



Daily-Level Associations Between Protective Behavioral Strategies, Transdermal Alcohol Concentration, and Alcohol-Induced Blackouts Among Young Adults

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Abstract

Objective: Alcohol-induced blackouts (AIBs) are more likely to occur when large quantities of alcohol are consumed quickly. Protective behavioral strategies (PBS) may mitigate the risk of experiencing an AIB by reducing the level, speed, and duration of drinking. This study examines daily associations between PBS, drinking measured using a transdermal alcohol concentration (TAC) biosensor, and AIBs among young adults.

Method: Participants ($N=168$, $M_{age}=20.8$, 53% female, 87% White, 10% Hispanic) wore TAC biosensors and completed daily surveys about their PBS use and AIBs over six social weekends (i.e., Thursday-Sunday). TAC drinking features (peak, rise rate, and rise duration) were extracted from TAC data for each day. Two-level multilevel structural equation models were conducted to examine the associations between PBS (total and individual domains: manner of drinking [MD], stopping/limiting drinking [SLD], serious harm reduction [SHR]) and AIBs.

Results: Approximately 80% of participants experienced at least 1 AIB ($M=3.08$, $SD=2.99$). On days when individuals reported using more total PBS and MD, the associated decrease in TAC features was associated with decreased odds of experiencing an AIB. Days when individuals used more SHR, the associated increase in TAC features was associated with increased AIB odds.

Conclusions: Days when participants used above average total PBS and MD were less indicative of risky TAC drinking and AIBs. Days with above average SHR were more indicative of risky TAC drinking and AIBs. Findings demonstrate the associations between PBS, real-world intoxication dynamics measured by TAC biosensors, and subsequent AIBs among young adults who engage in risky drinking.

Keywords

alcohol-induced blackouts; transdermal alcohol concentration; protective behavioral strategies

Introduction

Alcohol-induced blackouts (AIBs) are a serious consequence of risky drinking (Richards et al., 2023b). AIBs occur when an individual is unable to recover memories (en bloc blackout) or is able to partially recover memories (fragmentary blackout) that occurred while they were intoxicated (Hermens & Lagopoulos, 2018; Miller et al., 2018; Rose & Grant, 2010; White, 2003). When experiencing an AIB, individuals are awake and interacting with their environment, but they are unable to create memories (Wetherill & Fromme, 2016). AIBs are more likely to occur when large quantities of alcohol are consumed quickly, causing a rapid rise in blood alcohol concentration (BAC; Carey et al., 2022; Carpenter & Merrill, 2021). Reducing the level, speed, and duration of rising BAC may help mitigate the risk of experiencing an AIB (Wetherill & Fromme, 2016). Students who drink alcohol experience about 2 ($SD=2$) AIBs per academic year and 8 ($SD=8$) AIBs throughout their four years in college (Glenn et al., 2024). At large university campuses (e.g. ~40,000 students), it is estimated that AIB-associated emergency department visits cost around \$500,000 per year (Mundt & Zakletskaia, 2012).

Prevention efforts targeting AIBs may help reduce associated harm (Glenn et al., 2024; Merrill et al., 2019; Richards et al., 2023a) and limit emergency department medical utilization costs (Mundt & Zakletskaia, 2012; Voloshyna et al., 2018). One potential target of such efforts are protective behavioral strategies (PBS) – behaviors used before, during, or after a drinking episode to limit alcohol intoxication and/or prevent alcohol-related consequences (Martens et al., 2005; Treloar et al., 2015). Research has shown that individuals who use PBS experience lower levels of intoxication and fewer negative alcohol-related consequences (e.g., Cox et al., 2024; Howard et al., 2024; Peterson et al., 2021; Russell et al., 2023). Accordingly, PBS may be an effective target for preventing young adults from experiencing an AIB by reducing the level, speed, and duration of rising BAC (Carey et al., 2022; Wetherill & Fromme, 2016). The current study examines daily associations between PBS, drinking measured using a transdermal alcohol concentration (TAC) biosensor, and AIBs among a sample of young adults who engage in risky drinking.

Advances in Technology to Measure Risky Drinking and AIBs

AIBs involve memory loss for all or part of a drinking episode. This may increase errors in retrospective self-reporting of number of drinks consumed on nights when an individual experiences an AIB. The current study uses a wrist-worn TAC biosensor (the BACtrack Skyn) to measure risky drinking which is not dependent on individual self-reporting number

of drinks. The biosensor measures TAC repeatedly to provide a curve of biological alcohol intoxication for each day drinking day (Fridberg et al., 2022; Richards et al., 2024; Russell et al., 2022). Three TAC drinking features derived from this curve that are analogous to risky drinking are: 1) *rise rate*, the rate of TAC increase during a drinking event (analogous to the speed of alcohol consumption), 2) *peak*, the maximum level of TAC during a drinking event (analogous to the intensity/amount of alcohol consumption), and 3) *rise duration*, the number of hours spent under rising TAC during an event (analogous to the amount of time spent consuming alcohol) (Russell et al., 2025). Rise rate, peak, and rise duration TAC features may transfer effectively into prevention actions because individuals can change how much and how quickly they consume alcohol (Richards et al., 2024). For example, rise rate may be decreased by using PBS like drinking water while drinking alcohol or avoiding trying to “keep up with” or “out-drink” others. Recent work has also provided evidence for the use of TAC biosensors when examining PBS and its associations with real-time intoxication dynamics and alcohol-related consequences among young adult and college student samples (Richards et al., 2025; Russell et al., 2023). Identifying PBS that contribute to TAC drinking features that are indicative of less risk may help facilitate behavior change interventions by identifying specific protective pathways that may modulate risky drinking behavior. The current study will be the first to examine the associations between daily PBS use, TAC drinking features, and AIBs among young adults.

PBS, Risky Drinking, and AIBs

PBS are typically categorized into three domains, including: 1) manner of drinking (MD, e.g., avoiding drinking games), 2) stopping or limiting drinking (SLD, e.g., drinking water while drinking alcohol), and 3) serious harm reduction (SHR, eating before or during drinking), and can either be analyzed by domain or by creating a total score (Pearson, 2013; Treloar et al., 2015). There is extensive literature examining the associations between PBS, drinking, and alcohol-related consequences among young adults (e.g., Cox et al., 2024; Peterson et al., 2021). Research using cross-sectional (Frank et al., 2012; LaBrie et al., 2009; Lemoine et al., 2020; Martens et al., 2005; Nogueira-Arjona et al., 2021; Perez et al., 2021) or longitudinal (Dvorak et al., 2017; Fernández-Calderón et al., 2021; Lewis et al., 2012;) designs have shown that PBS use is associated with lower levels of intoxication and alcohol-related consequences. By comparison, fewer studies have used diary, ecological momentary assessment, or have included TAC biosensors to assess PBS and drinking (e.g., Howard et al., 2024; Pearson et al., 2013; Russell et al., 2023).

There is less known about the relationship between PBS and AIBs among young adults who drink alcohol (Carey et al., 2022; Ray et al., 2009; Richards et al., 2023b, 2025). Between-person associations between PBS and AIBs have been examined using cross-sectional study designs. Ray et al. (2009) found that individuals who used higher numbers of each PBS domain experienced significantly fewer AIBs, controlling for drinking. Carey et al. (2022) examined separate models and found students reporting more PBS use in general (i.e., total PBS), MD, and SLD were less likely to have experienced an AIB in the past month. They did not find an association between SHR and experiencing an AIB in the past-month. When they examined each PBS domain as predictors in a single model, only MD was significantly associated with AIBs. Within-person studies have focused on the

day-level to understand how changes within a person may impact the associations between PBS and AIBs. Richards et al. (2023b) assessed college students over 6 weekends (1 survey per weekend retrospectively assessing Thursday, Friday, and Saturday behaviors) and found that MD was associated with decreased odds of experiencing an AIB at the day (within-person), week (within-person), and person-levels (between-person), over and above estimated BAC. Using a more sophisticated prospective intensive longitudinal design over 4 weekends, Richards et al. (2025) observed that AIB nights with above average SHR PBS were associated with about 50% fewer consequences than AIB nights with below average SHR PBS. A unique element of the within-person findings from Richards et al. (2025) is they used TAC biosensors to include a more precise and unbiased assessment of alcohol intoxication in the analyses. Findings from these studies suggest the potential benefits of using PBS to avoid AIBs and other consequences. However, it is challenging to make definitive conclusions about these associations due to systematic differences in studies that examine between-person PBS vs. within-person PBS. This includes samples with different risk profiles (e.g., students mandated to an alcohol treatment program, students with a history of using alcohol with other drugs) and measurement differences (e.g., not all studies examine each PBS domain). Additional research is warranted using rigorous methods and examining total PBS and each of the three PBS domains at the daily-level to elucidate the relationship between PBS and AIBs.

The Current Study

The current study expands prior work by using intensive event-level data, TAC biosensors to assess near real-time drinking, and daily reports of PBS use and AIBs among young adults who engage in risky drinking. The study hypotheses focus on examining associations at the daily-level (within-person) rather than average differences (between-person) to answer why and when AIBs occur (which event-days result in an AIB vs. not). Between-person findings identify average differences in groups of people. Findings at this level help answer important questions about “who” is at greater odds of experiencing an AIB. Within-person findings identify days that individuals are at increased odds of experiencing an AIB. This helps answer “when” questions by examining how individuals may change across time. Within-person findings are further complemented by using a TAC biosensor to precisely assess drinking at the daily-level. Key study aims and hypotheses are described below.

Aim 1. The first aim of the study was to examine the effect of total PBS use (i.e., a sum score of all possible PBS behaviors) on TAC drinking features and AIBs (see Theoretical Figure 1). This modeling approach provides information about the common or shared variance of PBS and how this is associated with TAC drinking features and AIBs. The following hypotheses are supported by previous work suggesting total PBS is negatively associated with drinking and AIBs (e.g., Carey et al., 2022; Cox et al., 2024; Fernández-Calderón et al., 2021; Russell et al., 2023). It was hypothesized that total PBS use would be negatively associated with TAC drinking features (H1a, *path a2*) and AIBs (H1b, *path c2*). Indirect effects were tested to assess the within-person associations between total PBS, TAC drinking features, and AIBs (H1c, *paths a2 × b2*).

Aim 2. Previous work has tested the independent contributions of each PBS domain by examining each domain as a separate unique predictor in a single model (e.g., Carey et al., 2022; Frank et al., 2012; Lewis et al., 2012; Richards et al., 2023b; Russell et al., 2023). Other work has focused on testing separate models for each PBS domain individually (e.g., Carey et al., 2022; Russell et al., 2023). The former approach tests the unique contributions of each scale, adjusting for the others. This would test, for example, whether MD PBS is associated with AIBs among people who use the same amount of SLD PBS and SHR PBS. The latter approach is unadjusted for the other PBS scales, which allows both the shared and unique components of each subscale to predict outcomes. Russell et al. (2023) found that the PBS total score and all three subscales were predictive of alcohol-related consequences. But when all 3 PBS domains were included in a single model, the direct, indirect, and total associations between each subscale, TAC drinking, and alcohol-related consequences were reduced to non-significance. This pattern of results suggested that the shared variance in PBS subscales was most important for indexing TAC levels and predicting alcohol-related consequences. However, Russell et al. (2023) model examined frequency of past-year PBS use and did not include daily reports of PBS. The second aim of the study was to examine the independent contributions of each PBS domain as predictors of TAC drinking features and AIBs in a single model. Hypotheses are described for each PBS domain (see Theoretical Figure 2).

MD. It was hypothesized that MD would be negatively associated with TAC drinking features (H2a, *path a4*) and AIBs (H2b, *path c4*). Indirect effects were tested to assess the within-person associations between MD, TAC drinking features, and AIBs (H2c, *paths a4* $\times$ *b2*). The hypotheses are consistent with previous research showing significant negative associations between MD, drinking, and AIBs (Carey et al., 2022; Lewis et al., 2012; Richards et al., 2023b; Russell et al., 2023).

SLD. It was hypothesized that SLD would be negatively associated with TAC drinking features (H3a, *path a5*) and AIBs (H3b, *path c5*). Indirect effects were tested to assess the within-person associations between SLD, TAC drinking features, and AIBs (H3c, *paths a5* $\times$ *b2*). The hypotheses are consistent with past research showing negative associations between SLD, drinking, and AIBs (Carey et al., 2022; Martens et al., 2005; Russell et al., 2023).

SHR. It was hypothesized that SHR would be positively associated with TAC drinking features (H4a, *path a6*) and AIBs (H4b, *path c6*). Indirect effects were tested to assess the within-person associations between SHR, TAC drinking features, and AIBs (H4c, *paths a6* $\times$ *b2*). Previous research is mixed regarding the relationship between SHR PBS, drinking, consequences, and AIBs. Some studies suggest the association between SHR and drinking is negative (Fernández-Calderón et al., 2021; Marten et al., 2005), positive (Howard et al., 2024; Linden-Carmichael et al., 2019; Pearson et al., 2013), or has no association (Frank et al., 2012; Russell et al., 2023). A similar pattern appears between SHR PBS, alcohol-related consequences, and AIBs (e.g., Fernández-Calderón et al., 2021; Howard et al., 2024; Lewis et al., 2012; Linden-Carmichael et al., 2018). These hypotheses are supported by longitudinal and event-level data suggesting that when students implement

more SHR PBS, they engage in riskier drinking (Howard et al., 2024; Lewis et al., 2012; Linden-Carmichael et al., 2019; Pearson et al., 2013).

Methods

Recruitment Procedures

Young adults were recruited from a large, public university in the northeastern United States. Recruitment included a random selection of 15,000 students from the university registrar's database. Participants were sent an email invitation describing the study and inviting their participation. Recruitment email notifications, which included up to six reminder emails, contained a personalized URL to access a screening survey. Participants were also recruited via flyers posted at on and off-campus locations (e.g., dorms, restaurants, coffee shops). A total of 31 prospective participants sent emails to the specified project email address indicating their interest in participating in the study. These participants were then sent the same email invitation and followed the same procedures as participants who were randomly contacted from the university registrar's database. Recruitment procedures were completed over the span of 9 days (i.e., participants were notified and had 9 days to respond to the initial study invitation). A total of 15,031 individuals were invited to participate in the study. Of these individuals, 1,370 (9%) completed the screening survey, 319 (2%) declined to participate, and 13,342 (89%) did not respond (see Flow Chart in Figure 3). The percent of non-responders is similar to other published studies that have randomly invited students to participate in research wearing a wrist biosensor for multiple weekends of data collection (e.g., see Richards et al., 2024). The high non-response rate may be due the small window of time (9 days) participants had to respond to the study invitation. It may also be due to students self-selecting to not participate in the study because they are not interested in wearing a wrist biosensor for a long period of time. Study inclusion criteria included: 1) be between the ages of 18–23 years old, 2) own an iPhone, 3) past 3-month behavior that included 4+/5 drinks (women/men) on a typical Friday or Saturday, 4) past 3-month behavior that included experiencing at least 1 AIB, and 5) willingness to wear a wrist biosensor. Study exclusion criteria included: 1) currently being enrolled in high school, 2) not living or working in the area surrounding the university, or 3) planning to abstain from drinking during the dates of the data collection. There were 289 (21%) individuals who were deemed eligible and 1,081 (79%) who were deemed not eligible. Eligible students were immediately routed to a baseline survey which took approximately 20 minutes to complete. Of the 289 eligible participants, 227 (79%) completed the baseline survey and 62 (21%) did not. There were no significant differences on screening items by sex, drinking, or AIBs for those who completed baseline vs. those who did not complete baseline. At the end of the baseline survey participants were asked to schedule a 20-minute enrollment visit appointment to come into the laboratory to pick up the biosensor and to receive training on use of the biosensor and the study protocol. Of the 227 students who completed baseline, 175 participants (77%) were enrolled in the study. Fifty-two participants were not enrolled in the study due to: 1) dropping from the study after completing baseline ($n=9$), 2) not scheduling an appointment for the enrollment visit ($n=4$), 3) being deemed ineligible during the enrollment visit for things like not having a functional iPhone ($n=3$), and 4) not showing up for the enrollment visit appointment ($n=26$). There were 10 additional

participants who were dropped from the study due to achieving capacity on the number of biosensors available. There were no significant differences by sex, past three-month drinking, or past three-month AIBs for those who were enrolled vs. not enrolled. All procedures were approved by the University's Institutional Review Board.

Data Collection Procedures

Data collection spanned 6 social weekends (i.e., Thursday to Sunday) which occurred in two bursts (3 social weekends per burst) during the Spring Semester of 2025. Burst 1 occurred from the end of January 2025 to mid-February 2025. Burst 2 occurred from mid-March 2025 to early April 2025. The two data collection bursts were timed to avoid events that may be less representative of typical drinking patterns (e.g., spring break, final exams). After the first data collection burst, participants returned to the lab to return their biosensor and schedule a refresher appointment to pick up the same biosensor during the week preceding the second burst of data collection. Retention between burst 1 and 2 of data collection was high (90.9% retention rate).

BACtrack Skyn Biosensor. The BACtrack Skyn wrist biosensor uses fuel-cell technology and samples TAC every 20 seconds (Fairbairn & Bosch, 2021). Each biosensor is paired to the participants iPhone via Bluetooth using the BACtrack Skyn iPhone application. The Skyn application allows participants to confirm that the device is powered on and connected to their phone, view the biosensor's battery level (%), and automatically upload the TAC data from the biosensor to the cloud-based data portal. During each data collection burst, participants were instructed to wear the biosensor on their wrist continuously from Thursday evenings at 5:00pm through Sunday morning at 9:00am. Participants were instructed to remove the biosensor to shower or if they were engaging in any other activities that would submerge the biosensor in water, as the biosensor is not waterproof. At the end of each social weekend (i.e., Sunday morning at 9:00am), participants were asked to open the Skyn application on their iPhone while the biosensor was powered on and connected in order to sync and upload their TAC data. They were then asked to power off the device and charge it prior to the start of the next social weekend.

Daily and EMA Surveys. Participants also received a morning survey (open from 9:00am until 4:00pm) and evening survey (open from 4:00pm until 7:00pm) each Thursday, Friday, Saturday, and Sunday during the data collection periods (48 daily surveys total). Drinking behaviors and outcomes were only assessed on Friday through Sunday (about Thursday through Saturday behaviors). The average completion time for the morning surveys was 7.4 minutes ($SD = 21.7$ minutes) with an average completion rate of 87.1% (median = 100%). Average completion time for the evening surveys was 3.4 minutes ($SD = 11.3$ minutes) with an average completion rate of 80.6% (median = 91.7%). This resulted in an overall average completion rate of 83.9% (median = 95.8%) across the 48 total daily surveys.

Ecological momentary assessments (EMA) were also completed as part of this study. Participants were instructed to initiate a drinking survey when starting their first drink. Participants would then receive a follow-up survey every hour about their past-hour drinking until they a) missed three reminders or b) indicated that they were finished drinking. The

average time to complete the drinking EMAs was 54.6 seconds ($SD = 4.8$ minutes). Most participants (92.6%) completed at least one drinking EMA with an average of 8.9 ($SD = 4.8$) unique drinking episodes per person. Drinking episodes consisted of about 3 EMAs on average ($n = 3.2$, $SD = 1.9$). Approximately 80% of self-reported drinking days (morning and/or evening data) also had drinking EMA data.

Participants were able to select Amazon electronic gift cards or money deposited to the University payment system for their compensation. They were compensated \$20 for completing the baseline survey, \$4 for each morning survey, \$3 for each evening survey, and \$5 for each biosensor return visit. To increase compliance and retention, participants were awarded a “perfect weekend” bonus for each weekend that they completed all four morning surveys, all four evening surveys, and if they wore the alcohol biosensor 75% of the time. The bonus was \$2 during data collection period 1, resulting in up to \$30 of compensation per weekend. The bonus was increased to \$7 during data collection period 2, resulting in up to \$35 of compensation per weekend. The total amount of compensation possible during the entire study was \$225. An additional bonus was available based on total study completion. Once a participant completed 18 “perfect days” (days with morning and evening surveys completed and at least 75% biosensor wear), they were entered for a chance to win 1 of 20 \$100 gift cards. Completing 18 days resulted in 18 chances per participant, with this increasing by two for each additional completed day (up to 30 chances).

Participants

The current analyses include participants who self-reported drinking alcohol on the morning survey at least once during the 6 social weekends ($N = 168$, 96% of original sample retained). The average age of participants at the baseline survey was 20.8 ($SD = 1.10$). About half of the participants were female (53%). The majority of the sample identified as White (87%) and non-Hispanic/Latino (90%). A minority of participants identified as Asian (5%), Black (4%), Other (2%), or Multiracial (2%). Participants were primarily full-time students ($n=163$, 97%). This included freshman (7%), sophomores (14%), juniors (29%), seniors (45%), graduate students (3%) and integrated students (1%, e.g., students enrolled in dual undergraduate and graduate degree program).

Measures

Alcohol-Induced Blackouts. AIBs were adapted for daily use using 8 items from The Alcohol-Induced Blackout Measure-2 (ABOM-2; Boness et al., 2022). These items were assessed in the morning and evening surveys after drinking occurred on Friday, Saturday, and Sunday (standard drink count >0). The morning assessment was designed to measure AIB consequences that participants immediately remembered upon taking the survey. It is possible that a participant may not remember an AIB consequence until later in the (e.g., “able to remember a small part of the day after being reminded”, “reminded about things you had previously forgotten”). The evening assessment was designed to increase sensitivity of the AIB measure by asking participants if they recall any additional AIB consequences from the previous drinking episode. In the morning survey, participants were asked, “As a result of drinking yesterday, did you... (insert AIB item)?”. In the evening survey, participants were asked, “Since your morning report, did you find out or remember

that as a result of drinking yesterday you... (insert AIB item)?". Response options were dichotomous with 0 (no) and 1 (yes). The ABOM-2 measures both fragmentary (partial) and en bloc (complete) AIBs but was dichotomized if any AIB indicator was endorsed for the current analysis.

Protective Behavioral Strategies. PBS were assessed in the morning survey after drinking occurred (standard drink count >0) using 20 items from the Protective Behavioral Strategies Scale (PBSS-20; Treloar et al., 2015) and 1 item adapted from Ray et al., 2009 (i.e., avoid shots of liquor). Participants were asked, "Yesterday, did you... (insert PBS item)?". Response options were dichotomous with 0 (no) and 1 (yes). First, responses from all 21 items were summed to create a total PBS score (between-person $\omega = 0.96$, within-person $\omega = 0.91$). Second, responses were summed to create 3 separate subscales for each PBS domain. MD included 6 items, (e.g., "avoid shots of liquor", "avoid drinking games"; between-person $\omega = 0.93$, within-person $\omega = 0.84$). SLD included 7 items, (e.g., "drink water while drinking alcohol", "stop drinking at a predetermined time"; between-person $\omega = 0.92$, within-person $\omega = 0.85$). SHR included 8 items, (e.g., "eat before or during drinking", "use a designated driver"; between-person $\omega = 0.95$, within-person $\omega = 0.94$).

Control Variables. Sex at birth was coded as male (0) and female (1). Data collection burst was coded as burst 1 (0) and burst 2 (1).

Transdermal Alcohol Concentration Drinking Features. Procedures for TAC data have been published previously (Richards et al., 2024) and details are included in the Supplemental Materials. TAC data was segmented into "social days" because drinking often extends past midnight and does not fit neatly into a midnight-midnight calendar day. The boundary for the end of a social day aligned with the end of the timing of the morning survey at 9:00am. TAC drinking features were extracted from each social day with TAC positive data. Episodes containing multiple TAC episodes were calculated using all data for the social day. Drinking days were those with at least one drinking episode identified (i.e., positive TAC data). Non-drinking days were those with no identified drinking episodes but with at least 80% of biosensor wear for the social day since this suggested no drinking occurred. TAC features for non-drinking days were recoded to 0. Features were left missing if no episodes were present, but the biosensor was worn for less than 80% of hours of the social day (i.e., 9:00am-9:00am).

The current paper extracted 3 TAC drinking features derived from TAC data: rise rate (the speed of alcohol absorption), peak (the maximum intoxication level), and rise duration (the length of time spent under rising intoxication) (Richards et al., 2024; Russell et al., 2022). The hypotheses and analyses examine a latent factor for TAC drinking which includes indicators for rise rate, peak, and rise duration. This latent variable represents the shared variance between the 3 TAC drinking features and serves as our representation of biological intoxication.

Statistical Analysis

Analyses were conducted in MPlus version 8 (Muthén & Muthén, 2017). Two multilevel structural equation models (ML-SEM) using Bayesian estimation with non-informative priors were specified according to guidelines for when mediating variables vary at both the between- and within-person level (Fang et al., 2019; Preacher et al., 2010; Zhang et al., 2009). Each model was specified according to the following: PBS and TAC drinking features were daily-level predictors that varied both within- (Level 1) and between-persons (Level 2). Each PBS scale and TAC drinking feature were partitioned into their between- and within-person components using R 4.3.2 (R Core Team, 2023). Person-mean total PBS, MD, SLD, SHR, TAC rise rate, peak, and rise duration were used as between-person predictors (Level 2). Person-mean centered total PBS, MD, SLD, SHR, TAC rise rate, peak, and rise duration were used as within-person predictors (Level 1). Predictors at the between- and within-person levels (PBS and TAC) were z-scored prior to model estimation to allow for the comparison of effect sizes. Z-score variables were created using the level-specific standard deviations (e.g., between-person SD for between-person variables, within-person SD for within-person variables). All models included covariates¹ for biological sex (0=male, 1=female) at Level 2 and data collection burst at Level 1 (0=burst 1, 1=burst 2). Covariates were centered in R prior to model estimation in MPlus. Models were also specified with a latent construct for TAC drinking features (three indicators: rise rate, peak, rise duration). Random intercepts and slopes were included in each model to allow the day-level association between TAC drinking features and AIBs to differ between participants. TAC drinking features were modeled using linear paths because they are a continuous variable. AIBs were modeled using logistic paths to account for the dichotomous nature of the data. Bayesian models use Markov chain Monte Carlo sampling to generate a full posterior probability distribution of possible values for each parameter of interest. Our models used 10,000 iterations (50% warmup) across two chains to generate posterior distributions. Reported parameter estimates are the medians of posterior parameter distributions. Significance of parameter estimates was determined using 95% credibility intervals (CI) of the posterior distributions (Hespanhol et al., 2019; Makowski et al., 2019). Significant direct effects were determined by examining the 95% CIs surrounding the parameter estimate of the paths (e.g., *a* path, person-mean total PBS to person-mean TAC drink features). Significant indirect effects were estimated directly by generating the product of posterior PBS to TAC paths (*a* paths) and TAC to AIB paths (*b* paths) for each model iteration. The medians of *ab* posterior parameter distributions were reported as estimates of indirect effects; 95% CIs were used to determine significance of indirect paths. The indirect and direct paths generate the total association of PBS on AIBs (*c* paths = *a* paths × *b* paths + *c* paths). CIs that did not contain the value of 0 for linear paths were considered statistically significant. Logistic paths were exponentiated to obtain odds ratios (OR), interpreted as a multiplicative increase (if OR > 1) or decrease (if OR < 1). CIs that did not contain the value of 1 for logistic paths were considered statistically significant.

¹Models from Aim 1 and Aim 2 were also examined with previous day cannabis use included as a covariate at the between- and within-person levels. Results were not significantly different than the models presented here.

Transparency and Openness

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study. Sample size was determined using Monte Carlo power simulations in Mplus. A sample size of 175 with 90% compliance had >99% power to detect small effect sizes (.1 *SDs*) at the within-person level and 74%–96% power to detect small-to-medium effect sizes (.2–.3 *SDs*) at the between-person level. The current analytic sample includes 168 participants who self-reported drinking alcohol at least once during the data collection period. Data are publicly available through the NIMH Data Archive (<https://dx.doi.org/10.15154/6fpn-ck30>). Analytic code is not publicly available but will be made available (in accordance with IRB standards) upon request from the corresponding author. The analyses of the current manuscript and the study design were not preregistered.

Results

Descriptive Statistics

Participants were included in the analyses if they self-reported drinking on the morning survey ($n=168$ participants, 1,504 drinking days). Of the 1,504 self-reported drinking days, there were 1,319 (88%) corresponding days with TAC positive data. Days were excluded from analyses if the participant had missing data on all predictor variables ($n=2$). The final analytic sample resulted in 168 participants with 1,502 days of reports on whether an AIB was experienced or not. Approximately 80% of the sample reported experiencing at least 1 AIB on days when they drank (534 AIBs reported on drinking days, $n=133$). Participants experienced an average of 3.08 AIBs ($SD=2.99$) during the 18-day study period (this includes both fragmentary and en bloc AIBs).

Aim 1

Table 1 shows full results of the ML-SEM testing the associations between total PBS, TAC drinking features, and AIBs. At the within-person level, the indirect effect was significant. On days when individuals reported using above average total PBS, they were at decreased odds for experiencing an AIB, through its association with TAC drinking features ($OR=0.81$, 95% CI: 0.73, 0.88). On days when individuals reported using above average total PBS, they experienced less risky TAC drinking features ($b=-0.16$, 95% CI: -0.22 , -0.11). Days with above average total PBS were not directly associated with the odds of experiencing an AIB, controlling for the mediating variable of TAC drinking features ($OR=0.86$, 95% CI: 0.73, 1.01). Additional results from models testing each individual TAC feature can be found in Supplemental Table 1.

Aim 2

Table 2 shows full results of the ML-SEM testing the associations between MD PBS, SLD PBS, and SHR PBS on TAC drinking features and AIBs. At the within-person level, the indirect effect between MD PBS, TAC drinking, and AIBs was significant. On days when individuals reported using above average MD PBS, they were at decreased odds for experiencing an AIB, through its association with TAC drinking features ($OR=0.71$, 95% CI: 0.63, 0.78). On days when individuals reported using above average MD PBS, they

experienced less risky TAC drinking features ($b=-0.29$, 95% CI: $-0.35, -0.23$). Days with above average MD PBS were directly associated with decreased odds of experiencing an AIB, controlling for the mediating effect of TAC drinking ($OR=0.57$, 95% CI: $0.48, 0.69$).

SLD PBS did not indirectly impact the odds someone would experience an AIB through its association with TAC drinking features ($OR=0.95$, 95% CI: $0.89, 1.02$). On days when individuals reported using above average SLD PBS, TAC drinking features was not significantly affected ($b=-0.04$, 95% CI: $-0.10, 0.01$). Days with above average SLD PBS were not directly associated with the odds of experiencing an AIB, controlling for the mediating variable of TAC drinking features ($OR=0.91$, 95% CI: $0.77, 1.07$).

The indirect effect between SHR PBS, TAC drinking, and AIBs was significant. On days when individuals reported using above average SHR PBS, they were at increased odds for experiencing an AIB, through its association with TAC drinking features ($OR=1.11$, 95% CI: $1.04, 1.19$). On days when individuals reported using above average SHR PBS, they experienced riskier TAC drinking features ($b=0.09$, 95% CI: $0.03, 0.14$). Days with above average SHR PBS were directly associated with increased odds of experiencing an AIB, controlling for the mediating effect of TAC drinking ($OR=1.36$, 95% CI: $1.17, 1.60$). Results from models testing each individual TAC feature can be found in Supplemental Table 2.

Discussion

The current study used longitudinal, event-level data to examine PBS, TAC drinking features, and AIBs among a sample of young adults who engage in risky drinking. Aim 1 analyzed the associations between total PBS use, TAC drinking features, and AIBs. Full support was found for hypothesis 1a. On days when individuals reported using above average total PBS relative to what they typically use, they experienced less risky TAC drinking features. This finding builds on previous research (e.g., Cox et al., 2024; LaBrie et al., 2009; Russell et al., 2023) suggesting that individuals who use more total PBS experience less risky drinking. No support was observed for hypothesis 1b. There was no direct association between daily total PBS use and AIBs. This finding is inconsistent with Carey et al. (2022) who found that using more total PBS was negatively associated with AIBs experienced in the past month, controlling for drinking. Measurement differences between the current study and previous work examining PBS and AIBs are a potential reason for the difference in findings. Previous cross-sectional work examined the frequency of PBS use and its association with past-month AIBs whereas the current study examined these relationships at the daily-level (Carey et al., 2022). Full support was observed for the indirect effects (H1c). On days when individuals reported using above average total PBS relative to what they typically use, they experienced less risky TAC drinking features, which in turn decreased the odds of experiencing an AIB by 19%.

Aim 2 analyzed a single model examining each PBS domain as predictors of TAC drinking and AIBs. Full support was observed for hypothesis 2a and 2b. On days when individuals reported using above average MD PBS, they experienced less risky TAC drinking features and had decreased odds of experiencing an AIB. These findings are consistent with studies suggesting that using more MD PBS is directly associated with a decrease in drinking

(Lewis et al., 2012; Pearson et al., 2013), consequences (e.g., Howard et al., 2024; Lewis et al., 2012; Linden-Carmichael, et al., 2018), and AIBs (Carey et al., 2022; Richards et al., 2023b). Full support was also observed for the indirect effect hypothesis 2c. On days when individuals reported using above average MD PBS relative to what they typically use, they experienced less risky TAC drinking features, which in turn decreased the odds of experiencing an AIB by 29%.

No support was observed for hypothesis 3a or hypothesis 3b. SLD PBS was not associated with TAC drinking features or AIBs. These findings add to a mixed literature regarding the impact SLD PBS have on drinking and AIBs. Cross-sectional studies suggest that SLD PBS have a negative association with drinking (e.g., Frank et al., 2012). Carey et al. (2022) found that SLD PBS was negatively associated with AIBs, but this association was not significant when SLD PBS was analyzed in a model with all 3 PBS subscales. At the within-person level, diary and EMA studies have found that the association between daily SLD PBS and drinking is positive (Lewis et al., 2012) or that there is no association (e.g., Pearson et al., 2013, Howard et al., 2024). There was also no support for the indirect effect hypothesis 3c. This suggested that days when individuals used more SLD PBS, there was no significant effect on TAC drinking which in turn, did not impact AIBs. It is possible that these hypotheses were not significant due to the shared variance between SLD PBS and MD PBS. The current analytic approach was unable to account for how the shared variance among PBS subscales impacts TAC drinking features and subsequent AIBs.

Full support was observed for hypothesis 4a. Days when individuals used above average SHR PBS were associated with an increase in TAC drinking. Full support was also observed for hypothesis 4b which found that days with above average SHR PBS were associated with increased odds of experiencing an AIB. Finally, full support was observed for the indirect effect hypothesis 4c. On days when individuals reported using above average SHR PBS relative to what they typically use, they experienced riskier TAC drinking features, which in turn increased the odds of experiencing an AIB by 11%. These findings add to a mixed literature regarding the association between SHR PBS, drinking, and AIBs (e.g., Fernández-Calderón et al., 2021; Russell et al., 2023; Carey et al., 2022). Results align with longitudinal and event-level data suggesting that using more SHR PBS is associated with engaging in riskier drinking behaviors (e.g., Howard et al., 2024; Lewis et al., 2012).

Implications

The current study is the first to conduct a comprehensive examination of PBS and AIBs at the daily-level measuring risky drinking using a novel biomarker, TAC drinking features. Results underscore the importance of MD PBS in reducing the odds an AIB will occur. This makes sense, given that MD PBS include the avoidance of actions that can lead to the consumption of large quantities of alcohol in a short amount of time – e.g., avoiding drinking games and mixed drinks. On the other hand, SHR PBS are designed to protect against secondary effects resulting from risky drinking (e.g., refusing to ride in a car with a driver who has been drinking), rather than preventing alcohol consumption (e.g., avoiding mixing different alcohol; Pearson et al., 2013). Future research may benefit from exploring their positive relationship with AIBs. It is possible that young adults proactively plan to

employ these strategies (e.g., only go out with people they know and trust), on nights when they plan to engage in risky drinking, which could explain why they are associated with increased AIBs. It is also possible that young adults use more SHR PBS (e.g., use a designated driver, eat before/during drinking) after already engaging in risky drinking. This is evident in Richards et al. (2025) which demonstrated that on days when an individual experienced an AIB and used above SHR PBS, they experienced 50% fewer consequences than AIB days with below average SHR PBS use.

From a clinical standpoint, findings suggest the need to consider the role of PBS in personalized-feedback interventions (PFIs) – i.e., individually-focused brief interventions that incorporate personalized feedback on students' drinking behaviors (Cronce et al., 2018). PFIs typically include content on PBS use (Ray et al., 2014), and there is some evidence to show that PFIs have been successful at increasing use of PBS (Collins et al., 2014; Tan et al., 2023). Our results suggest that it may be important to consider providing nuanced feedback on the impact of PBS on reducing risk for AIBs for high-risk drinking populations. For example, PFIs may consider specifically highlighting how increased use of MD PBS, relative to students' typical use, are more effective at reducing risk for AIBs, compared to other types of strategies. Given the findings for SHR PBS, it is also important to consider how information on this topic is presented in future interventions studies. It may be helpful to explain that although SHR strategies are important for avoiding alcohol-related harm, they have little impact on actual alcohol use, so they are not as effective at preventing AIBs.

Future clinical trial interventions may also incorporate the use of TAC biosensors to have a near real-time method for assessing risky drinking. For example, TAC biosensors could be used to test the success of a PFI trying to increase individuals use of PBS to reduce risky drinking and subsequent AIBs. In a PFI designed to increase use of MD PBS, TAC biosensors can be utilized to assess near real-time changes in risky drinking among participants for whom the PFI successfully increases use of MD PBS.

Limitations

The current study is not without limitations. First, most participants in this study were recruited from a single large public university. Drinking rates at the university students were recruited from were similar to other large public universities with respect to national drinking norms (Johnston et al., 2019). These findings may not be generalizable to all college students and non-college attending young adults. Second, PBS were only measured in the morning survey after drinking occurred. It is possible that participants were unable to accurately recall which PBS they used on nights when an AIB occurred. For example, someone may remember that they avoided drinking games (MD PBS) and reported this on the survey the following morning. However, if an AIB occurred, it is possible that they played drinking games later in the drinking episode but were unable to recall this due to experiencing an AIB. This measurement design is also limited in providing detail about when a PBS was implemented during a drinking episode. For example, did a person implement drinking water while drinking alcohol at the start of a drinking episode or did they start doing this after risky drinking occurred? Findings from the current study were unable to identify if drinking predicted PBS use or if PBS use predicted the levels of

drinking that occurred. Future studies should consider measuring PBS using ecological momentary assessment methods to increase recall of PBS used during drinking episodes and to identify directionality of the associations between PBS and drinking. Third, response options for the PBS items were dichotomous with yes (1) and no (0). Future studies should consider including a third response option that can account for items that may not be applicable to participants. Certain items (e.g., leave the bar/party at a predetermined time, avoid drinking before going out) may not be relevant to participants given the social context of the drinking episode (e.g., if they drank alone or with others, did they stay at home or go to a bar). The current study was unable to distinguish participants who responded with “no” because they did not use that behavior vs. those who said “no” because they were not in a situation where that behavior was relevant. Fourth, approximately 15% ($n = 90$) of AIBs observed over the course of the study period were en bloc AIBs. The analyses were therefore unable to examine the relationship between PBS, TAC drinking features, and each specific AIB type (fragmentary vs. en bloc). Future work is needed to understand how PBS and TAC impact each specific AIB type. Fifth, it is possible that TAC biosensors missed lower intensity drinking days (Barnett et al., 2014). There is currently no standard algorithm for detecting drinking days for the BACtrack Skyn biosensor (Richards et al., 2024). The guidelines used in the current study to detect drinking days were informed by previous studies (Courtney et al., 2023; Didier et al., 2024; Richards et al., 2023c; 2024; 2025).

Conclusions

TAC drinking features were used to understand the associations between PBS use and AIBs among a sample of young adults who engage in risky drinking. About 80% of participants experienced an AIB at least once during the duration of the study. Participants experienced about 3.08 AIBs ($SD=2.99$) over the 18-day study period. At the daily-level, on days when participants used above average total PBS they experienced TAC drinking features that were less indicative of risk, which in turn decreased the odds of experiencing an AIB. When examining each PBS domain as predictors in a single model, MD and SHR, but not SLD, were significant predictors of TAC drinking and AIBs. MD was associated with TAC drinking features that were less indicative of risk, which subsequently reduced AIB odds. SHR was associated with TAC drinking features that were more indicative of risk, which subsequently increased AIB odds.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Public Health Significance Statement

This study shows that on days when young adults used more protective behavioral strategies (PBS), they experienced less risky transdermal alcohol concentration (TAC) drinking features, which in turn decreased the chances that an alcohol-induced blackout (AIB) would occur. However, results show that certain PBS domains, like serious harm reduction (SHR) may not be protective against risky drinking and AIBs. Findings suggest that focusing specifically on manner of drinking PBS (e.g., avoid drinking games) may be effective at reducing risky drinking and subsequent AIBs. These results support the use of using TAC biosensors to measure drinking in near-real time to understand the associations between PBS and AIBs among a sample of young adults who engage in risky drinking.

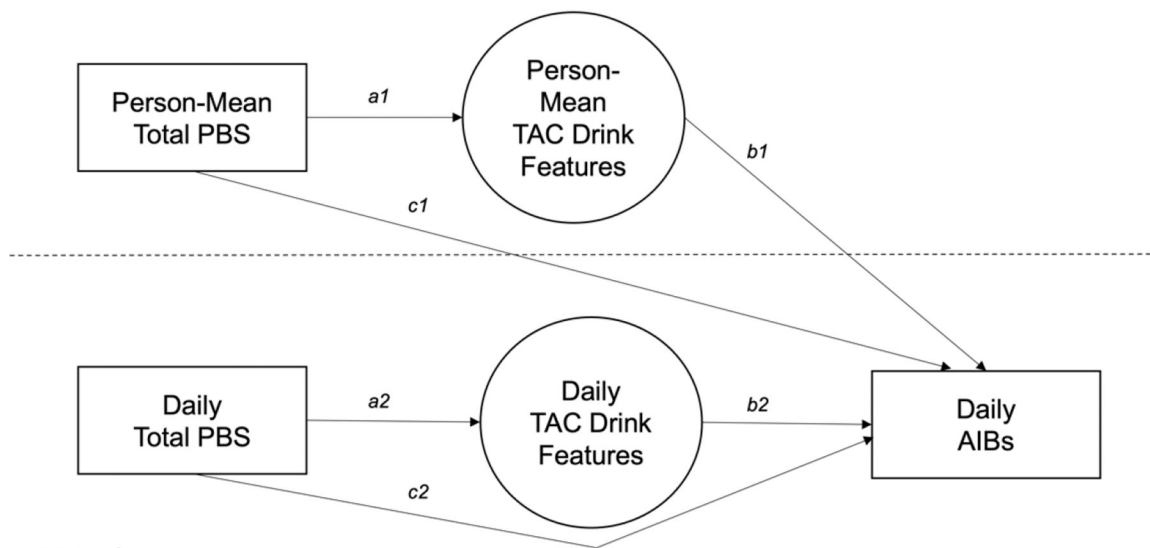
Between (Person Level)

Figure 1.
Theoretical Multilevel Structural Equation Model Presenting Hypothesized Direct and Indirect Paths Linking Total PBS, TAC Drinking Features, and AIBs.

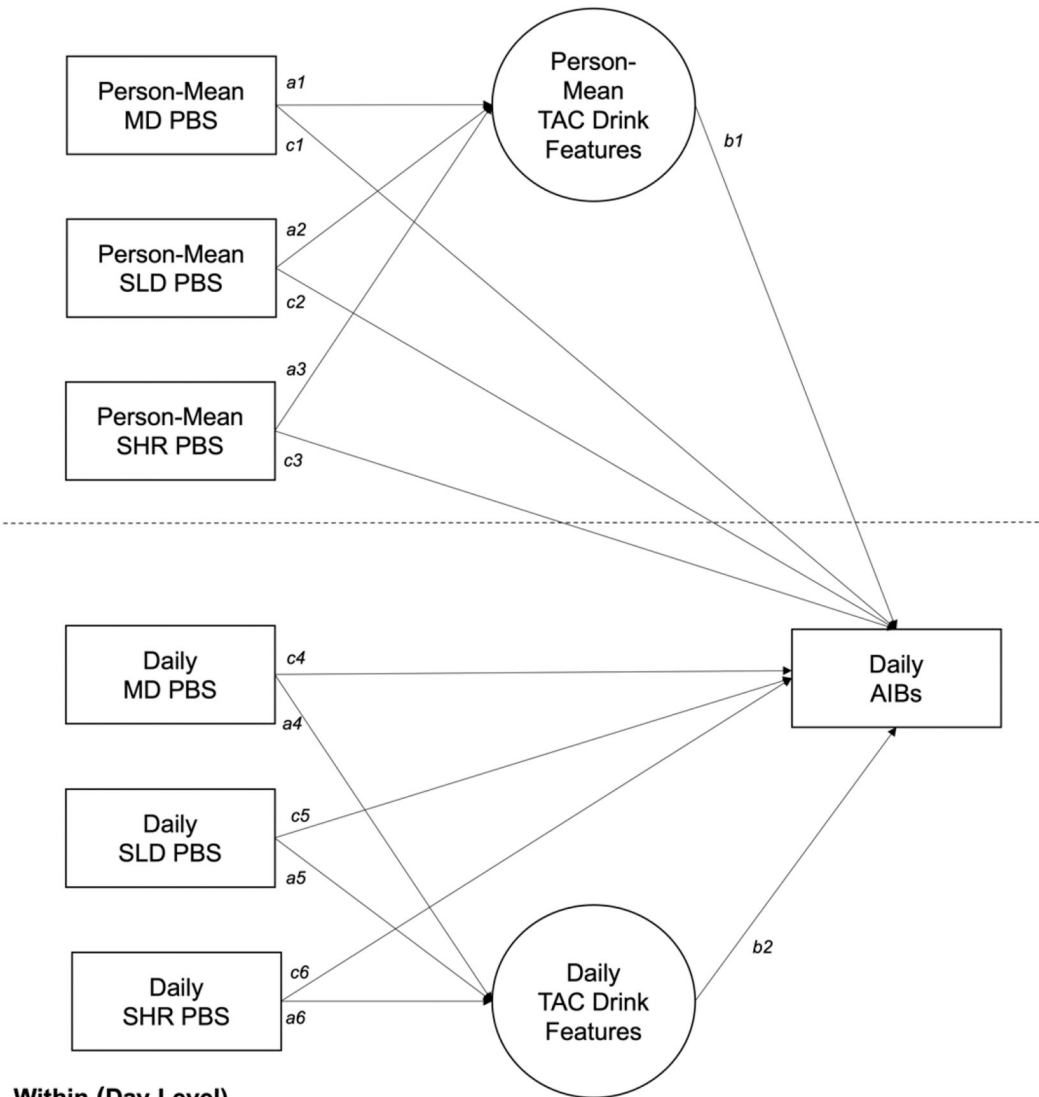
Between (Person Level)

Figure 2.
Theoretical Multilevel Structural Equation Model Presenting Hypothesized Direct and Indirect Paths Linking PBS Subscales, TAC Drinking Features, and AIBs.

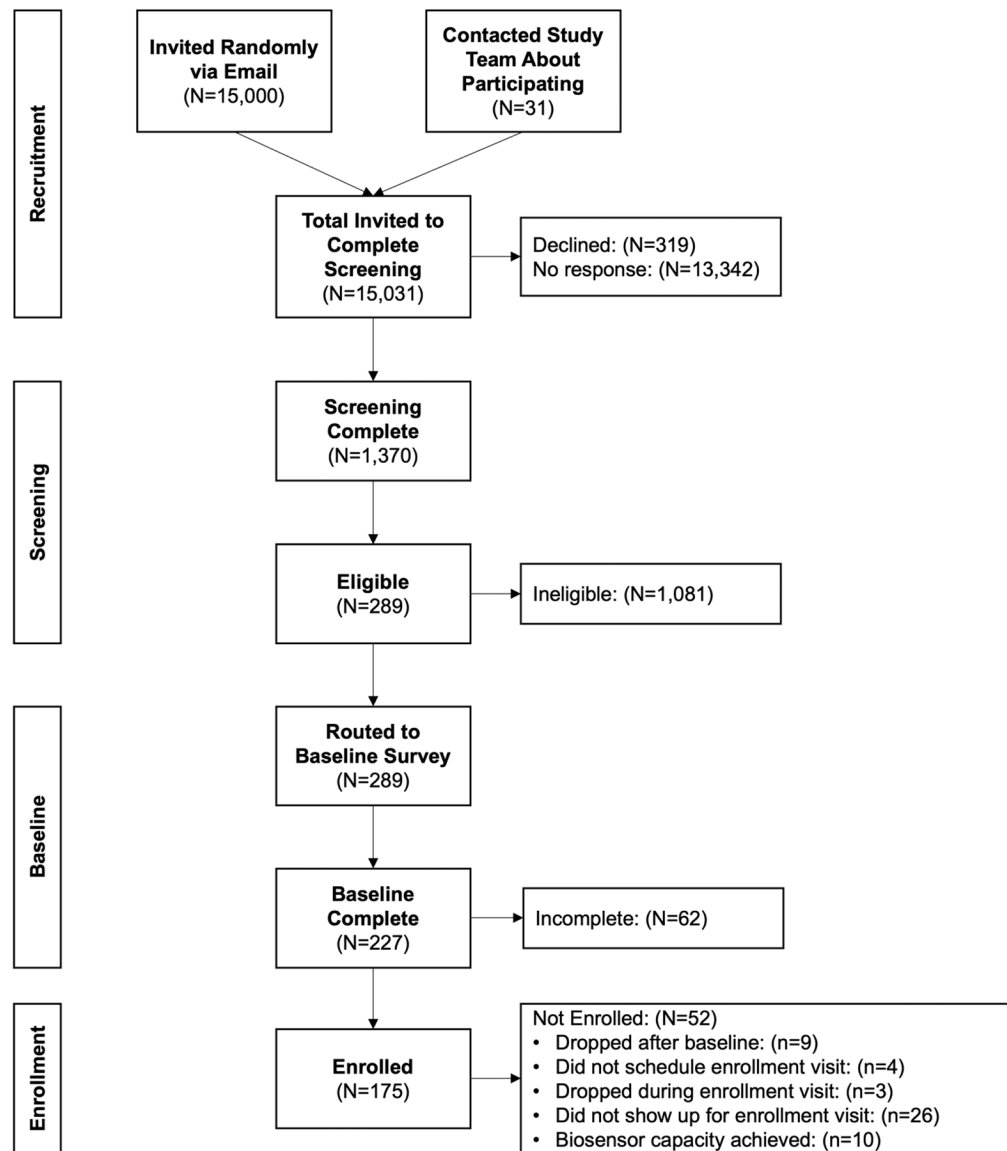


Figure 3.
Flow Chart Depicting Recruitment and Enrollment Process.

Table 1.
ML-SEM Results for Total PBS, TAC Drinking Features, and AIBs.

Within-Person	Paths	Est.	95% CI
TAC			
Total PBS	<i>a2</i>	-0.16	-0.22, -0.11
Burst		0.01	-0.10, 0.12
AIBs			
TAC	<i>b2</i>	3.71	2.78, 5.10
Total PBS	<i>c2</i>	0.86	0.73, 1.01
Burst		0.96	0.71, 1.30
Indirect Effect			
Total PBS → TAC → AIB	<i>a2 × b2</i>	0.81	0.73, 0.88
Total Effect			
Total PBS → TAC → AIB	<i>a2 × b2 + c2</i>	0.69	0.59, 0.85
Between-Person	Paths	Est.	95% CI
TAC			
Total PBS	<i>a1</i>	-0.09	-0.24, 0.07
Sex		0.09	-0.23, 0.42
AIBs			
TAC	<i>b1</i>	1.71	1.22, 2.36
Total PBS	<i>c1</i>	0.78	0.58, 1.04
Sex		1.28	0.71, 2.39
Indirect Effect			
Total PBS → TAC → AIB	<i>a1 × b1</i>	0.96	0.86, 1.04
Total Effect			
Total PBS → TAC → AIB	<i>a1 × b1 + c1</i>	0.75	0.55, 1.11

Notes. Paths correspond to labels in theoretical model (see Figure 1). Covariate paths are blank as they were not pictured in the theoretical model. Estimates on paths predicting AIBs are the exponentiated, OR values. Bolded values indicate the estimate is credibly significant.

Table 2.
ML-SEM Results for PBS Subscales, TAC Drinking Features, and AIBs.

Within-Person	Paths	Est.	95% CI
TAC			
MD PBS	<i>a4</i>	-0.29	-0.35, -0.23
SLD PBS	<i>a5</i>	-0.04	-0.10, 0.01
SHR PBS	<i>a6</i>	0.09	0.03, 0.14
Burst		0.01	-0.10, 0.12
AIBs			
TAC	<i>b2</i>	3.19	2.46, 4.32
MD PBS	<i>c4</i>	0.57	0.48, 0.69
SLD PBS	<i>c5</i>	0.91	0.77, 1.07
SHR PBS	<i>c6</i>	1.36	1.17, 1.60
Burst		0.96	0.70, 1.30
Indirect Effect			
MD PBS → TAC → AIB	<i>a4 × b2</i>	0.71	0.63, 0.78
SLD PBS → TAC → AIB	<i>a5 × b2</i>	0.95	0.89, 1.02
SHR PBS → TAC → AIB	<i>a6 × b2</i>	1.11	1.04, 1.19
Total Effect			
MD PBS → TAC → AIB	<i>a4 × b2 + c4</i>	0.41	0.35, 0.49
SLD PBS → TAC → AIB	<i>a5 × b2 + c5</i>	0.87	0.71, 1.09
SHR PBS → TAC → AIB	<i>a6 × b2 + c6</i>	1.51	1.21, 1.97
Between-Person	Paths	Est.	95% CI
TAC			
MD PBS	<i>a1</i>	-0.22	-0.42, -0.02
SLD PBS	<i>a2</i>	-0.14	-0.31, 0.04
SHR PBS	<i>a3</i>	0.22	0.01, 0.43
Sex		-0.01	-0.33, 0.31
AIBs			
TAC	<i>b1</i>	1.41	1.01, 1.98
MD PBS	<i>c1</i>	0.39	0.25, 0.58
SLD PBS	<i>c2</i>	0.91	0.62, 1.32
SHR PBS	<i>c3</i>	1.92	1.26, 2.97
Sex		1.09	0.58, 2.05
Indirect Effect			
MD PBS → TAC → AIB	<i>a1 × b1</i>	0.94	0.82, 1.00
SLD PBS → TAC → AIB	<i>a2 × b1</i>	0.96	0.87, 1.02
SHR PBS → TAC → AIB	<i>a3 × b1</i>	1.07	1.00, 1.23
Total Effect			
MD PBS → TAC → AIB	<i>a1 × b1 + c1</i>	0.36	0.25, 0.57
SLD PBS → TAC → AIB	<i>a2 × b1 + c2</i>	0.87	0.62, 1.36
SHR PBS → TAC → AIB	<i>a3 × b1 + c3</i>	2.08	1.26, 3.97

Notes. Paths correspond to labels in theoretical model (see Figure 2). Covariate paths are blank as they were not pictured in the theoretical model. Estimates on paths predicting AIBs are the exponentiated, OR values. Bolded values indicate the estimate is credibly significant.

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