated alcohol/drug reward value are theorized to synergistically increase risk for substance use severity (Bickel et al., 2017).

Delay Discounting.

Delay discounting is an index of intertemporal choice that quantifies the relative preference for smaller, immediate rewards versus larger, delayed rewards (Bickel et al., 2017). Steep discounting of delayed rewards has been associated with addictive and other health risk behaviors, including alcohol misuse and alcohol use disorder (AUD) among clinical and community samples (MacKillop et al., 2011). In addition, higher levels of discounting have been shown to negatively predict GPA and academic engagement among college students (Acuff et al., 2017). As such, repeated alcohol use appears to be a symptom associated with a more general disposition to select immediate rewards (alcohol) over temporally extended rewards that accumulate value over time (e.g., social relationships, education, career).

In contrast to the robust associations described above, the relationship between alcohol use and delay discounting has been less consistent in college samples (Acuff, Soltis, Dennhardt, Berlin, & Murphy, 2018; Teeters & Murphy, 2015). These results may be due in part to differences in sample severity, as findings from a meta-analysis of case-control studies indicated a significant medium effect size difference ($d = 0.50$) in levels of delay discounting for studies using clinical samples and a small effect size difference ($d = 0.26$) for studies using subclinical samples (MacKillop et al. 2011). Thus, delay discounting appears to differentiate individuals with more severe alcohol or drug use problems from controls, but may be less useful for differentiating individuals with mild to moderate alcohol misuse from controls (MacKillop, 2016). Other factors that may explain inconsistent findings among college samples include the fact that young adults may have little experience with independent financial decision-making, with many still being supported by their parents, thus their decision about immediate vs. delayed monetary amounts may not closely correspond with intertemporal decisions related to health risk behaviors.

Alcohol Demand.

Behavioral economic demand is an index of an individual's perceived value of alcohol as a reinforcer (Murphy, MacKillop, Skidmore, & Pederson, 2009). Alcohol demand can be examined using demand curves derived from hypothetical purchase tasks, which characterize the relationship between consumption and cost of alcohol. Demand curve analyses yield distinct indices of demand, which include consumption at zero cost (intensity), maximum self-reported expenditure (O_{max}), and sensitivity of purchase behavior to increases in cost (elasticity). These indices provide unique information on the strength of motivation to consume alcohol and have demonstrated robust cross-sectional and longitudinal relations with different indices of young adult alcohol use, including drinks per week (Murphy & MacKillop, 2006; Murphy et al. 2009), alcohol-related problems (Murphy et al. 2009; Bertholet, Murphy, Daeppen, Gmel, & Gaume, 2015), AUD symptoms (Gray & MacKillop, 2014; Bertholet et al., 2015), and drinking and driving (Teeters et al. 2014). A meta-analysis by Zvorsky and colleagues (2019) found that the relation between alcohol demand and alcohol misuse was statistically significant at medium effect size magnitudes.

Proportionate Substance-Related Reinforcement.

Proportionate substance-related reinforcement is defined as the relative allocation of time and enjoyment associated with substance use behaviors compared to substance-free reinforcement (Acuff, Dennhardt, Correia, & Murphy, 2019; Correia, Carey, & Borsari, 2002; Morris et al., 2017; Hallgren, Greenfield, & Ladd, 2016). High proportionate substance-related reinforcement is theorized to be an important indicator of individual differences in alcohol valuation (Murphy & Dennhardt, 2016). Previous research shows that substance-free reinforcement is negatively related to young adult alcohol misuse (Correia, Carey, Simons, & Borsari, 2003; Murphy, McDevitt-Murphy, & Barnett, 2005; Murphy et al. 2009). One study found that higher pre-treatment levels of proportionate substance-related reinforcement predicted poorer response to brief alcohol intervention (Murphy et al., 2005), while another reported that reductions in substance–related reinforcement following intervention predicted fewer alcohol problems and less problematic drinking at follow-up (Dennhardt et al., 2015).

Relations Among Behavioral Economic Constructs.

Several studies have examined the interrelations among delay discounting, alcohol demand, and proportionate substance-related reinforcement. Small to moderate bivariate associations have been established between alcohol demand and proportionate substance-related reinforcement (Acuff et al., 2018), suggesting that these concepts are related, but distinct. Studies reporting relations between delay discounting and measures of alcohol reward value have yielded inconsistent findings. Among college students, delay discounting was not significantly associated with either demand or proportionate substance-related reinforcement (Acuff et al., 2018). However, studies using more severe samples have reported moderate associations between delay discounting and alcohol demand (Amlung et al., 2017; MacKillop et al., 2010).

Although reinforcer pathology is theorized to result from the interplay between steep discounting of delayed rewards and elevated alcohol reward value (Bickel et al., 2017), few studies have examined the interaction between these two variables in relation to alcohol misuse. According to BE theory (Bickel et al., 2017), a pattern of low discounting/low reward value confers the lowest risk, patterns characterized by either low discounting/high reward value or high discounting/low reward value confer intermediate risk, while a pattern of high discounting/high reward value confers the greatest risk. Within this framework, individuals who exhibit steep levels of discounting are more likely to prefer the immediate reinforcement associated with alcohol use relative to delayed outcomes associated with future reward, and thus, are more likely to engage in frequent substance use, even if it results in negative consequences (which are delayed in time relative to the benefits of use). Acuff et al. (2018) failed to find synergistic interactive effects when testing a comprehensive model evaluating the effects of delay discounting, alcohol demand, and proportionate substance-related reinforcement in relation to alcohol consumption and alcohol problems. This study did find, however, direct associations between alcohol demand and proportionate substance-related reinforcement (but not delay discounting) and both alcohol use frequency and alcohol problems. In relation to reinforcer pathology theory, results suggest that the effects of these individual BE domains may be better understood as unique and independent, rather than synergistic, risk factors for alcohol misuse. Furthermore, another study investigated delay discounting and alcohol demand simultaneously among a small sample of college students (n = 80) and found delay discounting predicted alcohol problems, while demand predicted alcohol use frequency, but the two domains did not interact to influence alcohol misuse (Lemley et al., 2016). Follow-up analyses which used YAACQ cut scores to categorize students into high-risk and low/moderate risk drinkers supported reinforcer pathology theory, as results revealed that those who exhibited steep levels of discounting and elevated demand for alcohol also reported more problems.

Person-centered versus variable-centered approach.

Previous research that examined the interaction among these BE domains have relied on traditional variable-centered approaches, which produce a single set of averaged parameters based on the assumption that the population is homogeneous. Given that reinforcer pathology proposes that different patterns of BE variables confer varying levels of risk, variable-centered approaches that ignore potential population heterogeneity may overlook the multiplicative and conditional nature of these individual indices. In contrast, person-centered approaches that empirically identify relatively homogenous subgroups of individuals characterized by similar constellations of BE domains may provide a complementary perspective that increases understanding of the unique and combined influences of individuals BE domains.

Current Study

To date, it is unclear which specific patterns of BE processes exist and contribute to alcohol misuse among heavy drinking college students. The current study is a secondary analysis that extends the results of Acuff et al. (2018) by using a person-centered approach to examine BE influences on alcohol-related behavior in order to (a) identify latent profiles with similar constellations of BE variables among heavy drinking college students, (b) investigate whether students in these profiles differ in various alcohol-related risk behaviors, and (c) examine predictors of empirically derived patterns of BE domains. Given that no research has examined patterns of BE processes, we had no *a priori* expectations about the number of BE profiles evident within the sample and thus, we utilized an exploratory approach. Guided by the reinforcer pathology framework, we hypothesized that steep discounting and elevated alcohol reward value would interact to contribute to greater alcohol use, alcohol-related problems, and AUD symptoms.

Methods

Participants

Participants were 393 freshman and sophomore college students (mean age of 18.77 years [*SD* = 1.07], 60.8% female, 78.9% White/Caucasian) who reported at least two heavy drinking episodes in the previous month provided information on BE indices and self-reported alcohol-related behaviors. The current study is a secondary analysis of data collected as part of a brief alcohol intervention study and was collected at baseline, prior to intervention exposure. All participants were used in the current study. Study details have been published previously (Murphy et al., 2019), including the full list of measures given to participants and the power analysis used to determine the number of participants needed for the parent study. Study procedures were approved by The University of Memphis Institutional Review Board.

Latent Profile Indicators

Delay Discounting.—The 60-item Delay Discounting Task (DDT; Amlung & MacKillop, 2011) was used to assess the degree to which participants discounted hypothetical larger monetary rewards with delayed receipt relative to smaller, immediate rewards. Trials were presented individually, with varying immediate monetary rewards and delays while the larger, delayed reward remained constant at $100 (e.g., $75 now versus $100 in 1 month). Each trial contributed to participants' overall discounting parameter (k), a free parameter that indexes discounting rate, which was fit to a hyperbolic discounting model using a publicly available Graphpad Prism macro (https://ibrinc.org). Larger values of k indicate a more rapid decline in value of delayed rewards (i.e., greater discounting).

Alcohol Demand.—The Alcohol Purchase Task (APT; Murphy & MacKillop, 2006) was used to assess alcohol demand. The APT includes 20 items assessing the number of alcoholic drinks a participant would purchase and consume at a party between 9:00 PM and 1:00 AM at escalating price points ranging from free (0 dollars) to 20 dollars per drink. Of the five indices typically generated from demand curve analyses, we chose to use the three that have demonstrated the best reliability (Acuff & Murphy, 2017) and the most robust associations with alcohol misuse (Teeters et al., 2014), namely intensity, O_{max}, and elasticity. Intensity refers to the amount of drinks "purchased" at zero cost, or consumption without constraint. O_{max} refers to the maximum expenditure and is calculated by multiplying the number of drinks by the price of drinks at each price point, and then selecting the largest amount. Finally, elasticity refers to the rate at which consumption decreases as a function of increases in price and was calculated using an exponentiated demand equation based on the recommendations of Koffarnus and colleagues (2015). Lower elasticity values indicate less sensitivity to price and are indicative of *greater* demand, or continued consumption despite increases in price. Hypothetical purchase tasks such as the APT are correlated with actual alcohol purchase behavior (Amlung, Acker, Stojek, Murphy, & MacKillop, 2012). Although demand indices are conceptually related to each other, as evidenced by moderate to strong correlations (.27-.66 in the present sample), research has shown that each index represents distinct facets of alcohol valuation (MacKillop et al. 2015), and thus they were treated as independent constructs in the current analyses.

Proportionate substance-related reinforcement.—The Adolescent Reinforcement Survey Schedule-Substance Use Version (ARSS-SUV; Murphy et al., 2005) was used to derive the Reinforcement Ratio, which is a measure of proportionate substance-related reinforcement. The ARSS-SUV asks participants to rate the frequency with which they engaged in 32 different activities and how much they enjoyed each activity, such as "going on a date," "studying," or "hanging out with siblings." Frequency is assessed using a Likert scale ranging from 0 (*0 times*) to 4 (*more than once a day*) while enjoyment is assessed on a scale from 0 (*unpleasant/neutral*) to 4 (*extremely pleasant*). Participants rated frequency and enjoyment of each activity twice, once for when they *are* under the influence of alcohol or other substances and once for when they *are not* under the influence of alcohol or other substances. Reinforcement was calculated by multiplying the frequency and enjoyment ratings for each activity, which were then summed to create totals for substance-related reinforcement and substance-free reinforcement. Substance-related reinforcement totals were divided by total reinforcement (substance-related + substance-free) to obtain the ratio (between 0 and 1) of substance-related reinforcement relative to total reinforcement, with values closer to 1 reflecting greater proportionate reinforcement from substance-related activities. Cronbach's alpha in the current sample was .99 for substance-related items and .92 for the substance-free items.

Covariates

Covariates included sex (i.e., male, female), race (i.e., White, non-White), household income, Greek affiliation (i.e., sorority or fraternity member, nonmember), study site (i.e., Campus 1, Campus 2), family history of problem drinking, frequency of past-month cannabis use, depressive symptoms using the depression scale from the Depression, Anxiety, and Stress Scale-21 (DASS-21; Henry & Crawford, 2005), and consideration of future consequences (CFC; Strathman et al., 1994). The CFC is an alternative measure of future orientation containing nine items that assess the extent to which participants organize their behaviors around long-term goals, including “I only act to satisfy immediate concerns, figuring the future will take care of itself.” Internal consistency was adequate for both the depression scale of the DASS-21 (α = .89) and CFC (α = .80) in the current sample. The current covariate model was used due to previous findings of differences in alcohol-related outcomes and BE indicators across these variables (Acuff et al., 2018).

Outcomes

Alcohol consumption.—Alcohol use was measured with the Daily Drinking Questionnaire (DDQ; Collins, Parks, & Marlatt, 1985), which asks participants to report the total number of standard drinks that they consume each day during a typical week in the past month. Daily drinking was summed to create an estimate of typical weekly drinking. This measure has been widely used in college drinking samples and is well correlated with other measures of drinking behavior (MacKillop & Murphy, 2007).

Heavy episodic drinking.—Past-month HED episodes was assessed using a single item which asked, “During the past 30 days, how many times did you consume 4/5 drinks during one occasion?” (4 for women, 5 for men). Studies have shown this measure to be reliable and valid in college samples (Wechsler & Austin, 1998).

Alcohol-related problems.—The Young Adult Alcohol Consequences Questionnaire (YAACQ) is a 48-item scale that assesses the full spectrum of problems specific to college student experiences (Read, Merrill, Kahler, & Strong, 2007). Participants indicated which of 48 potential problems they experienced in the past-month, including “I have become very rude, obnoxious or insulting after drinking” and “I have felt badly about myself because of my drinking.” Internal consistency for the current sample was 0.90.

Alcohol use disorder symptoms.—AUD symptom count was assessed using 11 items assessing for each of the symptoms of a DSM-5 diagnosis of an AUD (American Psychiatric Association, 2013). Items asked “yes” or “no” questions related to the participant’s experience with different AUD symptoms during the past 12 months.

Statistical Analysis

Latent profile analysis (LPA) was conducted using Mplus Version 8.0 (Muthén, & Muthén, 1998 – 2017), using full-information maximum likelihood (FIML) estimation and the robust maximum likelihood estimator (MLR) to account for missing and non-normally distributed data. To identify the optimal number of latent classes within the current data, models with differing numbers of BE profiles were estimated. Models with correlated indicators were estimated using 1,000 random sets of start values with 100 iterations to ensure reproduction of global maxima and to avoid misidentification of a false local solution (Hipp & Bauer, 2006). Means and variances of the BE variables were freely estimated in all profiles. Wald chi-square tests were used to assess significant differences in indicators across profiles.

Several fit indices were used to compare models with differing numbers of classes including the Bayesian Information Criterion (BIC; Schwarz, 1978), the Lo-Mendell-Rubin test (LMR; Lo, Mendell, & Rubin, 2001), and the Bootstrap Likelihood Ratio test (BLRT; McLachlan & Peel, 2000). Lower BIC values are indicative of better fitting models (Rose et al., 2007). The LMR and BLRT examine whether a model with k latent classes fits the data better than a model with k-1 classes, with significant results indicating better fit with the inclusion of an additional class. Classification quality of competing models was assessed using entropy, which is an index that depicts the likelihood that participants are classified in the appropriate class (Magidson & Vermunt, 2002). Additionally, a scree-plot of each model's log-likelihood was examined, which can help to determine the optimal class solution (Nylund, Asparouhov & Muthén, 2007). Lastly, latent profile proportions were examined, as classes with less than 5% of the total sample may indicate data over-extraction (Berlin, Williams & Parra, 2014).

Once the optimal fitting model was identified, the manual three-step BCH method (Asparouhov & Muthén, 2014) was employed to estimate the effect of the latent class variable on a secondary auxiliary model that included both covariates and outcomes, adjusting for classification error. Multiple imputations (MI) with 10 generated data sets were utilized to account for missing data on covariates (0–3% missing; Graham, Olchowski, & Gilreath, 2007). All self-report measures were included as auxiliary variables in the imputation process and pooled estimates are reported in the results. Sex, race, household income, Greek status, recruitment site, family history of problem drinking, frequency of cannabis use, depressive symptoms, and CFC were then mean-centered and entered simultaneously as covariates predicting membership into the various BE profiles using multinomial logistic regression. Wald chi-square tests were employed to examine differences in weighted intercepts across profile-specific alcohol-related outcomes using a secondary auxiliary model that controlled for sex, race, Greek affiliation, site, family history of problem drinking, and mean levels of household income, cannabis use, depressive symptoms, and CFC. Hedge's g was used as a bias corrected effect size and statistical significance was set at .01 to control for Type-I errors. Past-month HED episodes and AUD symptoms were estimated using a negative binomial distribution to account for the count nature of these variables while alcohol-related problems were estimated controlling for levels of alcohol consumption.

Results

Latent Profile Analysis

Class enumeration.—A series of latent class models using the five BE indicators were first examined by extracting increasing numbers of latent class solutions. Models were first estimated with class variant means and class invariant variances and compared to models that freely estimated class means and variances. Model fit significantly improved when allowing both means and variances to vary across classes. Covariances were constrained to be equal across classes to aid in model convergence as models that were estimated with class variant covariances tended to converge on non-identified solutions that failed to replicate the highest log-likelihood.

Table 1 presents the class solutions, key fit indices, and conditional probabilities of the estimated models. Models did not converge beyond four classes. Information criteria failed to discriminate between solutions, as results revealed a decline in BIC values from the one-class solution through the four-class solution. The BLRT was also non-informative, given the failure to replicate the best log-likelihood during the BLRT procedure for the four-class model. Given that non-informative information criteria and BLRT *p* values are common in larger samples and may lead to the overestimation of classes, selection of the optimal class solution relied on the LMR test and inspection of the scree-plot (Morin, Meyer, Creusier, & Biétry, 2016). The LMR test was significant through the three-class model ($p < .05$), and then reached non-significance when the model was expanded to a four-class solution, suggesting that the inclusion of an additional class did not provide significant improvement over the three-class model. Further inspection of the three- and four-class solutions revealed that, in both solutions, three profiles were identical. In addition, the four-class model included an additional profile with BE scores that were similar to a class within the three-class model. Thus, it was determined that the addition of a fourth class did not provide any additional meaningful information. Based on the results from the LMR test and meaningful BE interpretation of classes (class three contributed a smaller, but unique, class with the highest discounting but low means on the other indicator variables), the three-class solution was retained as the optimal model. The three-class solution provided good classification certainty as reflected by entropy (0.87) and posterior probabilities for most likely class membership ranging from 0.94 to 0.97.

The final three-class solution probabilistically assigned participants in to a *low reward value, high discounting* class (LRHD; $n = 53$, 13.5%), a *moderate reward value, low discounting* class (MRLD; $n = 214$, 54.4%), and a *high reward value, high discounting* class (HRHD; $n = 126$, 32.1%). Figure 1 depicts the standardized mean profiles of the three-class solution. Unstandardized indicator means for each class as well as significant class differences can be found in Table 2.

Class Descriptions

Low reward value, high discounting (*n* = 53).—Participants in this class endorsed the lowest levels of intensity, O_{max}, and proportionate substance-related reinforcement, the highest levels of elasticity (sensitivity to price), and the steepest delay discounting (preference for smaller, immediate rewards) of the three profiles.

Moderate reward value, low discounting (*n* = 214).—Participants in this class displayed levels of intensity ($g = 0.01$) and proportionate substance-related reinforcement ($g = 0.03$) that were similar to the LRHD class, but had significantly higher levels of O_{max} ($g = 0.32$) and significantly lower levels of elasticity ($g = 1.78$). Participants in this class also endorsed significantly lower levels of delay discounting ($g = 1.15$; 0.94) relative to the LRHD and HRHD profiles, respectively.

High reward value, high discounting (*n* = 126).—Participants in this class endorsed significantly higher levels of intensity ($g = 0.77$; 0.85), O_{max} ($g = 2.04$; 2.34), proportionate substance-related reinforcement ($g = 0.30$; 0.28), and significantly lower levels of elasticity (*g* = 2.41; 0.74) relative to the LRHD and MRLD profiles, respectively. Participants in this class endorsed similar levels of delay discounting as those in the LRHD class (*g* = 0.01).

Predictors of Class Membership

The effects of covariates on latent profile membership are depicted in Table 3. Both continuous (household income, cannabis use, depressive symptoms, CFC) and categorical (sex, race, Greek affiliation, site, family history of problem drinking) covariates were mean-centered to facilitate interpretation of each coefficient in the context of the sample average. Using the HRHD class as the reference group, results indicate that being female was significantly associated with increased odds of being in both the MRLD class (OR = 1.45, 95% confidence interval [CI]: [1.12, 1.87]) and the LRHD class (OR = 1.55, 95% CI: [1.08, 2.21]). Being non-White was significantly associated with a decreased probability for expected classification in the MRLD class relative to the HRHD class (OR = 0.65, 95% CI: [0.50, 0.85]). Positive family history of problem drinking was significantly associated with a decreased probability for expected classification in both the MRLD class (OR = 0.51, 95% CI: [0.29, 0.78]) and the LRHD class (OR = 0.54, 95% CI: [0.24, 0.79]) relative to the HRHD class. Greater frequency of cannabis use was significantly associated with a decreased probability for expected classification in the MRLD class relative to the HRHD class (OR = 0.72, 95% CI: [0.55, 0.88]). Profile membership was also significantly predicted by levels of CFC, as a one-unit increase in CFC (greater future orientation) was significantly associated with increased odds of being in both the MRLD class (OR = 1.40, 95% CI: [1.06, 1.82]) and the LRHD class (OR = 1.23, 95% CI: [1.07, 1.74]) relative to the HRHD class. Race and cannabis use were not significant predictors of class membership when comparing the LRHD class to the HRHD class. Finally, household income, Greek affiliation, site, and depressive symptoms did not differentiate between either the MRLD class or the LRHD class relative to the HRHD class.

Using the MRLD class as the reference group, results indicate that being non-White significantly increased the odds of being in the LRHD class (OR = 1.82, 95% CI: [1.34, 2.49]). Profile membership was also significantly predicted by levels of household income, as greater household income was significantly associated with a decreased probability for expected classification in the LRHD class relative to the MRLD class (OR = 0.69, 95% CI: [0.47, 0.91]). Female sex, Greek affiliation, site, family history of problem drinking, cannabis use, depressive symptoms, and CFC were not significant predictors of class membership when comparing the LRHD class to the MRLD class.

Differences in Alcohol-Related Outcomes Across Classes

Significant differences in alcohol-related outcomes were tested using Wald's test (see Table 4 for means and Table 5 for significant differences) using means adjusted for sex, race, Greek status, site, family history of problem drinking, and mean levels of household income, cannabis use, depressive symptoms, and CFC. Significant and large mean differences were found based on latent class membership in overall alcohol consumption as the HRHD class (*est* = 22.06, *SE* = 1.30) reported significantly greater typical weekly drinking than the LRHD class [*est* = 14.31, *SE* = 1.70; LRHD vs. HRHD: $p < .001$, *g* = 0.57] and the

MRLD class [*est* = 14.06, *SE* = 0.77; MRLD vs. HRHD: $p < .001$, $g = 0.71$]. No significant differences emerged between the LRHD class and MRLD class ($g = 0.02$).

Past-month HED episodes of the HRHD class (*est* = 7.92, *SE* = 0.06) was significantly greater than that of MRLD class [*est* = 5.58, *SE* = 0.05, $p < .001$, $g = 0.57$] and the LRHD class [*est* = 4.01, *SE* = 0.11, $p < .001$, $g = 0.88$]. The MRLD class reported significantly more past-month HED episodes compared to the LRHD class [MRLD vs LRHD: $p = .008$, $g = 0.46$].

A similar pattern emerged when investigating alcohol-related problems while controlling for alcohol consumption. The HRHD class (*est* = 15.16, *SE* = 0.73) reported significantly more alcohol-related problems compared to the MRLD class [*est* = 12.62, *SE* = 0.56; $p = .009$, $g = 0.32$] and the LRHD class [*est* = 10.52, *SE* = 1.01, $p < .001$, $g = 0.59$]. However, no significant differences were found between the MRLD class and the LRHD class ($g = 0.27$).

The mean number of AUD symptoms reported by the HRHD class (*est* = 3.32, *SE* = 0.07) was significantly higher than that of MRLD class [*est* = 2.41, *SE* = 0.06; $p < .001$, $g = 0.39$] and the LRHD class [*est* = 2.08, *SE* = 0.12; $p < .001$, $g = 0.53$]. No significant differences were found between the MRLD class and the LRHD class ($g = 0.15$).

Discussion

This is the first study to explore patterns of delay discounting, alcohol demand, and proportionate substance-related reinforcement using a person-centered analysis. Findings provide evidence for three distinct *profiles* of BE domains within a sample of participants who reported two or more past-month heavy drinking episodes. The first profile represented the low reward value, high discounting class (LRHD). This class was the least prevalent in this sample of heavy drinkers (13.5%, $n = 53$) and characterized participants with low levels of demand and proportionate substance-related reinforcement, but high levels of delay discounting. The second profile represented the moderate reward value, low discounting class (MRLD). This class was most prevalent (54.4% of sample, $n = 214$) and characterized participants with medium levels of both demand and proportionate substance-related reinforcement and low levels of delay discounting. The final class, the high reward value, high discounting class (HRHD; $n = 126$), was defined by a pattern of high demand, proportionate substance-related reinforcement, and delay discounting.

In addition to demonstrating varying levels of BE risk, the three profiles also presented different configurations of their BE indicators, thus providing support for the utilization of a person-centered approach to evaluate the reinforcer pathology model. These qualitative differences (i.e., profiles demonstrating varying shapes) mitigate the common criticism that person-centered approaches lead to predictable profiles that are only quantitatively different (i.e., profiles are represented as a continuum of low to high on their indicators) and would be better represented by variable-centered approaches. These qualitatively different profiles would have been undetected in the application of traditional variable-centered approaches that investigate correlations between linear dimensions, given that descriptive statistics from the current sample revealed minimal correlations between observed measures of delay discounting with proportionate substance-related reinforcement, intensity, O_{max}, and elasticity. In the previous variable-centered analyses examined with this same data, the results suggested that alcohol demand and proportionate substance-related reinforcement were associated with each other, but not with delay discounting (Acuff et al., 2018). The current results reveal patterns in which these variables cluster together and demonstrate relations with substance misuse variables.

In support of the reinforcer pathology model (Bickel et al., 2017), the HRHD class was associated with greater levels of alcohol consumption, past-month HED episodes, alcohol problems, and AUD symptoms than the other classes. This finding provides support for the core reinforcer pathology hypothesis that steep discounting accompanied by elevated alcohol reward value are synergistic risk factors for alcohol problem severity. Although the elevated risk associated with the unique response pattern of the HRHD class is consistent with the reinforcer pathology model, it may be the case that the heightened risk was driven solely by high reward value, independent of delay discounting levels. No class characterized by elevated alcohol reward and low levels of discounting emerged, and thus it is not possible to rule out this alternative explanation. Given that levels of discounting generally decrease over one’s lifespan (Steinberg et al., 2009), further research using post-college samples may help to clarify the relationship between discounting and alcohol misuse.

Although the MRLD class reported more HED episodes compared to the LRHD class, these two classes reported similar levels of alcohol consumption, alcohol problems, and AUD symptoms. The results of the LPA indicated that a critical difference in BE patterns between the MRLD class and the LRHD class was an elevated level of discounting in one class but not the other. The emergence of the LRHD class with incongruent low levels of alcohol reward value and steep discounting and its relation to lower levels of alcohol outcomes may help explain previous results from variable-centered studies that failed to find an association between delay discounting and drinking (Murphy et al., 2012; Teeters & Murphy, 2015). Given the finding that lower household income increased the odds of membership in the LRHD class relative to the MRLD class, the observed difference in levels of discounting may reflect financial strain rather than a more general excessive preference for immediate rewards such as alcohol (Oshri et al., 2019). This reflects a limitation of hypothetical money choice measures of delay discounting, particularly with young adult samples who may have little personal experience with financial decision making and may still be partially supported by their family.

Despite equal intensity of demand compared to the MRLD group, the LRHD group showed the greatest level of drinking price sensitivity (i.e., highest elasticity and lowest O_{max}). It is possible that lower income and greater price sensitivity are protective factors against HED in this group (i.e., low income may reduce drinking opportunities for some students who may not have the time or money to drink). Furthermore, being non-White (a group that included primarily Black individuals) was associated with significantly greater odds of being in both the LRHD class and the HRHD class relative to the MRLD class, controlling for household income. This finding suggests that individuals who are members of racial minority groups and who drink heavily are more likely to have steeper discounting tendencies (see also Dennhardt & Murphy, 2011), but that this preference for immediate reward is unrelated to overvaluation of alcohol-reward or increased alcohol-related behaviors. Additionally, consistent with past research, female participants were significantly more likely to be categorized in the MRLD or LRHD classes (Skidmore & Murphy, 2010; Murphy et al., 2013).

Current findings also extend prior research indicating that family history of problem drinking and other drug use is related to steeper discounting (Acheson, Vincent, Sorocco, & Lovallo, 2011; VanderBroek, Acker, Palmer, de Wit, & MacKillop, 2016). Family history is often considered a proxy for the genetic variance in risk for alcohol misuse. Among college student heavy drinkers, the role of family history in predicting alcohol use has been less consistent than in older adults or heavy using populations. However, family history of problematic alcohol use has previously been shown to contribute directly to alcohol problems, and to exacerbate the risk for alcohol problems associated with deficits in substance-free reinforcement (Joyner et al., 2018) among college students. The current study extends these findings, suggesting that positive family history of problem drinking was related to an increased likelihood of being in the HRHD class, but not the MRLD or LRHD classes. Collectively, these findings suggest that the genetic variance may have a direct impact on reward functioning that increases the likelihood of high alcohol motivation combined with steep delay discounting (high reinforcer pathology), rather than an effect on either temporal choice or alcohol reward value alone. This pattern may increase lifelong risk for AUD through increased general alcohol reward value, which is robustly associated with alcohol misuse.

Results also showed that individuals with greater cannabis use were more likely to be in the HRHD class relative to the MRLD class, which is consistent with studies that have shown that concurrent cannabis use is associated with greater levels of alcohol demand (Ramirez et al., 2020; Morris et al., 2018; Naudé et al., 2020), lower substance-free reinforcement (Meshesha, Dennhardt, & Murphy, 2015), and higher rates of problematic alcohol use (Naudé et al., 2020). This result extends the findings of previous studies that demonstrate the association of polysubstance use and maladaptive decision-making. Future research may benefit from further assessing alcohol and cannabis use with comorbid use of other substances.

Strengths and Limitations

This study included a relatively large sample and a comprehensive measurement battery that allowed us to use a person-centered approach to identify patterns of BE domains implicated within the reinforcer pathology model in a sample of young adult heavy drinkers. Limitations included the self-report measurement approach and the fact that the cross-sectional, retrospective study design does not allow inferences regarding the stability of the observed profiles and their relations to drinking over time. Secondly, we cannot assume that the described profiles represent actual categories of people within the population, but rather these profiles are a useful way to represent the heterogeneity across BE variables (Lanza & Rhoades, 2013). Future studies that aim to replicate these profiles can provide support for the validity of the solution found within the current study. Additionally, the use of a single item related to HED may have been a limitation, and future research may benefit from incorporating more questions to better capture this behavior. Although previous research provides strong support for the role of delay discounting, demand, and proportionate substance-related reinforcement in predicting alcohol problems across various demographic groups (e.g., general adult samples, non-college young adults; Bertholet et al., 2015; MacKillop et al., 2010; Morris et al., 2017), systematic testing of the invariance of profile solutions across other demographic groups is necessary to fully establish the generalizability of the reinforcer pathology model as applied to alcohol misuse.

Prevention and Treatment Implications

Our results demonstrate how specific BE constructs may function together to enhance risk for heavy alcohol use and problems among young adult drinkers. These variables may be especially useful in that they have demonstrated that they are both predictive of change in drinking over time and malleable in response to various behavioral and pharmacological interventions (MacKillop et al., 2010; Murphy et al., 2005, 2015; Rung & Madden, 2018). The current findings offer support for intervention strategies that aim to increase environmental reinforcers, such as engaging in exercise, volunteering, or academic activity (Magidson et al., 2011; Murphy et al., 2012, 2019). Brief motivational interventions have also been shown to reduce alcohol demand and proportionate substance-related reinforcement (Murphy et al., 2005, 2015), and experiential interventions that enhance focus on future positive events (episodic future thinking) have been shown to reduce delay discounting and alcohol demand (Snider, LaConte, & Bickel, 2016). Another implication is that our results identified a particularly risky class of young adults with elevated vulnerability to experiencing alcohol-related harms. Concerted efforts should be made to specifically reach this highly at-risk group who display elevated alcohol demand, high proportionate substance-related reinforcement and steep delay discounting.

Conclusions

The current study builds on previous research investigating the concurrent interplay of BE processes (Acuff et al., 2018) through the use of a complementary person-centered approach, which may be a better approach for understanding the synergistic influences of delay discounting and elevated alcohol reward value within the conceptualization of addiction known as reinforcer pathology (Bickel et al., 2017). Results suggest that college students who discount the future more steeply and who have greater alcohol demand and proportionate substance-related reinforcement are at the greatest risk for risky alcohol-related behaviors, whereas students who only exhibit steep discounting may not be at risk.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Public Significance

The current study suggests that there are three distinct subgroups of college students defined by differing levels of delay discounting and alcohol reward value.

Results from this study suggest that college students who discount the future more steeply, and who have greater alcohol demand and proportionate substance-related reinforcement are highly vulnerable to experiencing alcohol-related harms, whereas students who only exhibit steep discounting may not be at risk. Concerted efforts should be made to specifically reach this at-risk group.

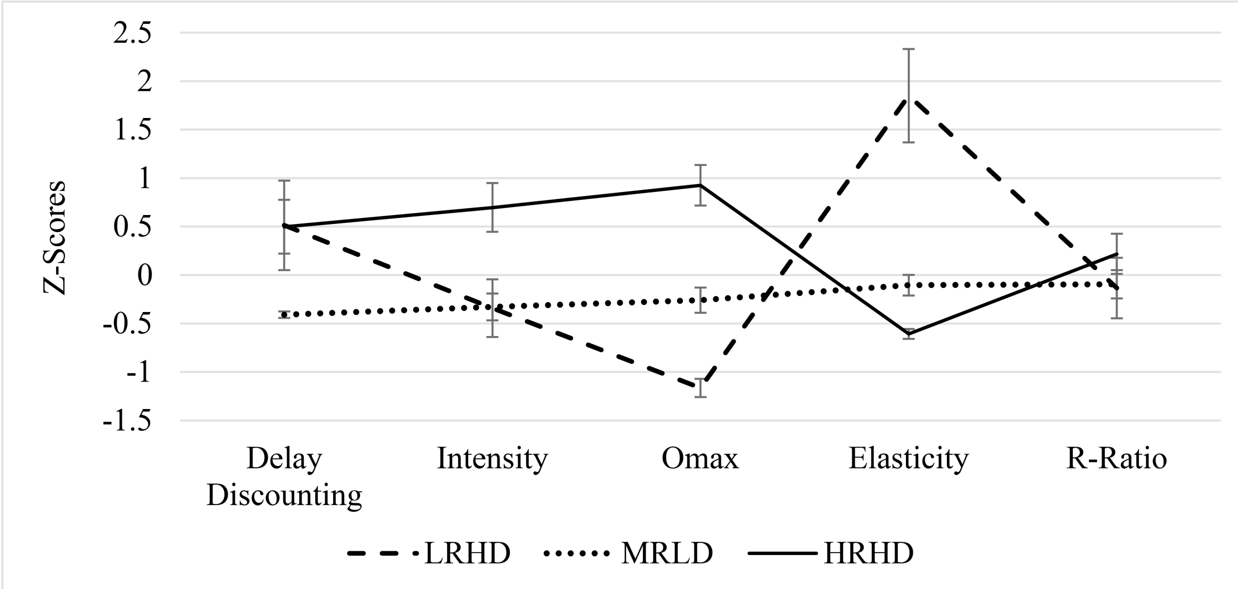

Figure 1.

Three Class Solution Reinforcer Pathology Profiles

Note: R-Ratio = proportionate substance-related reinforcement; LRHD = low reward value, high discounting; MRLD = moderate reward value, low discounting; HRHD = high reward value, high discounting.

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Table 1.

Fit Criteria for Different Model Specifications; Average Class Probabilities

Fit Statistics	**1 Class**	**2 Class**	**3 Class**	**4 Class**
Log-likelihood	−1334.700	−815.614	−545.255	−482.071
BIC	2747.060	1774.599	1299.594	**1238.938**
Entropy	N/A	0.869	**0.873**	0.871
LMR test	N/A	1022.611	532.611	124.474
LMR, *p* value	N/A	**<0.0001**	**0.0120**	0.4549
Two-class model	1	2		
1, *n* = 139, 35.4%	0.969	0.031		
2, *n* = 254, 64.6%	0.029	0.971		
Three-class model	1	2	3	
1, *n* = 126, 32.1%	0.949	0.046	0.005	
2, *n* = 214, 54.4%	0.047	0.936	0.017	
3, *n* = 53, 13.5%	0.000	0.027	0.973	
Four-class model	1	2	3	4
1, *n* = 25, 6.3%	0.972	0.008	0.012	0.008
2, *n* = 49, 12.4%	0.009	0.959	0.032	0.000
3, *n* = 189, 48.2%	0.001	0.022	0.920	0.057
4, *n* = 130, 33.1%	0.014	0.000	0.057	0.929

Note. BIC = Bayesian Information Criterion; LMR = Lo-Mendell-Rubin test. Models were estimated with class-varying variance. Boldface = lowest value. *N* = 393.

Table 2.

Means (SE) for Behavioral Economic Indicators for three-class Solution

	Latent behavioral economic risk profiles		
	LRHD (n = 53)	**MRLD (n = 214)**	**HRHD (n = 126)**
Delay discounting			
k	0.061 (0.014)[a]	0.008 (0.001)[ac]	0.060 (0.008)[c]
Alcohol Demand			
Intensity	7.186 (0.680)[b]	7.244 (0.319)[c]	11.832 (0.576)[bc]
O_{max}	5.852 (0.446)[ab]	14.244 (0.619)[ac]	25.242 (0.991)[bc]
Elasticity	0.315 (0.026)[ab]	0.112 (0.006)[ac]	0.059 (0.003)[bc]
R-Ratio	0.320 (0.023)[b]	0.325 (0.011)[c]	0.371 (0.015)[bc]

Note. SE = Standard error. LRHD = low reward value, high discounting; MRLD = moderate reward value, low discounting; HRHD = high reward value, high discounting; R-Ratio = proportionate substance-related reinforcement. Columns that are significantly different from one another share a superscript such that:

[a]= LRHD vs. MRLD

[b]= LRHD vs. HRHD

[c]= MRLD vs. HRHD.

Significant differences were tested using Wald's Test.

Table 3.

Predictors of Class Membership

	Low Reward, High Discounting vs. High Reward, High Discounting		Moderate Reward, Low Discounting vs. High Reward, High Discounting		Low Reward, High Discounting vs. Moderate Reward, Low Discounting	
Variable	***B* (SE)**	**OR (95% CI)**	***B* (SE)**	**OR (95% CI)**	***B* (SE)**	**OR (95% CI)**
Female	0.44 (0.18)	1.55 (1.08, 2.21)	0.37 (0.13)	1.45 (1.12, 1.87)	0.65 (0.18)	1.07 (0.75, 1.52)
Non-White	0.18 (0.15)	1.19 (0.88, 1.61)	−0.43 (0.14)	0.65 (0.50, 0.85)	0.60 (0.16)	1.82 (1.34, 2.49)
Household Income	−0.21 (0.19)	0.81 (0.56, 1.19)	0.16 (0.14)	1.18 (0.90, 1.55)	−0.37 (0.18)	0.69 (0.47, 0.91)
Greek Status	−0.13 (0.19)	0.88 (0.61, 1.28)	−0.12 (0.13)	0.89 (0.68, 1.15)	−0.01 (0.18)	0.99 (0.69, 1.43)
Site	0.17 (0.18)	1.18 (0.83, 1.69)	0.22 (0.14)	1.25 (0.96, 1.63)	−0.06 (0.17)	0.95 (0.67, 1.33)
Family History	−0.61 (0.15)	0.54 (0.24, 0.79)	−0.67 (0.13)	0.51 (0.29, 0.78)	0.10 (0.17)	1.11 (0.83, 1.35)
Cannabis Use	−0.12 (0.19)	0.89 (0.61, 1.20)	−0.34 (0.14)	0.72 (0.55, 0.88)	0.22 (0.18)	1.24 (0.87, 1.67)
Depressive symptoms	0.11 (0.15)	1.11 (0.82, 1.50)	−0.01 (0.14)	0.99 (0.75, 1.31)	0.11 (0.15)	1.12 (0.83, 1.52)
CFC	0.21 (0.18)	1.23 (1.07,1.74)	0.33 (0.14)	1.40 (1.06, 1.82)	−0.12 (0.17)	0.88 (0.63, 1.23)

Note. OR = Odds ratio; SE = standard error; CI = confidence interval; CFC = Consideration of Future Consequences. The second class of each contrast is the reference category. All measures were mean-centered, thus results reflect the probability of being classified into a particular profile holding all other variables at their average.

Table 4.

Intercepts (SE) and Comparisons Across Outcome Measures for Each Latent Class.

Measures	LRHD Estimate (*SE*)	MRLD Estimate (*SE*)	HRHD Estimate (*SE*)	Class Comparisons
Alcohol consumption	14.31 (1.70)	14.06 (0.77)	22.06 (1.30)	HRHD > MRLD & LHRD; MRLD = LRHD
HED[a]	4.01 (0.11)	5.58 (0.05)	7.92 (0.06)	HRHD > MRLD & LHRD; MRLD > LRHD
Alcohol-related problems[b]	10.52 (1.01)	12.62 (0.56)	15.16 (0.73)	HRHD > MRLD & LHRD; MRLD = LRHD
AUD symptoms[a]	2.08 (0.12)	2.41 (0.06)	3.32 (0.07)	HRHD > MRLD & LHRD; MRLD = LRHD

Note. SE = Standard error; LHRD = low reward value, high discounting; MRLD = moderate reward value, low discounting; HRHD = high reward value, high discounting; AUD = alcohol use disorder; HED = heavy episodic drinking.

All measures conducted using covariate-adjusted means, controlling for sex, race, Greek status, site, family history of problem drinking, and mean levels of household income, cannabis use, depressive symptoms, and CFC. Statistical significance was set at .01 to control for Type-I errors.

[a] Estimated using a negative binomial distribution.

[b] Estimated controlling for alcohol consumption.

Table 5.

Differences in Alcohol Consumption, Dependence, and Problems Across Profiles.

Profiles	Estimate	SE	Estimate/SE	*p*-value	Effect Size (g)
MRLD (ref) vs. LRHD					
Alcohol consumption	−0.25	1.90	−0.13	.897	−0.02
HED[a]	1.39	0.12	2.64	.008**	0.46
Alcohol-related problems[b]	2.09	1.18	1.78	.076	0.27
AUD symptoms[a]	1.16	0.14	0.09	.277	0.15
MRLD (ref) vs. HRHD					
Alcohol consumption	−8.00	1.58	−5.05	<.001**	−0.71
HED[a]	0.70	0.08	−4.37	< .001**	−0.57
Alcohol-related problems[b]	−2.54	0.97	−2.62	< .009**	−0.32
AUD symptoms[a]	0.73	.10	−3.28	< .001**	−0.39
LRHD (ref) vs. HRHD					
Alcohol consumption	−7.76	2.14	−3.62	< .001**	−0.57
HED[a]	0.51	0.13	−5.33	< .001**	−0.88
Alcohol-related problems[b]	−4.64	1.25	−3.71	< .001**	−0.59
AUD symptoms[a]	0.62	0.14	−3.38	< .001**	−0.53

Note. Significant differences were tested using Wald's Test. AUD = Alcohol use disorder; HED = heavy episodic drinking; Ref = reference group.

** $p < .01$.

[a] Estimated using a negative binomial distribution.

[b] Estimated controlling for alcohol consumption.