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Change in alcohol demand following a brief intervention predicts change in alcohol use: A latent growth curve analysis

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Abstract

Background: The association between behavioral economic demand and various alcohol use outcomes is well-established. However, few studies have examined whether changes in demand occur following a brief alcohol intervention (BAI), and whether this change predicts alcohol outcomes over the long-term.

Methods: Parallel process piecewise latent growth curve models were examined in a sample of 393 heavy drinking emerging adults (60.8% women; 85.2% white; M_{age} = 18.77) in which two linear slopes represented rates of change in alcohol use, heavy drinking episodes, alcohol-related problems, and demand (intensity and O_{max}) from baseline to 1-month (slope 1) and 1-month to 16-month (slope 2). Mediation analyses were conducted to estimate the effect of a BAI on 16-month alcohol outcomes through slope 1 demand.

Results: A two-session BAI predicted significant reductions in all five outcomes from baseline to 1-month follow-up. Although no further reduction was observed from 1-month to 16-month follow-up, there was no regression to baseline levels. Slope 1 demand intensity, but not O_{max}, significantly mediated the association between BAI and both outcomes, heavy drinking episodes

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(*Est.* = −0.23, *SE* = 0.08, $p < 0.01$) and alcohol-related problems (*Est.* = −0.15, *SE* = 0.07, $p < 0.05$) at 16-month follow-up.

Conclusions: Reducing high valuation of alcohol among heavy drinking emerging adults within the first month is critical for the long-term efficacy of a BAI. A two-session BAI was associated with enduring reductions in alcohol demand, and the change in demand intensity, but not O_{max}, was associated with sustained reduction in heavy drinking and alcohol-related problems.

Keywords

Behavioral Economics; Demand; Alcohol; Brief Motivational Intervention; Emerging Adults

Introduction

Alcohol demand curve analyses generate several behavioral economic indices that reflect individual's strength of desire to purchase and consume alcohol across a range of drink prices (Bickel et al., 2000). Although alcohol-related cost-benefit decision-making processes extend beyond the monetary price of alcohol and likely incorporate the personal, social, and health costs and benefits of drinking (Joyner et al., 2019), quantifying monetary cost-benefit decision-making may provide a convenient proxy for the reinforcing efficacy of alcohol. Hypothetical alcohol purchase tasks (APTs) are modeled after laboratory self-administration paradigms and allow for the convenient quantification of multiple indices of demand (Murphy and MacKillop, 2006). These indices include *intensity* (number of drinks consumed at price = $0.00), O_{max} (highest expenditure across all price points), *elasticity* (relative sensitivity of consumption to change in price), *breakpoint* (first price point at which alcohol consumption is suppressed to 0), and P_{max} (price point at which O_{max} occurs and demand shifts from being relatively inelastic to relatively elastic). These indices of alcohol demand correlate highly with laboratory self-administration paradigms that include actual drink purchases, providing evidence of their validity as indicators of an individual's degree of preference for alcohol (Amlung and MacKillop, 2015; Amlung et al., 2012).

Alcohol demand indices have also demonstrated unique associations with various indices of alcohol use severity, ranging from drinking levels to AUD symptoms and specific risk behaviors like drinking and driving, even in models that control for drinking level (Martínez-Loredo et al., 2021). This suggests that demand may provide unique information about individual differences in alcohol reinforcing efficacy that are not captured by recent drinking reports (Teeters et al., 2014). Because numerous factors influence an individual's recent drinking behavior (e.g., availability of alcohol for those who are underage, peer drinking, work/school responsibilities), recent drinking reports may not fully capture an individual's strength of desire to drink across a range of possible future situations. Alcohol purchase task assessments of maximum desired consumption, relative price sensitivity of consumption, and maximum monetary expenditure in a hypothetical scenario appear to provide unique information on alcohol reinforcing efficacy that might portend the degree of future consumption and sensitivity to social and health "costs" associated with drinking. As such, it could also be useful in assessing clinical risk and need for intervention services.

Although each of the demand indices contributes to a multifaceted estimate of the reinforcing efficacy of alcohol, intensity and O_{max} have demonstrated more consistent and robust associations with alcohol use and problem severity than other demand indices (Martínez-Loredo et al., 2021; Zvorsky et al., 2019). Both intensity and O_{max} are associated with alcohol use, and intensity has shown significant cross-sectional associations with hazardous and heavy drinking, AUD symptom criteria, and alcohol-related consequences (Bertholet et al., 2015; Martínez-Loredo et al., 2021; Skidmore et al., 2014). In both cross-sectional and longitudinal/experimental studies, mean effect sizes for alcohol intensity and O_{max} were greater than those for other alcohol demand indices (Zvorsky et al., 2019).

Alcohol Demand Indices: Stability and Malleability

Demand indices are relatively stable over one month, particularly for individuals whose actual consumption does not fluctuate substantially (Acuff and Murphy, 2017), thereby supporting their potential as individual difference measures. However, demand curve indices also appear to capture dynamic changes in alcohol reward efficacy in response to salient drinking contexts that might influence one's desire to seek alcohol rewards. For example, physiologically salient experiences such as craving or stress increase state-level demand intensity (Amlung and MacKillop, 2014; MacKillop et al., 2010; Owens et al., 2015b). Conversely, changing APT vignettes to include a next-day responsibility, such as work or a college class (Gentile et al., 2012; Skidmore and Murphy, 2011), or an alternative, such as a soft drink (Martinetti et al., 2019), can reduce alcohol demand intensity and O_{max}, and the experience of negative alcohol-related consequences is also associated with lower next-day demand intensity when measured using a daily diary assessment approach (Merrill and Aston, 2020).

Alcohol Demand and Response to Brief Alcohol Intervention.—Alcohol demand intensity and O_{max}, when measured prior to an intervention, have been shown to predict responsiveness to intervention, with greater baseline demand predicting greater follow-up drinking in models that controlled for baseline drinking. Moreover, several studies suggest that demand also decreases when measured before and immediately after a pharmacological or behavioral intervention (see Acuff et al., 2019). A meta-analysis by Acuff et al. (2019) found that five studies of primarily adult cigarette smokers demonstrated a significant but small-to-medium magnitude reduction in demand intensity following pharmacotherapy intervention. The same meta-analysis also detected a large effect size reduction in demand intensity and a medium effect size reduction in O_{max} following a behavioral intervention in six studies (3 with heavy drinking college students, 3 with adult smokers). Whereas pharmacotherapy mechanisms of action are likely related to their targeted effects on the brain's reward system (Bujarski et al., 2012), behavioral intervention mechanisms of action on demand are less clear. Many brief alcohol interventions include personalized normative feedback on drinking levels, as well as feedback on consequences of heavy alcohol use and discussion of protective behavioral strategies (Reid and Carey, 2015). These components may reduce the reinforcing efficacy of alcohol by making the potential social and health costs of drinking more salient. Indeed, Murphy et al. (2015) found that both baseline demand, reflecting strength of desire for alcohol rewards prior to the intervention, and change in demand from baseline to post-intervention, reflecting degree of impact of the intervention on desire to drink, predicted change in drinking following a BAI with heavy drinking college students. Intervention elements that increase alternatives to drinking or reduce stress may further decrease alcohol demand (Acuff et al., 2019; Dennhardt et al., 2015).

Taken together, demand may provide a clinically relevant baseline severity indicator and post-intervention marker of response to intervention that is relatively easy to administer and could signal either a successful response or the need for further intervention. However, brief intervention studies that have examined demand have been limited by short follow-up periods (i.e., ≤ 6-months; Dennhardt et al., 2015) and relatively small sample sizes ($n \leq 133$) and have not allowed for a determination of: (a) the extent to which alcohol demand, measured before intervention, predicts long-term change in drinking and problems in response to intervention, (b) the long-term impact of alcohol intervention on behavioral economic demand, or (c) the extent to which change in demand following intervention mediates change in drinking and problems associated with brief intervention.

The Present Study

The current study extends previous research by evaluating trajectories of change in alcohol demand intensity and O_{max} over 16 months using a longitudinal structural equation modeling approach with a large ($N = 393$) multi-site sample of emerging adults who report recent heavy episodic drinking (Murphy et al., 2019). Intensity and O_{max} are reliable indices of alcohol demand that have strong and consistent associations with alcohol-related outcomes (Martínez-Loredo et al., 2021; Murphy et al., 2009). Thus, we were interested in modeling the interrelationships between intensity, O_{max}, alcohol use (past-month typical drinks per week and past-month heavy drinking episodes [HDEs]), and past-month alcohol-related problems, which were assessed at baseline and at 1, 6, 12, and 16 months following brief alcohol interventions (BAIs) designed to reduce potentially hazardous alcohol use among college students. The current study was an original analysis of secondary outcomes of a randomized clinical trial conducted by Murphy et al. (2019) in which heavy drinking college students were randomized to one of three study conditions. Although previous research has established that BAIs are associated with reductions in demand, and that change in demand predicts short-term (6-month) change in drinking (Dennhardt et al., 2015; Murphy et al., 2015), this is the first study with a large sample and frequent follow-ups up to 16 months to formally evaluate alcohol demand as a mediator of intervention response. Importantly, in contrast to previous analytical approaches, the latent curve growth modeling (LGCM) approach in the current study is sophisticated and advantageous in that it incorporates and accounts for valuable intra- and inter-individual variability and heterogeneity in the model (Duncan and Duncan, 2009; McArdle, 1988; Meredith and Tisak, 1990).

Thus, to further evaluate demand as a potentially clinically significant baseline indicator of likely response to intervention, we hypothesized that baseline demand intensity and O_{max} would predict change in alcohol use (drinks per week and HDEs) and problems in the month immediately following the intervention. Next, to examine demand as a post-intervention marker of response to intervention, we hypothesized that intervention conditions (BAIs vs.

control) would predict change in demand intensity and O_{max} from baseline to one-month post-intervention. Specifically, we expected that the BAI conditions would be associated with larger reductions in both demand indices compared to the assessment only control condition. We also hypothesized that change in demand would be associated with change in alcohol use and problems from baseline to one-month post-intervention, such that larger reductions in demand would coincide with larger reductions in alcohol use and related problems. Finally, we hypothesized that change in demand from baseline to one-month post-intervention would mediate the association between intervention condition and alcohol use and problems at 16-month follow-up. In particular, we expected that the BAIs would be associated with larger reductions in demand, which would, in turn, predict lower alcohol use and fewer problems at 16-month follow-up.

Materials and Methods

Participants and Procedure

Participants were 393 first- and second-year undergraduate college students who were recruited from the University of Memphis and the University of Missouri, two large public universities in the mid-south United States (60.8% women; M_{age} = 18.77, SD = 1.07, range = 18-25). The University of Memphis is located in an urban area, and the University of Missouri is located in a rural college town. All participants reported at least two past-month HDEs (4/5+ standard drinks for women/men respectively in an occasion; see Table 1 for drinking characteristics). Participants were recruited from undergraduate courses and campus-wide emails in the fall of each academic year over four years and received extra course credit and/or research payments to compensate them for their participation in the study. All follow-ups occurred within the academic year. Eligible participants were randomized to one of three study conditions following the baseline assessment: (1) Assessment-only control (AO); (2) a Brief Alcohol Intervention (BAI) + Relaxation Training (RT); and (3) a BAI + Substance-Free Activity Session (SFAS). The SFAS is a behavioral economic-informed intervention approach that attempts to reduce desire for alcohol by increasing future orientation and engagement in substance-free activities that might serve as alternatives to drinking. Murphy et al. (2019) found significant reductions in alcohol use in both BAI conditions, relative to the AO condition, from baseline to 1-month follow-up. This treatment gain remained significant, albeit with some fluctuations, through the 16-month follow-up. There were no significant differences in drinking outcomes between the two BAI conditions. The university's Institutional Review Board approved all procedures. This study is registered with clinicaltrials.gov (NCT02834949).

Measures

All measures were administered in an online assessment survey that participants completed on computers in the laboratory.

Alcohol demand.—A hypothetical Alcohol Purchase Task (APT; Murphy and MacKillop, 2006) was used to assess alcohol demand. Participants read a standardized hypothetical drinking scenario vignette and were then asked how many drinks they would purchase and consume at each of the following prices: $0 (free), $0.25, $0.50, $1.00, $1.50, $2.00,

\$2.50, \$3.00, \$3.50, \$4.00, \$4.50, \$5.00, \$5.50, \$6.00, \$7.00, \$8.00, \$9.00, \$10.00, \$15.00, and \$20.00. Of the five indices that can be obtained from the APT (intensity, O_{max}, elasticity, breakpoint, P_{max}), only observed intensity (consumption at price = \$0) and O_{max} (maximum expenditure, determined by multiplying each price point by reported number of drinks consumed at that respective price) were used in the current study.[1] Several studies of the hypothetical APT have shown evidence for its reliability and validity (Amlung and MacKillop, 2015; Amlung et al., 2012; MacKillop and Murphy, 2007; Murphy and MacKillop, 2006). See Supplemental Material for the full task vignette.

Alcohol use.—The Daily Drinking Questionnaire (DDQ; Collins et al., 1985) asks participants to estimate the total number of standard drinks they consumed each day during a typical week in the past month, which are then summed to produce the total number of drinks per week. Additional questions were included to assess past-month frequency of heavy drinking episodes (HDEs), defined as four or more standard drinks in one occasion for women and five or more for men.

Alcohol-related problems.—The Young Adult Alcohol Consequences Questionnaire (YAACQ; Read et al., 2006) is a 48-item yes/no self-report measure that was used to assess past-month alcohol-related problems. Example items include “I often drank more than I originally had planned” and “I’ve not been able to remember large stretches of time while drinking heavily.” One additional item (“Because of my drinking I have had sex with someone I wouldn’t ordinarily have sex with”) was added for a total of 49 items. Internal consistency at each assessment time point in the current sample was excellent (Cronbach’s α = 0.90, 0.92, 0.93, 0.94, and 0.95).

Data Analysis

Prior to our longitudinal modeling procedures, we completed data screening procedures consistent with standard recommendations for APT data (Stein et al., 2015). Due to non-systematic or inconsistent responding, we omitted four participants from baseline APT data, one from 1-month follow-up, six from 6-month follow-up, two from 12-month follow-up, and four from 16-month follow-up. In contrast to standard recommendations, however, given that the focus of the study was to examine change in demand, we considered zero values for intensity and O_{max} as valid scores for individuals expressing no desire to purchase and consume alcohol. No participants reported zero demand at baseline. Eight participants reported zero demand at 1-month follow-up, 18 at 6-month, 12 at 12-month, and eight at 16-month. From the remaining participants who provided systematic APT responses, we extracted observed demand intensity and O_{max} from the individual participant demand curves. All variables were examined for skew and kurtosis. Only drinks per week was subsequently square root transformed at all five time points. Following the power transformation, distributions for drinks per week at all time points showed acceptable levels of skew and kurtosis ($-2 >$ and < 2).

[1]Descriptive statistics and correlations among alcohol use outcomes and demand indices of elasticity, breakpoint, and P_{max} are available in the Supplemental Materials.

We used Mplus version 8.2 (Muthén and Muthén, 1998-2017) to model our latent growth curves (LGCM). Missing data were handled using the full information maximum likelihood (FIML) estimation method, as it uses all available information from each participant and has demonstrated unbiased parameter estimates and standard errors for data missing at random (Acock, 2005; Enders and Bandalos, 2001). Although the assumption of missing at random (MAR) cannot directly be checked with data, this assumption is widely considered reasonable for typical longitudinal data analysis (Enders, 2010), including the one in the current study. Further, robust maximum likelihood (MLR) estimation used across all models for non-normal data also helps derive robust standard errors when missing data are present (see Enders, 2010, pp. 143-145). We examined three model fit indices to estimate how well the models fit our data: the Root Mean Square Error of Approximation (RMSEA; Steiger, 1990; Steiger and Lind, 1980), the Comparative Fit Index (CFI; Bentler, 1990), and the Standardized Root Mean Squared Residual (SRMR). RMSEA values below 0.08, CFI values greater than 0.90, and SRMR values less than 0.08 indicate good model fit (Garnier-Villarreal and Jorgensen, 2020; Schumacker and Lomax, 2004). We also include the Bayesian Information Criterion (BIC) to provide relative model fit comparisons for non-nested models, with relatively smaller values indicating better model fit and parsimony. Our modeling and analytic procedures were conducted in the following four steps.

Step 1: Determine the Individual Growth Trajectories for Demand Intensity, O_{max}, Drinks Per Week, Heavy Drinking Episodes, and Alcohol-Related Problems.—Univariate LGCMs with intercept only, linear, quadratic, and piecewise growth functions were tested separately for demand intensity, O_{max}, drinks per week, HDEs, and alcohol-related problems. Intercept models assume no change from baseline to 16-month follow-up. Linear models assume a steady rate of change over time. Quadratic models assume a slowing or accelerating rate of linear change over time. Finally, a piecewise growth model hypothesizes that there may be at least two distinctive growth phases. Graphing of mean scores for each outcome across the five assessment timepoints provided visual evidence that a linear-linear piecewise growth function could provide the best fit to our data (see Supplemental Figure 1). The piecewise growth function for demand intensity and O_{max} was estimated with the latent intercept at baseline and two linear slopes: baseline to 1-month (slope 1) and 1-month to 16-month (slope 2). We estimated the same piecewise growth functions for alcohol use outcomes (drinks per week, HDEs, related problems) with only one difference. We set 16-month alcohol use as the latent intercept (constrained to 0) instead of baseline, given that we anticipated predicting 16-month alcohol use in our final model. To identify the piecewise models, the variance of the latent residual variable at baseline for each outcome was fixed at zero.[2]

Step 2: Determine the Effects of Covariates on Individual Growth Trajectories. —With the piecewise model selected as the optimal growth function for each outcome, conditional piecewise models were estimated in which intervention condition, sex, race/

[2]Inspection of residual variance estimates in the previous linear and quadratic LGCMs for each outcome suggested significant unexplained variability at baseline (e.g., measurement error). As such, constraining the variance of latent residual variable at baseline to 0 likely overestimates the variance of the latent intercept variable (i.e., individual differences at baseline). Therefore, latent intercept variances at baseline need to be interpreted cautiously.

ethnicity, and university site were specified as dichotomous covariates of the latent growth factors. Given that the parent study observed intervention effects on alcohol use and problems for both BAI conditions vs. Assessment-only control condition, but no difference between the BAI conditions,[3] original intervention conditions were dichotomized as 0 = Assessment-only (AO; *n* = 138) and 1 = BAI (*n* = 255) in the current study. Sex and race/ethnicity were also dichotomized as 0 = males (*n* = 154) and 1 = females (*n* = 239), and 0 = Person of Color[4] (POC, *n* = 81) and 1= white (*n* = 312). Finally, university site was included dichotomously as 0 = urban (Memphis, *n* = 215) and 1 = college town (Missouri, *n* = 178).

Step 3: Evaluate Demand and Alcohol Growth Trajectories Simultaneously.— Three separate parallel process piecewise models were estimated to simultaneously model associations between demand (intensity and O_{max}) and alcohol outcomes (drinks per week, HDEs, problems) growth factors without (Model 3a) and with (Model 3b) the adjustment of the effects of the covariates on latent intercept, slope 1, and slope 2. Compared to Models 1 and 2, which were aimed at providing overall descriptive summaries and fit of each trajectory, Models 3a and 3b (multivariate, parallel process LGCMs) were intended to describe the conditional change process of alcohol outcomes given the set of covariates and covariate-modified alcohol demand growth parameters.

Step 4: Evaluate Demand as a Clinically Relevant Baseline Severity Indicator and Post-Intervention Marker of Response to Intervention.—Our final model, Model 4 (see Figure 1), was based on Model 3b and was aimed at examining our primary hypotheses represented in the following paths: baseline demand predicting the initial decline in alcohol outcomes (Alcohol Outcomes Slope 1), intervention condition predicting 1-month change in alcohol demand, and 1-month change in alcohol demand mediating the association between intervention condition and alcohol outcomes at 16-month follow-up. To test these, we included direct paths from the observed variable intervention condition to latent slope 1 factors of demand and all latent growth factors of alcohol outcomes (slope 1, slope 2, and intercept). Covariate paths were trimmed to include sex predicting demand intensity and alcohol outcomes latent intercepts, and sex, race/ethnicity, and university site predicting all alcohol outcomes latent intercepts. Given our hypotheses, our results focus on Models 3b and 4.

Results

Descriptive Analysis

In the hypothetical APT, alcohol purchases generally decreased in response to increasing prices at each time point. The exponentiated equation for fitting demand curve data provided excellent fit (sample mean and median R^2 values ranged from 0.89 to 0.91 across

[3]Linear regression models testing for a BAI condition effect (that is BAI + Relaxation Training vs. BAI + Substance-Free Activity Session) on alcohol demand intensity and O_{max} similarly found no significant differences in demand by intervention condition at any follow-up timepoint. Therefore, we deemed it appropriate to combine the BAI conditions into one group.

[4]We use the term POC to be inclusive of all individuals who identify their race/ethnicity beyond singly white, including Black/African American, Native Hawaiian, Pacific Islander, Alaska Native, Native American/First Nations/First Peoples, Asian or Asian American (e.g., Chinese, Japanese, Korean, Vietnamese), Hispanic/Latin American (e.g., Mexican, Puerto Rican, Dominican, Cuban), biracial, and multiracial. Due to the small sample of participants endorsing with one or more of these racial/ethnic identities, we were unable to examine within-POC differences.

timepoints). Descriptive statistics and between-group effect sizes for each of our primary variables over time and as a function of study condition (AO vs. BAI) can be found in the supplemental materials. Bivariate correlations among variables at each assessment time point are presented in the far right three columns in Table 1. All variables were significantly correlated with one another at corresponding assessment time points.

Attrition rates were low (1-month $n = 366$, 93% follow-up rate; 6-month $n = 344$, 88%; 12-month $n = 342$, 87%; 16-month $n = 311$, 79%; see Murphy et al., 2019 for additional details); however, there were some significant differences in participants who completed all four follow-ups and those that did not. Although the urban university site enrolled more participants ($n = 215$ vs. the rural college town university site $n = 178$), fewer completed all four follow-up assessments ($\chi^2 = 15.91$, df = 1, $p < 0.001$). Additionally, more women than men completed all four follow-up assessments ($\chi^2 = 3.99$, df = 1, $p = 0.046$). As such, university site and sex were included as covariates. Inclusion of covariates that explain missing responses in a larger longitudinal model would reasonably satisfy "non-ignorable" missing data as they would not bias resulting estimates. Furthermore, MLR estimation generally provides robust estimation with missing data and model misspecification (see Enders, 2010).

Model Fit

Table 2 shows absolute and relative model fit statistics for univariate (Models 1 and 2) and multivariate parallel process (Models 3a, 3b, and 4) piecewise LGCMs. Model fit indices suggested that piecewise LGCMs fit the data well for demand intensity, O_{max}, and alcohol-related problems, and fit the alcohol use data best.[5] See Figure 2 for a visual depiction of changes in alcohol demand, alcohol use, and alcohol-related problems over time as a function of intervention condition.[6] Two distinct growth phases may be observed in which a steep linear drop occurs from baseline to 1-month follow-up and is followed by a second linear trajectory from 1-month to 16-month follow-up.

Simultaneous Demand and Alcohol Outcomes Growth Trajectories (Step 3, Model 3b)

As reported previously (Murphy et al., 2019), the BAI conditions were significantly associated with fewer drinks per week, HDEs, and problems at 16-month follow-up, as well as greater slope 1 reductions in both demand and alcohol outcomes. Identifying as male, white, and attending university in a college town were all significantly associated with more drinks per week and HDEs, but not problems, at 16-month follow-up. Identifying as male was also significantly associated with greater baseline demand intensity but not O_{max}. Additionally, identifying as female and attending the urban university was associated with greater reductions in slope 1 problems. See Table 3 for coefficient estimates. Further, respective latent growth factors across alcohol demand and use outcomes were consistently and significantly associated (see Table 4 estimates in bold). Demand intensity latent growth factors appeared more strongly associated with all alcohol outcomes latent growth factors, as compared to O_{max}.

[5]Model fit indices for the intercept only, linear, and quadratic models, as well as other piecewise variations, are not shown but available upon request.
[6]A variation of Figure 2, panel C (drinks per week) was originally published in Murphy et al. (2019).

Demand as a Baseline Severity Indicator and Post-Intervention Marker of Response to Intervention (Step 4, Model 4)

Absolute model fit statistics for Model 4 alcohol-related problems were acceptable, but were on the cusp or outside the acceptable model fit statistic cut-offs for alcohol use and HDEs, although the relative model fit index (see BIC) for the HDE Model 4 was on par with Model 3b. Because both alcohol use variables showed similar associations and the HDE model showed acceptable model fit, we interpret both the HDE and alcohol-related problems Model 4. Intensity ($B = 0.22$, SE = 0.05, $p < 0.001$ 95% CI [0.117, 0.328]), but not O_{max} ($B = -0.07$, SE = 0.05, $p = 0.17$, 95% CI [−0.174, 0.030]), at baseline predicted slope 1 problems; however, neither intensity ($B = 0.03$, SE = 0.08, $p = 0.71$, 95% CI [−0.123, 0.181]) nor O_{max} ($B = -0.06$, SE = 0.06, $p = 0.37$, 95% CI [−0.181, 0.067]) at baseline predicted slope 1 HDEs. Intervention condition significantly predicted slope 1 intensity ($B = -0.57$, SE = 0.12, $p < 0.001$, 95% CI [−0.791, −0.340]), O_{max} ($B = -0.55$, SE = 0.12, $p < 0.001$, 95% CI [−0.794, −0.310]), HDEs ($B = -0.33$, SE = 0.06, $p < 0.001$, 95% CI [−0.449, −0.216]), and problems ($B = -0.33$, SE = 0.05, $p < 0.001$, 95% CI [−0.431, −0.230]); however, it was no longer a significant predictor of 16-month HDEs ($B = 0.06$, SE = 0.07, $p = 0.43$, 95% CI [−0.081, 0.192]) or problems ($B = -0.07$, SE = 0.07, $p = 0.30$, 95% CI [−0.198, 0.061]). In other words, whereas intervention significantly reduced demand intensity, O_{max}, HDEs, and problems from baseline to 1-month follow-up, it did not predict HDEs or problems at 16-month follow-up, presumably because most of the targeted effect occurred within the first month of intervention.

Using the numbered mediational paths in the conceptual model presented in Figure 1, (1) there was a significant indirect effect of intervention condition on slope 1 demand intensity predicting 16-month HDEs (Indirect Effect (SE) = −0.23 (0.08), $p = 0.004$, 95% CI [−0.385, −0.074] and problems (Indirect Effect (SE) = −0.15, $p = 0.04$, 95% CI [−0.288, −0.011]). Specifically, the BAI interventions (vs. AO) were associated with steeper reductions in demand intensity, and this, in turn, was predictive of fewer HDEs and problems at 16-month follow-up. In contrast, (2) a significant indirect effect was not found for intervention condition on slope 1 O_{max} predicting 16-month HDEs (Indirect Effect (SE) = 0.05 (0.07), $p = 0.50$, 95% CI [−0.086, 0.177]) or problems (Indirect Effect (SE) = 0.07 (0.06), $p = 0.20$, 95% CI [−0.039, 0.183]).

Discussion

The purpose of the current study was to extend research on alcohol demand and response to alcohol BAIs by utilizing parallel process latent growth curve modeling (LGCM) to examine the interrelationship between changes in alcohol demand and alcohol use and problems over 16 months in a large sample of college students. As noted previously, LGCM offers several advantages for testing hypotheses with longitudinal data, including the ability to account for within-individual changes and between-individual differences, as well as time-invariant and time-varying covariates, that are often observed in developmental and behavioral research (Duncan and Duncan, 2009; McArdle, 1988; Meredith and Tisak, 1990).

As expected, alcohol demand (intensity and O_{max}) and alcohol use (drinks per week and HDEs) and problems were significantly positively associated from baseline to 1-month and from 1-month to 16-month follow-up, even when accounting for sex, race/ethnicity, university site, and study condition, demonstrating that as demand for alcohol changed, so did actual alcohol use and related problems. Consistent with previous literature on the robustness of intensity, its latent growth factors were significantly associated with the respective latent growth factors of drinks per week, HDEs, and alcohol-related problems (Martínez-Loredo et al., 2021). However, associations between O_{max} latent growth factors and respective alcohol outcomes growth factors were somewhat less consistent. Whereas both baseline demand intensity and O_{max} were positively associated with 16-month drinks per week and HDEs after accounting for covariates, only demand intensity was associated with 16-month problems. These associations suggest that higher initial alcohol demand may portend continued heavy and/or problematic use and a lack of responsiveness to BAI.[7]

This study also extends previous research by Murphy et al. (2015), which demonstrated that demand intensity predicts change in alcohol use and problems at shorter follow-up durations. Indeed, the current study found that reduction in demand intensity from baseline to one-month follow-up was predictive of frequency of HDEs and number of alcohol-related problems at 16-month follow-up, in line with and extending results from Murphy et al. (2015). Demand intensity latent growth factors appeared more strongly associated with all alcohol latent growth factors, as compared to O_{max}, which is consistent with previous research and perhaps not surprising given that intensity is a direct measure of maximum desired drinking amount, whereas O_{max} reflects aspects of both desire to consume alcohol and willingness to allocate monetary resources to consume alcohol. Interestingly, there was no evidence for the effect of baseline demand intensity or O_{max} on immediate post-intervention change in HDEs from baseline to 1-month follow-up, which is inconsistent with previous research (Murphy et al., 2015). This may be because the current analyses included intervention condition in the model and it had a substantial impact on 1-month drinking, which might have limited the predictive utility of demand.

As hypothesized, individuals who received the alcohol BAI (plus a Substance-Free Activity Session or Relaxation Training session) demonstrated greater short-term reductions in demand intensity and O_{max} compared with the AO control condition, which is consistent with previous research showing that demand is malleable and responsive to brief intervention (see Acuff et al., 2019). Similarly, as reported previously (Murphy et al., 2019), the BAI condition was also associated with significantly greater reductions in drinks per week, HDEs, and problems from baseline to 1-month compared to the AO condition, which demonstrated little to no change in either demand or alcohol use over the 16-month study period. Moreover, our mediation analyses indicated that the reduction in demand intensity in the month following the intervention led to a reduced frequency of HDEs and fewer past-month problems 16 months after the intervention. Thus, BAIs may act as catalysts for reductions in alcohol demand that are associated with enduring change in heavy episodic drinking over time in non-treatment-seeking college students. Although a

[7]Steps 1 to 4 were conducted with the demand indices P_{max}, breakpoint, and elasticity, and model fit indices for each are included in the Supplemental Materials. Although the steps 1 and 2 piecewise univariate models (supplemental table 4) and steps 3a and 3b parallel process piecewise models (supplemental table 5) fit the data well, step 4 models demonstrated worse fit compared to intensity and O_{max} (supplemental table 6). Due to the poor fit of the step 4 models, we were unable to evaluate these other indices as predictors of alcohol outcomes or as mediators of intervention effect and, therefore, do not present the coefficient or indirect effect estimates.

variety of experimental manipulations have been shown to reduce demand in laboratory paradigms (Acuff et al., 2019), brief motivational and behavioral interventions are the only interventions tested to date that have shown evidence for sustained reductions in demand.

Our results also showed that demand increased slightly, though not significantly, from one month to 16 months post-intervention; however, both demand indices remained substantially lower than the baseline level for participants who completed an intervention. In contrast, all alcohol outcomes showed a continued linear decline from one month through 16 months. This finding illustrates that alcohol demand, consumption, and problems, while highly correlated at each timepoint, are not completely syntonic processes and are likely influenced by temporally proximal events such as acute craving, stress, the availability of alternatives, or other psychosocial factors (Acuff et al., 2019). For example, for an emerging adult who links HDEs with positive consequences such as social bonding (Sayette et al., 2012), demand for alcohol, in the abstract, may remain relatively high; however, actual recent HDEs may decrease due to external constraints, alternatives to drinking, or increasing skills to limit drinking in order to avoid harmful conquences. Thus, alcohol demand may be considered an implicit indicator of latent desire to drink that is not always expressed in actual drinking behaviors and may be dependent on several interacting personality (i.e., impulsivity, self-regulatory capacity) and contextual factors (i.e., craving, stress, event-specific drinking such as 21st birthdays or tailgating). An advantage of demand is that it can be easily measured before and after contextual events such as an intervention or alcohol-related event/consequence (Merrill and Aston, 2020), and has utility in predicting patterns of drinking over time as well as need for additional intervention elements (Motschman et al., 2022). Indeed, the demand indices we measured in this study (intensity and O_{max}) can be quickly measured with a 3-item purchase task that does not require any computations to score (Owens et al., 2015a).

Strengths, Limitations, and Future Directions

The current study utilized a randomized clinical trial methodology with a large sample of heavy drinking college students recruited from two universities. The analytical approach was another strength, as latent growth curve analysis models variables across time and accomodates complex representations of change. The ability to model the intervention effects on demand and the predictive utility of baseline demand and initial change in demand on change in drinking and problems over 16-months extends previous work in this area.

This study also had several notable limitations. First, our sample was relatively homogenous demographically (white college students), and we are thus unable to generalize the findings to other populations. Although most participants in our sample met criteria for AUD (see Murphy et al., 2021), an important next step will be to replicate this research in treatment-seeking samples. Second, our comparison groups had uneven sample sizes, potentially resulting in biased model estimates. Third, although the study modeled change over five assessment points across 16 months, it does not capture daily fluctuations in alcohol demand that might be necessary to develop a more elaborated model of the associations between alcohol demand, drinking, and problems. Indeed, substantial in-person variability in demand intensity has been found to occur over a 28-day period, and, in a sample of underage drinkers, negative drinking consequences significantly reduced next-day demand intensity, likely contributing at least in part to this variability (Merrill and Aston, 2020). As such, a more granular assessment of alcohol demand and drinking/problems could identify relevant risk factors that influence demand more proximally and could identify proximal implications of within-day or -week fluctuations in demand (Motschman et al., 2022). However, despite being unable to capture state-level processes, the current study suggests that overall reductions in trait-level or resting-rate demand are influential in longer-term, more sustained reductions in alcohol use.

Finally, though not a limitation of the current study, it is important to note that the interventions in the current study included two sessions plus a booster call, and a variety of elements that might all theoretically reduce demand. The alcohol BAI session (included in both treatment conditions) is identical to sessions that have been widely disseminated across college campuses (Huh et al., 2015) and have previously been shown to reduce demand for a one-month period (Murphy et al., 2015). These sessions included several elements intended to *directly* reduce motivation to drink, including normative feedback on drinking levels, a decisional balance exploring the pros and cons of drinking, and information on risk factors for alcohol use disorder. The current study found demand reductions that extended for 16 months for interventions that included an alcohol BAI plus either relaxation training or the SFAS. These supplemental sessions are intended to enhance the efficacy of alcohol BAIs and include elements that *indirectly* target alcohol motivation by increasing future orientation and enjoyable and/or goal-directed alternatives to drinking (SFAS) or by modeling strategies to reduce stress (relaxation). Many of the session elements also address factors that have been linked to demand. For example, the SFAS attempts to increase goal-directed activities, consistent with research indicating that the presence of next-day responsibilities reduces demand (Gentile et al., 2012). Both the SFAS and the relaxation training session also include elements that might improve mood and reduce stress (e.g., enjoyable and goal-directed activities are targeted in the SFAS, and the Relaxation Training session included anxiety and stress reduction strategies), consistent with research linking elevated stress and depressive symptoms with elevated demand (Acuff et al., 2019; Murphy et al., 2013). Future research is needed to determine if this combination of elements is required to generate sustained reductions in demand, or if this is possible with briefer approaches that might focus on fewer intervention elements, such as normative drinking feedback or episodic future thinking task.

Summary and Implications

Our results provide further support for behavioral economic models of addiction, which view elevated demand as a central feature of heavy alcohol use. Demand measured through a hypothetical APT appears to serve as an effective proxy of alcohol reinforcing efficacy that is sensitive to manipulation (i.e., intervention; Acuff et al., 2019) and yet also stable enough to adequately predict heavy alcohol use almost 16 months later. Overall, our findings are largely consistent with previous studies that demonstrate acute changes in demand following various theoretically relevant manipulations and extend these findings by suggesting that two-session alcohol BAIs have a long-term suppressing effect on alcohol demand. Our findings also suggest that hypothetical APTs could have clinical utility in predicting the likely efficacy of alcohol BAIs. Higher demand on the APT prior to intervention could indicate the necessity for more intensive intervention, and reductions in demand following intervention could be an indicator of a successful response. At this time, however, hypothetical purchase tasks lack normed data, and future research on the clinical utility of hypothetical purchase tasks should seek to empirically identify clinically meaningful changes in the APT demand indices, especially intensity, and to evaluate similar longitudinal models using abbreviated purchase tasks (Owens et al., 2015a). Establishing the predictive utility of demand derived from a brief purchase task could provide a real-time, clinically relevant measure of prospective heavy episodic alcohol use that could quickly and easily inform clinicians of an individual's risk level.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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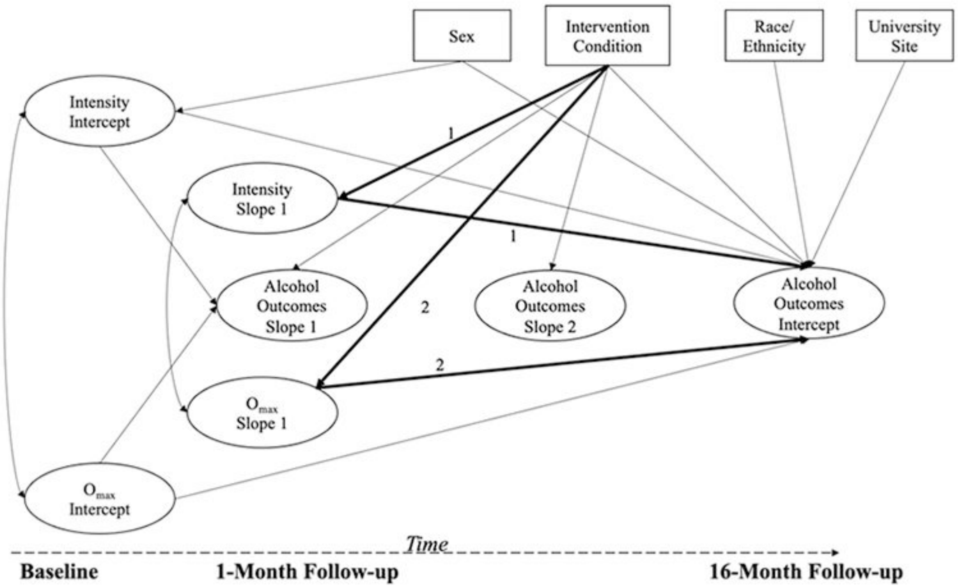

Figure 1. Conceptual Model of Demand-Mediated BMI Effects on Alcohol Use at 16-Month Follow-up (Model 4).

Note. "Alcohol Outcomes" is a placeholder for drinks per week (DPW), heavy drinking episodes (HDE), and alcohol-related problems (ARP) outcome models. Bold paths are mediated pathways: (1) Intervention condition intensity slope 1 DPW/HDE/ARP at 16-month follow-up, and (2) Intervention condition O_{max} slope 1 DPW/HDE/ARP at 16-month follow-up. Ovals indicate latent growth variables. Rectangles indicate time-invariant observed variables defined at baseline.

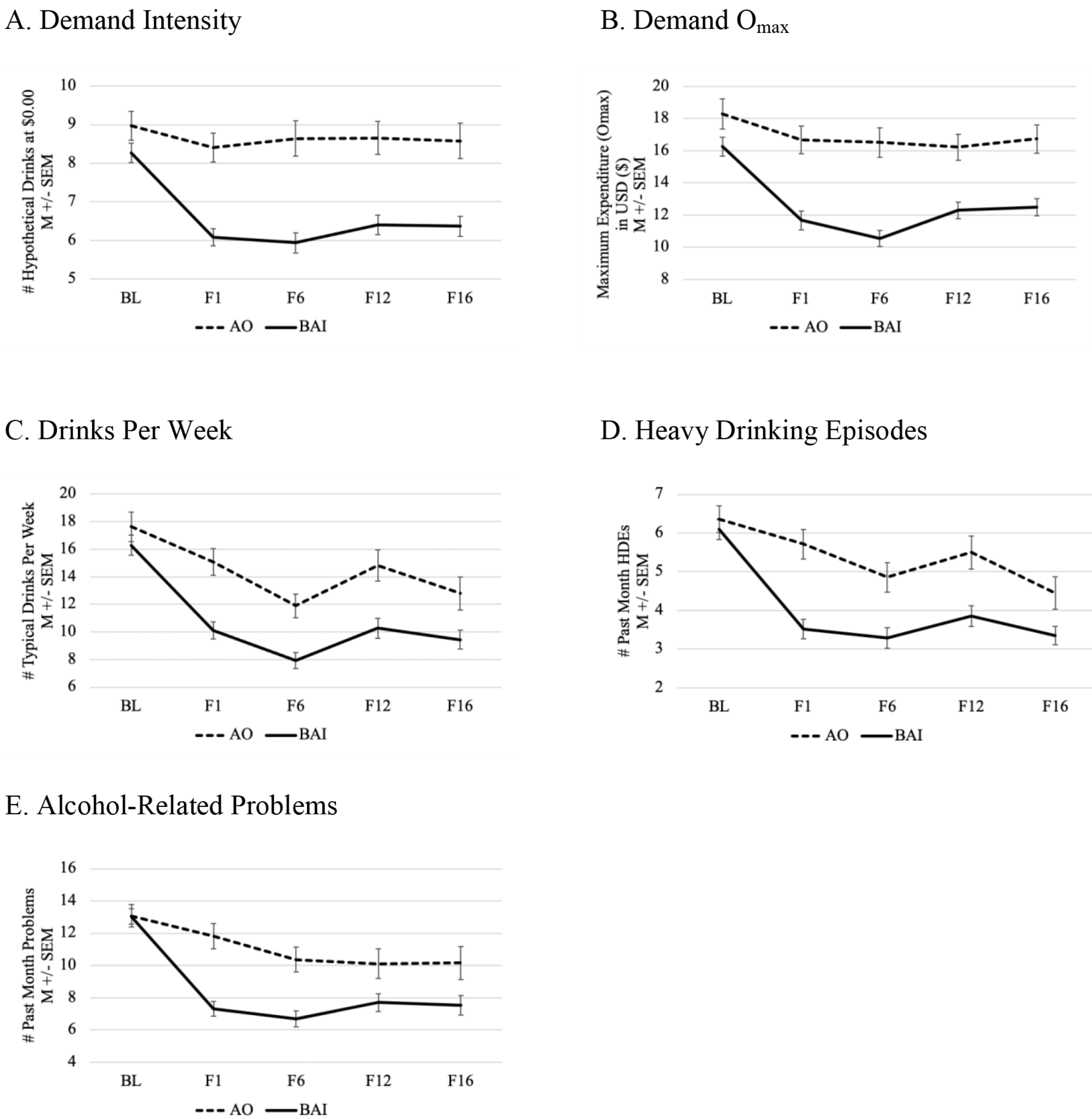

Figure 2.

Mean Scores for Demand and Alcohol Outcomes Variables at Baseline and Across all Follow-up Assessments by Study Condition. AO = Assessment only. BAI = Brief Alcohol Intervention. BL = baseline, F1 = 1-month follow-up, F6 = 6-month follow-up, F12 = 12-month follow-up, F16 = 16-month follow-up.

Table 1.

Descriptive Statistics and Correlations Among Outcome Variables at Each Assessment Timepoint for the Full Sample

Baseline	***N***	***M*(SD)**	**Range**	**HDE**	**ARPs**	**Intensity**	**O_{max}**
DPW	393	16.76 (11.97)	0-55	0.69**	0.36**	0.60**	0.28**
HDEs	393	6.19 (4.12)	0-21	-	0.46**	0.46**	0.28**
ARPs	393	13.05 (7.89)	0-39		-	0.31**	0.19**
Intensity	392	8.52 (4.15)	2-23			-	0.44**
O_{max}	393	16.97 (10.06)	1-61				-
1-Month	***N***	***M*(SD)**	**Range**	**HDE**	**ARPs**	**Intensity**	**O_{max}**
DPW	366	11.85 (10.28)	0-46.80	0.77**	0.54**	0.73**	0.52**
HDEs	366	4.28 (4.16)	0-20	-	0.52**	0.60**	0.47**
ARPs	365	8.88 (7.96)	0-35		-	0.45**	0.36**
Intensity	363	6.89 (3.90)	0-21			-	0.62**
O_{max}	362	13.41 (9.47)	0-51				-
6-Month	***N***	***M*(SD)**	**Range**	**HDE**	**ARPs**	**Intensity**	**O_{max}**
DPW	344	9.35 (9.00)	0-42.40	0.75**	0.59**	0.66**	0.49**
HDEs	344	3.85 (4.14)	0-24	-	0.56**	0.57**	0.46**
ARPs	343	8.01 (8.11)	0-34		-	0.41**	0.39**
Intensity	340	6.91 (4.49)	0-26			-	0.62**
O_{max}	338	12.70 (8.85)	0-41				-
12-Month	***N***	***M*(SD)**	**Range**	**HDE**	**ARPs**	**Intensity**	**O_{max}**
DPW	342	11.83 (11.59)	0-55	0.85**	0.58**	0.74**	0.47**
HDEs	343	4.41 (4.33)	0-20	-	0.58**	0.65**	0.45**
ARPs	343	8.52 (8.79)	0-36		-	0.49**	0.37**
Intensity	340	7.17 (4.20)	0-21			-	0.60**
O_{max}	340	13.63 (8.32)	0-41.50				-
16-Month	***N***	***M*(SD)**	**Range**	**HDE**	**ARPs**	**Intensity**	**O_{max}**
DPW	311	10.55 (10.89)	0-54	0.75**	0.53**	0.67**	0.48**
HDEs	311	3.71 (3.80)	0-16.20	-	0.50**	0.58**	0.44**
ARPs	311	8.40 (9.35)	0-39		-	0.47**	0.34**
Intensity	303	7.10 (4.13)	0-21			-	0.58**
O_{max}	301	13.91 (8.14)	0-37				-

Note. DPW = Drinks Per Week; HDEs = Heavy Drinking Episodes; ARPs = Alcohol-Related Problems. Significant correlations indicated

** $p < 0.001$

Table 2.

Univariate and Multivariate Parallel Process Piecewise LGCM Fit Indices

Step 1 Models	**RMSEA (90% CI)**	**CFI**	**SRMR**	**BIC**
Intensity	0.035 (0.000, 0.077)	0.994	0.03	8932.671
O_{max}	0.028 (0.000, 0.072)	0.995	0.019	11688.311
DPW	0.136 (0.104, 0.169)	0.907	0.051	5744.471
HDEs	0.059 (0.022, 0.096)	0.981	0.031	9270.937
ARPs	0.000 (0.000, 0.060)	1.000	0.025	11769.796
Step 2 Models	**RMSEA (90% CI)**	**CFI**	**SRMR**	**BIC**
Intensity	0.024 (0.000, 0.072)	0.996	0.025	8869.518
O_{max}	0.032 (0.000, 0.061)	0.992	0.021	11702.777
DPW	0.086 (0.064, 0.110)	0.943	0.036	5700.073
HDEs	0.039 (0.000, 0.067)	0.987	0.025	9259.019
ARPs	0.000 (0.000, 0.033)	1.000	0.023	11756.493
Step 3 Models (3a)	**RMSEA (90% CI)**	**CFI**	**SRMR**	**BIC**
Intensity & O_{max} with DPW	0.085 (0.07, 0.096)	0.929	0.042	25594.869
Intensity & O_{max} with HDEs	0.069 (0.058, 0.081)	0.949	0.036	29273.696
Intensity & O_{max} with ARPs	0.062 (0.050, 0.073)	0.956	0.034	31941.675
Step 3 Models (3b)	**RMSEA (90% CI)**	**CFI**	**SRMR**	**BIC**
Intensity & O_{max} with DPW	0.074 (0.064, 0.083)	0.936	0.036	25600.624
Intensity & O_{max} with HDEs	0.062 (0.052, 0.072)	0.952	0.032	29268.274
Intensity & O_{max} with ARPs	0.054 (0.043, 0.064)	0.961	0.030	31920.156
Step 4 Models	**RMSEA (90% CI)**	**CFI**	**SRMR**	**BIC**
Intensity & O_{max} with DPW	0.086 (0.078, 0.094)	0.869	0.080	25628.557
Intensity & O_{max} with HDEs	0.077 (0.070, 0.085)	0.887	0.075	29270.349
Intensity & O_{max} with ARPs	0.066 (0.058, 0.074)	0.912	0.072	31854.565

Note. DPW = Drinks Per Week. HDEs = Heavy Drinking Episodes. ARPs = Alcohol-Related Problems. DPW was square root transformed for better model fit. Fit indices may be compared between Model 1 and Model 2 for respective variables, and fit indices may be compared between Models 3a, 3b, and 4 for respective parallel processes. Good model fit = RMSEA < 0.05, CFI > 0.95, and SRMR < 0.04. Acceptable model fit = RMSEA < 0.08, CFI > 0.90, SRMR < 0.08. BIC balances model fit to the data and model parsimony. Lower BIC values indicate better fit relative to model parsimony.

Table 3.

Standardized Coefficient Estimates and Standard Errors (Model 3b)

Multivariate Parallel Process Model Predicting Drinks Per Week Latent Growth Factors				
	Condition	**Sex**	**Race**	**Site**
DPW 16-Month FU	−0.17 (0.06)**	−0.28 (0.06)***	0.10 (0.05)*	0.21 (0.05)***
Slope 1	−0.30 (0.06)***	−0.05 (0.06)	0.11 (0.07)	0.05 (0.05)
Slope 2	0.07 (0.07)	0.02 (0.07)	0.10 (0.07)	0.04 (0.07)
Intensity****** Baseline	−0.07 (0.05)	−0.31 (0.05)***	−0.05 (0.05)	0.04 (0.05)
Slope 1	−0.25 (0.06)***	−0.02 (0.06)	0.11 (0.07)	0.06 (0.05)
Slope 2	0.02 (0.08)	−0.02 (0.08)	0.12 (0.08)	0.02 (0.07)
$\mathbf{O_{max}}$ Baseline	−0.09 (0.05)	−0.04 (0.05)	0.02 (0.06)	−0.08 (0.05)
Slope 1	−0.20 (0.06)**	−0.05 (0.06)	0.07 (0.06)	0.10 (0.05)
Slope 2	0.05 (0.07)	0.08 (0.07)	0.09 (0.07)	−0.04 (0.06)
Multivariate Parallel Process Model Predicting HDE Latent Growth Factors				
	Condition	**Sex**	**Race**	**Site**
HDEs 16-Month FU	−0.17 (0.06)**	−0.15 (0.06)*	0.12 (0.05)*	0.13 (0.06)*
Slope 1	−0.32 (0.06)***	−0.07 (0.06)	−0.02 (0.06)	−0.06 (0.06)
Slope 2	0.12 (0.08)	0.07 (0.08)	0.07 (0.07)	−0.12 (0.07)
Intensity Baseline	−0.07 (0.05)	−0.31 (0.05)***	−0.05 (0.05)	0.04 (0.05)
Slope 1	−0.24 (0.06)***	−0.01 (0.06)	0.11 (0.07)	0.06 (0.05)
Slope 2	0.02 (0.07)	−0.04 (0.08)	0.11 (0.07)	0.03 (0.07)
$\mathbf{O_{max}}$ Baseline	−0.09 (0.05)	−0.04 (0.05)	0.02 (0.06)	−0.08 (0.05)
Slope 1	−0.20 (0.06)**	−0.05 (0.06)	0.07 (0.06)	0.10 (0.05)
Slope 2	0.05 (0.07)	0.06 (0.07)	0.09 (0.07)	−0.04 (0.06)
Multivariate Parallel Process Model Predicting ARP Latent Growth Factors				
	Condition	**Sex**	**Race**	**Site**
ARPs 16-Month FU	−0.17 (0.06)**	−0.05 (0.06)	0.05 (0.05)	0.10 (0.06)
Slope 1	−0.34 (0.05)***	−0.21 (0.05)***	−0.03 (0.06)	0.13 (0.05)*
Slope 2	0.10 (0.07)	−0.01 (0.07)	0.08 (0.07)	−0.08 (0.07)
Intensity Baseline	−0.07 (0.05)	−0.31 (0.05)***	−0.05 (0.05)	0.04 (0.05)
Slope 1	−0.24 (0.06)***	−0.01 (0.06)	0.11 (0.07)	0.06 (0.05)
Slope 2	0.01 (0.07)	−0.04 (0.08)	0.11 (0.07)	0.02 (0.07)
$\mathbf{O_{max}}$ Baseline	−0.09 (0.05)	−0.04 (0.05)	0.02 (0.06)	−0.08 (0.05)
Slope 1	−0.19 (0.06)**	−0.05 (0.06)	0.07 (0.06)	0.10 (0.05)
Slope 2	0.04 (0.07)	0.07 (0.07)	0.09 (0.07)	−0.04 (0.06)

Note. Condition is 0 = Assessment-only, 1 = BAI; Sex is 0 = men, 1 = women; Race (includes ethnicity) is 0 = Black, Indigenous, Person of Color, 1 = non-Hispanic white; Site is 0 = urban/commuter 4-year university, 1 = rural/residential 4-year university. Intensity and O_{max} estimates are presented for all models of alcohol related outcomes. DPW = Drinks per week. HDE = Heavy Drinking Episodes. ARP = Alcohol Related Problems.

Table 4.

Standardized Cross-Domain Correlations Between Alcohol Demand and Alcohol Use Outcomes (Model 3B)

	Intensity			O_{max}		
	Baseline level	**Slope 1**	**Slope 2**	**Baseline level**	**Slope 1**	**Slope 2**
DPW						
16-Month FU level	0.36 (0.7)***	−0.01 (0.08)	0.54 (0.08)***	0.16 (0.07)*	0.03 (0.07)	0.32 (0.08)***
Slope 1	−0.16 (0.07)*	**0.39 (0.08)***	−0.22 (0.09)*	−0.06 (0.08)	**0.34 (0.08)***	−0.17 (0.09)
Slope 2	−0.07 (0.09)	−0.23 (0.10)*	**0.94 (0.11)***	−0.10 (0.09)	−0.28 (0.11)*	**0.74 (0.10)***
HDEs						
16-Month FU level	0.36 (0.06)***	−0.004 (0.07)	0.49 (0.08)***	0.17 (0.07)*	0.04 (0.08)	0.30 (0.09)**
Slope 1	−0.14 (0.07)	**0.38 (0.07)***	−0.21 (0.10)*	−0.01 (0.08)	**0.22 (0.09)** *	−0.16 (0.09)
Slope 2	−0.10 (0.09)	−0.23 (0.10)*	**0.85 (0.10)***	−0.20 (0.10)*	−0.16 (0.11)	**0.65 (0.13)***
ARPs						
16-Month FU level	0.32 (0.07)***	−0.07 (0.07)	0.38 (0.09)***	0.13 (0.08)	0.01 (0.07)	0.22 (0.10)*
Slope 1	−0.04 (0.06)	**0.23 (0.07)** **	−0.14 (0.08)	0.06 (0.05)	0.10 (0.07)	−0.20 (0.08)**
Slope 2	0.001 (0.08)	−0.13 (0.10)	**0.57 (0.10)***	−0.11 (0.09)	−0.06 (0.12)	**0.45 (0.12)***

Note. DPW = Drinks per week. HDEs = Heavy drinking episodes. ARPs = Alcohol-related problems. These associations account for sex, race/ethnicity, university site, and intervention condition.

*** $p < 0.001$

** $p < .01$

* $p < 0.05$