

Characterising patterns of alcohol use among heavy drinkers: A cluster analysis utilising alcohol biosensor data

RACHEL L. GUNN¹ , JON A. STEINGRIMSSON², JENNIFER E. MERRILL¹,
TIMOTHY SOUZA³ & NANCY BARNETT¹

¹Department of Behavioral and Social Sciences, Center for Alcohol and Addiction Studies, Brown University School of Public Health, Providence, USA, ²Biostatistics, Center for Alcohol and Addiction Studies, Brown University School of Public Health, Providence, USA, and ³Data Management Systems, Center for Alcohol and Addiction Studies, Brown University School of Public Health, Providence, USA

Abstract

Introduction. Previous research has predominately relied on person-level or single characteristics of drinking episodes to characterise patterns of drinking that may confer risk. This research often relies on self-report measures. Advancements in wearable alcohol biosensors provide a multi-faceted objective measure of drinking. The current study aimed to characterise drinking episodes using data derived from a wearable alcohol biosensor. **Methods.** Participants ($n = 45$) were adult heavy drinkers who wore the Secure Continuous Remote Alcohol Monitoring (SCRAM) bracelet and reported on their drinking behaviours. Cluster analysis was used to evaluate unique combinations of alcohol episode characteristics. Associations between clusters and self-reported person and event-level factors were also examined in univariable and multivariable models. **Results.** Results suggested three unique clusters: Cluster 1 (most common, slowest rate of rise to and decline from peak), Cluster 2 (highest peak transdermal alcohol concentration and area under the curve) and Cluster 3 (fastest rate of decline from peak). Univariable analyses distinguished Cluster 1 as having fewer self-reported drinks and fewer episodes that occurred on weekends relative to Cluster 2. The effect for number of drinks remained in multivariable analyses. **Discussion and Conclusions.** This is the first study to characterise drinking patterns at the event-level using objective data. Results suggest that it is possible to distinguish drinking episodes based on several characteristics derived from wearable alcohol biosensors. This examination lays the groundwork for future studies to characterise patterns of drinking and their association with consequences of drinking behaviour. [Gunn RL, Steingrimsdottir JA, Merrill JE, Souza T, Barnett N. Characterising patterns of alcohol use among heavy drinkers: A cluster analysis utilising alcohol biosensor data. *Drug Alcohol Rev* 2021]

Key words: alcohol biosensor, alcohol, SCRAM, cluster analysis.

Introduction

Alcohol research has long relied on use of self-report measures of alcohol consumption that can be prone to bias or error. Breath and blood alcohol tests are objective measures of alcohol consumption but pose challenges for assessment in the natural environment due to the need for frequent or invasive assessment. Recent advancements in the measurement of alcohol consumption via wearable biosensors allow objective and continuous measurement of alcohol use in the natural environment [1,2]. In the current study, we seek to comprehensively characterise drinking patterns using data from wearable biosensors.

Transdermal alcohol biosensors

Wearable biosensors measuring transdermal alcohol concentration (TAC) detect the small amount (approximately 1%) of alcohol vapor diffused through the skin via sweat glands [3]. These sensors sample and store data continuously throughout the day, allowing for consistent measurement of drinking while participants are wearing the device. TAC sensors have shown robust correlations with breath alcohol concentration (BrAC) sensors in well-controlled laboratory-based alcohol administration [4–6]. Such sensors provide data that allow us to characterise features of drinking events, including rate of rise to peak TAC

Rachel L. Gunn PhD, Assistant Professor, Department of Behavioral and Social Sciences, Jon A. Steingrimsdottir PhD, Assistant Professor, Biostatistics, Jennifer E. Merrill PhD, Associate Professor, Department of Behavioral and Social Sciences, Timothy Souza BS, Data Management Systems Coordinator, Nancy Barnett PhD, Professor, Department of Behavioral and Social Sciences. Correspondence to: Dr Rachel Gunn, PhD, Center for Alcohol and Addiction Studies, Brown University, Box G-S121-5, Providence, RI 02912, USA. Tel: +1 (401) 863 6630; Fax: +1 (401) 863-6697; E-mail: rachel_gunn@brown.edu

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(rate of rise: a function of physiological absorption rate and behavioural factors such as drinking pace and stomach contents), rate of decline from peak (rate of decline: a function of physiological elimination rate and behavioural factors), area under the TAC curve (i.e. providing an approximation of volume of alcohol consumed) and peak TAC [4,7]. This continuous data provides a stable indicator of within-person variability [7,8], allowing for the examination of time-varying effects (e.g. other substance use or contextual factors) on patterns of consumption. Examination of between- and within-person indicators of alcohol consumption provides an invaluable method for characterising patterns of alcohol use as they naturally occur. Furthermore, significant literature has studied TAC during either laboratory-based [9–11] or ambulatory self-reported drinking events [12] to reveal consistent, yet delayed detection of positive TAC relative to self-reported drinking and BrAC readings.

Episode-level drinking patterns

Previous work has examined patterns of drinking via self-reported person-level characteristics of drinking, for example frequency, volume and other drinking behaviours such as number of binge drinking days [13–15]. Overall, these studies suggest that distinct patterns can be distinguished at the person-level based on drinking behaviours. An additional body of work has examined event-level aspects of drinking that increase risk. For instance, recent work suggests that number of drinks at the event-level is an important indicator of consequences related to drinking [16–19]. However, prior work typically has not considered clustered characteristics of consumption patterns at the episode level, especially via the use of objective measures. Only two studies we are aware of have characterised drinking at the episode level using multiple characteristics. The first examined drinking episodes by context, consumption and consequences in an adolescent sample and found that drinking episodes can be distinguished by setting and social context [20]. The second used growth mixture models to characterise Saturday evening drinking patterns based on self-reported number of drinks and rates of consumption and found two distinct patterns of drinking: stable low and accelerated evening drinking [21]. This study also found that person-level, such as motives, and event-level characteristics, such as number of same-sex friends present, were associated with these drinking patterns.

Unique characteristics of drinking episodes with TAC

Several studies suggest that the fine-grained characteristics of drinking episodes derived from TAC measurement are valuable markers of problematic drinking and may indicate risk for alcohol use disorders (AUD). For instance, studies in the laboratory and field suggest that high risk drinkers are more likely to consume drinks at an accelerated pace, which can be reflected by rate of rise [22,23]. Individual differences in response to alcohol have also been linked with risk for AUD [24–26]. For example, a stronger history of heavy alcohol use has been associated with faster rate of decline [27]. In one study that examined these specific TAC indicators, higher peak TAC and faster time-to-peak were significantly associated with symptoms of alcohol dependence [6].

Single characteristics of drinking episodes (e.g. number of drinks, BrAC) are often used as markers of problematic use. For example, crossing the heavy episodic or “binge drinking” threshold increases risk for a range of negative consequences [28]. Furthermore, higher blood alcohol concentrations (BAC) increase the odds of alcohol-induced blackouts [29]. Drinking alcohol quickly accelerates the increase in BAC and is associated with cognitive impairment [30–32]. Moreover, an increasing pace of drinking over the course of a drinking episode (more drinks per hour) has been shown to be associated with 17× as many negative consequences compared to when drinking pace remained steady [21]. Recent work demonstrates that rate of change in estimated BAC and peak estimated BAC uniquely predict drinking related outcomes and consequences [33], further suggesting the value of understanding different and/or combined aspects of a drinking episode that confer risk. However, much of the prior work has relied on self-reported aspects of a drinking episode, with a focus on only a single indicator. The use of alcohol biosensors to characterise a single drinking episode using numerous objective measures is valuable, as such data are not biased by self-report and can capture multiple aspects of a drinking episode (e.g. rate of rise and decline) not available via self-report. Such information can allow us to consider whether there are patterns of drinking that can be identified based on these unique characteristics and whether those patterns are predictable from other between-person information about drinkers.

Current study

Previous studies have categorised groups of drinkers by examining between-person indicators of drinking patterns, such as daily or weekly quantity, frequency or number of binge-drinking episodes [13–15,34]. Some

event-level, self-report studies have identified specific aspects of a drinking episode that increase risk. Research also has studied the correspondence between transdermal measures and measured BrAC and between transdermal values and self-reported drinking [4,35]. However, to our knowledge, no studies to date have examined how characteristics of objectively measured drinking episodes cluster together at the event-level among heavy drinkers. The purpose of the present study was to examine whether distinct subtypes of drinking episodes could be identified based on the clustering of previously established characteristics of transdermal alcohol episode curves. We employed cluster analysis to evaluate unique combinations of alcohol episode characteristics. As a secondary goal, we explored whether clusters differed on self-reported individual differences and event-level factors.

Methods

Data for the present study are from two investigations of contingency management [36,37] which used the Secure Continuous Remote Alcohol Monitoring (SCRAM) ankle monitor (Alcohol Monitoring Systems, Inc.; Littleton, CO, USA) to detect alcohol use. All procedures were approved by the University Institutional Review Board and methods, as described below, were similar for both studies.

Participants

Participants were recruited using online and newspaper advertisements and with flyers posted in the community inviting adult drinkers interested in reducing or stopping their drinking to participate. Telephone screening identified participants who met the following inclusion criteria (same for both studies): (i) were 18 years of age or older; (ii) reported past-month drinking rates of >7 of 14 drinks per week for women and men, respectively; (iii) reported two or more past-month heavy drinking episodes per week; (iv) interest in cutting down or stopping drinking; (v) had an email address and daily internet access; and (vi) had a landline phone for transmission of bracelet data or were willing to come to the research office three times per week to download data from the bracelet. Exclusion criteria were: (i) significant alcohol withdrawal symptoms (score of 23 or higher on the Alcohol Withdrawal Symptom Checklist [38]); and (ii) self-report of drug use other than marijuana in the past month or more often than once a month in the past year.

Procedures

All inclusion criteria were confirmed in person at a baseline session. Once deemed eligible, participants provided informed consent and completed self-report and interview measures. The SCRAM bracelet was secured on the participant's ankle and monitoring was initiated via the SCRAM website. Participants were expected to wear the SCRAM bracelet for 21–28 days (depending on the study). Participants received instructions regarding daily web surveys and utilising the SCRAM modem at home to download SCRAM readings (if applicable). Participants received \$25 for the baseline session and \$5 for each completed daily survey and a \$25 bonus for submitting 90% of surveys.

Participants completed a baseline week (i.e. before intervention) of data collection via SCRAM monitoring and self-report web surveys in order to confirm drinking inclusion criteria. Participants were instructed not to change their drinking during this week. Participation always started on a Monday. Following the baseline week, some participants were assigned to a condition that implemented contingencies for showing no evidence of drinking. Details of this intervention design can be found in prior publications [36,37].

Measures

Baseline session. In-person assessments included a breathalyser to verify $\text{BrAC} = 0.000$ and urine screen verified no recent drug use other than marijuana. The Structured Clinical Interview for Diagnostic and Statistical Manual of Mental Disorders, fourth edition [39] substance abuse module was administered to determine current alcohol and substance use disorder. The 30-day Timeline Follow-back [40,41] was used to assess percentage of drinking days and average number of drinks per week. Part 1 of the Impaired Control Scale [42] was used to assess the degree of attempt to exert control over one's drinking in the past 6 months. Example items included: “*I tried to limit the amount I drank*” and “*I tried to resist the opportunity to start drinking*”.

Daily self-report. Participants received an e-mail each morning containing a link to a web-based survey that assessed drinking and marijuana use on the previous day. Participants indicated the number of standard drinks (12 oz. beer, 5 oz. wine, 1.5 oz. liquor) they had consumed, from which the average number of drinks per week was calculated. Each survey asked “*How many drinking episodes did you have on [day of week]? We ask that you think about your drinking on that day and decide for yourself whether you had more than one episode. Typically, this would include episodes that are*”

separated by time. They may or may not occur in different locations. Please include any episodes for which you drank more than a sip of alcohol." Participants were shown a grid that allowed them to enter the number of drinks, time of first drink (hours and minutes and AM/PM) and end of last drink (hours and minutes and AM/PM) for up to three episodes.

Transdermal data. The SCRAM bracelet (versions SCRAM II and SCRAMx) is strapped on the participant's ankle, worn continuously and cannot be removed by the wearer without cutting or breaking the closure on the strap. It samples vapor from the skin every 30 min. The bracelet was installed in the baseline session and all procedures were explained by research staff. Bracelet data were transmitted overnight via a SCRAM modem in the participant's home or were downloaded three times per week in the research office. Bracelet data are available immediately on a secure Alcohol Monitoring Systems website. TAC data were coded as reflecting alcohol use using criteria developed in prior work [8,36]; alcohol use was coded as detected when: (i) TAC reached at least 0.02 g/dl; and (ii) either therate of rise <0.05 g/dl per hour or the rate of decline <0.025 g/dl per hour (when peak <0.15 g/dl) and <0.035 g/dl per hour (when peak >0.15 g/dl).

Data analysis

Given our interest in characterising naturalistic drinking patterns and that contingencies were effective at changing drinking levels and presumably drinking patterns [36,37], only days on which contingencies were not in effect (i.e. days where intervention was not being administered) were examined ($n = 401$ total calendar days). These included days during the baseline week for participants who completed the trial in either the treatment or control groups (205 days) and all days during the post-baseline data collection period for control participants (196 days). Within these 401 days, we also had data from participants who dropped out of the study or were removed for ineligibility upon completion of the baseline week (56 days). (*Note:* Participants were informed that they could withdraw from the study at any time. Participants were also informed that they might be removed from the study if they no longer met inclusion criteria. Participants who withdrew or were removed from the study were compensated for their participation up to the point they withdrew.) Data were processed using a macro [43] developed in our laboratory which produces start and end times of episodes and episode-based variables [peak TAC, average TAC, area under the curve

(AUC)] which resulted in 358 drinking episodes (i.e. number of positive TAC events). A breakdown of number of episodes by participant and cluster is provided in Table S1, Supporting Information. Given that TAC detection from SCRAM may be delayed following drink consumption [35] and participants may not have always self-reported their drinks immediately, we used the following approach to align the detected SCRAM episodes with self-reported drinking episodes: if (i) a SCRAM episode start time was within 3 h of the self-reported drink start time; or (ii) a SCRAM episode start time was within 3 h of the self-reported drink-end time; or (iii) the self-reported drink start or end time was within a SCRAM episode. These criteria allowed for a margin of error with self-reported drinking start and end times to ensure SCRAM episodes occurred within a reasonable timeframe of self-reported drinking episodes.

K-means clustering using the ClusterR package [44] was used to cluster drinking episodes. Variables used in clustering were all continuous: peak TAC (highest TAC recorded within an episode), AUC (sum of the area of trapezoids under the TAC curve), rate of rise (peak TAC divided by time from last zero reading to peak TAC) and rate of decline (peak TAC divided by time from peak TAC to next zero reading). Prior to clustering, all continuous variables were standardised by dividing each value by their standard deviation. Optimal number of clusters was selected by considering the fit based on the Akaike information criterion, Bayesian information criterion and adjusted R-squared (Figure 1).

Univariate models were used to first examine differences between clusters on event (i.e. episode) and person-level characteristics with participant as a random effect (to account for imbalance of episodes provided across participants), followed by a multinomial mixed effects regression to examine association between clusters and person- (level 2) and day- or episode-level characteristics (level 1). In the multivariable model, cluster was regressed onto self-report number of drinks (continuous event-level) social day of week [binary day-level: weekend (Friday–Sunday) versus weekday (Monday–Thursday)], impaired control (continuous person-level), marijuana use (binary day-level: yes or no marijuana use) and a random effect of participant. Given that several investigations suggest individual differences can impact the detection of drinking episodes using TAC [5,45], we controlled for age (continuous person-level), gender (binary person-level), body mass index (continuous person-level), race (binary person-level: White versus non-White) and current AUD diagnoses (binary person-level: Abuse or Dependence versus neither). Missing data only existed in two predictors for the multinomial

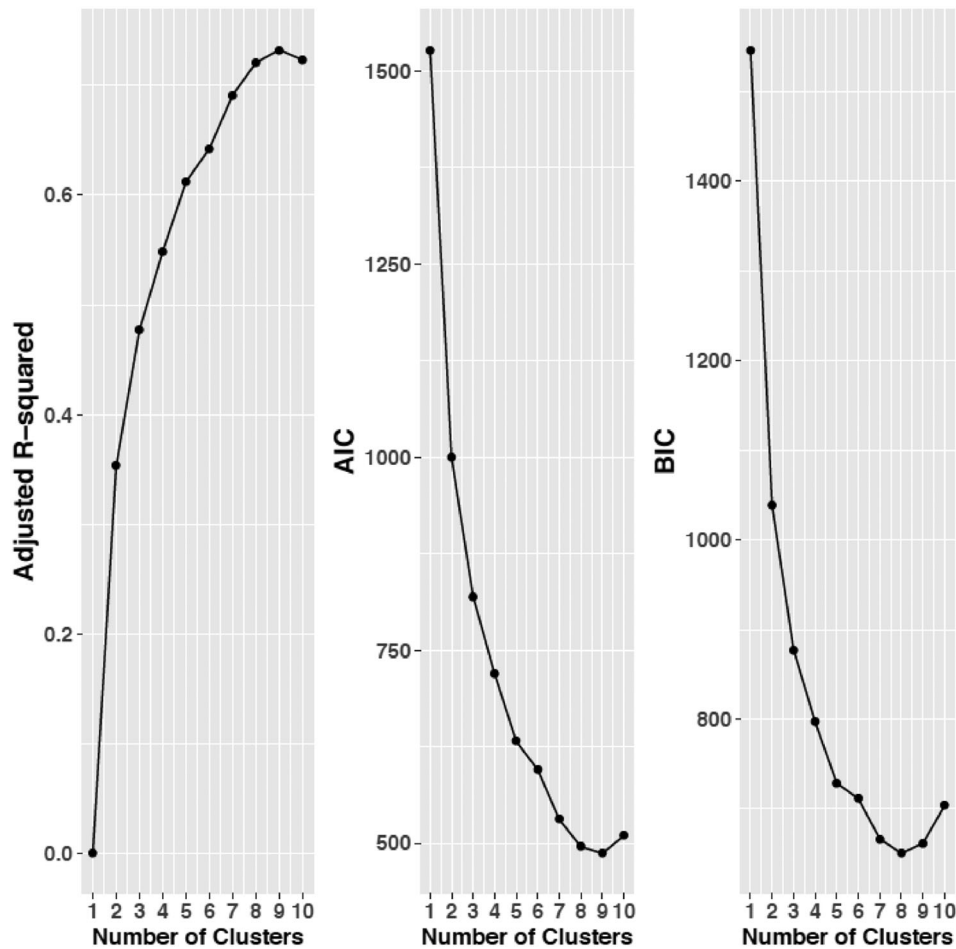


Figure 1. Criteria for selecting number of clusters. AIC, Akaike information criterion; BIC, Bayesian information criterion.

mixed model (17.6% of values for self-reported number of drinks and 0.8% for AUD) and was handled using predictive mean matching multiple imputation with 50 imputations. Given the exploratory nature of analyses, effects at $P < 0.10$ are discussed. Due to the lack of multiple comparison adjustments, all P -values reported are descriptive statistics that quantify a degree of statistical association and inferences should be considered exploratory.

Results

Descriptive statistics

The sample was 48.9% female with a mean age of 30.1 years ($SD = 10.8$). Of the 45 participants, 75.6% were Caucasian/White, 15.6% African-American/Black, 4.4% Asian, 4.4% were multiracial and 2.2% chose not to report race. 6.7% reported being Hispanic/Latinx. Average years of completed education was 13.7 ($SD = 4.3$). Regarding marriage status, 68.9% reported never being married, 26.7% reported

currently married or living with their partner and 4.4% were divorced, separated or widowed. At baseline, participants reported an average of 20.2 alcohol use days in the past month ($SD = 6.6$), an average of 7.5 drinks per drinking day and 34 drinks per week ($SD = 14.2$). Average body mass index was 26.9 ($SD = 5.0$) for men and 30.3 ($SD = 8.3$) for women. A little over half (59.0%) met criteria for AUD (recorded as Diagnostic and Statistical Manual of Mental Disorders, fourth edition, Alcohol Abuse or Alcohol Dependence at the time of data collection). Correlations between all variables are reported in Table 1.

Cluster analysis

A 3-cluster solution was chosen based on the most parsimonious solution with adequate fit (Figure 1). Although the 4-cluster solution was also considered, results of this solution offered little differentiation in unique drinking patterns, as Cluster 2 (in the solution presented below) was split into two clusters based on peak TAC. Episode clusters by each continuous TAC

Table 1. Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. SR drinks ^a	—												
2. Age ^a	—0.16*	—											
3. BMI ^a			—0.13*	—0.13*	0.49*	0.18*	0.12*	0.48*	0.22*	0.14*	—0.02	0.04	—0.18*
4. Imp con ^a			0.19*	0.30*	—0.17*	—0.25*	0.10*	—0.14*	—0.55*	—0.04	—0.15*	0.21*	0.13*
5. Peak TAC ^a			—	0.39*	—0.21*	—0.04	—0.02	—0.14*	—0.27*	—0.21*	—0.28*	—0.12*	—0.02
6. Rate rise ^a				—	—0.30*	—0.20*	—0.08	—0.18*	—0.20*	—0.05	—0.49*	0.33*	—0.02
7. Rate dec ^a					—	0.43*	0.12*	0.88*	0.13*	0.23*	0.15*	—0.10	—0.08
8. AUC ^a						—	0.10	0.26*	0.12*	0.11*	0.06	—0.09	—0.17*
9. Gender ^b							—	0.03	—0.07	0.08	0.10	—0.05	—0.04
10. Race ^b								—	0.16*	0.18*	0.08	—0.10	—0.07
11. AUD ^b									—	—0.05	0.30*	—0.09	—0.06
12. MJ use ^b										—	—0.13*	0.33*	0.04
13. Weekend ^b											—	—0.48*	0.01
													0.07

*Denotes significant at 0.05 level. ^aContinuous. ^bBinary, Pearson coefficient for two continuous variables, Point-biserial correlation for binary and continuous, Phi Coefficient for two binary. AUC, area under the curve; AUD, alcohol use disorder (Diagnostic and Statistical Manual of Mental Disorders, fourth edition abuse or dependence); BMI, Body Mass Index; Imp con, impaired control; MJ, marijuana; Race, binary White versus non-White (ref: White); Rate dec, Rate of decline from peak TAC; Rate rise, rate of rise to peak TAC; SR drinks, self-report number of drinks; TAC, transdermal alcohol concentration.

indicator are shown in Figure 2. As shown in Table 2, Cluster 1 consisted of the most common type of drinking episode, had the slowest rate of rise, slowest rate of decline and moderate levels of peak TAC and AUC. Cluster 2 was distinguished based on the highest peak TAC and AUC compared to the other two clusters. Although this cluster also had the fastest average rate of rise, rates cannot be as strongly distinguished (see Figure 2). Cluster 2 was moderate regarding rate of decline compared to other clusters. Cluster 3 consisted of the least common drinking episodes and can be most strongly distinguished from the other clusters by its faster rate of decline (see Figure 2). Rates of rise in cluster 3 were moderate and this cluster had the lowest peak TAC and AUC.

Mixed effects regression analysis

Univariate analyses (Table 3) found that episodes in Cluster 1 averaged significantly fewer self-reported drinks, compared to episodes in Cluster 2 and had significantly fewer episodes occurring on weekends. Episodes in Cluster 1 were more likely to be from participants who were not White and who had higher impaired control scores (versus Cluster 2, trending effect). Cluster 2 episodes were less likely to occur among females (versus Cluster 1, trending effect). Cluster 3 episodes consisted of self-reported number of drinks similar to Cluster 1, but were more likely to occur on weekend days (trending effect). Findings from the multivariable model show that the significantly higher number of self-reported drinks in Cluster 2 compared to Cluster 1 remained when controlling all other characteristics (Est = 0.19. $P = 0.05$).

Discussion

The overarching goal of this study was to characterise distinct subtypes of drinking episodes based on objective fine-grained characteristics derived from an alcohol biosensor (i.e. rate of rise, rate of decline, AUC and peak TAC). To our knowledge, this is the first study to attempt to characterise drinking patterns at the episode level in this way. These clusters consisted of episodes distinguished most notably by: Cluster 1, episodes with the slowest rates of rise and decline; Cluster 2, highest average peak TAC that differed significantly from the other two clusters; and Cluster 3, significantly faster rate of decline compared to Cluster 1.

The current examination builds on prior work using single indicators of drinking episodes by examining

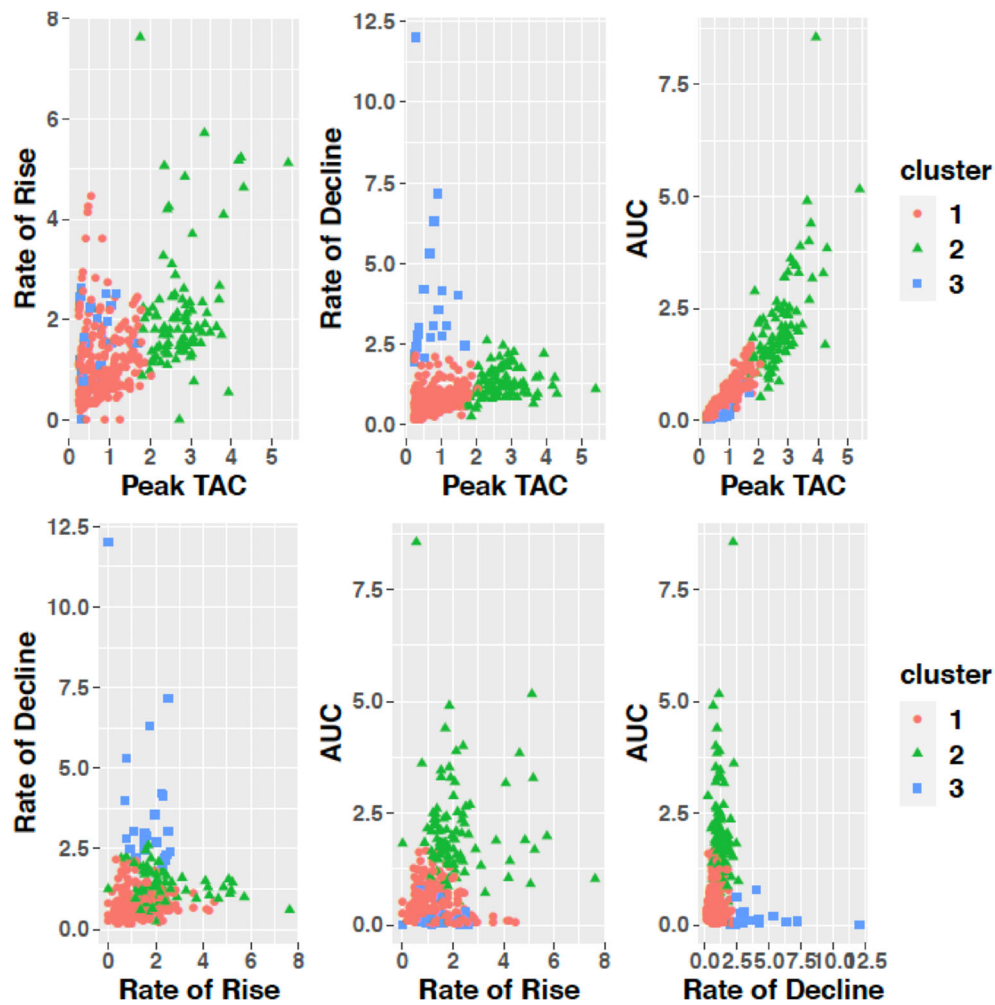


Figure 2. Episode clusters by each continuous variable. Note. All values are standardised. AUC, area under the curve; TAC, transdermal alcohol concentration.

Table 2. Distribution of TAC characteristics among drinking events across clusters

	Cluster				P-value		
	1 (n = 241)	2 (n = 92)	3 (n = 25)	Overall (n = 358)	(3:1)	(2:1)	(3:2)
Peak TAC	0.066 (0.038)	0.22 (0.051)	0.052 (0.033)	0.11 (0.081)	0.065 (−1.84)	<0.01 (10.9)	<0.01 (−5.42)
Rate rise	0.022 (0.014)	0.040 (0.023)	0.031 (0.013)	0.027 (0.018)	<0.01 (2.93)	<0.01 (5.92)	0.06 (−1.86)
Rate dec	0.015 (0.0078)	0.026 (0.0090)	0.071 (0.044)	0.022 (0.020)	0.02 (2.31)	<0.01 (6.43)	0.062 (1.87)
AUC	18 (16)	90 (47)	5.4 (8.0)	36 (42)	<0.01 (−3.53)	<0.01 (6.26)	0.13 (−1.53)

Note. Values are in original scales. AUC, area under the curve; Rate dec, rate of decline from peak; Rate rise, rate of rise to peak; TAC, transdermal alcohol concentration. P-values are presented as P-value (test statistic).

multiple characteristics of drinking episodes derived from objective measures of alcohol consumption. Results indicate important distinctions not just based

on peak TAC, but also area under the TAC curve and rates of rise and decline. In particular, results suggest that rate of decline can be quite disassociated from

Table 3. Distribution of event and person-level characteristics across clusters

	Cluster				P-value		
	1 (n = 241)	2 (n = 92)	3 (n = 25)	Overall ^a (n = 358)	(3:1)	(2:1)	(3:2)
SR drinks, M (SD)	6.63 (4.34)	10.6 (3.91)	6.82 (4.07)	7.83 (4.56)	0.84 (0.21)	0.026 (2.22)	0.33 (−0.97)
Weekend, n (%)	116 (48.1%)	54 (58.7%)	17 (68.0%)	187 (52.2%)	0.071 (1.80)	0.048 (1.98)	0.66 (0.44)
Female, n (%)	122 (50.6%)	35 (38.0%)	13 (52.0%)	170 (47.5%)	0.84 (0.21)	0.057 (−1.90)	0.14 (1.49)
Age, M (SD)	33.5 (12.0)	30.0 (9.00)	34.8 (15.6)	32.7 (11.7)	0.61 (0.50)	0.087 (−1.71)	0.13 (1.53)
BMI, M (SD)	28.0 (6.55)	25.0 (5.28)	27.4 (5.95)	27.2 (6.32)	0.86 (−0.18)	0.21 (−1.25)	0.43 (0.79)
Non-White, n (%)	75 (31.1%)	8 (8.7%)	5 (20.0%)	88 (24.6%)	0.57 (−0.58)	0.06 (−1.91)	0.25 (1.14)
AUD, n (%)	156 (64.7%)	37 (40.2%)	15 (60.0%)	208 (58.1%)	0.47 (−0.72)	0.32 (−1.00)	0.97 (0.038)
Imp con, M (SD)	6.48 (3.48)	3.78 (4.37)	6.04 (3.53)	5.76 (3.90)	0.52 (−0.64)	0.058 (−1.90)	0.48 (0.70)
MJ use, n (%)	51 (21.2%)	16 (17.4%)	6 (24.0%)	73 (20.4%)	0.24 (1.17)	0.24 (−1.17)	0.25 (1.16)

^aDescriptives are calculated at the event-level. All *P*-values are calculated using univariate mixed effects models for each characteristic with participant as a random effect. *P*-values are presented as *P*-value (test statistic). AUD, alcohol use disorder (Diagnostic and Statistical Manual of Mental Disorders, fourth edition abuse or dependence); BMI, Body Mass Index; Imp con, impaired control; MJ marijuana; SR drinks, self-report number of drinks.

AUC and peak TAC, which may reflect unique risk factors for drinking episodes. It is essential for future studies to examine the association of these clusters of drinking episodes with event-level drinking related consequences, such as hangover, negative affect and social and personal conflicts in order to fully understand the unique risks associated with these drinking patterns. Additional consideration of these objective measures of TAC may help to further elucidate specific aspects of a drinking episode that may increase the likelihood of drinking-related consequences, while minimising the burden that can be associated with intensive self-report data collection (e.g. ecological momentary assessment).

As a secondary goal, we explored whether the identified clusters were associated with event- or person-level characteristics from multiple levels of analysis. In univariate models, we found that Cluster 1 (vs. 2) was significantly distinguished by self-reported number of drinks and day of week. In multivariable models, only the effect of self-reported drinks remained a significant predictor of whether an episode fell in Cluster 1 versus 2. These results suggest that Cluster 2, which was marked by the highest rate of rise, AUC and peak TAC across episodes also reflected the drinking episodes with the highest number of drinks, as might be expected. These significant differences between Cluster 1 and 2 provide initial validation for this approach to clustering drinking episodes based on biosensor data. Although Cluster 3 revealed no significant differences with event- or person-level characteristics relative to other clusters (Table 3), results suggest that these drinking episodes though characterised by a number of drinks similar to Cluster 1, have different

TAC characteristics in that they show a faster rate of rise (possibly reflecting faster drinking), faster rate of decline and lower AUC than Cluster 1.

Several marginal effects on cluster at the person-level were also identified. In univariate analyses, these suggested that those who were male, of younger age, White race and lower in impaired control were more likely to have Cluster 2 versus Cluster 1 drinking episodes. In multivariable analyses, only the effect of White race remained trending. The signal observed for these individual-level characteristics that relate to cluster type may indicate a need to further explore these variables. The effect of race in particular may have important clinical implications, as the higher Peak TAC and larger AUC values observed in Cluster 2, which were more likely to be White participants, may represent a riskier pattern of drinking (increased consumption). However, as our small sample size did not allow the examination of specific races outside of the non-White versus white dichotomy, it is essential that this effect is further explored in a larger, more diverse sample.

Strengths and limitations

Several important strengths of the present investigation should be noted. First, the use of data derived from TAC measurement allowed for an objective measurement of alcohol consumption, rather than traditional self-report measures. Second, the use of cluster analysis allowed for the first characterisation of drinking based on several important biosensor-derived TAC characteristics of a drinking episode simultaneously. Third, this approach allowed for the consideration of both within-

and between-person characteristics of drinking episodes, providing a more comprehensive examination and characterisation of these drinking episodes.

This study should also be understood in the context of a few limitations. First, the sample was a relatively homogeneous group in terms of key demographic factors and drinking-related characteristics; results may differ in a more diverse sample of lighter or social drinkers. Although we only examined drinking episodes before the intervention began, participants that selected into the study were those interested in reducing their drinking, which may have affected patterns of drinking. Additionally, the sample size was relatively small for this type of analysis. Also, some participants contributed more drinking episodes than others, which may have contributed to null findings regarding person-level predictors in particular. Future work should examine more drinking episodes in a larger and more diverse sample with more equal representation in number of drinking episodes. Finally, while our objective measures of rate of rise and decline are a strength in that they control for within- versus between-person differences in drinking episodes, they do not allow us to distinguish individual biological differences in alcohol metabolism from actual pace of drinking. Future work should measure timing of drinking in addition to rate of rise and decline, in order to gain an advanced perspective on how these unique characteristics distinguish drinking episodes and their outcomes.

Conclusions

This study found that it is possible to distinguish drinking episodes based on a number of factors derived from alcohol biosensor data, including peak TAC, AUC, rate of rise and rate of decline. This work provides an essential first step for future work aimed at characterising drinking episodes from advanced datasets. We also found that these clusters of drinking episode are related to self-reported factors, primarily number of drinks. Future studies should examine how unique, objectively measured drinking patterns relate to event-level drinking-related consequences, which may have important implications for intervention and prevention efforts. Objective measurement of alcohol use in combination with a nuanced understanding of which patterns predict risk could inform just-in-time intervention [46]. For instance, as recent work suggests that rate of drinking confers particular risk for alcohol-related harms [23,30,33], objective assessment of such high risk drinking patterns that would otherwise be burdensome to assess could be used to provide comprehensive or real-time feedback to reduce drinking-related harms.

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Conflict of Interest

The authors have no conflicts of interest to declare.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Table S1: Number of episodes from each individual in each cluster.