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Defining and Characterizing Differences in College Alcohol Intervention Efficacy: A Growth Mixture Modeling Application

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Abstract

Objective—While college alcohol misuse remains a pervasive issue, individual-level interventions are among the most efficacious methodologies to reduce alcohol-related harms. Growth mixture modeling (GMM) was used as an exploratory moderation analysis to determine how many types of college drinkers exist with regards to intervention efficacy over a 12-month period.

Method—Data from three randomized-controlled clinical trials were combined to yield a sample of 1,040 volunteer and mandated college students who were given one of three interventions: a brief motivational intervention, Alcohol Edu for Sanctions, or Alcohol 101 Plus. Participants were assessed at baseline, and 1, 6, and 12 months following intervention.

Results—Through the examination of heavy drinking behaviors, piecewise GMMs that identified 6 subpopulations of drinkers. Most of the sample (76%) was lighter drinkers that demonstrated a strong intervention response, but returned to baseline behaviors over the subsequent 12 months. In contrast, 11% of the sample reported no significant change over the 12-month period. Four minority subpopulations were also identified. In sum, 82% of the sample responded to intervention, but 84% of the sample reported intervention decay over the subsequent 12 months. Women, upperclassmen, beginning drinking later in life, not engaging in drinking games, and lower norms predicted a greater likelihood of responding to intervention.

Conclusions—Individual-level interventions are successful at effecting change in most college students, but these effects tend to decay to baseline behaviors by 12 months. These results suggest intervention efforts need to find ways to engage freshmen men and those who play drinking games.

Public Health Significance—This study suggests that there are distinct subgroups of college students defined by how they respond to alcohol intervention, and that interventions need to target freshmen men and those who play drinking games. Although most students initially response to

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intervention effects, most also show intervention decay over the next 12 months, which suggests that we need to determine ways of improving the long-term effects of alcohol interventions.

Keywords

intervention efficacy; growth mixture modeling; college student alcohol intervention; brief motivational interventions; computer-delivered interventions

Estimates reveal more than 500,000 student injuries, more than 600,000 assaults, more than 80,000 sexual assaults, and nearly 2,000 deaths occur annually because of college student drinking (Hingson, Zha, & Weitzman, 2009; Hingson & White, 2014). Generally, individual-level alcohol interventions targeted toward college students have been shown to be efficacious, but the effects of these interventions tend to be small and short-lived (for meta-analyses, see Carey, Scott-Sheldon, Carey, & DeMartini, 2007; Carey, Scott-Sheldon, Elliott, Garey, & Carey, 2012). These interventions range from face-to-face individual or group interventions to computer-delivered interventions. Thus, it is important to determine which students benefit from these interventions and which need alternative approaches to effectively reduce drinking consequences.

College Student Interventions

Although several approaches to campus-based alcohol prevention strategies are currently in use (e.g., policy, environmental; DeJong & Langford, 2002), individual-level college alcohol interventions are among the most promising mechanisms to reduce alcohol misuse (Carey et al., 2007). Typically, these interventions have been delivered either face-to-face or via a computerized format. Face-to-face interventions that include personalized feedback on consumption, normative comparisons, protective behavioral strategies, BAC education, or challenged positive alcohol expectancies are most effective; however, computerized interventions have also been shown to be effective in decreasing alcohol consumption for up to three months (Carey et al., 2012).

Moderators of Intervention Efficacy

Heterogeneity in intervention response is common (Kraemer, Wilson, Fairburn, & Agras, 2002). Thus, moderation analyses are frequently used to identify for whom the intervention is more (or less) efficacious. Several potential intervention moderators of alcohol-related outcomes have been examined among college students. These include historical variables, such as age of drinking onset (Mallett, Ray, Turrisi, Belden, Bachrach, & Larimer, 2010) and family history of alcohol abuse (LaBrie, Feres, Kenney, & Lac, 2009), stable individual difference variables, such as gender (Carey, Henson, Carey, & Maisto, 2009; Carey, Carey, Henson, Maisto, & DeMartini, 2011), self-regulation (Carey, Henson, Carey, & Maisto, 2007) and self-determination (Neighbors, Lewis, Bergstrom, & Larimer, 2006), and more malleable variables, such as identification with the typical college student (Neighbors, Jensen, Tidwell, Walter, & Fossos, 2011) and readiness to change (Carey et al., 2007; Tomaka, Palacios, Morales-Monks, & Davis, 2012). Briefly, some interventions have been found to be more effective for more at-risk students including students with an earlier age of drinking onset (Mallett et al., 2010) or with a positive family history of alcohol abuse

(LaBrie et al., 2009). However, lower-risk individuals have also been shown to respond more strongly to alcohol interventions including individuals higher in self-regulation (Carey et al., 2007), self-determination (Neighbors et al., 2006), and readiness to change (Tomaka et al., 2012).

Moderators as distinct populations

Significant moderation suggests that different *types of participants*, or subpopulations as defined by the moderator, will respond differently to an intervention. Ignoring population heterogeneity can yield misleading parameter estimates and effect sizes, limiting generalizability. Intervention effects may be large for one group, but small for others (Mallett et al., 2013), and when combined the resulting aggregate effect size would be modest. If an intervention is not universally efficacious for everyone, it is important to understand the population characteristics of individuals who may or may not respond to the intervention.

Traditional moderation analyses are variable-centered approaches that explain population heterogeneity by examining *a priori* hypothesized variables. Thus, both a strength and a limitation to traditional moderation analyses is that they are confirmatory in nature, because they confirm or fail to confirm the moderating effect of an *a priori* hypothesized moderator. Because potential moderators must be identified prior to data collection using known or theoretically-derived correlates of outcomes, researchers potentially omit important moderators.

As an alternative to testing *a priori* moderators, Growth Mixture Models (GMMs; Muthén et al., 2002) represent a person-centered, exploratory approach to identifying population heterogeneity that characterizes intervention effects by empirically identifying homogenous longitudinal patterns. These unique patterns represent empirical subpopulations of college drinkers that differ with respect to intervention efficacy, and subsequent analyses use explanatory variables to characterize the subpopulations. Therefore, GMMs can be used (a) to determine how many homogenous patterns, or subpopulations best fit the data, (b) to provide probabilistic estimates of subpopulation membership for each participant, and (c) to estimate distinct developmental trajectories for each estimated subpopulation. Further, additional analyses can be conducted *post-hoc* to identify predictors or correlates of subpopulation membership.

GMMs and Alcohol Intervention Research

At least two studies have used GMMs to examine drinker subpopulations following alcohol intervention. Witkiewitz and Masyn (2008) used GMM to identify subpopulations of drinkers who a) met criteria for alcohol abuse or dependence, b) received a community alcohol intervention, and c) reported at least one relapse. Specifically, GMMs were fit with regard to the drinking patterns across the 7 months following an initial relapse post-treatment. Results suggested 3 subpopulations of drinkers following relapse: infrequent, moderate drinkers (82%), frequent heavy drinkers (6%), and drinkers who decreased consumption following relapse (12%). These findings reveal that distinct drinking trajectories can be identified after a discrete event, such as post-treatment relapse.

In addition, Mun, White, and Morgan (2009) used piecewise GMMs on a sample of students mandated to alcohol education in order to examine patterns of post-intervention response. GMMs revealed four types of drinkers among mandated students: the most frequent subpopulation (53.4%) decreased consumption after intervention and then increased over time; one subpopulation (20.4%) exhibited minimal decreases after intervention, but returned to baseline levels; one subpopulation (19.3%) reported slight increases after intervention, but returned to baseline levels; and one subpopulation (6.9%) reported large increases in consumption post-intervention with steady reduction over time. These last three groups were combined to yield an “non-improved” group (46.6%) relative to the “improved” group (first subpopulation; 53.4%), and Mun et al. found that delivery method (in-person vs. computer-based BMI) did not distinguish these two subpopulations. Importantly, using the outcome trajectory patterns, intervention effects were found (favoring in-person BMI over computer-delivered BMI) for participants with higher levels of baseline problems and more serious incidents. Thus, in this case, GMM allowed patterns to emerge that were not previously detectable.

The Present Study

The present research combined data from three large alcohol intervention studies (Carey, Carey, Maisto, & Henson, 2006; Carey et al., 2009, 2011) to identify and characterize types of college drinkers with respect to intervention efficacy. This combined sample yields 1,040 college students, consisting of both volunteers and sanctioned students, who were exposed to one of three interventions; outcomes were evaluated using the same follow-up assessment schedule. This opportunity allows us to extend the work of Mun et al. (2009) with a larger sample (n = 1,040 vs. n = 348) comprised of a broader range of student drinkers and intervention types; the larger and more diverse sample affords greater power and generalizability in identifying and characterizing smaller subpopulations. In addition, whereas Mun et al. collected follow up data at 4 and 15 months post-intervention, the present studies assessed each participant at 1, 6, and 12 months following intervention, an assessment strategy that is better able to characterize short-term intervention efficacy. Last, the present study used an alternate, “curve-of-factor” (Duncan, Duncan, & Stryker, 2006) modeling strategy by characterizing subpopulation behaviors according to participants’ heaviest drinking patterns through the creation of latent variables from several drinking indicators.

There are two primary aims for the present research. First, because harm-reduction strategies often target extreme behaviors, we sought to identify distinct subpopulations of college student drinkers based on change in *heavy drinking* over time following a brief alcohol intervention. By focusing on the heaviest-drinking behaviors specifically, we will characterize the intervention efficacy for each type of college-student drinker with respect to their most extreme (and potentially dangerous) behaviors rather than aggregate drinking patterns.

Our second aim was to identify key explanatory variables related to subpopulation membership to better describe the distinct types of drinkers and to determine moderators of intervention efficacy. Explanatory variables used in this research fell into four major categories: study design variables, demographics, substance use / history variables, and psychological predictors of heavy drinking. Study design variables included sampling strategy (i.e., mandated vs. volunteer) and type of intervention (i.e., BMI, Alcohol 101, Alcohol EDU). Basic demographic information included race, gender, year in school, and membership in a Greek organization. Substance use variables included history of drug use, age of first drink, drinking game participation, and alcohol-related problems.

In addition, incorporating key psychological predictors of subpopulation membership elucidate potential mechanisms as to why these subpopulations experience differential outcomes. Although we were limited to examining constructs that were collected across all three studies, research suggests these constructs might be among the most salient psychological moderators of intervention efficacy. Specifically, we examined four psychological constructs: readiness to change, self-regulation, decisional balance, and perceived drinking norms. Increased readiness-to-change and self-regulation have both been linked to stronger intervention effects (Carey et al., 2007). In addition, decisional balance predicts alcohol outcomes more than alcohol expectancies among college students (Noar, Laforge, Maddock, & Wood, 2003). Furthermore, perceived drinking norms are among the strongest predictors of alcohol use (Borsari & Carey, 2003; Neighbors, Lee, Lewis, Fossos, & Larimer, 2007).

Last, we used these explanatory variables to identify the strongest unique predictors of subpopulation membership. The ultimate goal of this research is for college drinking interventionists to better understand for whom the interventions work. These aims will help clinicians understand who is least and best served by standard college-student alcohol interventions as well as help intervention developers identify underserved and unresponsive population(s).

Method

Participants

The sample consisted of participants from three different alcohol intervention studies, and only participants who received an intervention were included in the sample. Study 1 characterized the efficacy of BMIs over controls for reducing college-drinking (Carey et al., 2006). Study 2 compared BMIs to a computerized intervention (Alcohol 101 Plus) among mandated students (Carey et al., 2009). Using mandated students, Study 3 compared the efficacy of BMIs to two different computerized interventions: Alcohol 101 Plus and Alcohol Edu for Sanctions (Carey et al., 2011).

Across the three studies, a total of 1,040 participants were randomly assigned by gender to one of the three interventions: an in-person BMI (n = 602), a computerized, in-lab intervention (n = 271; Alcohol 101 Plus; Century Council, 2003), or an online intervention (n = 167; Alcohol EDU for Sanctions; Outside the Classroom, Inc., 2009). Participants were assessed at baseline (n = 1,040), and then follow-up attempts were made at 1-month (n = 1,002), 6-months (n = 699), and 12-months (n = 753) post-intervention.

All participants were enrolled in a private, northeastern university, and demographic statistics by study are listed in Table 1. The final sample was 53% male, and 87% self-reported their race as White, whereas 2% self-reporting their race as Black, 3% as Latino/a, 5% as Asian, and 3% as other or missing. The sample was predominantly freshmen (60%) and sophomores (34%). Roughly a third of the sample (n = 339) participated in the baseline survey and first follow-up for course credit, whereas the remaining subjects participated to fulfill a campus sanction for violation of alcohol policy (n=701); all participants were paid for the 6- and 12-month follow-up surveys.

Procedures

Recruitment—The Institutional Review Board approved all procedures and Certificates of Confidentiality were obtained for all studies. Volunteer participants were eligible if they reported at least one binge episode in an average week. They enrolled for course credit and were administered baseline surveys in small groups after providing consent; eligible students were contacted by phone to schedule follow-up participation. Sanctioned participants were referred by Residence Life staff, and were eligible to participate if a) it was their first sanction, b) no other drugs were involved, and c) the violation did not meet requirements for a Judicial Affairs referral (see original reports for details on the samples). The mandated students could choose to complete the standard campus sanction, Alcohol Edu for Sanctions, or they could enroll in the study and be randomly assigned to study conditions.

Interventions—The BMI was a manualized intervention that combined personalized feedback with alcohol education, and participants met one-on-one with an interventionist that used motivational interviewing (Miller & Rollnick, 2002) to help participants to identify and resolve ambivalence about reducing their drinking. BMI sessions took roughly an hour to complete. Alcohol 101 Plus is an interactive computer program that was administered in a controlled, lab setting. For the Alcohol 101 Plus intervention, students freely navigated a “virtual campus” to learn about the consequences of alcohol misuse, and participants were required to spend at least 1 hour using the program. Alcohol Edu for Sanctions is an online course that takes roughly two hours to complete, and a grade of at least 70% on the final exam is required for students to pass. All three interventions had the same core components: personalized feedback, descriptive norms of other college drinkers, alcohol education, and tips for reducing use and consequences.

The sequence of procedures was consistent across the three studies. Interventions were scheduled 1 week following baseline assessment, and appointments for the 1-month follow-up were scheduled after the intervention was complete. Participants completed the intervention in a private room either with an interventionist (BMI) or a computer (Alcohol 101 Plus). Intervention sessions were videotaped for supervision and quality assurance. Participants who chose the Alcohol EDU intervention completed the intervention from their own personal computer.

Follow-ups—Participants completed the first follow-up for course credit or to complete their sanction requirements; 6- and 12-month follow-up participation was incentivized with up to $35 and $40, respectively. Additional details regarding the sampling procedures and study methodologies can be found in Carey et al. (2006, 2009, 2011).

Measures

Substance Use Outcomes

Heavy Alcohol Use: Assessment of alcohol use over the previous 30 days included: number of drinks during the heaviest drinking week, peak BAC in the last month, and number of heavy drinking episodes (see Table 2). The Daily Drinking Questionnaire (Collins, Parks, & Marlatt, 1985) was used to assess drinks per heaviest week. Using a 7-day grid, participants estimated how many standard drinks were consumed on each day for the heaviest drinking week in the past 30 days. Participants also reported the maximum number of drinks and the time elapsed while drinking for the heaviest drinking day in the past month. These data were used to compute peak BAC estimates using the formula provided by Matthews and Miller (1979): $BAC = [(consumption/2) \times (GC/weight)] - (.016 * hours)$, where GC is the gender constant (9.0 for women and 7.5 for men). Last, to determine frequency of heavy drinking episodes, participants reported how many times they consumed five or more drinks (for a male) or four or more drinks (for a female) in the previous month (Wechsler, Davenport, Dowdall, Moeykens, & Rimm, 1995).

Covariate

Social Desirability: Because our evaluation of intervention efficacy relied upon self-report, social desirability was included in the models as a covariate of each person's change over time. Social desirability was assessed using the 13-item, short-form (Form C) of the Marlowe-Crowne Social Desirability scale (Reynolds, 1982). The Cronbach's reliability coefficient for the current sample was .66.

Explanatory Variables

Alcohol-related Consequences: The Rutgers Alcohol Problem Index (RAPI; White & Labouvie, 1989) assessed alcohol-related consequences over the previous 30 days using a 5-point scale (Never to 10+ times). The alpha reliability coefficient for the current sample was .83.

Other Drug Use: Participants reported drug use during the past 30 days (yes/no) on a variety of recreational substances: marijuana, PCP, tranquilizers, cocaine, GHB, amphetamines, stimulants, ecstasy, hallucinogens, inhalants, heroin, opiates, painkillers, rohypnol, and other.

Demographics and Alcohol Use Variables: Participants provided demographic information that included gender, race, age, year in school, and height and weight (for BAC calculations). In addition, participants were asked about their drinking history including the age of their first drink, if they engaged in drinking games during the previous 30 days, and if they were a member of a fraternity or sorority.

Descriptive Norms: Participants used the Drinking Norms Rating Form (DNRF; Baer, Stacy, & Larimer, 1991), which uses the same grid format as the DDQ to report the number of standard drinks consumed each day of a typical week for a close same-gender friend.

Injunctive Norms: To assess injunctive norms, we used a modified version of a 10-item scale (Larimer et al., 2001) that assessed how much the participant's close friend would approve of the participant's drinking behaviors. An example item is "How much would your friend approve if they knew you drank every weekend?" Items were assessed using a 5-point, Likert-type scale from strongly disapprove to strongly approve. The alpha reliability coefficient for these data was .79.

Decisional Balance: The Decisional Balance for Immoderate Drinking Scale (Migneault, Velicer, Prochaska, & Stevenson, 1999) is a 20-item scale that assesses one's view toward alcohol misuse. This 2-factor scale assesses the perceived pros and cons in alcohol misuse. Items are assessed using a 5-point, Likert-type scale. The alpha reliability coefficient for the Drinking Pros subscale (10-items) was .84, and the reliability for the Drinking Cons subscale (10-items) was .76.

Readiness-to-change: The Readiness-to-Change Questionnaire (RTCQ; Rollnick, Heather, Gold, & Hall, 1992) was used to assess motivation to change one's drinking. Participants responded to a 12-item measure using a 5-point Likert-type scale; a continuous readiness-to-change score was computed (Budd & Rollnick, 1996). The alpha reliability coefficient for the current sample was .85.

Self-regulation: The Short Self-Regulation Questionnaire (Carey, Neal, & Collins, 2004) was used to assess general self-regulation capacity. The scale is comprised of 31 items that are assessed using a 5-point, Likert-type scale. The reliability coefficient for the current sample was .92.

Analysis Design

Growth Model: Because all students received an intervention, we expected everyone in the sample to initially improve their drinking outcomes, but would fade over the subsequent 12 months (Carey et al., 2007). Therefore, the piecewise, curve-of-factor latent growth model identical to the model used in Carey et al. (2011) was fit to the data to assess discontinuous change over time (see Figure 1). Specifically, heavy-drinking consumption was modeled as a factor comprised of three drinking variables: drinks per heaviest drinking week, number of binge episodes, and peak BAC. Estimated model parameters are interpreted in the drinks per heaviest week metric. Further, growth was modeled discontinuously as two components: a) change from baseline to 1-month (intervention effect) and b) change from 1-month to 12-months (maintenance effect). Because the intervention effect growth factor was based only on two time points (change from baseline to 1-month), the latent variable disturbance at time 1 was fixed to 0.

Mixture Modeling: In contrast to most analytic strategies that assume participants are randomly sampled from a single population, GMM was used to empirically identify the number of subgroups in reference to change over time. The mixture modeling component is represented by the latent class variable in Figure 1. Growth parameters were estimated controlling for mean-centered, social desirability; therefore, growth functions are for participants with average social desirability. The critical parameters estimated by this latent growth mixture model are the baseline averages, intervention effects (slope 1), and maintenance effects (slope 2) for each subpopulation. In addition, the variances of the baseline and intervention effect factors were allowed to freely vary across factors, but the variance for the maintenance slope was fixed to 0 because it was non-significant for all groups and was required for estimation convergence.

Number of Classes: A critical aspect of GMM is determining the number of subpopulations that best fit the data. Current recommendations (Nylund, Asparouhov, & Muthén, 2007) suggest that the bootstrapped likelihood ratio test (BLRT) exhibits the most power in determining the number of classes, followed by the Bayesian Information Criteria (BIC). Therefore, models were run where the number of classes ranged from 1 to 8, and the BLRT and BIC were compared to ascertain which model best fits the data.

Results

Descriptive Statistics

Descriptive statistics for the alcohol use variables are listed by study in Table 2. Across all three heavy drinking variables there is a sharp decrease in drinking behaviors immediately following the intervention (between baseline and 1-month), with an increase toward baseline drinking levels over the subsequent 12 months. These statistics suggest that the piecewise growth model is most appropriate because it decomposes change into three pieces: baseline drinking, change from baseline to 1-month (intervention effect), and change from 1-month to 12-months (maintenance effect).

Growth Mixture Modeling Results

Models with increasing number of classes were fit and the BIC and bootstrapped LRT were compared. According to the BIC, when compared to the 5- (BIC = 40379.12) and the 7-class solutions (BIC = 40365.27), the 6-class solution provided the best fit to the data (BIC = 40350.30); BIC values for 1 to 4 classes were as follows: 41024.39, 40787.69, 40569.06, and 40421.66, respectively. Further, in comparison to the 6-class solution, the 7-class bootstrapped LRT was not significantly better (bootstrapped χ^2 difference = 26.71, p = .052); the remaining bootstrapped LRT comparisons for classes 2 through 6 were all significant at a $p < .0001$ level. Last, the 6-class solution yielded an entropy statistic of .83 in the data, which surpassed the 5- and 7-class solutions (entropies = .79 and .76, respectively), which indicates better classification in the data (Celeux & Soromenho, 1996); entropy statistics for classes 2 through 4 were as follows: .83, .80, and .89, respectively. The 8-class solution failed to converge reliably, suggesting an overextraction of classes.

Table 3 lists the unstandardized piecewise growth model results for the six class solution, which are depicted in Figure 2. The results represent estimated heavy drinking behaviors across all three heavy drinking variables even though drinks per heaviest week is used as the arbitrary metric. Class 1 represents 76% of the sample, and has the lightest drinkers in the sample (16.62 drinks per heaviest week at baseline). This class is typified by a moderate decrease in drinking post-intervention (−4.71 drinks per heaviest week) with a modestly increasing maintenance effect (.29 drinks per heaviest week estimated per month). Class 2 (11%) is comprised of more moderate drinkers (32.19 drinks per heaviest week at baseline) who were intervention resistant (i.e., no significant change) and exhibited no significant change across the 12 months. Class 3 (5%) represents a minority of individuals who were lighter drinkers at baseline (20.48 drinks per heaviest week), but who did not respond to intervention and instead consistently *increased* their drinking over the 12 months (2.15 drinks per heaviest week increase each month). Class 4 (3%) consisted of the heaviest drinkers in the sample (76.39 drinks per heaviest week at baseline) who exhibited a strong intervention effect (39.83 drinks per heaviest week decrease) without additional change over the subsequent 12-months. Class 5 (3%) exhibited a strong intervention effect (22.44 drinks per heaviest week decrease) that quickly decayed over the subsequent 12 months (3.20 increase in drinks per heaviest week each month), whereas Class 6 (2%) exhibited an increase in drinking post-intervention (20.64 increase in drinks per heaviest week) with a steady decrease in consumption over the subsequent 12 months (3.08 drinks per heaviest week decrease each month). According to these results, 82% of the sample responded to the intervention by decreasing their heavy drinking behaviors from baseline to 1-month (i.e., Classes 1, 4, and 5); however, 96% of these individuals increased their drinking over the subsequent 11 months. In fact, 84% of all participants reported increases in their heavy-drinking behaviors over the subsequent 11 months during the maintenance period (i.e., Classes 1, 3, and 5).

Table 3 also reports the residualized standard deviation for each group's baseline drinking and intervention effect after controlling for social desirability. As reported in Table 3, baseline drinking standard deviations ranged from ~8 to ~20 drinks per heavy drinking week, which suggests that the individual baseline estimates vary meaningfully across subjects. Further, the intervention effects (i.e., baseline to 1-month change) also varied a great deal, from ~6 drinks per heavy drinking week to ~19. Classes with more extreme consumption also tended to have more variability.

Intervention Effect Size—There was a medium effect size for the intervention effect for the entire mixed sample (d = .50); however, the intervention efficacy effect size for class 1 was much larger (d = .71) because of the reduced variability due to mixing different types of individuals. Other effects sizes were not estimated because of small class sizes.

Characterizing the Classes

Class Membership and Study Variables—In order to characterize the classes, individuals were assigned to the class of highest probability. Class membership was independent of type of intervention (i.e., BMI, Alch 101, Alch EDU; $\chi^2(10) = 8.90$, $p = .54$), type of sampling method (i.e., volunteer vs. mandated students; $\chi^2(5) = 8.37$, $p = .14$), and of research project ($\chi^2(10) = 12.84$, $p = .23$). This suggests that how the participants responded to an intervention did not depend on which intervention was delivered or on study characteristics. Therefore, type of intervention, sampling strategy, and research project were not included in subsequent analyses.

Alcohol consequences and other drug use—Class membership was used to predict baseline difference in alcohol-related consequences (i.e., RAPI score) and other drug use in the previous 30 days (coded yes/no); these results are listed at the top of Table 4. The typical college drinkers, Class 1, had the lowest RAPI scores and were least likely to use other drugs over the previous 30 days. As expected, only Class 3 (i.e., the other lighter baseline drinkers) did not report significantly higher baseline drinking consequences as compared to Class 1. Further, Classes 2, 4, and 5 all reported significantly higher proportions of individuals who used other drugs during the previous 30 days. Last, Class 1 had a significantly higher age of first drink (i.e., 16.02) as compared to all other classes, and had the lowest proportion of those who engaged in drinking games over the previous 30 days. These findings suggest that the typical individual likely to respond to intervention is a relatively lighter drinker who has fewer alcohol-related consequences and is less likely to be using other drugs.

Demographic Variables—Using Class 1 as a reference class, further characterization of the classes is depicted in Table 4. Gender was the strongest demographic predictor, and compared to Class 1 (54% female), every other class had significantly fewer females. In addition, Classes 3, 4, and 5 had significantly more freshman as compared to Class 1 (57% freshmen). Students who reported the highest drinking at baseline (i.e., Class 4) had significantly more Greek members than Class 1, and there were no significant race differences (where race was coded white vs. non-white).

Psychological Factors—The strongest psychological predictors were descriptive norms and injunctive norms. Specifically, Class 1 had significantly lower descriptive norms and injunctive norms compared to every other class. Class 1 also had the highest self-regulation score (116.38), and the lowest decisional balance pros and cons scores (30.95 and 27.26, respectively). Last, the heaviest baseline drinkers reported significantly higher readiness-to-change as compared to Class 1; this is the only significant difference among readiness-to-change means.

Intervention Efficacy and Individual Differences

Predicting Intervention Responsivity—To understand the individual difference factors that predict intervention efficacy, we compared those who responded to the intervention (Classes 1, 4, and 5 [82% of the sample]; coded '1') to those who did not (Classes 2, 3, and 6 [18% of the sample]; coded '0'). A backwards stepwise binary logistic regression was used to empirically ascertain the strongest, unique predictors of intervention efficacy. As opposed to listwise-deletion, maximum likelihood estimation was used assuming data were MAR to maximize sample size and all effects are significant at alpha = .001. Results suggest that those who respond to the intervention were more likely to be female ($b^* = .18$, $\Delta R^2 = .01$), not freshmen ($b^* = -.18$, $\Delta R^2 = .03$), started drinking later in life ($b^* = .13$, $\Delta R^2 = .01$), did not engage in drinking games ($b^* = -.20$, $\Delta R^2 = .04$), and had significant lower norms at baseline (both descriptive [$b^* = -.17$, $\Delta R^2 = .02$] and injunctive [$b^* = -.22$, $\Delta R^2 = .04$]). These six predictors explained 31% of the variance in intervention efficacy.

Predicting maintenance over time—Last, the same backward stepwise logistic regression procedure was use to ascertain the significant, unique predictors of maintaining or reducing their drinking over the final 11 months (Classes 2, 4, & 6 [16% of the sample] vs. Classes 1, 3, and 5 [84% of the sample]). Results indicate similar important predictors with an alpha of .001. Those who began drinking at an earlier age ($b^* = -.14$, $\Delta R^2 = .01$), those who engaged in drinking games over the previous 30 days ($b^* = .24$, $\Delta R^2 = .06$), and those with higher descriptive ($b^* = .35$, $\Delta R^2 = .03$) and injunctive ($b^* = .28$, $\Delta R^2 = .05$) norms were *more likely* to maintain or reduce drinking over time. These four predictors explained 43% of the variance in change from 1- to 12-months. These results suggest that although the lighter and moderate drinkers were more likely to respond to intervention, they were also more likely to return to original drinking patterns over the subsequent 12-months. In contrast, heavier drinkers were more likely to maintain or reduce their drinking.

Discussion

The purpose of this research was to identify factors related to successful brief alcohol intervention for college students by determining who was most likely to respond to intervention and by characterizing both short- and long-term change trajectories while controlling for social desirability. Using growth mixture modeling, we determined that there were 6 classes, or subpopulations of individuals, who differ in how they respond to intervention (i.e., intervention effect) as well as how the intervention effects maintain or fade over the subsequent 12-months (i.e., maintenance effect). Most of the sample reducing their drinking from baseline to one-month (82% of the sample); however, most participants also reported *increasing* their drinking over the subsequent 12-months (84% of the sample). Understanding the type of individual who is most likely to change as well as how they are changing can enhance our understanding of intervention efficacy as well as identify those who are resistant to intervention.

Types of Intervention

Interestingly, the type of intervention given (i.e., BMI, Alcohol 101, Alcohol EDU) was unrelated to class membership. In other words, an in-person BMI did not make an individual more or less likely to be part of an intervention-resistant or an intervention-responsive class. Replicating the findings in Mun et al. (2009), this finding suggests that the type of intervention is less critical than the type of person receiving it. Some research supports the relative superiority of the BMI over computerized interventions (e.g., Barnett, Murphy, Colby, & Monti, 2007; Carey, et al., 2009), whereas other research does not (Butler & Correia, 2009). This research suggests that the predisposition of the participant is a more decisive factor, and thus, for most people, a more cost-effective computerized intervention may be most appropriate.

Types of College Drinkers

We identified a large class of individuals (Class 1; 76% of the sample) that exhibited a reduction in heavy drinking behaviors after intervention followed by a decay of intervention effects. Relative to the other types of drinkers, these college students tended to drink less, to experience fewer alcohol-related consequences, to not use other drugs, to be female, and to have had their first drink later in life. Further, these individuals reported significantly lower pros and cons to drinking as well as greater self-regulation than most other classes. Last, these individuals reported the lowest descriptive and injunctive norms. In other words, this class represents the lightest drinkers in the sample who tended to be younger, female, and less experienced drinkers.

As the largest class in the sample, Class 1 reveals valuable information about the ‘typical’ college student drinker as well as how he or she responds to intervention. At baseline, the typical college drinker (77% of this sample) tended to consume, on average, 16.6 drinks during their heaviest drinking week, which is still quite high for the lightest drinkers in the sample, but is also reassuring that most fell into this class of lighter, inexperienced drinkers. In addition, we are successful in decreasing drinking behaviors among these individuals, and the effect size for this class (d = .71) implies a meaningful change in drinking behaviors following intervention (~5 drinks per week). However, these are young, inexperienced, and light drinkers are likely the easiest to change. Perhaps this is why there was no effect of the type of intervention (i.e., BMI vs. computerized intervention); light drinkers are just easily changed. Furthermore, their drinking eventually returns to baseline behaviors. Although interventions can be used successfully with this subpopulation, intervention boosters may be necessary to maintain or increase the intervention effects.

More disconcerting is Class 2 (11% of the sample) who reported no change over the 12 months; this suggests that one in ten college students are likely to be resistant to a college drinking intervention. This class consisted of mostly freshmen men who reported the lowest readiness-to-change scores, as well as significantly lower self-regulation, and higher pros to drinking, descriptive norms, and injunctive norms (relative to Class 1). Although this class was intervention-resistant, they were not the most extreme drinkers in the sample. Thus, their resistance may not necessarily be attributable to severe alcohol problems, such as alcohol dependence. These data suggest that these are young, freshmen men who drink more heavily than Class 1 and who have little intention of decreasing their drinking. Their elevated alcohol consequences make this an important group to target, and a single-session intervention is not enough to effect change in this population. Future research should explore the characteristics of this population that resist intervention influences.

Although the data suggest that there are two primary subpopulations of college drinkers (Classes 1 and 2 comprise 88% of the sample), there are also 4 small subpopulations (≤ 5% of the sample). Individuals in Class 3 (5% of the sample) increased their drinking over the study with no intervention effect. Besides Class 1, Class 3 had the lightest drinkers in the sample, had a large proportion of freshmen, engaged in more drinking games, but also had the second highest self-regulation. The data suggest these individuals are not problem-drinkers, but rather consistent, moderate drinkers who are likely not going to change from intervention. Additional research is needed to discern Class 1 drinkers, who respond to intervention, from Class3, who do not.

In contrast, Class 4 (3% of the sample) can be characterized as problem drinkers and potentially individuals with a substance use disorder. These individuals reported the greatest amount of consumption as well as consequences. As with Class 2, Class 4 is comprised mostly of freshmen males. Nearly all of the individuals in the class engaged in drinking games during the prior month and 81% used other drugs. They exhibited the highest descriptive norms, were among the lowest in self-regulation, and began drinking at the youngest age. However, in contrast to Class 2, this class *did* respond to intervention and maintained the effects over 12 months. This suggests that brief interventions can effect major behavior change in the most problematic population of drinkers. Most notably, this class had the highest percentage of Greek members, which may reflect unique drinking patterns among Greek organizations.

Last, Classes 5 and 6, the smallest classes, consisted of moderate-to-heavy drinkers at baseline who exhibited opposite trajectories. A “heavy-drinking” version of Class 1, Class 5 (3% of the sample) responded to intervention, but increased their drinking over the subsequent 12-months. In contrast to Class 1, participants in Class 5 were much more likely to be men, were most likely to use other drugs, reported the second lowest self-regulation, and reported significantly higher descriptive and injunctive norms at baseline. Conversely, participants in Class 6 (2% of the sample) *increased their drinking* following intervention (the only class to do so), but similarly returned to baseline behaviors over the subsequent 12 months. Almost all men (78%), Class 6 reported more pros and cons to changing their drinking at baseline, but did not stand out on other variables.

In the current research, 76% of the sample was light-to-moderate drinkers who responded to intervention. Likewise, Mun and colleagues (2009) found a similar primary population of light college drinkers that responded to intervention, but returned to baseline drinking (53.4% of the sample). This proportion is similar to the proportions of naturally occurring light-to-moderate drinkers among college students (62%; Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005) and adults (84%; Cerda, Vlahov, Tracy, & Galea, 2008), which reaffirms that risk reduction efforts are most efficacious among light-moderate drinkers.

Similarly, Class 2 (11%) was comprised of consistent, stable drinkers. Greenbaum and colleagues (2005) similarly reported a subpopulation of stable drinkers (10% of the sample). In contrast, Mun et al. (2009) reported that consistent, stable drinkers made up 40% of their college sample. This discrepancy may stem from the assessment schedule of the Mun et al. study. Specifically, participants were assessed at baseline and 4 months as opposed to the 1-month assessment schedule used for the current research. It may be that by four months the intervention effects would have deteriorated and illustrated non-change. These discrepant findings suggest that multiple short-term follow-ups are needed to capture intervention effects before they decay.

Who responds to intervention?

We identified six predictors of who would respond to alcohol intervention (82% of the sample). The only unique psychological predictors of intervention efficacy were injunctive and descriptive norms. Although change in norms is commonly examined as a mediator of alcohol interventions with a normative feedback component (Doumas, Haustveit, & Coll, 2010; Neighbors et al., 2006), we are unaware of research demonstrating baseline norms to moderate intervention effects. In addition, female upperclassmen are the most likely to respond to intervention, whereas those who started drinking earlier in life are not. Finally, the strongest predictor was playing drinking games during the previous month. Taken together, we should be revising interventions to target freshmen men who play drinking games and have elevated norms because our intervention efforts among these individuals yield limited efficacy.

Who maintains or decreases their drinking?

Only four predictors emerged for understanding the maintenance effect. Findings suggest that those with higher norms, who play drinking games, and who started drinking at an earlier age exhibited long-term intervention effects of maintaining or decreasing their drinking, which seems counterintuitive. First, only 16% of the sample maintained or decreased their drinking across the maintenance period. Second, individuals with those characteristics were moderate-to-heavy drinkers at baseline, and as such, had an easier time maintaining or even reducing their drinking. Greenbaum et al. (2005) found 20% of college drinkers naturally decreased their drinking, which might explain the 16% in our sample to do so. Therefore, these results suggest that intervention efficacy has little impact on long-term growth trajectories except for perhaps among the heaviest drinkers. Unfortunately, few participants fell into this category with most of the sample increasing their drinking over the last 12 months (84%).

Strengths

The current exploratory study had many strengths. First, by collapsing across several large-scale, randomized-controlled clinical trials, we were able to achieve a large sample size (n = 1,040) of individuals exposed to intervention. Second, by assessing college students who received different interventions (i.e., BMI, Alcohol EDU, Alcohol 101) as well as different recruitment strategies (i.e., volunteers and campus sanction), we are able to generalize our results across a wide range of students and interventions. Third, we used a *latent variable* growth mixture modeling strategy that allowed us to assess change in heavy drinking while minimizing the effects of measurement error. Fourth, the study design that included baseline data collection along with 1-, 6-, and 12-month follow-ups allowed precision in characterizing the short-term intervention effect as well as maintenance patterns over the subsequent 11 months. Last, the original studies included a range of historical, behavioral, and psychological variables to help characterize the estimated classes.

Limitations

As with all mixture modeling research, interpreting the results depends on ability to characterize the estimated classes with relevant explanatory variables. Although we had a variety of explanatory variables, we may be missing predictors that distinguish among the estimated classes. Further, the precision of mixture modeling depends on the timing of the assessments, and more frequent assessments may reveal distinct drinking trajectories. Another limitation is the reliance on retrospective self-reports, which have been shown to be associated with significant recall biases in time windows as short as seven days (Gmel & Daeppon, 2007). Additionally, we treated class membership as deterministic by assigning individuals to their most likely class for class characterization, which allowed us to collapse groups for further analysis (i.e., intervention responders to non-responders). Our entropy statistic (.83) suggested some meaningful misclassification in the data, however, which can obfuscate class characterization. Additional group comparisons using the 3-step approach (not reported; Asparouhov & Muthén, 2013) assumed a probabilistic approach to class membership and found no differences in our original conclusions, which suggests minimal impact of class misclassification on reported conclusions.

It is important to note that the GMM aggregates data within a class. Therefore, although an average trajectory can be discerned for each class, it doesn't imply that all individuals within a class follow that trajectory. This is indicated by the size of the standard deviations around baseline drinking and the intervention effect. Classes that consumed more alcohol on average had much more variability, because there was much more possibility of variation at extreme consumption. Although we can identify which trajectory an individual is most likely to belong to, this implies that there is still a great deal of meaningful variability one can predict regarding inter- and intra-individual differences and trajectories. In other words, we must not mistake the 'average' trajectory for the 'typical' trajectory; there still is a great deal of variability.

Conclusions

Using a large, diverse sample, we determine there are two primary subpopluations of college drinkers with regard to intervention efficacy as well as four minor ones. Most of the samples were light-moderate drinkers who respond to an alcohol intervention, but return to baseline drinking behaviors; a much smaller group of individuals are intervention-resistant. Our findings highlight the heterogeneity among college drinkers and suggest that college administrators and/or health staff need a range of intervention types to achieve risk reduction across identified subpopulations. Stepped care models may be particularly appropriate responses to students who do not change after a brief alcohol intervention (cf. Borsari et al., 2012). These findings suggest that we need to find ways to meaningfully engage young men who started drinking at a young age as well as who play drinking games in risk reduction efforts. In addition, baseline descriptive and injunctive drinking norms are significant predictors of response to intervention, which highlights the need of normative feedback as part of individual and campus-based interventions for college students.

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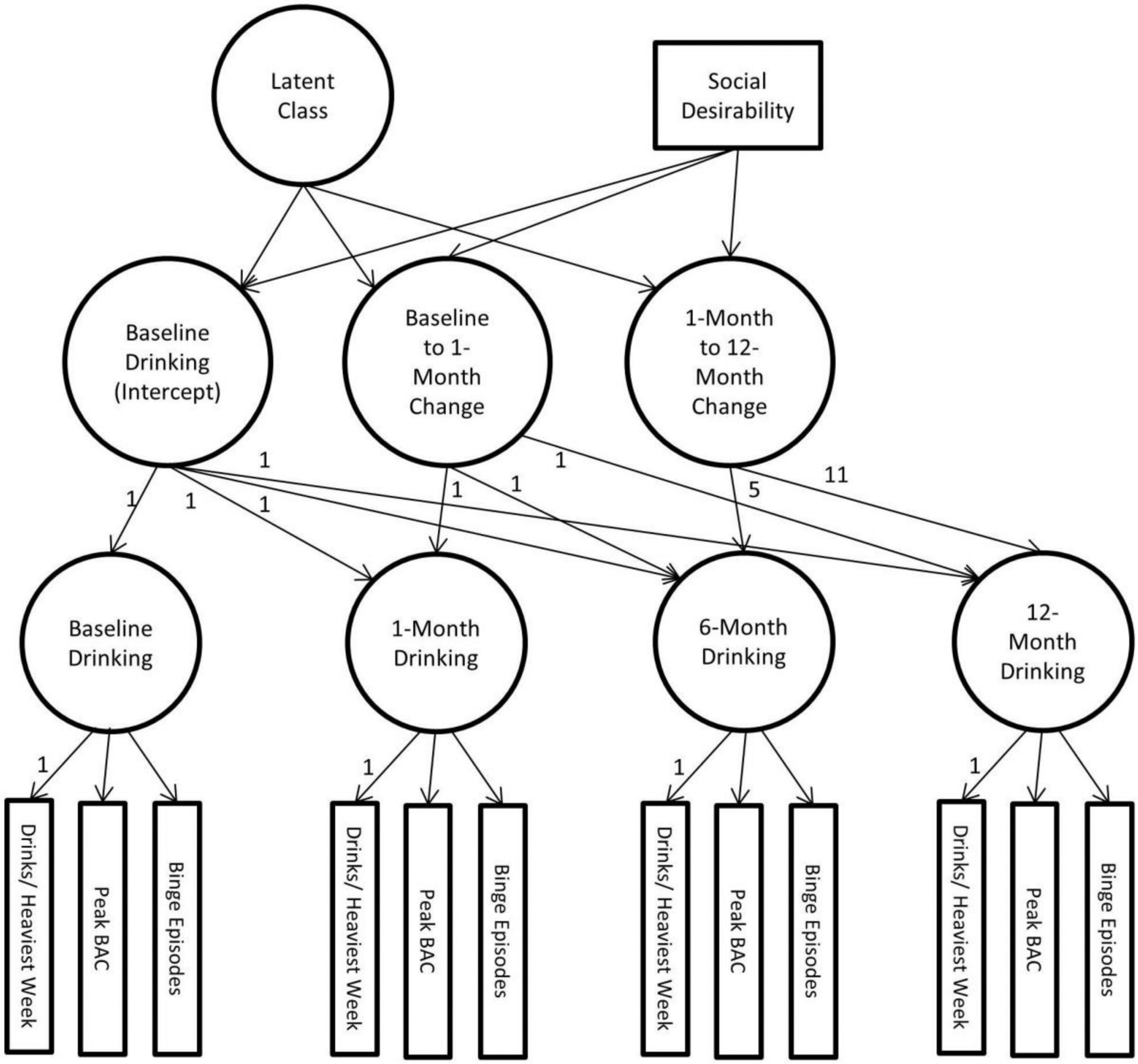

Figure 1.
Piecewise, curve-of-factor latent growth mixture model to assess subpopulation differences in heavy drinking following intervention

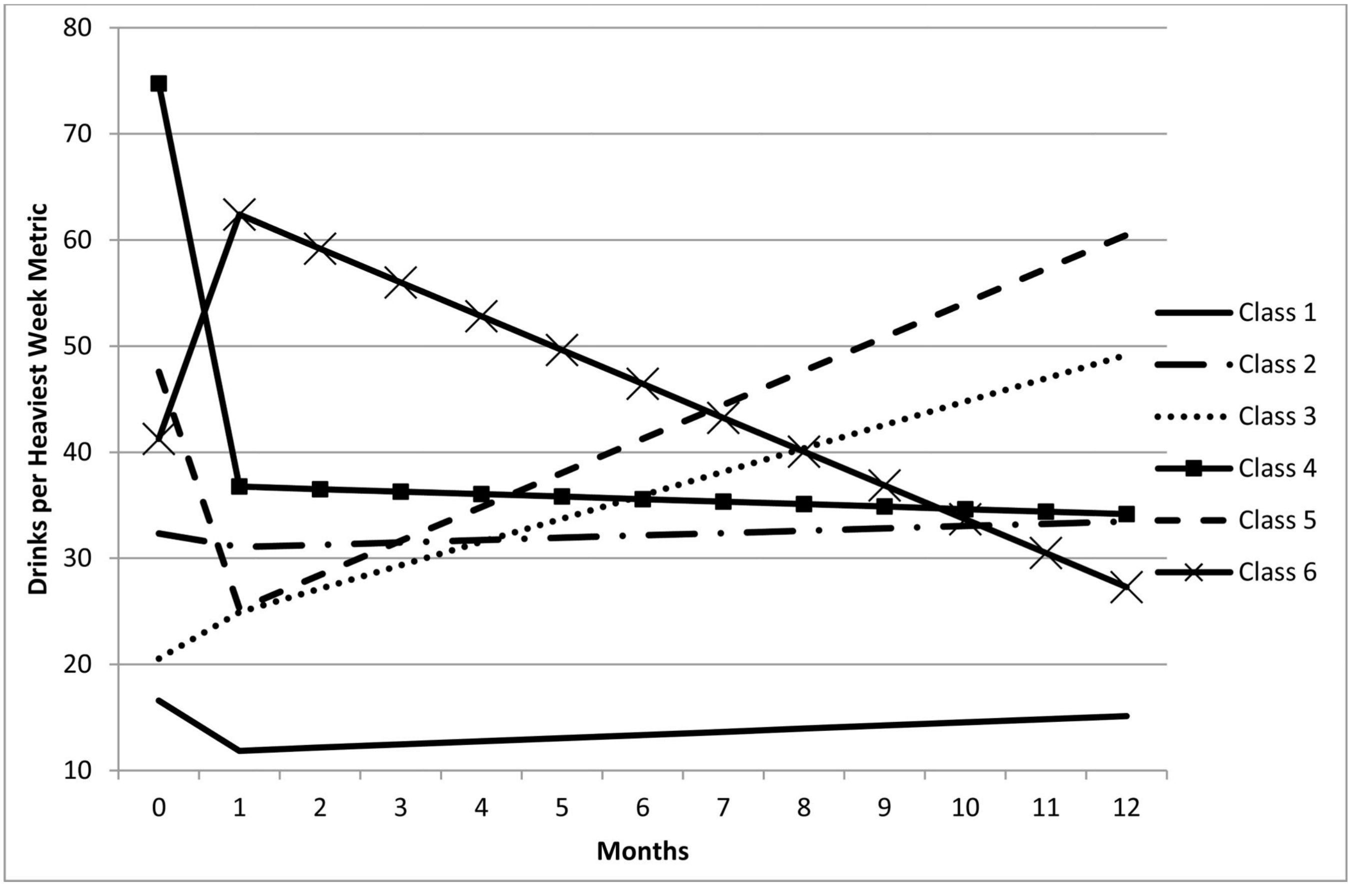

Figure 2.

Unstandardized results for the estimated six classes regarding their expected change in drinking following intervention, which was administered between 0 and 1 months

Table 1

Demographic Information by Research Study and Across All Studies

	Study 1[a]	Study 2[b]	Study 3[c]	Total
Gender				
Men	121 (36%)	107 (54%)	320 (64%)	548 (53%)
Women	218 (64%)	91 (46%)	182 (36%)	491 (47%)
Year				
Freshmen	186 (56%)	111 (56%)	324 (65%)	621 (60%)
Sophomore	119 (35%)	78 (39%)	152 (31%)	349 (34%)
Junior	25 (7%)	9 (5%)	20 (4%)	54 (5%)
Senior	5 (2%)	0 (0%)	0 (0%)	5 (1%)
Race / Ethnicity				
White	299 (91%)	179 (91%)	420 (84%)	898 (87%)
Black	6 (2%)	2 (1%)	10 (2%)	18 (2%)
Hispanic	2 (1%)	6 (3%)	20 (4%)	28 (3%)
Asian/ Pacific Islander	11 (3%)	8 (4%)	37 (7%)	56 (5%)
Other	12 (3%)	2 (1%)	14 (3%)	28 (3%)

Note.

[a]Carey, Carey, Maisto, & Henson, 2006;

[b]Carey, Henson, Carey, & Maisto, 2009;

[c]Carey, Henson, Maisto, & DeMartini, 2011.

Table 2

Descriptive Statistics by Study for the Three Heavy Alcohol Consumption Variables Across all Four Assessments.

	Study 1[a]		Study 2[b]		Study 3[c]		Total	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Drinks / Heaviest week								
Baseline	26.68	16.51	21.92	18.78	18.95	13.56	22.04	16.00
1-Month	19.48	15.35	17.24	14.37	15.85	13.13	17.31	14.21
6-Months	21.42	17.45	20.78	15.36	19.23	14.95	20.36	16.01
12-Months	21.35	16.92	23.08	15.76	20.95	15.58	21.49	16.09
Binge Frequency								
Baseline	7.16	4.58	5.78	5.20	5.12	4.64	5.91	4.82
1-Month	4.93	4.16	4.30	4.36	3.91	3.97	4.32	4.13
6-Months	6.05	4.72	5.76	5.54	4.57	4.38	5.36	4.80
12-Months	5.56	4.40	6.72	5.73	5.11	4.94	5.57	4.94
Peak BAC								
Baseline	0.212	0.090	0.167	0.105	0.160	0.090	0.178	0.096
1-Month	0.165	0.105	0.134	0.091	0.126	0.086	0.140	0.095
6-Months	0.172	0.102	0.164	0.102	0.144	0.088	0.158	0.097
12-Months	0.165	0.105	0.160	0.109	0.145	0.087	0.155	0.098

Note.

[a] Carey, Carey, Maisto, & Henson, 2006;

[b] Carey, Henson, Carey, & Maisto, 2009;

[c] Carey, Carey, Henson, Maisto, & DeMartini, 2011.

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Table 3

Unstandardized Latent Growth Coefficients for each of the Six Estimated Classes.

Class	Baseline Drinking		Intervention Effect[a]		Maintenance Effect[b]	*N* (%)
	Mean	SD[c]	Mean	SD[c]	Mean	
1	16.62*	8.35	−4.71*	6.15	0.29*	795 (76%)
2	32.19*	12.93	−1.26	14.53	0.21	115 (11%)
3	20.48*	10.54	4.69	8.81	2.15*	51 (5%)
4	76.39*	20.19	−39.83*	10.84	−0.20	28 (3%)
5	47.47*	17.88	−22.44*	18.82	3.20*	28 (3%)
6	41.01*	20.68	20.64*	13.98	−3.08*	23 (2%)

Note. Unstandardized coefficients are interpreted as drinks per heaviest drinking week.

* indicates significantly different from 0 where $p < .05$.

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

[b] Expected monthly change from the 1-month to the 12- month assessment.

[c] SD indicates the residual standard deviation after controlling for social desirability.

Table 4

Baseline Differences across Classes on Key Study Variables using Class 1 as the Comparison Group.

	Class						F/χ^2	R^2
	1	2	3	4	5	6		
Consequences and Other Substance Use								
RAPI Score[a]	4.76	8.92*	5.84	13.21*	7.96*	9.87*	25.08	0.11
Other drug use[b]	0.51	0.79*	0.70	0.81*	0.89*	0.64	36.53	0.09
Age of 1st Drink[a]	16.02	15.18*	15.34*	14.67*	14.87*	15.09*	13.68	0.06
Drinking Games[b]	0.79	0.97*	0.90*	0.96*	0.93*	1.00*	43.82	0.07
Demographic and Behavioral Variables								
Female[b]	0.55	0.29*	0.20*	0.21*	0.14*	0.22*	78. 56	0.10
Freshman[b]	0.57	0.72	0.76*	0.32*	0.57	0.78*	28.30	0.04
White[b,c]	0.86	0.93	0.94	0.86	0.96	0.96	10.35	0.01
Greek Member[b]	0.17	0.26	0.22	0.39*	0.14	0.30	13.90	0.02
Psychological Variables								
RTCQ[a]	19.13	17.95	18.62	23.11*	20.15	22.43	2.94	0.02
SSRQ[a]	116.38	110.04*	115.67	112.04	111.75	112.48	5.07	0.02
Pros[a]	30.95	33.359*	33.78*	33.25*	34.50*	35.00*	8.52	0.04
Cons[a]	27.26	27.67	28.71	29.57*	27.43	29.96*	2.47	0.01
Desc. Norms[a]	18.55	35.47*	25.11*	48.41*	42.34*	35.72*	33.22	0.14
Inj. Norms[a]	2.92	3.49*	3.19*	3.48*	3.63*	3.52*	16.60	0.11

Note. Table lists unstandardized coefficients. All factors exhibited significant class differences except White and RTCQ.

[a] values in the table represent means.

[b] values in the table represent proportions.

[c] indicates non-significant at $p < .05$.

* indicates a significant difference from Class 1 at $p < .05$.