Title

Trajectories of reward availability moderate the impact of brief alcohol interventions on alcohol severity in heavy-drinking young adults.

Journal

Alcoholism, clinical and experimental research, 45(10)

ISSN

0145-6008

Authors

Murphy, James G
Campbell, Kevin W
Joyner, Keanan J
et al.

Publication Date

2021-10-01

DOI

10.1111/acer.14681

Peer reviewed

Published in final edited form as:
Alcohol Clin Exp Res. 2021 October ; 45(10): 2147–2159. doi:10.1111/acer.14681.

Trajectories of reward availability moderate the impact of brief alcohol interventions on alcohol severity in heavy-drinking young adults

James G. Murphy, PhD[1], **Kevin W. Campbell, MA**[1], **Keanan J. Joyner, MS**[2], **Ashley A. Dennhardt, PhD**[1], **Matthew P. Martens, PhD**[3], **Brian Borsari, PhD**[4,5]

[1]The University of Memphis, Department of Psychology, 400 Innovation Dr, Memphis, TN 38152

[2]Florida State University, Department of Psychology, 1107 West Call Street, Tallahassee, Florida, 32306

[3]University of Missouri, Department of Educational, School, and Counseling Psychology, 16 Hill Hall, Columbia, MO, 65211, USA

[4]Brian Borsari, Ph.D., Mental Health Service (116B), San Francisco VA Health Care System, San Francisco, CA 94143

[5]Department of Psychiatry, University of California, 401 Parnassus Ave, San Francisco, CA 94143

Abstract

Background: Behavioral economic theory predicts that low access to environmental reward is a risk factor for alcohol use disorder (AUD). The Substance-Free Activity Session (SFAS) is a behavioral economic supplement to standard brief alcohol interventions that attempts to increase environmental reward and may therefore have beneficial effects, particularly for individuals with low levels of environmental reward.

Methods: Participants were 393 college students who reported at least 2 heavy drinking episodes in the past month. Participants were randomized to one of three conditions following a baseline assessment: standard alcohol-focused brief motivational intervention plus relaxation training session (BMI+RT), BMI plus Substance-Free Activity Session (BMI+SFAS), or assessment-only control condition (AO). This secondary analysis uses person-centered statistical techniques to describe trajectories of alcohol severity and environmental reward over a 16-month follow-up, and to examine if environmental reward levels moderated the effectiveness of the interventions.

Results: Piecewise growth mixture modeling identified two trajectories of reward availability: low-increasing (LR; n = 120) and high-stable (HR; n = 273). Depressive symptoms, cannabis use, sensation-seeking, and low life satisfaction were associated with a greater probability of classification in the LR trajectory. Alcohol severity was greater in the LR trajectory compared to the HR trajectory. For students in the LR trajectory, BMI+SFAS led to greater increases in reward availability and reduced levels of alcohol severity at 1, 6, and 12 months compared to BMI+RT and AO conditions, and also at 16 months compared to AO.

Corresponding Author: James G. Murphy, Ph.D., Department of Psychology, 400 Innovation Dr., Memphis, TN, 38152, jgmurphy@memphis.edu; Phone: (901) 678-2630.

Conclusions: Young adults with low levels of environmental reward are at heightened risk for greater alcohol severity, and these individuals may show greater relative benefit from brief alcohol interventions that focus on increasing substance-free reward.

Keywords

alcohol use disorder; behavioral economics; substance-free reinforcement; alcohol problems; brief alcohol interventions

Introduction

Heavy drinking among young adults is a major public health concern, with one in three college-aged individuals reporting past-month heavy episodic drinking (Hingson et al., 2017). This is concerning given that more than half of young adult drinkers experience negative consequences related to their drinking, including loss of consciousness, sexual risk taking, academic problems, and alcohol-related injuries (Hingson et al., 2017). In addition to experiencing negative alcohol-related consequences, the prevalence of alcohol use disorder (AUD) peaks during the young adult developmental period (Grant et al., 2015). Estimates based on DSM-5 criteria (American Psychiatric Association, 2013) suggest that 27% of young adults (aged 18–29) meet criteria for past-year AUD and 37% meet criteria for lifetime AUD (Grant et al., 2015).

Reward Deprivation and Alcohol Use Disorder

Behavioral economic theories of addiction posit that both the accessibility of substances as well as constraints on the availability and valuation of naturally occurring substance-free alternative reinforcers influence levels of substance use (Acuff et al., 2019; Bickel et al., 2014; Lamb & Ginsburg, 2018). Consistent with this tenet, greater access to and engagement with substance-free reinforcing activities is associated with less alcohol and drug use whereas constraints on access to substance-free sources of reward (e.g., social or recreational activities) is associated with greater levels of alcohol and drug use (Bickel et al., 2012; Higgins et al., 2004), an effect that may be partially mediated by increases in depressive symptoms and drinking to cope (McPhee et al., 2020). In addition, research has demonstrated that prolonged substance misuse is related to diminished dopaminergic responses to substance-free rewards, such as food and erotic stimuli (Koob & Le Moal, 2008; Lubman et al., 2009). Although reward deficits are implicated in depression and other forms of psychopathology (Carvalho et al., 2011), research with young adults has demonstrated that lack of access to reward uniquely predicts drug use and AUD severity beyond other related forms of psychopathology, such as depressive symptoms (Joyner et al., 2016) or trauma (Acuff et al., 2018), and shows robust small-to-medium associations with AUD severity (Meshesha et al., 2015; Morris et al., 2017). One longitudinal study with teens indicated that the association between parent education (as proxy for SES) and alcohol and other drug use initiation and frequency was partially mediated by reward deficits (i.e., low engagement and enjoyment in substance-free activities; Lee et al., 2018), and another study found that reward deficits predicted smoking escalation longitudinally in young adults (Audrain-McGovern et al., 2011). Individuals who successfully quit smoking also report increases in substance-free reward (Schnoll et al., 2016). Moreover, the protective effects of increased substance-free activity engagement are most pronounced among individuals at dispositional risk for alcohol misuse (e.g., positive family history of alcohol problems; Joyner et al., 2018), highlighting the important interplay of substance-free reward on already-established predictors of alcohol misuse (Hogarth & Field, 2020).

The studies reviewed above suggest that deficits in reward availability may be implicated in the premorbid development and potential maintenance of AUDs, but to date no longitudinal studies have directly examined these proposed associations. A further question concerns the potential for interventions to mitigate the impact of reward deprivation on alcohol severity. Treatment approaches that attempt to increase substance-free activities have shown promising effects for reducing alcohol and other substance use (Daughters et al., 2008; Fazzino et al., 2019; Higgins et al., 2004), but no work has examined the extent to which response to reinforcement-based alcohol interventions is moderated by level of environmental reward.

Brief Motivational Interventions (BMIs) for College Drinking

Brief motivational interventions (BMIs) are promising approaches for reducing drinking and alcohol-related consequences among college students (Cronce & Larimer, 2011). BMIs have been efficacious in decreasing drinking across numerous clinical trials (Scott-Sheldon et al., 2014), with approximate reductions ranging from 30–50% that are maintained between 6 and 12 months. However, recent meta-analyses indicate that these BMIs generally produce small to moderate effect sizes (Foxcroft et al., 2016; Tanner-Smith & Lipsey, 2015). Furthermore, response to BMIs differ widely in terms of efficacy, suggesting important individual differences in response (Huh et al., 2015; Murphy et al., 2005). This may be due to the fact that most BMIs include only a single intervention session that is focused explicitly on discussing risk associated with drinking and correcting normative beliefs about drinking rates without addressing the underlying reasons why students drink. Although many students' drinking motives may be primarily celebratory and social, students with AUD may drink in order to reduce stress and because they have few behavioral alternatives to drinking (Hogarth & Field, 2020; Joyner et al., 2016). Thus, novel intervention elements may be necessary to improve the efficacy of these interventions (Huh et al., 2015), particularly for young adult drinkers with elevated risk including AUD symptoms.

BMIs that also include components that target underlying reasons for heavy drinking, including stress and lack of behavioral alternatives to drinking may enhance treatment efficacy (DeMartini et al., 2015; Murphy et al., 2005, 2012). A recent multisite randomized clinical trial found that two-session interventions that augmented an alcohol BMI with either a behavioral economic session that attempted to increase engagement in goal-directed and enjoyable activities or a relaxation training session were associated with significant moderate to larger reductions in alcohol use and problems relative to an assessment control condition across a 16-month follow-up period (Murphy et al., 2019).

Identifying Moderators of Intervention Response with Growth Mixture Modeling

Given the heterogeneity in intervention response to BMIs for heavy drinking, person-centered approaches are useful for determining which individuals benefit from particular interventions. Growth Mixture Modeling (GMM; Muthén, 2001), is a person-centered statistical approach that attempts to capture sample heterogeneity by empirically identifying distinct subgroups of individuals characterized by relatively homogenous patterns of change over time. GMM is well suited to analyze intervention effects as it is capable of uncovering varying patterns of change in relevant mediator variables, thus detecting heterogeneity in intervention response among individuals. GMM allows for the identification of various unobserved subgroups that are permitted to differ in intercept and slope, while allowing variation in these parameters as a function of subgroup. GMM also allows for the inclusion of different treatment effects in different trajectory classes and can identify subgroup differences in treatment response.

Current Study

The current study is a secondary analysis of a randomized controlled trial comparing the efficacy of a BMI plus Substance Free Activity Session (BMI+SFAS) to a BMI plus Relaxation (BMI+RT) and an assessment only (AO) control condition for reducing alcohol consumption and associated negative consequences (Murphy et al., 2019). In the parent trial, both BMI conditions were associated with significant reductions in alcohol use and problems compared to the AO condition across a 16-month follow-up period. There were no differences between the two BMI conditions, and reductions in proportional reinforcement from substance-related activities partially mediated the treatment effects (on drinking and alcohol problems) of both active conditions. Additionally, a previous cross-sectional analysis of baseline data in this sample indicated that a measure of reward deprivation was uniquely associated with severity of alcohol problems and AUD symptoms (Joyner et al., 2016). The current study applies growth mixture modeling (GMM) to further explore the data from this trial. Specifically, GMM models were constructed to: (1) identify distinct trajectories of reward availability over the course of 16 months in a sample of heavy drinking college students, (2) investigate variation in impact of BMI+SFAS and BMI+RT on rate of change in different trajectories of reward availability, (3) identify predictors of reward trajectory membership, and (4) determine if treatment condition differentially impacts trajectories of alcohol severity as a function of level of reward availability.

Consistent with existing research examining reward availability and AUD (Joyner et al., 2016), we hypothesize that (1) there will be at least two trajectories of reward availability that vary in levels of alcohol severity. Contingent on evidence that two or more trajectories are apparent, the trajectory with the lowest levels of reward availability will be used as a reference group to test additional hypotheses predicting that (2) students who receive the BMI+SFAS and report initially low reward will report larger increases in reward availability following intervention, compared to those in the BMI+RT and AO conditions, (3) consistent with previous cross-sectional research (Magidson et al., 2017; Meshesha et al. 2015), trajectories characterized by low reward availability will be linked to greater levels of depression, cannabis use, lower life satisfaction, higher sensation-seeking, and greater alcohol severity, and (4) levels of alcohol severity will be lower across time among those who receive the BMI+SFAS and are characterized by a low reward availability trajectory, compared to those in the BMI+RT and AO conditions.

Materials and Methods

Participants

Participants were 393 first- or second-year college students from two public universities in the southeastern United States (Murphy et al., 2019). Approximately 60.8% of participants were female, 78.9% were White/Caucasian, 8.7% were Black/African American, and 5.9% were Hispanic. The mean age was 18.77 years (SD = 1.07). Inclusion criteria required that participants were at least 18 years old and reported two or more binge drinking episodes in the past month (4/5+ standard drinks in one occasion for women/men, respectively).

Procedures

Participants attended a laboratory session that included a computer-administered baseline assessment and were then randomly assigned to one of three conditions: BMI+SFAS (n = 130), BMI+RT (n = 125), and AO (n = 138). Participants then completed follow-up assessments at 1, 6, 12, and 16-months. Participants in the BMI+SFAS and BMI+RT conditions also completed a brief telephone booster session one week prior to the beginning of the semester following the 1-month assessment. Detailed information about the study design has been previously reported (see Murphy et al., 2019; ClinicalTrials.gov Identifier: NCT02834949). The current study utilized assessments of demographics, cannabis frequency, sensation-seeking, and life satisfaction collected at baseline and measures of reward availability, depression, and alcohol severity collected at all time points. Participants provided consent after reviewing and signing a consent form detailing study procedures. All study procedures were approved by the University Institutional Review Boards. The current study represents a secondary analysis that utilizes a person-centered approach to enhance understanding of effects of the intervention on the course of reward availability and alcohol severity. Our hypotheses were guided by behavioral economic theory, but the analyses were not pre-registered and should be considered exploratory in nature.

Measures

Environmental Reward

Reward availability.—Reward availability was measured using the Environmental Suppressors subscale of the Reward Probability Index (RPI), which has demonstrated strong convergent and discriminant validity (Carvalho et al., 2011). The Environmental Suppressors subscale is composed of nine items that measure obstacles to obtaining or engaging in rewarding experiences (e.g., “I have had many unpleasant experiences,” “changes have happened in my life that have made it hard to find employment,” and “I have few financial resources, which limits what I can do”). Responses are assessed using a four-point Likert scale ranging from “strongly disagree” to “strongly agree”. The nine items are summed to create a total score (range 9 –36) with higher scores indicating greater access to reward. The subscale in the current sample displayed adequate internal consistency (Cronbach’s α’s = .84–86, ω’s [omega] = .85–.86). The current analyses did not use the second subscale of the RPI, the Reward Probability subscale, which assesses the extent to which potential rewards can be enjoyed given that there appeared to be no heterogeneity in trajectories of one's ability to experience reward (i.e., all participants were found to follow approximately the same mean growth curve reflecting one's ability to experience reward over time).

Predictors of Trajectory Class Membership

Demographics.—Potential demographic covariates in the final auxiliary models included sex (i.e., male, female), race and age. Due to small minority group cell sizes, the race variable was coded as White and non-White.

Depression.—Depression was measured using the Depression scale of the Depression, Anxiety, and Stress Scale (DASS-21; Henry & Crawford, 2005), which includes seven items that measure the extent to which an individual has experienced the negative emotional state of depression over the past week and was internally consistent in this sample (α's = .85–93, ω's = .85–.93).

Cannabis frequency.—Cannabis use was measured using a single item assessing the frequency of past month cannabis use. Nearly 50% of the current sample reported past month use, with the overall sample using an average of 5.38 days (SD = 8.50).

Sensation-seeking.—The Brief Sensation Seeking Scale (BSSS-4; Hoyle et al., 2002) included four items that assess domains of sensation-seeking: experience seeking, boredom susceptibility, thrill seeking, and disinhibition. Responses are assessed using a 5-point Likert scale ranging from "strongly disagree" to "strongly agree" and are summed to create a total score (range 4 –20). The BSSS-4 displayed adequate internal consistency in this sample (α's = .76–.80, ω's = .78–.82).

Life satisfaction.—Participants were given a subset of questions from the Extended Satisfaction with Life Scale (Alfonso et al., 1996). One item from each subscale of the measure were administered[1]. Responses were summed to create a composite score (α's = .77–.84, ω's = .78–.85).

Alcohol Severity

Heavy drinking.—To determine frequency of heavy drinking, a single item from the Daily Drinking Questionnaire (DDQ; Collins et al., 1985) was used that asked participants to report the number of times that they consumed 4+/5+ alcoholic beverages (for women/men) during the past month.

Alcohol-related problems.—The 48-item Young Adult Alcohol Consequences Questionnaire (YAACQ; Read et al., 2006) was used to assess negative alcohol-related consequences specific to college student populations. Participants indicated whether or not they had experienced any of the 48 potential problems as a result of their drinking in the past month. The measure demonstrated good internal consistency in this sample (α's = .89–.95, ω's = .90–.95).

[1]The administered items were item #s 3, 8, 31, 28, and 48 from the Extended Satisfaction with Life Scale (Alfonso et al., 1996).

Alcohol use disorder symptom count.—Consistent with the DSM-5 (American Psychiatric Association, 2013), AUD symptom count was determined based on the number of AUD symptoms experienced in the past 12 months. Participants indicated whether or not they had experienced each of the 11 symptoms consistent with a DSM-5 diagnosis of an AUD (American Psychiatric Association, 2013).

Statistical Analysis

Alcohol Severity Measurement Model.—Confirmatory factor analysis (CFA) was used to estimate an alcohol severity latent factor at baseline using measures of heavy drinking, alcohol-related consequences, and AUD symptom count as indicators. The use of CFA allowed us to model a single underlying continuum of alcohol severity based on multiple indicators and account for bias due to measurement error. To ensure that the alcohol severity latent factor was invariant across all five waves of data, repeated measures of each indicator were incorporated to extend the baseline model and tests assessing configural, weak, and strong measurement invariance were conducted to assess equality of intercepts and factor loadings across time (see Supplemental Materials). Residual covariances between the same indicators at different time point were estimated. Model comparison standards of ΔCFI/ΔTFI ≥ .01 (Cheung & Rensvold, 2002) and ΔRMSEA ≥ .015 (Chen, 2007) were used to indicate a violation of invariance when comparing increasingly constrained models.

Primary Analysis.—For aim 1, growth mixture modeling (GMM; Muthén, 2001) was used to identify latent trajectories of reward availability. The analysis was carried out in multiple stages. First, separate latent growth curve models (LGCMs) with various growth functions (intercept only, linear, quadratic, latent basis, and piecewise) were estimated for each study condition separately to determine the optimal form of growth representing reward availability over time (see Supplemental Materials for more details of the analysis).

Growth mixture modeling (GMM; Muthén, 2001) was next used to determine the number of trajectories needed to describe the five waves of reward availability. To identify the optimal number of students with distinct growth trajectories in the absence of intervention, models with differing numbers of trajectories were first estimated separately for the AO condition. Analyses that systematically tested multiple trajectory solutions were then repeated separately for the BMI+SFAS and BMI+RT conditions.

For aim 2, to evaluate the impact of intervention on the growth of reward availability, general growth mixture modeling (GGMM; Muthén et al., 2002) was employed to determine the optimal number of latent trajectory classes in a joint analysis of the full sample. Models with differing numbers of latent trajectory classes were estimated. Growth parameters were estimated controlling for mean levels of depressive symptoms (Joyner et al., 2016). Once the optimal number of latent trajectory classes was established, slope parameters specific to each trajectory were regressed on dummy coded intervention status variables representing intervention effects for BMI+SFAS and BMI+RT relative to the AO condition. To determine whether the impact of the BMI+SFAS was significantly different from the BMI+RT, a second set of dummy coded variables were used that specified BMI+RT as the reference group. To determine whether intervention effects varied by latent trajectory, we compared a model in which intervention effects were constant across all trajectories to a model in which intervention effects varied between trajectories using a likelihood ratio test.

For aims 3–4, established predictors of reward availability and/or alcohol severity (e.g., baseline alcohol severity, sex, race, age, depressive symptoms, cannabis frequency, sensation-seeking, and life satisfaction) were assessed simultaneously using multinomial logistic regression and path analysis, respectively. Logistic regression was conducted using the R3STEP method (Asparouhov, & Muthén, 2014a), which accounts for classification error when estimating the relationship between predictor and latent trajectory class. Significant predictors were then controlled for in auxiliary models which examined differences in alcohol severity at 1, 6, 12, and 16 months across trajectory and study condition using the manual three-step BCH method (Asparouhov & Muthén, 2014b) which takes into account participants' partial membership in trajectories. Multiple imputation with 100 imputed data sets were used to account for missing data on covariates (0–3% missing; Graham et al., 2007), permitting the full sample ($n = 393$) to be used for outcome analyses.

All models (i.e., CFAs, separate LGCMs, GMMs, GGMMs) were estimated in Mplus 8.0 (Muthén & Muthén, 1998 – 2017) using full-information maximum likelihood estimation (FIML) with robust standard errors and scaled-log likelihood statistics to account for non-normality and missing data. The use of MLR was supported by a previous exploration of missing data patterns within the current sample which revealed no significant differences between those students with complete data and those that were lost to follow-up (Murphy et al., 2019). The TYPE = COMPLEX function in Mplus was utilized for all analyses to account for clustering of participants by study site (Campus 1, Campus 2). Models were estimated using 1,000 sets of random start values with 100 iterations to ensure reproduction of global maxima and to avoid solutions at false local maxima.

Selection of the best fitting and most parsimonious solution for our data was based on recommendations for model selection (Berlin et al., 2014; Muthén & Muthén, 2000). The Bayesian Information Criterion (BIC; Schwarz, 1978), the Lo-Mendell-Rubin test (LMR; Lo et al., 2001), and entropy were used to determine the optimal class solution (see Supplemental Materials for more details). Additionally, size and interpretability of class solutions were considered, as classes that contain less than 5% of the total sample may signify data over-extraction (Berlin et al., 2014).

Results

Preliminary Analysis

At baseline, 31.6% of participants met criteria for past-year mild AUD, 19.6% met criteria for moderate AUD, and 13.7% met criteria for severe AUD. Preliminary analyses revealed no significant differences in demographic or baseline alcohol severity variables (e.g., heavy drinking, alcohol-related consequences, AUD symptom count) between study conditions. Retention rates were high; 93% of participants completed the follow-up at 1 month, 88% at 6 months, 87% at 12 months, and 79% at 16 months, resulting in minimal data missingness that was assumed to be missing at random (MAR). Dropout was not correlated with any measure at baseline (see Murphy et al., 2019).

Alcohol Severity Measurement Model

The alcohol severity latent factor was found to be invariant (configural, weak, and strong invariance was met; see Supplemental Table S1) across all five time points. Evidence of strong measurement invariance suggests that differences in latent factor means across time are attributable to true change in the alcohol severity construct.

Determining the Best Growth Model for Reward Availability

To determine the optimal growth function which would serve as the base model for subsequent GMMs, intercept, linear, quadratic, latent basis, and piecewise single-group LGCMs were estimated in each condition separately (Berlin et al., 2014; see Supplemental Materials). Fit statistics for each model tested can be found in Supplementary Table S2.

Mixture Modeling

To evaluate whether qualitatively distinct solutions existed in each study condition, GMMs with increasing numbers of reward availability trajectories were estimated in AO, BMI+RT, and BMI+SFAS conditions separately (see Supplemental Materials for more details of the analysis). Based on information criteria, likelihood ratio tests, and interpretability, the two-trajectory model was determined the optimal class solution (see Table 1 for fit statistics for competing piecewise growth models). These results are consistent with those obtained from the analyses conducted in each condition separately. The two-class solution resulted in good classification precision as reflected by entropy (entropy = 0.81) and posterior probabilities for most likely class membership ranging from 0.95 to 0.97.

Next, growth factors (i.e., intercept, initial change slope, maintenance slope) were simultaneously regressed on intervention status for each trajectory separately to allow for class-specific intervention effects. Analyses examining differences between AO, BMI+RT, and BMI+SFAS students in each trajectory were found to be non-significant. The two trajectories did not significantly differ in proportion of students assigned to BMI+SFAS and BMI+RT (LR trajectory: 0.33, 0.33; HR trajectory: 0.33, 0.32). Table 2 presents unadjusted comparisons between trajectories on baseline covariates using Wald chi-square tests. Unstandardized estimates from the final two trajectory piecewise model are presented in the lower panel of Table 2.

Latent Trajectories Descriptions

High-stable reward availability.—Figure 1 depicts the estimated trajectories of the final two class piecewise model for each study condition. The majority of students were classified into a *high-stable reward availability* trajectory (HR; $n = 273$, 69.5%). Students in this trajectory began with the highest rates of environmental reward at baseline which remained consistently high throughout. Students in the AO condition in this trajectory showed a significant decrease in reward availability from baseline to one month ($b = -1.725$, $p = 0.001$, $d = -0.54$). The regression coefficients of both BMI+RT (β_{RT} on slope = 1.190, $p = 0.030$, $d = 0.17$) and BMI+SFAS (β_{SFAS} on slope = 1.461, $p = 0.001$, $d = 0.22$) on the initial change slope were positive and significant (Table 2), indicating that the significant decrease in reward availability displayed by the students in the AO condition was not observed in students in either of the BMI conditions. No significant effects were found for intervention status on the maintenance slope suggesting that the steady levels of reward availability from one to 16 months did not differ for AO, BMI+SFAS, and BMI+RT students.

Low-increasing reward availability.—The remaining students were classified into a *low-increasing reward availability* trajectory (LR; $n = 120$, 30.5%). Students in this trajectory reported significantly lower levels of environmental reward at baseline ($M =$ 20.9, $SE = 0.65$) relative to the HR trajectory [$M = 29.8$, $SE = 0.32$; $p < .001$, $g = 2.32$] which was sustained across all follow-ups (all p's <.001). Students in the AO condition in this trajectory displayed low levels of environmental reward at baseline, followed by a significant increase in reward over the initial change period, without additional change over the subsequent 15 months. Of note, this increase still did not reach absolute greater levels than the high-stable reward availability trajectory group at any time point. Inspection of intervention effects revealed a non-significant BMI+RT regression coefficient (β_{RT} on slope $= -0.394$, $p = 0.729$, $d = -0.04$) on the initial change slope suggesting that the trajectory of reward availability for AO students was similar for BMI+RT students. The regression coefficient of BMI+SFAS on the initial change slope was significant, indicating that students in the LR trajectory receiving BMI+SFAS had significantly greater increases in reward availability from baseline to one month, compared to their AO counterparts (β_{SFAS} on slope $= 2.800$, $p = 0.001$, $d = 0.29$). In addition, BMI+SFAS students also displayed a significantly greater slope in reward availability from baseline to one month (β_{SFAS} on slope = 3.173, $p = 0.001$, $d = 0.32$) when compared to BMI+RT students. These results indicate that the BMI+SFAS was associated with an increasing rate of reward availability for students in the LR trajectory compared to AO and BMI+RT. The effects of intervention status on the maintenance slope were not significant, suggesting students in each condition displayed similar stable trajectories of reward availability from one to 16 months.

Predictors of Latent Trajectory Membership

To assess baseline predictors of trajectory membership, simultaneous entry multinomial logistic regression was used to calculate adjusted odds ratios (*aORs*), holding all other predictors at their average. Using the HR trajectory as the reference class, results revealed that students with greater levels of depression (*aOR* = 1.50, 95% confidence interval [CI]: [1.21, 1.86]), cannabis use (*aOR* = 2.65, 95% CI: [1.67, 4.21]), sensation-seeking (*aOR* = 1.37, 95% CI: [1.10, 1.71]), and lower levels of life satisfaction (*aOR* = 0.88, 95% CI: [0.80, 0.95]) were more likely to belong to the LR trajectory. The students following the two distinct trajectories did not significantly differ by sex, race, age, Greek affiliation, and baseline alcohol use.

Impact of BMI+SFAS on Alcohol Severity Across Latent Trajectories

To assess intervention effects within latent trajectories, differences in alcohol severity at 1, 6, 12, and 16 months were examined using estimates adjusted for sex, race, mean levels of depressive symptoms, household income, and baseline alcohol severity. Estimated model parameters are interpreted in the AUD symptom count metric. At baseline, students in the LR trajectory reported significantly greater alcohol severity relative to those in the HR trajectory ($b = 3.91$, SE = 0.12, $p < 0.001$). Additional comparisons revealed similar results, alcohol severity was significantly greater in the LR trajectory compared to the HR trajectory at 1, 6, 12, and 16 months (all p's <.001). There were no significant baseline differences in level of alcohol severity as a function of study condition for students in the HR trajectory and LR trajectory (all p's > .05)

High-stable reward availability.—Regression of the alcohol severity latent factors on intervention status is presented in Table 3. For those in the HR trajectory, students in the AO condition reported significantly greater alcohol severity at 1 month post treatment relative to students in the BMI+SFAS ($b = 0.66$, SE = 0.20, $p < 0.001$) and BMI+RT condition ($b = 1.04$, SE = 0.21, $p < 0.001$). Levels of alcohol severity did not significantly differ for students in this trajectory as a function of study condition (all p's > .05) for all remaining comparisons.

Low-increasing reward availability.—For those in the LR trajectory, students in the AO condition reported significantly greater alcohol severity at 1, 6, 12, and 16 months post treatment (bs ranging from 1.18 to 1.90) relative to students in the BMI+SFAS condition. In addition, students in the BMI+RT condition reported significantly greater alcohol severity at 1, 6, and 12 months post treatment (bs ranging from 0.78 to 0.96) relative to students in the BMI+SFAS condition. Results revealed that students in the AO condition reported significantly greater alcohol severity at 1 month relative to students in the BMI+RT condition ($b = 0.89$, SE = 0.32, $p = 0.005$). No other significant differences in alcohol severity emerged at 6, 12, and 16 months between AO and BMI+RT in this trajectory.

Discussion

Although a number of laboratory and cross-sectional studies have demonstrated that reward deprivation increases risk for drug and alcohol misuse, relatively few prospective studies have investigated the role of environmental reward and alcohol severity in humans (Higgins et al., 2004; Lamb & Ginsburg, 2018; Murphy et al., 2019; Tucker et al., 2016). To our knowledge the current study is the first to identify distinct trajectories of reward availability in a sample of heavy drinking college students, and the first to assess the impact of brief alcohol interventions on trajectories of reward and on alcohol severity within subgroups of young adults with high versus low levels of environmental reward. Results from GMMs supported a two-trajectory solution: a low-increasing reward availability trajectory (LR), and a high-stable reward availability trajectory (HR). The LR trajectory displayed significantly lower levels of environmental reward that increased within the first month, but remained substantially lower than the HR trajectory across the 16-month follow-up (Figure 1). Individuals in the LR trajectory also reported significantly higher levels of alcohol severity across all five time points compared to the HR trajectory, highlighting the consistent association between lack of environmental reward and AUD (Joyner et al., 2016). This is consistent with extant laboratory and naturalistic research demonstrating that rates of alcohol and drug use are sensitive to the environmental context, and specifically environments that are devoid of non-drug reinforcers increase risk for substance use (Audrain-McGovern et al., 2011; Hogarth & Field, 2020).

Another aim of the current study was to identify baseline predictors of trajectory class membership. Depression, cannabis use, sensation-seeking, and low life satisfaction were all associated with increased probability for classification in the LR trajectory. This extends prior cross-sectional work (Joyner et al., 2016; Magidson et al., 2017; Meshesha et al., 2015) by also connecting these baseline predictors to patterns of growth in reward availability longitudinally. Thus, these risk factors are associated with enduring deficits in reward which increase risk for greater levels of alcohol severity in this sample of non-treatment seeking young adult drinkers.

Reward Trajectory as a Moderator of Treatment Effects

For students in the LR trajectory, the BMI+SFAS was associated with moderate to large effect-size increases in reward availability that persisted across the 16-month follow-up compared with both the BMI+RT and AO conditions. These increases in reward availability seen in the LR trajectory were associated with lower levels of alcohol severity at 1, 6, and 12 months for those in the BMI+SFAS compared to BMI+RT and across all follow-ups when compared to AO.

Although the primary overall group treatment effects reported by Murphy et al. (2019) did not focus on AUD symptomatology, the effect size for treatment effects observed in the current work on alcohol severity was larger for the LR students than the overall treatment effect on alcohol problems without consideration of reward availability trajectory. In addition, this analysis revealed a specific (moderated) treatment advantage for the BMI+SFAS relative to the BMI+RT that was not evident in the primary outcomes, which indicated significant treatment effects for both BMI+SFAS and BMI+RT for weekly drinking and alcohol problems relative to AO, but no difference between the two active treatments (Murphy et al., 2019). Interestingly, the previous analysis from this trial indicated that the treatment effects for both BMI conditions relative to AO were mediated by decreases in recent activity participation and enjoyment related to substance use compared to total activity participation and enjoyment (reinforcement ratio) (Murphy et al., 2019). Taken together, these analyses suggest that both interventions are effective overall and that the effects of both intervention approaches are mediated by a relative shift in recent behavior away from substance-related activities, but that the BMI+SFAS approach is particularly effective for reducing alcohol severity among the relatively small subgroup (30.5%) of participants with more chronic and global deficits in access to environmental reward.

It is encouraging that these higher-risk young adults, who report heavy drinking in addition to low environmental reward and associated risk factors (depressive symptoms, cannabis use, elevated sensation-seeking), are highly responsive to the two session (plus booster phone call) brief alcohol intervention package that focuses on both enhancing motivation to reduce drinking and also identifying future goals and increasing engagement in enjoyable and goal-directed substance-free activities (Murphy et al., 2012). The initial increase in reward in these students in the month after the BMI+SFAS was substantial and the reduction in alcohol severity remained significant over the 16-month follow-up. Although this group remained at higher risk than the HR trajectory, they clearly had a substantial response to the BMI+SFAS intervention. This is consistent with a more general body of basic and applied research indicating that increasing substance-free reward is associated with reductions in drinking and drug use (Higgins et al., 2004; Lamb & Ginsberg, 2018), and provides specific support for reinforcement-based intervention approaches (Daughters et al. 2008; Fazzino et al., 2019; Meshesha et al., 2020), in particular for individuals who present with low levels of environmental reward.

For students in the HR trajectory, BMI+SFAS and BMI+RT only attenuated the slight decline of reward availability compared to AO out to 1 month, and no significant treatment effects were observed between 1–16 months. Students in this trajectory reported high levels of reward across the 16-month follow-up period and low levels of alcohol severity, which only significantly differed across study condition at 1 month. It is possible that these more modest results are due to the fact that these students may experience little functional impairment related to their drinking and may thus be relatively less motivated to change their drinking. They may benefit equally from various assessment or brief intervention approaches.

Strengths and Limitations

Strengths of this study include the fact that it is the first longitudinal study to establish that reward deprivation among young adults is associated with greater levels of alcohol severity. Moreover, this is the first study to establish that a brief intervention that focuses on both reducing drinking and increasing substance-free reward is associated with significant and enduring reductions in alcohol severity among young adults with low levels of environmental reward. There are also several noteworthy limitations. First, the size of the LR trajectory was relatively small ($n = 120$) and the extraction of a small number of classes from the mixture model may suggest a larger than expected amount of homogeneity within the studied population (college student heavy drinkers). While this population may be more homogenous than outpatient treatment or other populations of interest (Blanco et al., 2008), college student drinking has distinct and substantial public health implications on its own even if the results do not fully generalize to other high risk populations (e.g., Caudill et al., 2006; White & Hingson, 2013). That said, future research should attempt to replicate these results with other high-risk groups, including young adult drinkers who are not college students.

Although alcohol use and reward availability were assessed with psychometrically sound indices, our assessments entailed retrospective self-reports and may thus be prone to measurement error related to recall and the need to aggregate past experiences. Additionally, the construct of environmental reward, and in particular substance-free reward, has been operationalized using a number of different measurement approaches (reviewed by Acuff et al., 2019; Heinz et al., 2012) and it remains challenging to precisely measure reward outside of laboratory settings where behavioral allocation (choice) to drugs versus alternatives can be precisely quantified.

Conclusion

Our results indicate that there is important heterogeneity in the course of reward availability over time and identify a distinct subpopulation of college student drinkers who are at increased risk for alcohol misuse and AUD. Among individuals with low levels of environmental reward, the BMI+SFAS intervention was effective in increasing the level of environmental reward and decreasing levels of alcohol severity. These results provide support for brief intervention approaches that attempt to enhance motivation to both reduce drinking and to increase engagement in enjoyable and goal-directed substance-free activities, particularly for higher-risk young adults with low levels of environmental reward. Future research is necessary to explicitly test the feasibility and efficacy of a brief alcohol intervention treatment matching or stepped-care decision heuristic that is based on baseline level of environmental reward.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

This work was supported by NIAAA (R01AA020829; James G. Murphy).

References

Acuff SF, Dennhardt AA, Correia CJ and Murphy JG (2019). Measurement of substance-free reinforcement in addiction: A systematic review. Clinical Psychology Review, 70, 79–90. [PubMed: 30991244]

Alfonso VC, Allison DB, Rader DE and Gorman BS (1996). The extended satisfaction with life scale: Development and psychometric properties. Social Indicators Research, 38(3), 275–301.

American Psychiatric Association (2013). Diagnostic and statistical manual of mental disorders (DSM-5). American Psychiatric Pub.

Asparouhov T and Muthén B (2014a). Auxiliary variables in mixture modeling: Three-step approaches using M plus. Structural Equation Modeling: A Multidisciplinary Journal, 21(3), 329–341.

Asparouhov T and Muthén B (2014b). Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model. Mplus web notes, 21(2), 1–22.

Audrain-McGovern J, Rodriguez D, Rodgers K and Cuevas J (2011). Declining alternative reinforcers link depression to young adult smoking. Addiction, 106(1), 178–187. [PubMed: 20840206]

Berlin KS, Williams NA and Parra GR (2014). An introduction to latent variable mixture modeling (part 1): Overview and cross-sectional latent class and latent profile analyses. Journal of Pediatric Psychology, 39(2), 174–187. [PubMed: 24277769]

Bickel WK, Jarmolowicz DP, MacKillop J, Epstein LH, Carr K, Mueller ET and Waltz TJ (2012). The behavioral economics of reinforcement pathologies: Novel approaches to addictive disorders, in APA Addiction Syndrome Handbook, Vol. 2: Recovery, Prevention, and Other Issues. (pp. 333–363). American Psychological Association.

Bickel WK, Johnson MW, Koffarnus MN, MacKillop J and Murphy JG (2014). The behavioral economics of substance use disorders: reinforcement pathologies and their repair. Annual Review of Clinical Psychology, 10, 641–677.

Blanco C, Okuda M, Wright C, Hasin DS, Grant BF, Liu SM and Olfson M (2008). Mental health of college students and their non–college-attending peers: Results from the national epidemiologic study on alcohol and related conditions. Archives of General Psychiatry, 65(12), 1429–1437. [PubMed: 19047530]

Carvalho JP, Gawrysiak MJ, Hellmuth JC, McNulty JK, Magidson JF, Lejuez CW and Hopko DR (2011). The Reward Probability Index: Design and validation of a scale measuring access to environmental reward. Behavior Therapy, 42(2), 249–262. [PubMed: 21496510]

Caudill BD, Crosse SB, Campbell B, Howard J, Luckey B and Blane HT (2006). High-risk drinking among college fraternity members: A national perspective. Journal of American College Health, 55(3), 141–155. [PubMed: 17175900]

Chen FF (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. Structural Equation Modeling: A Multidisciplinary Journal, 14(3), 464–504.

Cheung GW and Rensvold RB (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. Structural Equation Modeling, 9(2), 233–255.

Cronce JM and Larimer ME (2011). Individual-focused approaches to the prevention of college student drinking. Alcohol Research & Health, 34(2), 210. [PubMed: 22330220]

Collins RL, Parks GA and 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. [PubMed: 3998247]

Daughters SB, Braun AR, Sargeant MN, Reynolds EK, Hopko DR, Blanco C and Lejuez CW (2008). Effectiveness of a brief behavioral treatment for inner-city illicit drug users with elevated depressive symptoms: the life enhancement treatment for substance use (LETS Act!). Journal of Clinical Psychiatry, 69(1), 122.

DeMartini KS, Fucito LM and O'Malley SS (2015). Novel approaches to individual alcohol interventions for heavy drinking college students and young adults. Current Addiction Reports, 2(1), 47–57. [PubMed: 26258001]

Fazzino TL, Bjorlie K and Lejuez CW (2019). A systematic review of reinforcement-based interventions for substance use: Efficacy, mechanisms of action, and moderators of treatment effects. Journal of Substance Abuse Treatment, 104, 83–96. [PubMed: 31370989]

Foxcroft DR, Coombes L, Wood S, Allen D, Santimano NMA and Moreira MT (2016). Motivational interviewing for the prevention of alcohol misuse in young adults. Cochrane Database of Systematic Reviews, (7).

Graham JW, Olchowski AE and Gilreath TD (2007). How many imputations are really needed? Some practical clarifications of multiple imputation theory. Prevention Science, 8(3), 206–213. [PubMed: 17549635]

Grant BF, Goldstein RB, Saha TD, Chou SP, Jung J, Zhang H, Pickering RP, Ruan WJ, Smith SM, Huang B and Hasin DS (2015). Epidemiology of DSM-5 alcohol use disorder: results from the National Epidemiologic Survey on Alcohol and Related Conditions III. JAMA Psychiatry, 72(8), 757–766. [PubMed: 26039070]

J Heinz A, C Lilje T, D Kassel J and de Wit H (2012). Quantifying reinforcement value and demand for psychoactive substances in humans. Current Drug Abuse Reviews, 5(4), 257–272. [PubMed: 23062106]

Henry JD and Crawford JR (2005). The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample. British Journal of Clinical Psychology, 44(2), 227–239.

Higgins ST, Heil SH and Lussier JP (2004). Clinical implications of reinforcement as a determinant of substance use disorders. Annu. Rev. Psychol, 55, 431–461. [PubMed: 14744222]

Hingson R, Zha W and Smyth D (2017). Magnitude and trends in heavy episodic drinking, alcohol-impaired driving, and alcohol-related mortality and overdose hospitalizations among emerging adults of college ages 18–24 in the United States, 1998–2014. Journal of Studies on Alcohol and Drugs, 78(4), 540–548. [PubMed: 28728636]

Hogarth L and Field M (2020). Relative expected value of drugs versus competing rewards underpins vulnerability to and recovery from addiction. Behavioural Brain Research, 112815. [PubMed: 32707138]

Hoyle RH, Stephenson MT, Palmgreen P, Lorch EP and Donohew RL (2002). Reliability and validity of a brief measure of sensation seeking. Personality and Individual Differences, 32(3), 401–414.

Huh D, Mun EY, Larimer ME, White HR, Ray AE, Rhew IC, Kim SY, Jiao Y and Atkins DC (2015). Brief motivational interventions for college student drinking may not be as powerful as we think: An individual participant-level data meta-analysis. Alcoholism: Clinical and Experimental Research, 39(5), 919–931.

Joyner KJ, Acuff SF, Meshesha LZ, Patrick CJ and Murphy JG (2018). Alcohol family history moderates the association between evening substance-free reinforcement and alcohol problems. Experimental and Clinical Psychopharmacology, 26(6), 560. [PubMed: 30148404]

Joyner KJ, Pickover AM, Soltis KE, Dennhardt AA, Martens MP and Murphy JG (2016). Deficits in access to reward are associated with college student alcohol use disorder. Alcoholism: Clinical and Experimental Research, 40(12), 2685–2691.

Kline RB (2016). Principles and practice of structural equation modeling. Guilford publications.

Koob GF and Le Moal M (2008). Addiction and the brain antireward system. Annu. Rev. Psychol, 59, 29–53. [PubMed: 18154498]

Lamb RJ and Ginsburg BC (2018). Addiction as a BAD, a behavioral allocation disorder. Pharmacology Biochemistry and Behavior, 164, 62–70.

Lee JO, Cho J, Yoon Y, Bello MS, Khoddam R, & Leventhal AM (2018). Developmental pathways from parental socioeconomic status to adolescent substance use: Alternative and complementary reinforcement. Journal of Youth and Adolescence, 47(2), 334–348. [PubMed: 29188410]

Lewis CC, Simons AD and Kim HK (2012). The role of early symptom trajectories and pretreatment variables in predicting treatment response to cognitive behavioral therapy. Journal of Consulting and Clinical Psychology, 80(4), 525. [PubMed: 22730951]

Lo Y, Mendell NR and Rubin DB (2001). Testing the number of components in a normal mixture. Biometrika, 88(3), 767–778.

Lubman DI, Yücel M, Kettle JW, Scaffidi A, MacKenzie T, Simmons JG and Allen NB (2009). Responsiveness to drug cues and natural rewards in opiate addiction: associations with later heroin use. Archives of General Psychiatry, 66(2), 205–212. [PubMed: 19188543]

MacKillop J and Murphy JG (2007). A behavioral economic measure of demand for alcohol predicts brief intervention outcomes. Drug and Alcohol Dependence, 89(2–3), 227–233. [PubMed: 17289297]

Magidson JF, Robustelli BL, Seitz-Brown CJ and Whisman MA (2017). Activity enjoyment, not frequency, is associated with alcohol-related problems and heavy episodic drinking. Psychology of Addictive Behaviors, 31(1), 73. [PubMed: 27631613]

McPhee MD, Keough MT, Rundle S, Heath LM, Wardell JD and Hendershot CS (2020). Depression, environmental reward, coping motives and alcohol consumption during the COVID-19 pandemic. Frontiers in Psychiatry, 11, 1128.

Meshesha LZ, Dennhardt AA and Murphy JG (2015). Polysubstance use is associated with deficits in substance-free reinforcement in college students. Journal of Studies on Alcohol and Drugs, 76(1), 106–116. [PubMed: 25486399]

Meshesha LZ, Soltis KE, Wise EA, Rohsenow DJ, Witkiewitz K and Murphy JG (2020). Pilot trial investigating a brief behavioral economic intervention as an adjunctive treatment for alcohol use disorder. Journal of Substance Abuse Treatment, 113, 108002. [PubMed: 32359674]

Morris V, Amlung M, Kaplan BA, Reed DD, Petker T and MacKillop J (2017). Using crowdsourcing to examine behavioral economic measures of alcohol value and proportionate alcohol reinforcement. Experimental and Clinical Psychopharmacology, 25(4), 314. [PubMed: 28627926]

Murphy JG, Correia CJ, Colby SM and Vuchinich RE (2005). Using behavioral theories of choice to predict drinking outcomes following a brief intervention. Experimental and Clinical Psychopharmacology, 13(2), 93. [PubMed: 15943542]

Murphy JG, Dennhardt AA, Martens MP, Borsari B, Witkiewitz K and Meshesha LZ (2019). A randomized clinical trial evaluating the efficacy of a brief alcohol intervention supplemented with a substance-free activity session or relaxation training. Journal of Consulting and Clinical Psychology, 87(7), 657. [PubMed: 31070386]

Muthén B (2001). Second-generation structural equation modeling with a combination of categorical and continuous latent variables: New opportunities for latent class–latent growth modeling.

Muthén B, Brown CH, Masyn K, Jo B, Khoo ST, Yang CC, Wang CP, Kellam SG, Carlin JB and Liao J (2002). General growth mixture modeling for randomized preventive interventions. Biostatistics, 3(4), 459–475. [PubMed: 12933592]

Muthén LK and Muthén BO (1998–2017). Mplus, user's guide. eight edition. Los Angeles, CA: Muthén & Muthén.

Muthén LK and Muthén BO (2000). Mplus. Statistical analysis with latent variables. User's guide, second edition. Los Angeles, CA: Muthén & Muthén.

Noyes ET, Levine JA, Schlauch RC, Crane CA, Connors GJ, Maisto SA and Dearing RL (2018). Impact of pretreatment change on mechanism of behavior change research: An applied example using alcohol abstinence self-efficacy. Journal of Studies on Alcohol and Drugs, 79(2), 223–228. [PubMed: 29553349]

Nylund KL, Asparouhov T and Muthén BO (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. Structural Equation modeling: A Multidisciplinary Journal, 14(4), 535–569.

Oslin D (2011). Personalized addiction treatment: how close are we?. Alcohol and Alcoholism, 46(3), 231–232. [PubMed: 21508195]

Raftery AE (1995). Bayesian model selection in social research. Sociological Methodology, 111–163.

Read JP, Kahler CW, Strong DR and Colder CR (2006). Development and preliminary validation of the young adult alcohol consequences questionnaire. Journal of Studies on Alcohol, 67(1), 169–177. [PubMed: 16536141]

Schwarz G (1978). Estimating the dimension of a model. Annals of Statistics, 6(2), 461–464.

Scott-Sheldon LA, Carey KB, Elliott JC, Garey L and Carey MP (2014). Efficacy of alcohol interventions for first-year college students: a meta-analytic review of randomized controlled trials. Journal of Consulting and Clinical Psychology, 82(2), 177. [PubMed: 24447002]

Tanner-Smith EE and Lipsey MW (2015). Brief alcohol interventions for adolescents and young adults: A systematic review and meta-analysis. Journal of Substance Abuse Treatment, 51, 1–18. [PubMed: 25300577]

Tucker JA, Cheong J, Chandler SD, Lambert BH, Pietrzak B, Kwok H and Davies SL (2016). Prospective analysis of behavioral economic predictors of stable moderation drinking among problem drinkers attempting natural recovery. Alcoholism: Clinical and Experimental Research, 40(12), 2676–2684.

White A and Hingson R (2013). The burden of alcohol use: excessive alcohol consumption and related consequences among college students. Alcohol Research: Current Reviews.

Public Significance

Among individuals with low levels of environmental reward, a brief alcohol intervention that also includes a focus on increasing substance-free activities was effective in increasing the level of environmental reward and decreasing levels of alcohol severity. These results provide support for brief intervention approaches that attempt to enhance motivation to both reduce drinking and to increase engagement in enjoyable and goal-directed substance-free activities, particularly for higher-risk young adults with low levels of environmental reward.

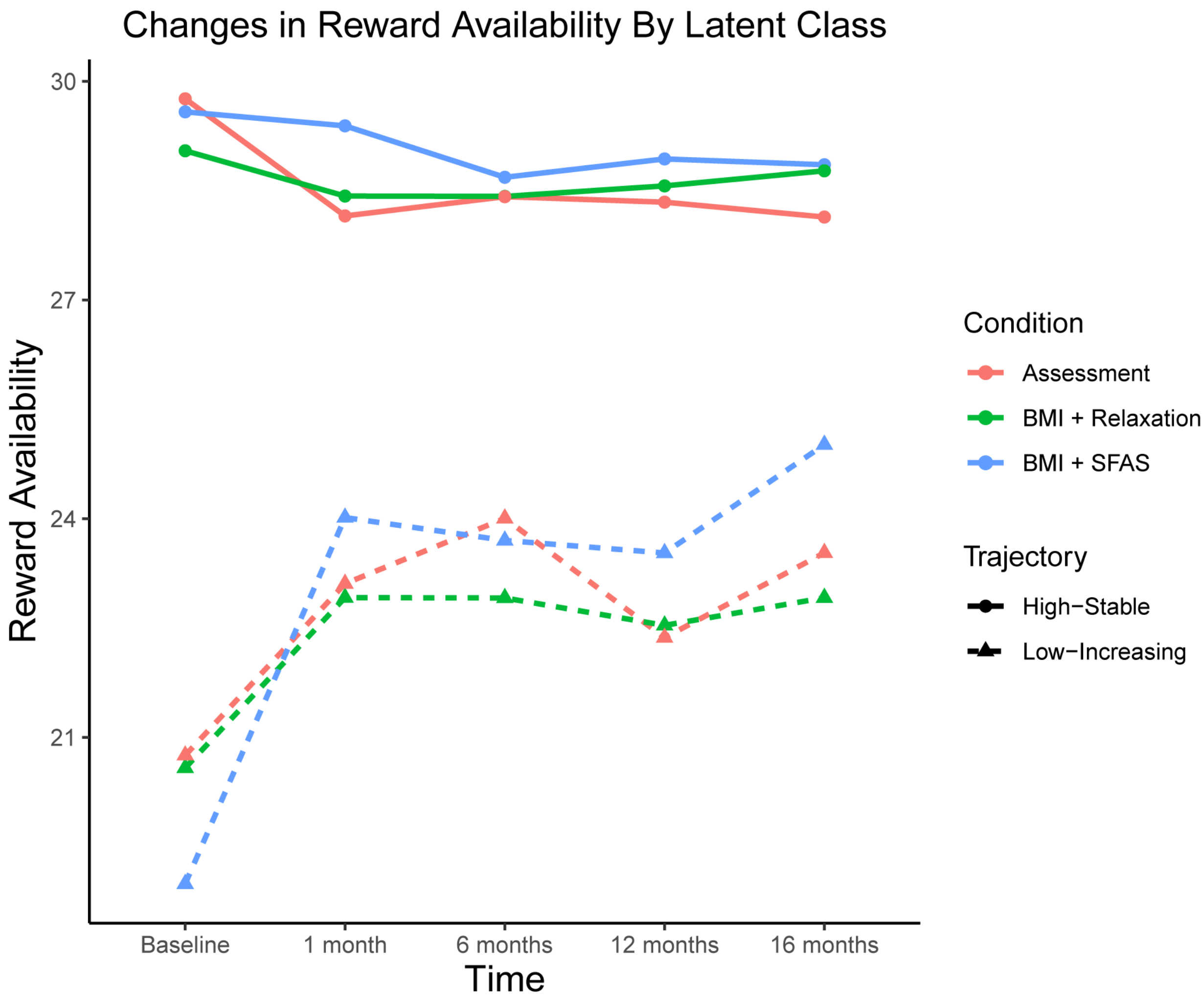

Figure 1. Changes in Reward Availability by Condition and Class.

Note. BMI = Brief motivational intervention; SFAS = Substance-Free Activity Session; RT = Relaxation Training; AO = Assessment only. For students in the High-Stable Reward trajectory (n = 273), the AO condition showed a significant decrease in reward availability from baseline to one month. This significant decrease in reward availability was not found in either BMI condition. In the Low-Increasing Reward trajectory (n = 120), students receiving BMI+SFAS had significantly greater increases in reward availability from baseline to one month, compared to both BMI+RT and AO. Trajectories of reward availability did not significantly differ between BMI+RT and AO conditions.

Table 1.

Fit Statistics for GMM Class Solutions One Through Four for Joint Analysis

	Number of Classes			
Fit Statistics	**1**	**2**	**3**	**4**
LL	−5103.95	−4969.04	−4927.47	−4894.59
BIC	10303.47	**10117.30**	10117.78	10135.67
LMR	-	266.61	82.18	64.97
LMR *p*	-	**< .001**	0.27	0.09
Entropy	-	**0.81**	0.76	0.79
Count (%)				
Class 1	393 (100.0%)	273 (69.5%)	161 (41.0%)	168 (42.8%)
Class 2	-	120 (30.5%)	152 (38.7%)	127 (32.3%)
Class 3	-	-	80 (20.3%)	78 (19.8%)
Class 4	-	-	-	20 (5.1%)

Note. LL = log likelihood; BIC = Bayesian Information Criterion; LMR = Lo-Mendell-Rubin. A five-class solution was also tested, but the model did not converge.

Table 2.

Characteristics of Students Following the Two Latent Trajectories

	Low-Increasing Reward *n* = 120		High-Stable Reward *n* = 273		Comparison	
	Mean (*n*)	**SE (%)**	**Mean (*n*)**	**SE (%)**	**F/χ^2**	***p***
Demographics						
Female	67	55.8%	121	63.0%	2.33	0.127
Non-White	35	29.2%	48	17.6%	3.25	0.071
Age	18.9	0.12	18.9	0.07	1.27	0.261
Greek Status	36	30.0%	89	32.6%	0.72	0.699
Campus 1	48	40.0%	132	48.4%	0.76	0.388
Baseline Characteristics						
Depressive Symptoms	14.7	1.01	2.8	0.44	82.07	<.001
Cannabis Frequency	7.6	0.96	3.9	0.54	8.44	.004
Sensation-Seeking	15.3	0.31	14.1	0.20	9.01	.003
Life Satisfaction	21.6	0.65	28.8	0.31	91.61	< .001
Heavy Drinking	6.5	0.41	6.0	0.30	0.66	0.418
Alcohol Problems	16.2	0.81	10.9	0.53	23.34	<.001
AUD Symptom Count	4.4	0.23	2.08	0.11	104.29	<.001
Past-Year AUD					75.99	<.001
No AUD	13	10.8%	125	45.8%		
Mild	33	27.5%	91	33.3%		
Moderate	38	31.7%	39	14.3%		
Severe	36	30.0%	18	6.6%		
Treatment Group						
BMI+SFAS	39	32.5%	90	33.0%	2.33	0.127
BMI+RT	39	32.5%	86	31.5%	0.002	0.963
Unstandardized Estimates from Two Trajectory Piecewise Model						
Baseline Reward Availability	20.9**	0.65	29.8**	0.32	79.57	< .001
Initial Change Slope	2.3**	0.64	−1.7**	0.41	-	-
Maintenance Slope	−0.1	0.07	0.03	0.03	-	-
Effect of BMI+SFAS On:						
Initial Change Slope[a]	2.8**	0.71	1.5**	0.56	-	-
Maintenance Slope[b]	0.01	0.08	−0.02	0.04	-	-
Effect of BMI+RT On:						
Initial Change Slope[a]	−0.4	0.84	1.19*	0.60	-	-
Maintenance Slope[b]	0.04	0.11	−0.01	0.06	-	-

Note. SE = Standard error;

* = $p < .05$;

** = $p < .01$.

Demographics and baseline characteristics are displayed as means and standard errors for continuous variables, and as the number of participants and percentages for categorical variables.

[a.]Expected change from baseline to 1 month.

[b.]Expected monthly change from the 1 month to the 16 month assessment.

Table 3.

Regression Analysis Examining Alcohol Severity Latent Factors on Intervention Condition by Latent Trajectory

		Intervention Status					
		AO vs BMI+SFAS *b* [95% CI]	***p***	**BMI+RT vs BMI+SFAS *b* [95% CI]**	***p***	**AO vs BMI+RT *b* [95% CI]**	***p***
High-Stable Reward							
Alcohol Severity	1	0.66 [0.33, 0.99]	<.001	−0.37 [−0.85, 0.11]	.053	1.04 [0.63, 1.45]	<.001
	6	0.52 [−0.02, 1.06]	.060	−0.01 [−0.41, 0.42]	.965	0.53 [−0.01, 1.06]	.053
	12	0.01 [−0.68, 0.69]	.982	−0.04 [−0.57, 0.49]	.893	0.05 [−0.62, 0.72]	.878
	16	−0.16 [−0.83, 0.50]	.629	−0.15 [−0.76, 0.46]	.633	−0.01 [−0.67, 0.65]	.978
Low-Increasing Reward							
Alcohol Severity	1	1.64 [1.08, 2.21]	<.001	0.78 [0.20, 1.31]	.024	0.89 [0.27, 1.51]	.005
	6	1.18 [0.35, 2.02]	.020	0.96 [0.17, 1.65]	.028	0.23 [−0.71, 1.16]	.638
	12	1.90 [0.98, 2.82]	<.001	0.92 [0.10, 1.75]	.046	0.98 [−0.03, 1.98]	.056
	16	1.63 [0.61, 2.65]	.009	0.37 [−0.61, 2.65]	.532	1.25 [−0.07, 2.58]	.071

Note. Unstandardized estimates are interpreted in AUD symptom count metric. CI = Confidence interval. The second intervention condition contrast is the reference category. Regression coefficients were estimated using covariate-adjusted means, controlling for sex, race, mean levels of depressive symptoms, household income, and baseline alcohol severity.