Common and Unique Latent Transition Analysis (CULTA) as a Way to Examine the Trait-State Dynamics of Alcohol Intoxication

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Abstract

Objective: This paper introduces the Common and Unique Latent Transition Analysis (CULTA), a novel approach to studying alcohol intoxication dynamics in young adults engaged in heavy episodic drinking (HED). CULTA merges the Common and Unique Trait-State (CUTS) model with Latent Transition Analysis (LTA) to separate stable, trait-like intoxication components from transient fluctuations while modeling transitions between distinct drinking profiles. **Method:** A sample of 222 young adults wore transdermal alcohol concentration (TAC) sensors for six days, capturing real-time alcohol levels. The CULTA model decomposed intoxication variability into common and unique influences across four TAC features—peak, rise rate, fall rate, and duration. Latent intoxication profiles were identified, and transition probabilities between profiles were estimated with a focus on the influence of alcohol use disorder (AUD) risk. **Results:** Two latent intoxication profiles emerged. The first, high trait HED, was characterized by persistently high intoxication without significant inertia, while the second, state HED, featured moderate episodic intoxication with a strong autoregressive effect, reflecting lingering intoxication that dissipates over time. Individuals with higher AUDIT scores were more likely to remain in or transition to the high trait HED profile. Although peak intoxication and rise rate showed limited individual variability, fall rate and duration varied substantially, marking them as potential targets for intervention. **Conclusion:** CULTA advances our understanding of alcohol intoxication by distinguishing stable from transient influences and modeling transitions between drinking states. These findings suggest that interventions should address both persistent and situational aspects of intoxication—especially by reducing duration and fall rate—and encourage research across longer periods and populations.

Public Health Significance Statement

This study highlights how tracking daily alcohol intoxication with wearable sensors, combined with dynamic modeling, can offer near-real-time insights into heavy episodic drinking among young adults. The findings emphasize the importance of early screening tools, like AUDIT, to identify individuals at risk of chronic heavy drinking and guide personalized interventions. By focusing on patterns of intoxication persistence and shifts between drinking profiles, this research provides actionable strategies for reducing harmful drinking behaviors and promoting healthier outcomes in this vulnerable population.

Keywords: transdermal alcohol concentration, latent transition analysis, autoregression, ecological momentary assessment, alcohol use disorder risk, drinking, young adults

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Alcohol consumption among young adults remains a critical public health concern. According to the 2022 National Survey on Drug Use and Health, 50.2% of individuals aged 18 to 25 reported drinking in the past month, with 29.5% engaging in heavy episodic drinking (HED)[1] and 7.6% engaging in heavy alcohol use[2] (SAMHSA, 2023). Alcohol-related incidents contribute significantly to morbidity and mortality in this age group, with an estimated 1,519 deaths annually among college students aged 18 to 24, and an additional 2,586 deaths from alcohol-related injuries, such as motor vehicle accidents (Hingson et al., 2017). In addition to health risks, alcohol misuse carries substantial economic costs, putting a strain on the healthcare and social systems (Sacks et al., 2015).

Given these impacts, understanding and mitigating risky drinking behavior among young adults is essential. Historically, the best available option for the measurement of alcohol consumption has been self-reported drink counts, which are both cost-effective and predictive. Concerns have been raised about the field's near-exclusive reliance on self-report measures during and after heavy drinking events because their accuracy may become diminished due to intoxication or concurrent consequences such as alcohol-induced blackouts (Greenfield et al., 2014; Northcote & Livingston, 2011; Piasecki, 2019; Richards, Glenn, et al., 2024; Russell et al., 2022). Advances in wearable technology, such as transdermal alcohol concentration (TAC) sensors, enable continuous and objective monitoring of intoxication levels, providing near-real-time insights into drinking patterns without reliance on self-reports (Courtney & Russell, 2021; Swift, 2000). Wearable TAC sensors measure alcohol levels repeatedly through the skin and provide a curve of alcohol intoxication for each drinking event. From these curves, TAC *features* are generated to summarize the intoxication dynamics, including *peak* (the maximum intoxication level), *rise rate* (the speed of alcohol absorption), *fall rate* (the speed of alcohol elimination), and *duration* (the length of time spent biologically exposed to alcohol) (see Figure 1; Didier et al., 2023; Fridberg et al., 2022; Richards, Glenn, et al., 2024; Richards, Turrisi, & Russell, 2024; Richards et al., 2022; Russell et al., 2022, 2023, 2024). These TAC features provide unique information about drinking behavior that contributes to the prediction of important alcohol-related consequences, including hangovers, blackouts, illnesses, and injuries (Richards, Glenn, et al., 2024; Russell et al., 2022, 2023; Simons et al., 2015).

[1] Heavy episodic drinking (HED) is defined differently for males and females. For males, it involves consuming five or more drinks on a single occasion at least once in the past 30 days, while for females, it refers to consuming four or more drinks on a single occasion within the same timeframe.

[2] Heavy alcohol use is defined as engaging in HED on five or more days within the past 30 days, following the previously stated thresholds for males and females.

The multidimensionality of TAC features creates many opportunities for the characterization and analysis of alcohol use days. A growing number of approaches are in use to characterize TAC events and analyze TAC feature associations with alcohol-related behaviors and outcomes. Each of these approaches has its own unique strengths and weaknesses.

One approach has been to reduce the more “elementary” TAC features (e.g., peak, rates, duration) into a single comprehensive summary, such as the *area under the curve* (AUC) of a TAC event. AUC offers a single number describing the overall cumulative “burden” of biological alcohol exposure associated with the drinking event(s) that day (Didier et al., 2023; Leffingwell et al., 2012; Russell et al., 2022), but the known variation in the shapes of TAC events—even among those with the similar AUCs—creates difficulty in interpreting to what “kind” of event a high AUC refers (Russell et al., 2022, 2024). For example, the same AUC could refer to a long but low-intensity drinking event *or* a short but very high-intensity drinking event. The attendant risks of these two types of events would likely be very different, but AUC would not be able to distinguish between the two.

Another approach has been to use multiple “elementary” TAC features (e.g., peak, rise rate, fall rate, duration) in a multiple regression, in which their individual/unique contributions (e.g., Richards, Glenn, et al., 2024) and/or their statistical interactions are tested (e.g., Simons et al., 2015). Testing of the unique contributions of TAC features to alcohol-related outcomes is important, but such an approach discards the common variance that TAC features share, focusing solely on what is unique to each. As TAC features can be highly correlated (see, e.g., Russell et al., 2022), discarding the common variability between them may remove a large portion of their most important and meaningful variance. Moreover, tests of interactions between features can be informative (Simons et al., 2015) but they become increasingly cumbersome, underpowered, and difficult to interpret with increasing numbers of TAC features considered.

Other approaches to handle the multidimensionality of TAC features include clustering methods, including k-means clustering (Gunn et al., 2021) and multilevel latent profile analysis (MLPA; Russell et al., 2024). These approaches characterize days according to their specific multidimensional profile of TAC feature levels, creating a latent *day type* variable that varies at the day level. The frequencies of these latent day types can vary between individuals and can be tested as predictors and/or outcomes of important alcohol-related behaviors at both between- and within-person levels. For example, Russell et al., 2024 used MLPA to identify four drinking day types: 1) high-peak, fast-rate days (8.5% of days); 2) moderate-peak, fast-rate days (12.8% of days); 3) low-peak, slow-rate days (20.4% of days); and 4) little-to-no-drinking days (58.2% of days). The prevalence of each of day type differed significantly for each person (random intercept variances were significantly greater than 0) and day types showed significant between- and within-person associations with risky drinking behaviors, alcohol-related consequences, and alcohol use disorder (AUD) risk (Richards et al., 2025; Russell et al., 2024). Although latent clustering approaches allow multidimensional characterization of daily TAC features and testing of between- and within-person associations, they do not parse the common versus unique contributions of each TAC feature to risk associations. Models that can parse the common and unique contributions of TAC features simultaneously could be highly informative in prevention efforts by helping us answer questions such as "should we focus solely on reducing overall intoxication?" or "should we focus on reducing only specific attributes (e.g., speed, duration, intensity) of a drinking episode?"

Although existing methods (e.g., AUC, multiple regression, clustering) provide valuable insights into alcohol intoxication patterns, they each fail to simultaneously capture both shared and unique influences of TAC features while accounting for transitions in drinking behavior over time. A framework that can incorporate both latent trait-state structures and temporal transitions would allow for a more nuanced understanding of intoxication patterns. To address this gap, we propose the Common and Unique Latent Transition Analysis (CULTA) model, a novel statistical modeling framework that allows us to examine both the common *and* unique contributions of each TAC feature to alcohol-related outcomes. The CULTA model combines the strengths of the Common and Unique Variance Trait-State (CUTS; Hamaker et al., 2016) model with Latent Transition Analysis (LTA; Chow et al., 2015; Collins & Wugalter, 1992). The CULTA model is unique in that it allows us to 1) separate and model both the common and unique variance in TAC features, testing the associations of similar and unique components with alcohol-related outcomes; 2) test the *inertia* in alcohol intoxication, or the degree to which a person's drinking today influences their drinking on subsequent days; and 3) the ability to categorize high- versus low-intoxication days from both common and unique aspects of each TAC feature, and examine the day-specific probability of transitioning from high- to low-intoxication days and vice versa. Inertia and transition between high- and low-intoxication day types have not been tested in TAC data, despite evidence of autoregressive effects in alcohol use (DeMartini et al., 2022; Ray et al., 2020). By capturing enduring and transient intoxication patterns while accounting for the carryover effects of intoxication in everyday life, the CULTA model facilitates a nuanced understanding of drinking behaviors in natural environments (Piasecki, 2019), providing insights to inform targeted interventions for those at risk of chronic heavy drinking.

The next section will present the CULTA model as a framework to identify stable, trait-like components of drinking behavior alongside more situational, state-dependent fluctuations. It will explore the model's ability to categorize individuals based on enduring intoxication profiles, capturing both persistent and variable aspects of drinking behavior, leading to the specific research questions we address in the current paper.

Common and Unique Latent Transition Analysis (CULTA)

To effectively capture the complex, time-dependent dynamics of alcohol intoxication, the CULTA model extends the CUTS model's focus on common and unique variability (Hamaker et al., 2016) to incorporate LTA as a means of identifying high- and low-risk intoxication days and examining the shifts in these intoxication patterns over time. CULTA achieves this by distinguishing stable, trait-like components from transient, state-like variations, accounting for the lingering but dissipating effects of intoxication.

In the current application of the CUTS framework, four TAC features (peak, rise rate, fall rate, and duration) are treated as exchangeable indicators of alcohol intoxication. They are conceptualized like items on a scale. In the CUTS framework (see Figure 2), four key sources of variability are delineated using the four TAC features. The first is the *common trait* ($\text{Trait}_{\text{intoxication}}$), representing the person-mean level of latent intoxication (as indicated by the four TAC features) across all study days. This represents the person's overall liability to alcohol intoxication, representing how intoxicated they tend to become on average. The second source of variability comes from the *unique traits* (e.g., $\text{Unique}_{\text{peak}}$ through $\text{Unique}_{\text{dura}}$) one for each TAC feature. These represent the differences in the person-mean of each TAC feature and the person-mean for their latent intoxication. $\text{Unique}_{\text{peak}}$ represents the extent to which the person's peak tends to be higher or lower than their overall latent intoxication score. If their $\text{Unique}_{\text{peak}}$ tends to be higher than their $\text{Trait}_{\text{intoxication}}$, this suggests that this person's peak levels tend to be higher than those of the other features. The third source of variability comes from *common states* (e.g., $\text{State}_{\text{intoxication}}$), which represent the day-specific level of latent intoxication, adjusting for the person's trait latent intoxication. If a person's $\text{State}_{\text{intoxication}}$ is higher than their $\text{Trait}_{\text{intoxication}}$, then this indicates that they achieved a greater intoxication level that day than what is typical for them. The fourth source of variability comes from the *unique states* ($\varepsilon_{\text{peak}_t}$ through $\varepsilon_{\text{dura}_t}$), representing the day-specific difference between each TAC feature and the $\text{State}_{\text{intoxication}}$ score that day. If $\varepsilon_{\text{peak}_t} - \text{State}_{\text{intoxication}}$ is greater than 0, this suggests that the day-specific peak score is higher than the day-specific average of the other features. By decomposing the variance in TAC features in this way, we can both estimate and model the common and unique aspects of TAC features at both between- and within-person levels. Equation 1 shows the CULTA model we use, along with the four sources of variability we delineated previously:

$$Y_{k,i,t} = \lambda_{T_k} \times \text{Trait}_{\text{intoxication}_i} + \lambda_{S_k} \times \text{State}_{\text{intoxication}_{i,t}} + \alpha_{k,i} + \varepsilon_{k,i,t}, \quad \varepsilon_{k,i,t} \sim \mathcal{N}\left(0, \theta_k\right). \tag{1}$$

In this equation, the observed variable $Y_{k,i,t}$ for TAC feature k (peak TAC, rise rate, fall rate, duration) of individual i at time t is influenced by the stable *common trait* ($\text{Trait}_{\text{intoxication}_i}$) scaled by the factor loading λ_{T_k}; the *common state* ($\text{State}_{\text{intoxication}_{i,t}}$) scaled by λ_{S_k}; the random intercept $\alpha_{k,i}$ which decomposes into the *unique traits* ($\text{Unique}_{k,i}$) and the class-specific means ($\mu_{k,c}$), where c represents a specific categorical latent class; and the residual term $\varepsilon_{k,i,t}$ following a normal distribution with mean of zero and variance θ_k.

The LTA portion of the model is captured by the class-specific means $\mu_{k,c}$, which estimate one or more separate categorical "states" defined by the state levels of the common intoxication construct and the unique aspects of each TAC feature. Building on the CUTS foundation and integrating LTA, CULTA (see Figure 3) incorporates latent categorical variables ($\text{Cat}_{\text{intoxication}}$) that represent distinct drinking profiles, such as high- and low-intoxication classes, capturing systematic patterns in TAC data over time. These profiles encompass occasion-specific latent classes, each reflecting a unique configuration of drinking behavior that can change across days. Through LTA, CULTA models transition between these profiles across consecutive days, accounting for shifts in drinking behavior driven by individual predispositions or situational factors. Class-specific parameters (μ_{peak_c} through μ_{dura_c}) represent baseline levels for each TAC feature within each latent class, allowing for nuanced distinctions between classes in terms of intoxication dynamics. The substantive meaning of the latent classes (e.g., high- vs. low-intoxication) depends on the configuration of the values of μ_{peak_c} through μ_{dura_c}. The autoregressive effect (β_c) within each profile captures the inertia, or carryover effect, of prior intoxication on subsequent behavior. As depicted in Figure 3, the gray rectangle highlights model components where parameters vary by latent class, with arrows from the categorical latent variables to this rectangle indicating class-based variation. The subscripts c denotes parameters that vary by class, such as the autoregressive effects (β_c) and feature means (μ_{peak_c} through μ_{dura_c}), while arrows between categorical latent classes across time points represent transitions between latent classes over time, providing insight into the likelihood of individuals moving between different drinking profiles. Transitions between drinking profiles are important to assess because they may give clues to a person's risk for AUD. Those who tend to remain in high-risk drinking days, unlikely to transition out, may be at unique risk for AUD. By integrating autoregressive paths and class-based mean adjustments, CULTA extends the CUTS model to offer a refined approach to understanding alcohol use, differentiating stable drinking traits from transient, profile-specific fluctuations. This combination is novel in research using TAC. This provides actionable insights for interventions aimed at managing chronic heavy drinking behavior by addressing both enduring and situational aspects of intoxication.

In the following sections, we delve into the foundational concepts of alcohol intoxication inertia and transitions in intoxication profiles—core aspects that shape the CULTA model's framework. While the CULTA model captures enduring and situational influences on intoxication dynamics, these features add essential layers of insight. Intoxication inertia refers to the carryover effects from prior intoxication levels, indicating a potential habitual cycle in drinking behavior. Transitions in intoxication profiles, on the other hand, highlight shifts in drinking patterns that may respond to individual and environmental factors. We will explore these components' modeling and interpret their substantive implications for understanding risk behaviors associated with alcohol consumption.

Alcohol Intoxication Inertia

We use the term ***alcohol intoxication inertia*** to describe the carryover in alcohol intoxication levels from one day to the next . Alcohol intoxication inertia would imply that the intoxication level a person achieved yesterday is statistically associated with the level of intoxication a person achieves today. High inertia implies high stability in drinking behavior, and may represent an imperviousness to context and situation with regard to drinking. Persistent intoxication may characterize those at risk for AUDs (e.g., Prince et al., 2019).

Autoregressive (AR) models provide a mathematical representation of intoxication inertia. These models capture how previous intoxication levels influence future drinking behavior. This is reflected in Figure 3, particularly the paths from $\text{State}_{\text{intoxication}}$ for time t to $\text{State}_{\text{intoxication}}$ on the next time point. Or more precisely

$$\text{State}_{\text{intoxication}_{i,t}} = \beta_c \times \text{State}_{\text{intoxication}_{i,t-1}} + \zeta_{i,t}, \quad \zeta_{i,t} \sim \mathcal{N}\left(0, \psi_S\right) \tag{2}$$

where β_c is the AR(1) coefficient, which measures the influence of intoxication at a previous time point on the current time point, and $\zeta_{i,t}$ represents the normally distributed process noise. Recall that the subscript c indicate that this coefficient varies depending on the categorical latent classes.

The sign of β has important implications for the stability of alcohol intoxication. A positive β indicates that if yesterday's intoxication is high, today's intoxication is also likely to be high, in a manner proportionate to the magnitude of β. A positive β also implies that if the previous intoxication level was low, the current value is likely to be low. The magnitude of a positive β suggests the degree of persistence. If β is close to 1, then strong persistence is observed, meaning that high intoxication persists longer than if β is closer to 0. A negative β indicates that the current value of the series is negatively related to the previous value. If the previous value was high, the current value is likely to be low, and vice versa. To illustrate these patterns graphically, we generated data from Equation 2 without process noise, as shown in Panel 4a of Figure 4. For positive β values, specifically 0.95 and 0.75, notice that high intoxication on the previous time results in high intoxication on the next day, although the magnitude of intoxication diminishes over time. Note that the decline is slower for 0.95, indicating a higher inertia from previous states. For both cases, high intoxication from previous day will result in high intoxication on the next day but this association is stronger for 0.95 compared to 0.75. For negative β values, such as -0.95 and -0.75, observe the oscillations. Higher absolute values also suggest greater inertia from previous states, but in this case, it results in the intoxication level to swing to the opposite sign until it eventually reaches the stable mean (zero in this case). The reversion to the mean takes longer for -0.95 compared to -0.75. For both cases, high intoxication from the previous day will result on low intoxication on the next day. The magnitude of the swing to the opposite sign, however, is greater for -0.95 compared to -0.75.

This inertia highlights the challenges of interrupting heavy drinking patterns, particularly in environments that encourage alcohol use. Understanding the dynamics of intoxication inertia can inform interventions, as individuals caught in such cycles may require targeted strategies to shift behavior patterns. Moreover, incorporating TAC data allows researchers to observe these patterns in real time, providing deeper insights into the persistence of intoxication across episodes and helping design personalized intervention efforts.

Transitions in Intoxication Profiles

The CULTA model identifies latent groupings using mixture structural equation modeling with regime-switching (MSEM-RS; Chow et al., 2015). Regime-switching is an alternative name for latent transition that is popular within state-space literature (Kim & Nelson, 1999). Integrating latent transitions into the CUTS framework allows a more nuanced understanding of how individuals may transition through phases of distinctly different drinking states over longer periods. In other words, such latent transitions allow membership in latent classes or profiles to change over time as related to environmental, contextual, and other time- and person-specific differences. This modeling aspect allows researchers to capture nonlinear dynamics in behavior, such as sudden shifts in intoxication attitudes or behaviors that traditional linear models might miss. If a study finds that certain individuals are more likely to transition to more problematic intoxication profiles, tailored support strategies can be developed for those at higher risk.

In the current study, we use CULTA to estimate latent categorical states of intoxication. This allows us to understand how likely individuals are to shift from states that are higher versus lower than their own average. This is novel in the literature using TAC features and allows estimation of how individuals may differ in their consistency/stability of high- and low-intoxication states.

Research Questions

Building on the conceptual foundations and dynamic modeling capabilities of the CULTA framework, this study bridges critical gaps in understanding the nuanced interplay between stable and transient factors in alcohol intoxication patterns. The incorporation of both trait-like and state-like dynamics enables a comprehensive analysis of the common and unique contributions of intoxication features. These contributions have not only methodological significance but also profound implications for identifying and intervening in problematic drinking behaviors.

Sources of Variability in TAC Features

Research Question 1: To what extent is the variability in TAC features explained by common versus unique components at both the between-person and within-person levels? This question focuses on understanding whether intoxication patterns are primarily driven by overarching common factors or by feature-specific dynamics. By disentangling these sources, the CULTA model provides insights into whether interventions should target overall intoxication patterns or specific features such as peak, rise rate, fall rate, or duration.

Emergence of Latent Intoxication Profiles

Research Question 2: What categorical latent intoxication profiles emerge from the CULTA model, and how are they characterized? By identifying categorical profiles that encompass trait and state influences, we can compare and validate findings against prior research. This extends the field's understanding of high- and low-intoxication behaviors and their implications for risk behaviors.

Persistence and Transitions in Intoxication Profiles

Research Question 3: What is the probability of remaining in or transitioning between different intoxication profiles, such as high versus low intoxication, from one drinking day to the next? Does an individual's baseline AUD influence their initial profile membership or their likelihood of transitioning between profiles? These questions address the dynamics of intoxication inertia and the influence of stable traits and situational factors on profile transitions. They also highlight the potential role of baseline alcohol use risk in shaping these transitions.

The answers to these questions have significant implications for public health and behavioral science. They can illuminate the mechanisms underlying persistent heavy drinking and its association with AUD; enhance the predictive accuracy of screening tools by incorporating nuanced measures of intoxication dynamics; and inform the design of tailored interventions that address both stable traits and transient situational factors influencing drinking behavior. Ultimately, this research aims to refine theoretical frameworks and translate findings into actionable strategies for mitigating the adverse impacts of heavy episodic drinking in vulnerable populations.

Method

Participants

The study involved 222 young adults with an average age of 22.3 years (64% female, 79% non-Hispanic White, 84% undergraduates). Participants were recruited from the vicinity of a northeastern

US university. The analyses of the current report and the study design were not preregistered. Given the lack of relevant previous effect sizes on which to base power calculations, we did not conduct *a priori* power analyses for these data. Participants completed a screening survey prior to enrollment. For eligibility, participants needed to: (1) be between the ages of 21-29, (2) have engaged in HED at least weekly on average during either the past calendar year or typically during the academic year, and (3) be sufficiently proficient in written English to complete study procedures. HED was defined as consuming 4+/5+ drinks in a row for females/males (Wechsler et al., 1995). Before enrollment, 531 individuals completed an initial screening, 419 of whom were eligible. Invitations were sent on a "first-come, first serve" basis according to the order in which screening surveys were received. Time and resource limitations prevented invitations to all eligible participants, leading us to invite 343 individuals to participate. Of the 343 invited, 222 completed the study. No evidence of bias was observed comparing those completing versus not completing by gender, race/ethnicity, student status, or past-two-week binge drinking (ps>.10).

Procedure

The study consisted of five 24-hour periods spanning six consecutive days. All participants began on a Wednesday and finished on a Monday, capturing the social weekend of Thursday, Friday, and Saturday. Data collection took place across 25 weeks from November 2017 to November 2018 and across 8 weeks from November 2019 to March 2020. The study included baseline and endpoint assessments, three-times daily ecological momentary assessment (EMA), participant-initiated drinking-episodic EMA, and transdermal sensors. The current study uses only data from the TAC sensors and baseline reports. All procedures were approved by the university institutional review board. Data and analytic code are not publicly available but will be made available (in accordance with IRB standards) upon request from the first author. We report all data exclusions, manipulations, and measures in the study.

TAC sensor protocol. Participants wore the SCRAM-CAM anklet during wake and sleep hours for the duration of the study. After data collection, SCRAM-CAM data are uploaded to the company's online server (SCRAMNet), which houses TAC data, records TAC "positives", and tracks compliance with device wear through skin temperature and sensor quality (infrared voltage) readings. Compliance rates were high. Only 2.0% of TAC data showed evidence of device removal or interference; these data points were clustered within a minority of individuals ($n = 24$). No evidence suggested that compliance was associated with study demographics (gender, age, race/ethnicity, student status) or AUDIT scores (ps > .05). We began with 52,726 TAC observations collected from 218 individuals; data from 4 participants were lost due to device failure. Drinking episodes were then identified and coded using validated research guidelines informed by controlled administration studies (Roache et al., 2019). Following episode identification and exclusions, we retained 608 TAC drinking events containing 16,385 data points among

195 participants (87.8% of sample). Prior to analysis, TAC data were smoothed to remove noise and facilitate feature extraction using penalized *b*-splines (Eilers & Marx, 1996). Because drinking behavior does not conform to the midnight-to-midnight boundaries of a calendar day and retrospective morning reports of yesterday's/last night's drinking likely included hours after midnight. Day boundaries for TAC data were therefore redefined with 10 AM marking the start of a new "social" day. 10 AM was chosen because it was the modal prompt time for the morning report which asked participants to reflect on their drinking the day/night before. If the morning report was provided before 10 AM but TAC or episodic EMA data were present between 5-10 AM, the social day boundary was reset to the time of the morning report (104 TAC and 7 episodic EMA observations were shifted). TAC features and EMA drink counts were defined by the social day in analysis.

Measures

TAC Features

Four TAC features were extracted from each day with TAC-positive (TAC > 0) data: 1) *peak TAC*, the maximum TAC value that day; 2) *rise rate*, the average of all ascending point-to-point TAC rates, interpreted as the day's average rate of TAC increase per hour; 3) *fall rate*, the average rate of all descending point-to-point TAC rates, interpreted as the day's average rate of TAC decrease per hour; and 4) *duration*, the number of hours a person spent under the alcohol concentration curve that day. Days without alcohol detection were coded as zero for these features unless there was evidence of non-compliance. Outliers above the 99^{th} percentile were removed, leaving 1,274 valid days of data across 218 individuals for analysis.

AUDIT

The Alcohol Use Disorders Identification Test (AUDIT; Babor et al., 2001) was employed to evaluate various aspects of participants' alcohol use disorder (AUD) risk. This comprehensive screening tool is designed to identify individuals with hazardous and harmful drinking patterns. The AUDIT assesses three main domains: alcohol consumption, drinking behaviors, and alcohol-related problems. Each item on the AUDIT is scored on a scale from 0 to 4, with higher scores indicating more severe alcohol use problems. The total score, which ranges from 0 to 40, provides an overall assessment of the participant's alcohol use and helps to identify those who may need further evaluation or intervention. An AUDIT score of 8 or more suggests risk for AUD; AUDIT scores of 15 or more suggest likely AUD (Babor et al., 2001).

Data Analysis

For Research Question 1, we evaluated the statistical significance of trait and state variances, as illustrated in Figure 3. The variance of the general intoxication trait ($\text{Trait}_{\text{intoxication}}$) is denoted by ψ_T. To ensure comparability across time points, the factor loadings for peak in the general intoxication trait were constrained to 1. The factor loadings for the other features——rise, fall, and duration—were set to be invariant across time and are represented by $\lambda_{T_{\text{rise}}}$, $\lambda_{T_{\text{fall}}}$, and $\lambda_{T_{\text{dura}}}$, respectively. Feature-specific trait variances (ψ_{peak}, ψ_{rise}, ψ_{fall}, and ψ_{dura}) correspond to the unique traits of peak, rise, fall, and duration. The factor loadings for these feature-specific traits were constrained to 1. State intoxication variance at the initial time point ($\text{State}_{\text{intoxication}_{t_0}}$) is denoted by $\psi_{S_{t_0}}$. For subsequent time points, residual state intoxication variances were constrained to equality and represented by ψ_S. Similar to the trait factors, the factor loadings for peak in the state factors were constrained to 1, while the factor loadings for rise, fall, and duration were constrained to be time-invariant and are denoted by $\lambda_{S_{\text{rise}}}$, $\lambda_{S_{\text{fall}}}$, and $\lambda_{S_{\text{dura}}}$, respectively. The variances of the unique state components (ε_{peak_t} through ε_{dura_t}) are represented by θ_{peak} through θ_{dura} and were constrained to remain constant over time. Our analysis revealed that ψ_T, ψ_{peak}, and ψ_{rise} were not statistically significant. Consequently, to simplify interpretation, we omitted $\text{Trait}_{\text{intoxication}}$, $\text{Unique}_{\text{peak}}$, and $\text{Unique}_{\text{rise}}$ from the final model (see Figure 5).

For Research Question 2, we evaluated models with one, two, and three latent profiles and compared the results to previous findings. The class specific parameters μ_{peak_c} through μ_{dura_c} and β_c were allowed to vary per profile but were constrained to be invariant across time points. Ultimately, we selected a two-profile solution for intoxication, which is illustrated in Panel 6a of Figure 6.

For Research Question 3, we estimated the probabilities of transitioning between the two intoxication profiles across drinking days. Additionally, we examined the impact of AUD on profile membership at the initial time point and its influence on the likelihood of transitioning between profiles at subsequent time points.

Results

The CULTA model was estimated using Mplus 8.11 (Muthén & Muthén, 2017), with models specifying one, two, and three latent profiles tested. Notably, the one-profile model corresponds to the CUTS model with the autoregressive (AR) component added. Comparisons between the one- and two-profile solutions, based on information criteria (AIC, BIC, and aBIC), indicated that the two-profile solution provided a better fit to the data. Detailed results of the model comparisons are presented in Table 3.

Expanding the model to accommodate three or more profiles presented challenges with convergence, despite extensive efforts to explore different specifications. Specifically, although the estimation procedure ran successfully, we were unable to replicate the best log-likelihood (LL) value across a large number of random starts. To address this, we conducted extensive explorations with and without additional constraints on the latent profile structures to aid identification, using up to 5,000 random starts with 1,000 final stage optimizations. Despite these efforts, convergence remained elusive, indicating potential instability in solutions with more than two profiles.

Closer examination of the three-profile models with differing LL values revealed that the resulting profiles were not meaningfully distinct. Some profiles had very low sample sizes, and the characteristics of the profiles overlapped considerably, further undermining their interpretability. These inconsistencies suggested that models with more than two profiles do not represent stable or robust solutions for this data.

Research Question 1: To what extent is the variability in TAC features explained by common versus unique components at both the between-person and within-person levels?

Variance parameters capturing the extent of between-individual differences in common ($\text{Trait}_{\text{intoxication}}$) and unique traits ($\text{Unique}_{\text{peak}}$, $\text{Unique}_{\text{rise}}$, $\text{Unique}_{\text{fall}}$ and $\text{Unique}_{\text{dura}}$) were evaluated. The factor loadings and variance of the between-individual common trait factor ($\text{Trait}_{\text{intoxication}}$) were not statistically significant. This suggested that peak, rise, fall, and duration each captured unique, as opposed to shared sources of variability across time and individuals.

Substantial variability was found in individuals' occasion-specific (i.e., state) variances in the TAC features. The AR parameter β_c was also significant for one of the two profiles. However, with the exception of the unique trait variance associated with fall (ψ_{fall}) and duration (ψ_{dura}), the variances of the two remaining unique trait factors—ψ_{peak}, and ψ_{rise}, corresponding to TAC peak, and rise—were not statistically significant. This suggested substantial between-person differences in fall rate and drinking duration that persisted throughout the six-day study span, but no enduring between-person differences in other unique TAC features.

Results from addressing research question 1 have several implications. First, the results suggests that managing and reducing the length of intoxication episodes as well as the sobering process (fall rate) may be more impactful than focusing on peak intensity or rise rates. Prolonged intoxication episodes and sobering process carry heightened risks, such as accidents or negative health outcomes, underscoring the importance of targeting duration in interventions. Additionally, duration may be a stronger predictor of cumulative intoxication burden, making it essential for designing strategies aimed at reducing harm.

The minimal variability in both common and indicator-specific traits points to the importance of state-based changes in intoxication. Rather than being driven by consistent individual differences, intoxication levels appeared to fluctuate based on situational factors. This finding highlighted the need to better measure proximal risk and protective factors that may contribute to some of these state intoxication dynamics.

Research Question 2: What categorical latent intoxication profiles emerge from the CULTA model, and how are they characterized?

As hypothesized, we identified two distinct latent intoxication profiles, which are presented in Figure 6a. Each profile is characterized by the mean values of key TAC features—peak, rise, fall, and duration—which provide a comprehensive view of individuals' intoxication patterns.

The high profile, which we labeled as high trait HED, was associated with elevated mean values across the TAC features, indicating more intense and prolonged intoxication episodes. Individuals within this profile manifested higher peak intoxication levels and longer episodes of intoxication. This pattern reflected sustained, problematic drinking behavior, aligning with the hypothesis that individuals in the high profile engage in more frequent or heavy drinking episodes.

In contrast, the low profile, which we labeled as state HED, corresponds to lower mean values for the same TAC features, suggesting milder or shorter intoxication episodes relative to the high profile. Individuals in this profile exhibit lower peak intoxication levels and more moderate drinking patterns, with shorter episodes and quicker changes in alcohol concentration. This profile represents the "typical" drinking behavior within the sample, which, as noted earlier, is composed of individuals who engage in HED. Therefore, typical in this context refers to less intense but still episodic drinking behavior, which may be common among the majority of participants.

When examining the profile probabilities, a small proportion of individuals (11%) were classified under the high trait HED, indicating more problematic drinking behavior. In contrast, the majority (89%) belonged to the state HED, reflecting more moderate drinking patterns, despite the sample's overall focus on HED. These results align with our hypothesis, as the high profile represents a subset of individuals with sustained, elevated intoxication levels, while the low profile captures the more common, episodic drinking behavior within the sample.

The two profiles also exhibited differences in the AR parameter reflecting different dynamics in alcohol intoxication inertia. For the state HED profile, the AR parameter $\beta = 0.311$ is statistically significant ($p < 0.001$), indicating a significant inertia effect. This means that for individuals in the low profile, intoxication from the previous day tends to persist into the following day before gradually converging toward the profile's mean values, which are close to zero. This pattern suggests that even low levels of intoxication may have a lingering effect, potentially contributing to ongoing drinking behavior. For the high trait HED profile, the AR parameter β is not significantly different from zero, indicating no detectable inertia effect. In this case, individuals tend to converge rapidly toward the profile's elevated mean intoxication level, regardless of their intoxication state on the previous day. This finding suggests that individuals in the high trait HED profile exhibit consistently high levels of intoxication, with each day's drinking episode quickly returning to the high mean, irrespective of prior consumption.

Both profiles present challenges. For the low profile, the significant AR parameter reflected alcohol intoxication inertia that lingered beyond one drinking episode, but eventually dissipated over the 6 days. Even though the mean intoxication level was low, the lingering effects from previous drinking episodes gave rise to low to moderate levels of transient HED. In contrast, the high profile's rapid convergence to elevated intoxication levels, despite the non-significant AR parameter, indicates a consistent pattern of heavy drinking. This consistent return to high levels of intoxication is problematic, as it suggests a tendency toward sustained heavy consumption that may have serious health and behavioral consequences.

While the AR parameters differed between the two profiles, both drinking patterns raise concerns. The low profile reflects persistent, lingering intoxication, which may promote ongoing drinking over time. Meanwhile, the high profile shows a pattern of consistently high intoxication, with individuals repeatedly returning to a problematic drinking baseline. These findings highlight the need for targeted interventions to address both low-level alcohol inertia and the risks associated with chronic high-level drinking.

The final class proportions for the latent class patterns are presented in Figure 7. The majority of individuals (62.84%) remained in a stable state HED (2) latent class across time, indicating that most individuals exhibited primarily state-dependent episodic heavy drinking behaviors. Several other latent class patterns emerged with smaller proportions. Some individuals were classified as having a high trait HED (1) profile, either from the outset or through transitions over time. However, these patterns were relatively uncommon, with each representing less than 5% of the total sample. Despite their low prevalence, these individuals are of particular concern due to their sustained and trait-like heavy drinking tendencies, which place them at a heightened risk for persistent problematic alcohol consumption.

The second-largest class proportion (5.05%) involved individuals who exhibited a moderate stability pattern, maintaining intermediate drinking behaviors without strong transitions into or out of high trait HED or state HED classifications. Other transition patterns were observed but were relatively rare, each representing less than 4% of the sample. These findings suggest that while movement between drinking profiles occurred, it was not a dominant trend in the data.

Overall, these results highlight that while state HED was the most prevalent drinking pattern, a small subset of individuals demonstrated high trait HED, which suggests a more stable and enduring form of heavy drinking behavior. Understanding the factors contributing to these transitions—and identifying those most at risk—may be critical for targeted interventions aimed at mitigating long-term alcohol-related harms.

Research Question 3: What is the probability of remaining in or transitioning between different intoxication profiles, such as high versus low intoxication, from one drinking day to the next? Does an individual's baseline AUD influence their initial profile membership or their likelihood of transitioning between profiles?

The results indicate that individuals do shift between high and low intoxication profiles over time, with transition probabilities influenced by both their previous day's profile and their AUDIT scores. The transition between these latent profiles is modeled through the following log-odds equations:

$$\begin{array}{cc} & \begin{array}{cc} c_{t+1}=1 & c_{t+1}=2 \end{array} \\ \begin{array}{c} c_t=1 \\ c_t=2 \end{array} & \begin{pmatrix} \alpha_1 + \beta_{11} + \gamma_{11} \times \text{AUDIT} & 0 \\ \alpha_1 + \gamma_{12} \times \text{AUDIT} & 0 \end{pmatrix} \end{array}$$

$$\begin{array}{cc} & \begin{array}{cc} c_{t+1}=1 & c_{t+1}=2 \end{array} \\ \begin{array}{c} c_t=1 \\ c_t=2 \end{array} & \begin{pmatrix} -3.586 + 2.250 + 0.063 \times \text{AUDIT} & 0 \\ -3.586 + 0.094 \times \text{AUDIT} & 0 \end{pmatrix} \end{array}$$

Here, c_t refers to the individual's intoxication profile on the current day, and c_{t+1} refers to their profile on the following day. The α and β parameters, which capture the base transition dynamics, are significant at $p < 0.001$. The γ parameters, reflecting the influence of AUDIT scores on transitions, are significant at $p < 0.05$. These results indicate that both profile persistence and transitions between profiles are meaningful and significantly related to baseline alcohol use risk (AUDIT).

When the AUDIT score is zero, indicating minimal alcohol use risk, the transition probabilities reveal distinct patterns. Individuals in the high intoxication profile have a 20.8% chance of staying in the high profile on the following day, while the probability of transitioning from the high to the low profile is 79.2%. This suggests that individuals with high intoxication on one day are more likely to moderate their behavior and move into the low intoxication profile the next day.

In contrast, individuals in the low intoxication profile exhibit a strong tendency to remain in that profile, with a 97.3% chance of staying in the low profile from one day to the next. The probability of transitioning from the low to the high profile is only 2.7%, indicating that individuals who exhibit low intoxication levels are unlikely to escalate to higher levels of intoxication on the following day. These transition probabilities reflect a general tendency toward stability in the low profile, with limited upward shifts to the high profile.

This pattern suggests that participants tend to reduce their intoxication levels over time, with moderation being the more likely outcome for those initially in the high profile. The results also highlight the stability of the low profile, where individuals are unlikely to escalate their drinking behavior to problematic levels. These baseline probabilities provide insights into the natural fluctuations in intoxication within this sample, emphasizing the dynamics of moderation and stability across drinking episodes.

Table 4 presents the effect of AUDIT on the transition probabilities. The table reveals a clear pattern in how increasing AUDIT scores influence the probabilities of staying in or transitioning between the high and low intoxication profiles. As AUDIT scores rise, individuals in the high intoxication profile become increasingly likely to remain in that profile, while the probability of transitioning from the high to the low profile decreases. This trend reflects a growing persistence of heavy drinking behavior as alcohol use severity increases. For example, when the AUDIT score reaches the dependence threshold (AUDIT = 15), the likelihood of remaining in the high profile rises to 40.3%, compared to just 20.8% when the AUDIT score is zero. At the same time, the probability of transitioning from high to low drops steadily, indicating that higher AUDIT scores reduce the tendency to moderate intoxication levels over time.

Similarly, for individuals in the low intoxication profile, the probability of remaining in the low profile remains relatively high across all AUDIT levels but shows a gradual decline as AUDIT scores increase. While individuals with low AUDIT scores have a strong tendency to stay in the low profile (97.3% at AUDIT = 0), this probability decreases to 89.8% at AUDIT = 15 and further declines at higher scores. Concurrently, the likelihood of transitioning from the low to the high profile increases with rising AUDIT scores, reflecting an elevated risk of engaging in more problematic drinking. For example, at AUDIT = 31, individuals in the low profile have a 33.8% chance of shifting into the high profile, compared to only 2.7% at AUDIT = 0.

As AUDIT scores increase, the probability of remaining in the high profile rises, while the probability of transitioning from high to low decreases, reflecting greater persistence of heavy drinking among individuals with more severe alcohol use. At the same time, individuals in the low profile show a decreasing likelihood of remaining there and a growing tendency to shift into the high profile, indicating that those with higher AUDIT scores are more prone to escalating their drinking behavior over time. These patterns highlight the importance of addressing alcohol use risk early to prevent individuals from becoming entrenched in sustained high-intoxication states.

To determine the probability of an individual belonging to either the high or low intoxication profile at the initial time point, we used a log-odds table with the estimated parameters.

$$\begin{array}{cc} c_0=1 & c_0=2 \\ \left(\alpha_{01} + \gamma_{01} \times \text{AUDIT} \right. & \left. 0 \right) \end{array} = \begin{array}{cc} c_0=1 & c_0=2 \\ \left(-3.563 + 0.122 \times \text{AUDIT} \right. & \left. 0 \right) \end{array}$$

In this model, the high intoxication profile is represented by $c_0 = 1$, and the low intoxication profile is represented by $c_0 = 2$. The parameters $\alpha_{01} = -3.563$ and $\gamma_{01} = 0.122$ (associated with the AUDIT score) are statistically significant at $p < 0.001$. When the AUDIT score is zero, the probabilities of membership in each profile are 0.028 for high and 0.972 for low. These probabilities suggest that, at baseline, individuals with minimal alcohol use risk (AUDIT = 0) are highly likely to belong to the low intoxication profile (97%) and only have a 3% chance of being in the high intoxication profile. As the AUDIT score increases, the probability for membership in the high profile also increase, indicating that individuals with higher alcohol use risk are more likely to belong to the high intoxication profile at the initial time point. Probabilities of profile membership for the initial time point for some values of AUDIT are given in Table 5.

Discussion

This study utilized the CULTA model to explore the day-to-day dynamics of alcohol intoxication among young adults who engage in HED. The model enabled us to distinguish between trait-like and state-like variations in intoxication, allowing for precise analysis of both habitual and situational drinking behavior. We identified two distinct profiles of state intoxication features indicating 1) sustained heavy drinking and 2) more episodic, moderate patterns, respectively. Results highlight the persistence of intoxication over time (alcohol intoxication inertia) and dynamic transitions between intoxication profiles, emphasizing the influence of baseline alcohol risk as measured by the AUDIT.

CULTA vs. MLPA

Similar to Russell et al. (2024) we analyzed TAC data to examine drinking behaviors among young adults, but they employ different statistical approaches to address their research questions. Russell et al. (2024) applied Multilevel Latent Profile Analysis (MLPA) to identify day-level profiles of TAC features, including peak, rise rate, fall rate, and duration. MLPA captures variations at both within-person and between-person levels, classifying drinking days into distinct profiles and testing their associations with drinking behaviors and AUD risk. In contrast, we introduced the Common and Unique Latent Transition Analysis (CULTA), which integrates the Common and Unique Trait-State (CUTS) model with Latent Transition Analysis (LTA). CULTA separates stable, trait-like components of intoxication from transient, state-level fluctuations and models transitions between latent drinking profiles over time.

The research questions addressed by these methods differ in scope. Russell et al. (2024) focuses on identifying TAC-based drinking day profiles, testing how these profiles relate to drinking behaviors and contexts, and assessing whether individuals with higher AUDIT scores exhibit different profile memberships. In contrast, we aimed to decompose alcohol intoxication variability into stable and fluctuating influences, model transitions between drinking states over time, and assess the role of AUD risk in influencing profile transitions.

The key methodological distinction lies in the temporal aspect of the analyses. MLPA assumes static drinking profiles, classifying days based on observed TAC patterns without accounting for transitions over time. CULTA, on the other hand, explicitly models these transitions, allowing for a more dynamic understanding of how individuals move between drinking states. Moreover, CULTA separates common and unique sources of variability, providing a finer-grained decomposition of intoxication patterns. It captures intoxication inertia, the carryover effect from one drinking episode to the next, which is absent in MLPA.

CULTA adds valuable insights by identifying patterns of sustained versus situational heavy drinking, which can inform intervention strategies. By distinguishing between stable traits and state-dependent fluctuations, CULTA enhances the prediction of persistent heavy drinking behaviors and provides a more personalized risk assessment. This is particularly useful in targeting intervention efforts toward reducing intoxication duration and fall rate, which show substantial person-specific variability.

While MLPA effectively classifies drinking behaviors into latent profiles, CULTA extends this analysis by incorporating temporal dynamics and distinguishing between stable and fluctuating intoxication components. The application of CULTA could refine risk prediction models and intervention strategies by offering a more comprehensive understanding of drinking behavior transitions over time.

Common and Unique Sources of Variability

Our analysis using the CULTA model addresses an elusive goal—to model both state and trait levels of device-measured alcohol intoxication features while acknowledging both their common and unique aspects. TAC features (peak, rise rate, fall rate, duration) share common causes by definition, being driven by alcohol consumption, absorption, and elimination dynamics. However, they may differ in their behavioral antecedents and their ability to shape the consequences of alcohol consumption. Crafting prevention and intervention recommendations that work in the real world requires an ability to separate the common and unique causes and sequelae of TAC features (and their behavioral antecedents) so that common (e.g., reduce intoxication levels overall) and unique prevention messages (e.g., reduce the rate of alcohol consumption) can be emphasized accordingly. The CULTA model gets us closer to such goals.

Using the CULTA model, we failed to capture a common trait intoxication latent variable that captures the between-individual variability in the common stable trait intoxication captured by all TAC features across the six days. Furthermore, looking at unique TAC feature traits show that while peak TAC and rise rate had minimal unique individual variability, the fall rate and duration of intoxication episodes exhibited significant unique trait variability across participants. Individuals varied more in how in the alcohol elimination rate and how long they stayed intoxicated than in how high their intoxication levels reached, suggesting that fall rate and duration are unique drivers of behavioral differences and cumulative alcohol-related risks relative to other TAC features. This finding suggests that specifically targeting the *fall rate* and *duration* of alcohol consumption (and its associated intoxication) may have unique prevention impacts over and above reducing overall consumption levels.

Alcohol Intoxication Inertia and Habitual Drinking

Our CULTA model approach allowed us to enhance our understanding of the inertia of alcohol intoxication as measured through passive sensing. The concept of alcohol intoxication inertia reflects the persistence of intoxication patterns across consecutive drinking episodes through the autoregressive (AR) parameter. The AR parameter was significant for the low profile, suggesting that low intoxication levels tended to show carry over from one day to the next. This inertia points to habitual drinking behaviors, where intoxication on one day increases the likelihood of continued drinking in subsequent days. These findings underscore the importance of interventions that address both the immediate and cumulative effects of alcohol consumption. Behavioral strategies such as cognitive-behavioral therapy (CBT) can be particularly effective in breaking this cycle by promoting awareness and self-regulation in drinking behaviors.

For individuals in the high intoxication profile, the lack of a significant AR parameter in combination with high average intoxication levels suggests rapid convergence toward high levels of intoxication, independent of prior episodes. This indicates that these individuals maintain a consistently high baseline of drinking, and that decreases in intoxication are likely to be only transient. Such a profile is likely driven by entrenched behavioral patterns. The persistence of high-intoxication behavior highlights the need for more intensive interventions, such as motivational interviewing,and mindfulness-based stress reduction techniques to interrupt automatic alcohol-seeking behaviors, promote alignment of alcohol use behaviors with personally held goals, and promote safer alcohol consumption.

Transitions Between Intoxication Profiles and the Role of AUD

Our CULTA approach also allowed us to identify types of days characterized by high and low levels of specific TAC features relative to what is normal for each person. Our approach also allowed us to examine *transitions* between these latent intoxication profiles across multiple drinking episodes. The results revealed that most individuals tended to remain in the low profile, but that those with higher versus lower AUD risk show greater odds of shifting into the high profile. Additionally, the probability of staying in the high profile rises steadily with higher AUD risk, while the likelihood of transitioning from high to low decreases. This dynamic reflects the reinforcing nature of severe alcohol use: individuals with elevated AUD risk are more likely to persist in problematic drinking patterns in their day-to-day lives. The significant variability in intoxication duration further complicates these transitions. Individuals with longer intoxication episodes may be more likely to experience shifts into the high-intoxication profile, reinforcing problematic drinking patterns.

Implications for Intervention and Prevention

The identification of two distinct profiles and their transitions has several practical implications for personalized interventions and public health strategies. For individuals at high risk, as indicated by elevated AUDIT scores, interventions should aim to reduce both peak intoxication levels and the duration of drinking episodes. Educational programs targeting young adults can help raise awareness about the risks associated with prolonged intoxication and promote safer drinking strategies, such as protective behavioral strategies (PBS). Additionally, wearable TAC sensors can provide real-time feedback, enabling individuals to monitor and adjust their drinking behavior proactively.

The findings also emphasize the importance of early intervention. Since higher AUD are associated with a greater likelihood of remaining in or escalating to the high profile, screening tools like AUDIT should be widely implemented in settings such as college health centers. Early identification of high-risk individuals can facilitate timely interventions that prevent long-term alcohol-related problems and promote healthier drinking habits. Given the variability in intoxication duration, interventions should focus not only on reducing peak levels but also on limiting the length of drinking episodes to mitigate cumulative risks.

Limitations and Future Directions

While the CULTA model provides valuable insights into the common and unique aspects of intoxication dynamics, several limitations must be acknowledged. First, the sample consists entirely of young adults engaging in HED, which limits the generalizability of the findings to broader populations, such as older adults or individuals with less frequent drinking patterns. While this population is relevant for studying risky drinking behavior, future studies should include more diverse samples to capture the variability in drinking behaviors across different demographic groups.

Second, the study's six-day data collection period may not fully capture long-term drinking behavior or profile transitions. While the findings highlight the persistence of intoxication and transitions between profiles, a longer study period would provide a more comprehensive view of these dynamics over time. Longitudinal research spanning several weeks or months is recommended to confirm the robustness of these patterns and explore how external factors (e.g., social or environmental influences) affect both intoxication levels and episode duration.

Third, the convergence issues encountered when testing three- and four-profile solutions highlight some constraints in the modeling approach. Although the two-profile solution (high and low intoxication) fits well with the data and aligns with the literature on heavy episodic drinking, the inability to model additional profiles suggests potential underlying heterogeneity that may not have been fully captured. Future research should explore alternative modeling techniques or larger, more diverse samples to identify whether additional profiles exist beyond the two identified in this study.

Despite these limitations, the study makes meaningful contributions to the understanding of drinking behavior through the use of TAC sensors and dynamic modeling, providing important implications for both research and clinical practice. Future studies should continue to refine the model and extend the study period to better capture long-term drinking dynamics and explore how individual and contextual factors influence profile transitions, particularly focusing on the role of intoxication duration.

Conclusion

This study advances our understanding of the dynamic interplay between stable and transient factors in alcohol intoxication, while separating and modeling the common and unique aspects of alcohol intoxication. Our results demonstrate that both low-level alcohol inertia and persistent heavy drinking require targeted strategies to promote healthier drinking behaviors among young adults. The significant unique variability in intoxication duration underscores the need to prioritize interventions that limit the length of drinking episodes, as prolonged intoxication may pose greater cumulative risks. The use of TAC sensors and AUD screening tools offers a practical pathway for early detection and intervention. Future research should aim to extend the study period and refine the model to capture more complex drinking patterns and better inform policy and intervention efforts.

References

Babor, T. F., Higgins-Biddle, J. C., Saunders, J. B., & Monteiro, M. G. (2001). *The Alcohol Use Disorders Identification Test: Guidelines for use in primary care* (2nd ed.). Department of Mental Health; Substance Dependence, World Health Organization.

Chow, S.-M., Witkiewitz, K., Grasman, R., & Maisto, S. A. (2015). The cusp catastrophe model as cross-sectional and longitudinal mixture structural equation models. *Psychological Methods*, *20*(1), 142–164. https://doi.org/10.1037/a0038962

Collins, L. M., & Wugalter, S. E. (1992). Latent class models for stage-sequential dynamic latent variables. *Multivariate Behavioral Research*, *27*(1), 131–157. https://doi.org/10.1207/s15327906mbr2701_8

Courtney, J. B., & Russell, M. A. (2021). Testing affect regulation models of drinking prior to and after drinking initiation using ecological momentary assessment. *Psychology of Addictive Behaviors*, *35*(5), 597–608. https://doi.org/10.1037/adb0000763

DeMartini, K. S., Gueorguieva, R., Taylor, J. R., Krishnan-Sarin, S., Pearlson, G., Krystal, J. H., & O'Malley, S. S. (2022). Dynamic structural equation modeling of the relationship between alcohol habit and drinking variability. *Drug and Alcohol Dependence*, *233*, 109202. https://doi.org/10.1016/j.drugalcdep.2021.109202

Didier, N. A., King, A. C., Polley, E. C., & Fridberg, D. J. (2023). Signal processing and machine learning with transdermal alcohol concentration to predict natural environment alcohol consumption. *Experimental and Clinical Psychopharmacology*, *32*(2), 245–254. https://doi.org/10.1037/pha0000683

Eilers, P. H. C., & Marx, B. D. (1996). Flexible smoothing with B-splines and penalties. *Statistical Science*, *11*(2). https://doi.org/10.1214/ss/1038425655

Fridberg, D. J., Wang, Y., & Porges, E. (2022). Examining features of transdermal alcohol biosensor readings: A promising approach with implications for research and intervention. *Alcoholism: Clinical and Experimental Research*, *46*(4), 514–516. https://doi.org/10.1111/acer.14794

Greenfield, T. K., Ye, Y., Bond, J., Kerr, W. C., Nayak, M. B., Kaskutas, L. A., Anton, R. F., Litten, R. Z., & Kranzler, H. R. (2014). Risks of alcohol use disorders related to drinking patterns in the U.S. general population. *Journal of Studies on Alcohol and Drugs*, *75*(2), 319–327. https://doi.org/10.15288/jsad.2014.75.319

Gunn, R. L., Steingrimsson, J. A., Merrill, J. E., Souza, T., & Barnett, N. (2021). Characterising patterns of alcohol use among heavy drinkers: A cluster analysis utilising alcohol biosensor data. *Drug and Alcohol Review*, *40*(7), 1155–1164. https://doi.org/10.1111/dar.13306

Hamaker, E. L., Schuurman, N. K., & Zijlmans, E. A. O. (2016). Using a few snapshots to distinguish mountains from waves: Weak factorial invariance in the context of trait-state research. *Multivariate Behavioral Research*, *52*(1), 47–60. https://doi.org/10.1080/00273171.2016.1251299

Hingson, R., Zha, W., & Smyth, D. (2017). Magnitude and trends in heavy episodic drinking, alcohol-impaired driving, and alcohol-related mortality and overdose hospitalizations among emerging adults of college ages 18–24 in the United States, 1998–2014. *Journal of Studies on Alcohol and Drugs*, *78*(4), 540–548. https://doi.org/10.15288/jsad.2017.78.540

Kim, C.-J., & Nelson, C. R. (1999). *State-space models with regime switching: Classical and Gibbs-sampling approaches with applications*. The MIT Press. https://doi.org/10.7551/mitpress/6444.001.0001

Leffingwell, T. R., Cooney, N. J., Murphy, J. G., Luczak, S., Rosen, G., Dougherty, D. M., & Barnett, N. P. (2012). Continuous objective monitoring of alcohol use: Twenty-first century measurement using transdermal sensors. *Alcoholism: Clinical and Experimental Research*, *37*(1), 16–22. https://doi.org/10.1111/j.1530-0277.2012.01869.x

Muthén, L. K., & Muthén, B. O. (2017). *Mplus user's guide. Eighth edition*. Los Angeles, CA, Muthén & Muthén.

Northcote, J., & Livingston, M. (2011). Accuracy of self-reported drinking: Observational verification of 'last occasion' drink estimates of young adults. *Alcohol and Alcoholism*, *46*(6), 709–713. https://doi.org/10.1093/alcalc/agr138

Piasecki, T. M. (2019). Assessment of alcohol use in the natural environment. *Alcoholism: Clinical and Experimental Research*, *43*(4), 564–577. https://doi.org/10.1111/acer.13975

Prince, M. A., Read, J. P., & Colder, C. R. (2019). Trajectories of college alcohol involvement and their associations with later alcohol use disorder symptoms. *Prevention Science*, *20*(5), 741–752. https://doi.org/10.1007/s11121-018-0974-6

Ray, L. A., Du, H., Grodin, E., Bujarski, S., Meredith, L., Ho, D., Nieto, S., & Wassum, K. (2020). Capturing habitualness of drinking and smoking behavior in humans. *Drug and Alcohol Dependence*, *207*, 107738. https://doi.org/10.1016/j.drugalcdep.2019.107738

Richards, V. L., Barnett, N. P., Cook, R. L., Leeman, R. F., Souza, T., Case, S., Prins, C., Cook, C., & Wang, Y. (2022). Correspondence between alcohol use measured by a wrist-worn alcohol biosensor and self-report via ecological momentary assessment over a 2-week period. *Alcohol: Clinical and Experimental Research*, *47*(2), 308–318. https://doi.org/10.1111/acer.14995

Richards, V. L., Glenn, S. D., Turrisi, R. J., Mallett, K. A., Ackerman, S., & Russell, M. A. (2024). Transdermal alcohol concentration features predict alcohol-induced blackouts in college students. *Alcohol, Clinical and Experimental Research*, *48*(5), 880–888. https://doi.org/10.1111/acer.15290

Richards, V. L., Mallett, K. A., Turrisi, R. J., Glenn, S. D., & Russell, M. A. (2025). Profiles of transdermal alcohol concentration and their prediction of negative and positive alcohol-related consequences in young adults' natural settings. *Psychology of Addictive Behaviors*. https://doi.org/10.1037/adb0001054

Richards, V. L., Turrisi, R. J., & Russell, M. A. (2024). Subjective intoxication predicts alcohol-related consequences at equivalent alcohol concentrations in young adults using ecological momentary assessment and alcohol sensors. *Psychology of Addictive Behaviors*, *38*(3), 334–346. https://doi.org/10.1037/adb0000993

Roache, J. D., Karns-Wright, T. E., Goros, M., Hill-Kapturczak, N., Mathias, C. W., & Dougherty, D. M. (2019). Processing transdermal alcohol concentration (TAC) data to detect low-level drinking. *Alcohol*, *81*, 101–110. https://doi.org/10.1016/j.alcohol.2018.08.014

Russell, M. A., Richards, V. L., Turrisi, R. J., Exten, C. L., Pesigan, I. J. A., & Rodriguez, G. C. (2024). Profiles of alcohol intoxication and their associated risks in young adults' natural settings: A multilevel latent profile analysis applied to daily transdermal alcohol concentration data. *Psychology of Addictive Behaviors*. https://doi.org/10.1037/adb0001022

Russell, M. A., Smyth, J. M., Turrisi, R., & Rodriguez, G. C. (2023). Baseline protective behavioral strategy use predicts more moderate transdermal alcohol concentration dynamics and fewer negative consequences of drinking in young adults' natural settings. *Psychology of Addictive Behaviors*, *38*(3), 347–359. https://doi.org/10.1037/adb0000941

Russell, M. A., Turrisi, R. J., & Smyth, J. M. (2022). Transdermal sensor features correlate with ecological momentary assessment drinking reports and predict alcohol-related consequences in young adults' natural settings. *Alcoholism: Clinical and Experimental Research*, *46*(1), 100–113. https://doi.org/10.1111/acer.14739

Sacks, J. J., Gonzales, K. R., Bouchery, E. E., Tomedi, L. E., & Brewer, R. D. (2015). 2010 national and state costs of excessive alcohol consumption. *American Journal of Preventive Medicine*, *49*(5), e73–e79. https://doi.org/10.1016/j.amepre.2015.05.031

SAMHSA. (2023). *Key substance use and mental health indicators in the United States: Results from the 2022 National Survey on Drug Use and Health (HHS Publication No. PEP23-07-01-006, NSDUH Series H-58)*. Rockville, MD, Center for Behavioral Health Statistics; Quality, Substance Abuse; Mental Health Services Administration. https://www.samhsa.gov/data/report/2022-nsduh-annual-national-report

Simons, J. S., Wills, T. A., Emery, N. N., & Marks, R. M. (2015). Quantifying alcohol consumption: Self-report, transdermal assessment, and prediction of dependence symptoms. *Addictive Behaviors*, *50*, 205–212. https://doi.org/10.1016/j.addbeh.2015.06.042

Swift, R. (2000). Transdermal alcohol measurement for estimation of blood alcohol concentration. *Alcoholism: Clinical and Experimental Research*, *24*(4), 422–423. https://doi.org/10.1111/j.1530-0277.2000.tb02006.x

Wechsler, H., Dowdall, G. W., Davenport, A., & Rimm, E. B. (1995). A gender-specific measure of binge drinking among college students. *American Journal of Public Health*, *85*(7), 982–985. https://doi.org/10.2105/ajph.85.7.982

Table 1

Probability of Starting Out in a Specific Class for a Two Class Solution

Class 1	Class 2
$\frac{\exp\left(\alpha_0+\gamma_{0_1} x_{1,it}+\cdots+\gamma_{0_j} x_{j,it}\right)}{\exp\left(\alpha_0+\gamma_{0_1} x_{1,it}+\cdots+\gamma_{0_j} x_{j,it}\right)+1}$	$\frac{1}{\exp\left(\alpha_0+\gamma_{0_1} x_{1,it}+\cdots+\gamma_{0j} x_{j,it}\right)+1}$

Table 2

Probability of Transitioning from One Class to Another for a Two Class Solution

	Class 1 (t)	Class 2 (t)
Class 1 $(t-1)$	$\frac{\exp\left(\alpha_1+\beta_{11}+\gamma_{11_1}x_{1,it}+\cdots+\gamma_{11_j}x_{j,it}\right)}{\exp\left(\alpha_1+\beta_{11}+\gamma_{11_1}x_{1,it}+\cdots+\gamma_{11_j}x_{j,it}\right)+1}$	$\frac{1}{\exp\left(\alpha_1+\beta_{11}+\gamma_{11_1}x_{1,it}+\cdots+\gamma_{11_j}x_{j,it}\right)+1}$
Class 2 $(t-1)$	$\frac{\exp\left(\alpha_1+\gamma_{12_1}x_{1,it}+\cdots+\gamma_{12_j}x_{j,it}\right)}{exp\left(\alpha_1+\gamma_{12_1}x_{1,it}+\cdots+\gamma_{12_j}x_{j,it}\right)+1}$	$\frac{1}{exp\left(\alpha_1+\gamma_{12_1}x_{1,it}+\cdots+\gamma_{12_j}x_{j,it}\right)+1}$

Table 3

Information Criteria for the One- and Two-Profile Solutions

Model	AIC	BIC	aBIC
One-profile model	10,371.269	10,445.728	10,376.012
Two-profile model	9,842.342	9,926.955	9,847.732

Note. AIC = Aikaike Information Criteria. BIC = Bayesian Information Criteria. aBIC = sample size adjusted BIC.

Table 4

Probability of Transitioning from One Class to Another for a Two Class Solution as a Function of AUDIT

	High Trait HED (t)	State HED (t)
	No AUD	
High Trait HED ($t-1$)	0.208	0.792
State HED ($t-1$)	0.027	0.973
	High risk	
High Trait HED ($t-1$)	0.303	0.697
State HED ($t-1$)	0.056	0.944
	Dependence	
High Trait HED ($t-1$)	0.403	0.597
State HED ($t-1$)	0.102	0.898
	Max score	
High Trait HED ($t-1$)	0.650	0.350
State HED ($t-1$)	0.338	0.662

Note. No AUD corresponds to an AUDIT score of 0. High risk corresponds to an AUDIT score of 8. Dependence corresponds to an AUDIT score of 15. Max score corresponds to the maximum AUDIT score in the sample which is 31.

Table 5

Probability of Starting Out in a Specific Class for a Two Class Solution as a Function of AUD

AUD	High Trait HED	State HED
No AUD	0.028	0.972
High risk	0.070	0.930
Dependence	0.150	0.850
Max score	0.555	0.445

Note. No AUD corresponds to an AUDIT score of 0. High risk corresponds to an AUDIT score of 8. Dependence corresponds to an AUDIT score of 15. Max score corresponds to the maximum AUDIT score in the sample which is 31.

Figure 1

Transdermal Alcohol Concentration (TAC) Features

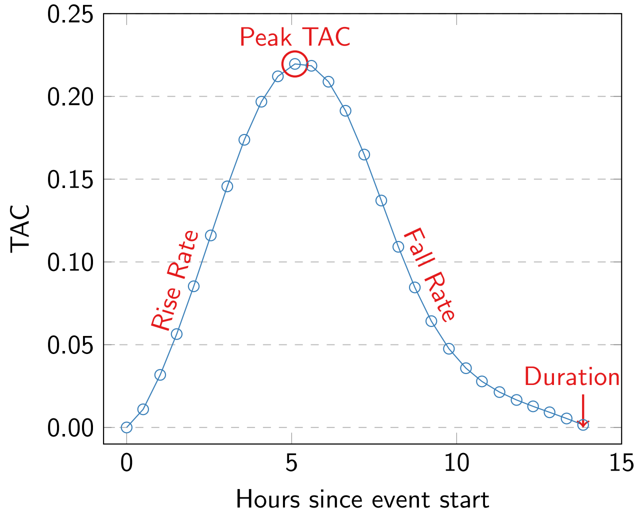
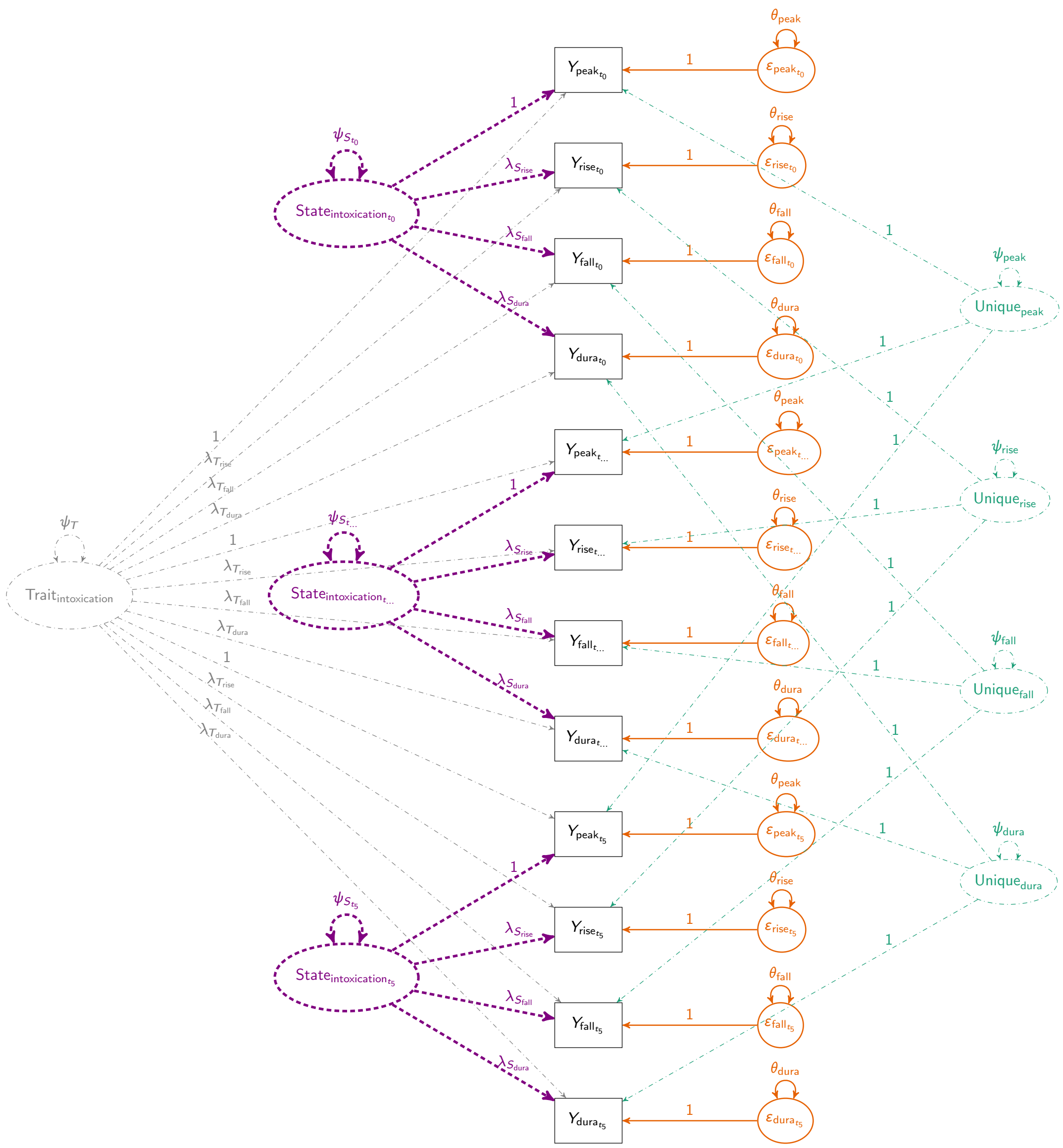


Figure 2

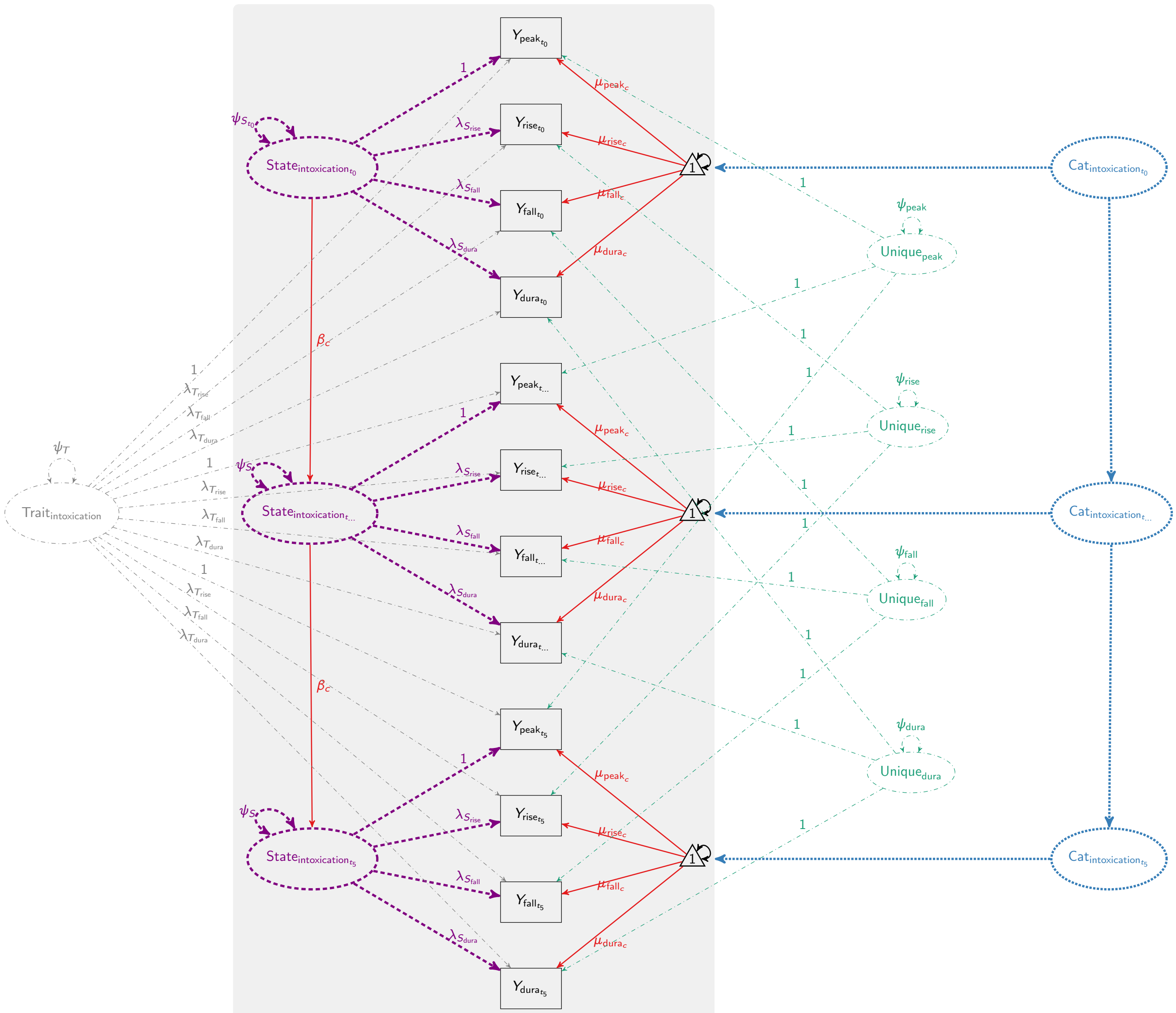
The Common and Unique Trait-State Model (CUTS)



Note: The CUTS model with four TAC features as observed indicators, one common trait $\text{Trait}_{\text{intoxication}}$, and six ($t_0, t_{\dots}, t_5$; only three are explicitly shown because of space constraints) occasion-specific $\text{State}_{\text{intoxication}}$ factors that capture shared information across the TAC features on each day. The latent variables Unique_{peak} through Unique_{dura}, as analogous to the concept of random intercepts in the multilevel modeling literature, represent unique, feature-specific traits that persist throughout all occasions. $\varepsilon_{peak_{t0}}$ through $\varepsilon_{dura_{t5}}$ represent process noises or other sources of feature- and occasion-specific deviations that are unaccounted for by other modeling elements.

Figure 3

The Common and Unique Latent Transition Analysis Model (CULTA).

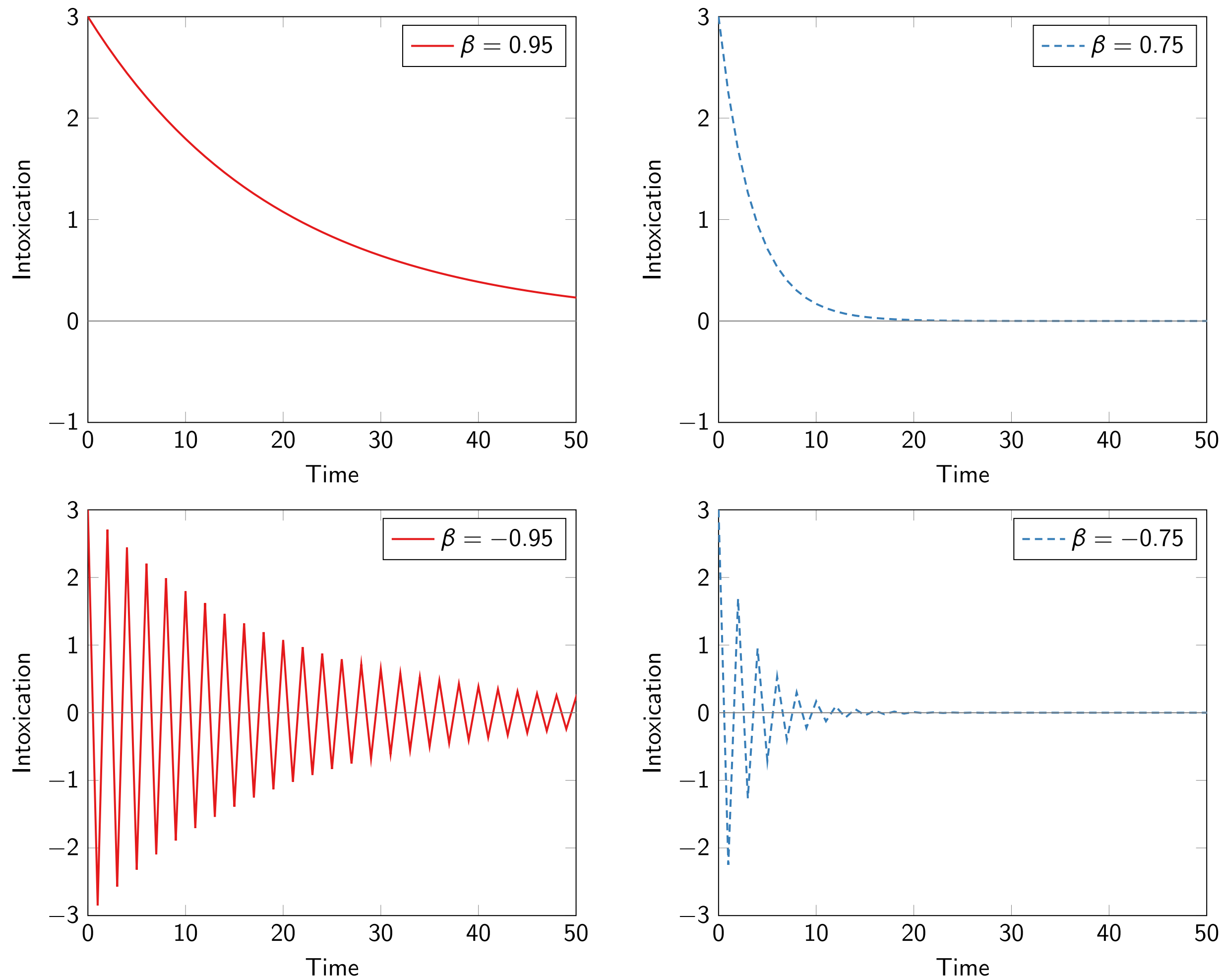


Note: In addition to the elements in the CUTS model in Figure 2, the CULTA model includes latent variables $\text{Cat}_{\text{intoxication}_{t0}}$ to $\text{Cat}_{\text{intoxication}_{t5}}$ representing six occasion-specific categorical latent classes. The gray rectangle highlights model components where parameters vary by latent class. Arrows from the categorical latent variables to the gray rectangle indicates this class-based variation. The subscript c indicate parameters that vary by class. β_c represents autoregressive effects within each profile, and μ_{peak_c} through μ_{dura_c} captures indicator means for each profile. Arrows between categorical latent classes across time points represent transitions between latent classes over time. The latent variables $\varepsilon_{\text{peak}_{t0}}$ through $\varepsilon_{\text{dura}_{t5}}$ were omitted for ease of presentation.

Figure 4

Simulated data to highlight qualitative differences between systems showing (a) AR dynamics and (b) latent transition in AR and intercept (mean) values

(a)



(b)

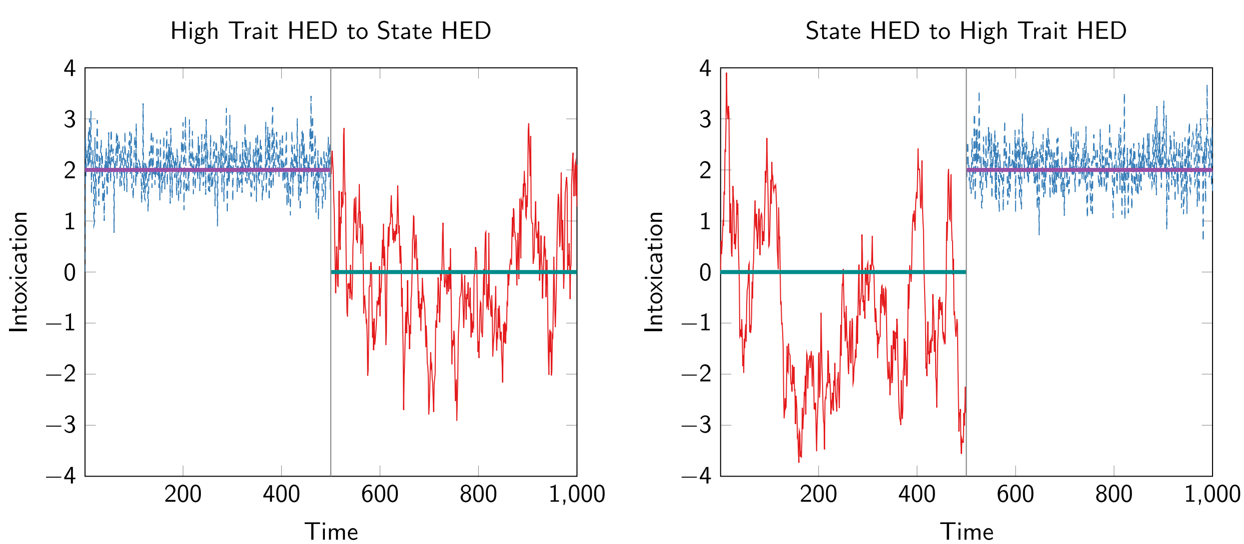
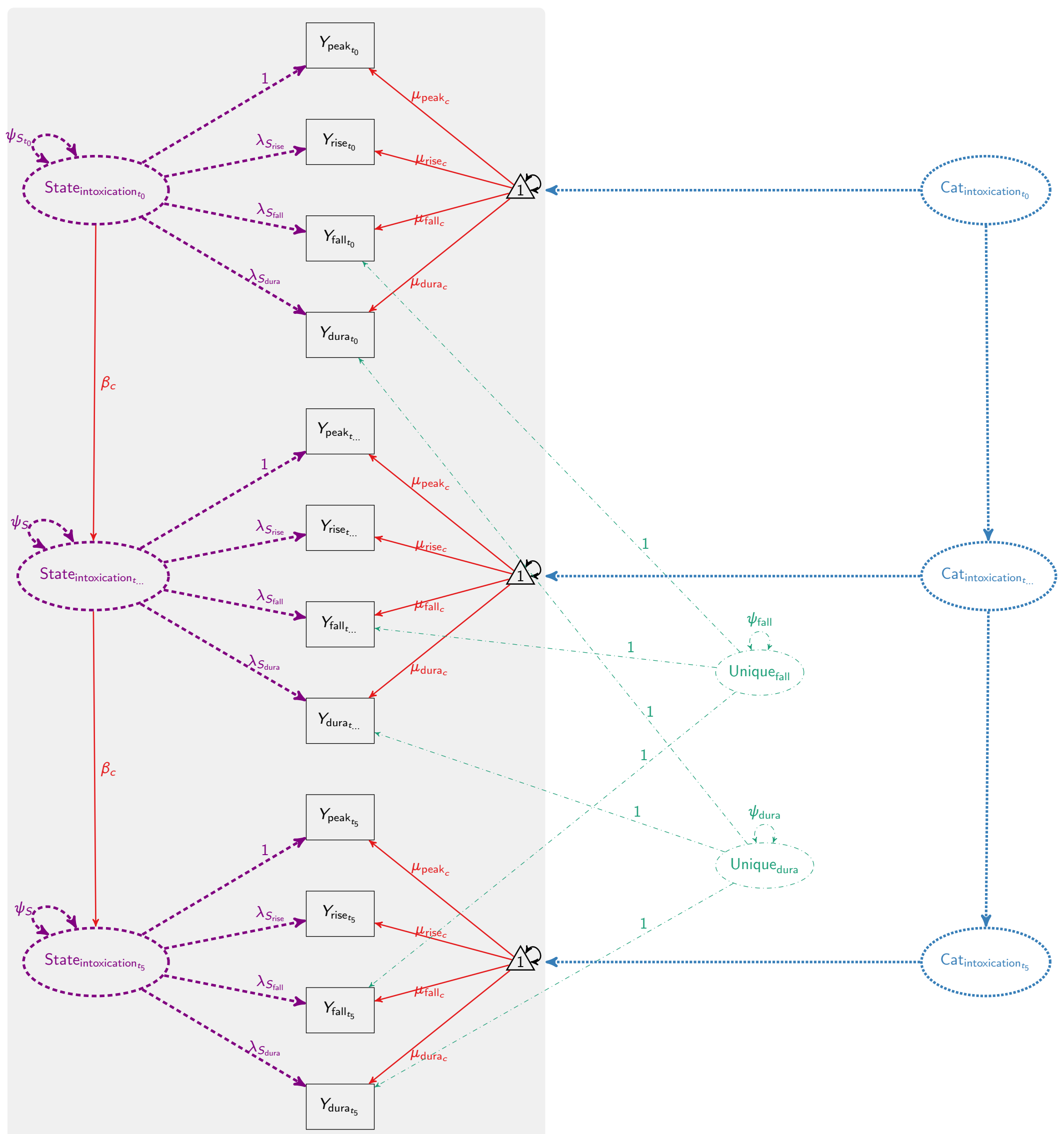


Figure 5

The Final Common and Unique Latent Transition Analysis Model (CULTA).

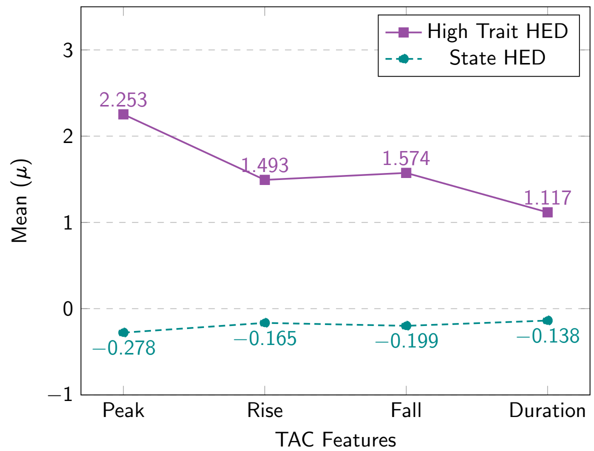


Note: The latent variables $\varepsilon_{\mathrm{peak}_{t0}}$ through $\varepsilon_{\mathrm{dura}_{t5}}$ were omitted for ease of presentation.

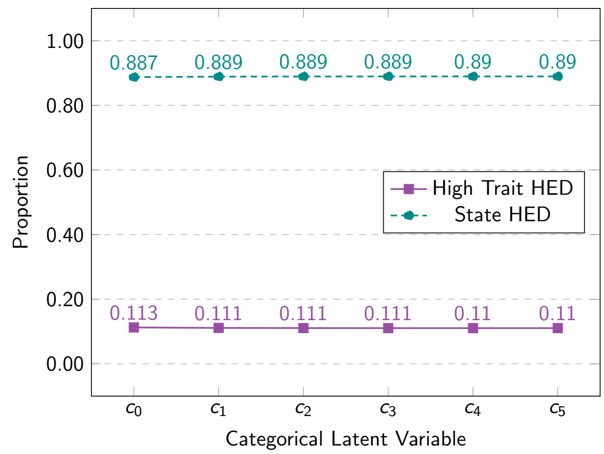
Figure 6

Two-Profile Solution

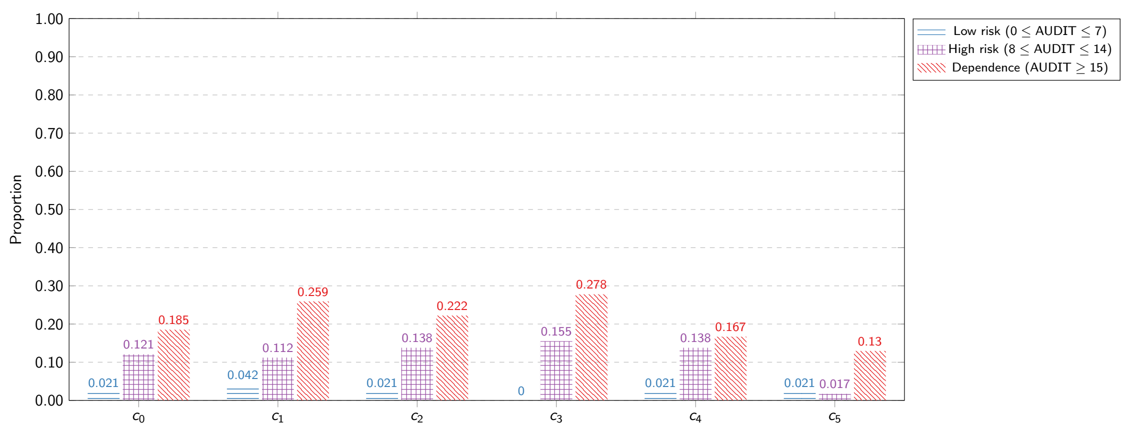
(a) *Latent Profile Indicator Means*



(b) *Profile Proportions*



(c) *Proportions for the High Class by AUDIT Risk Levels*



(d) *Proportions for the Low Class by AUDIT Risk Levels*

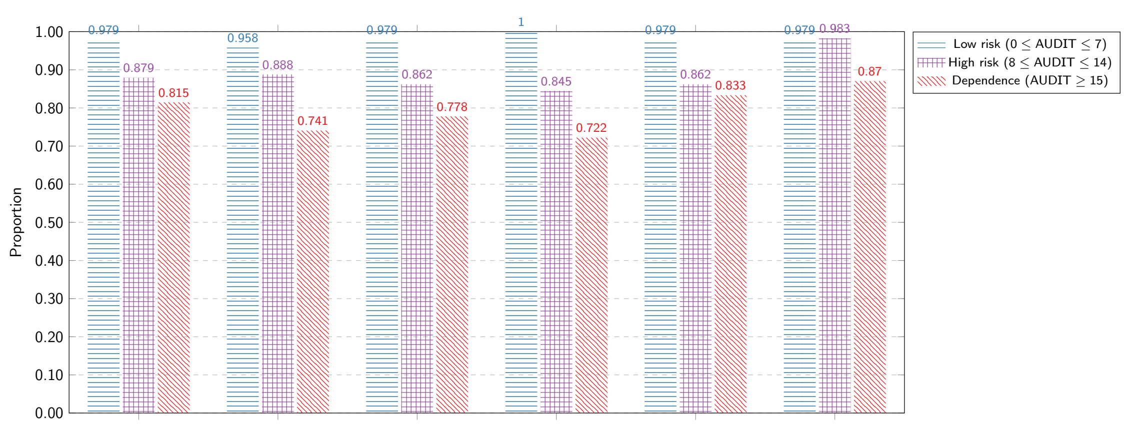
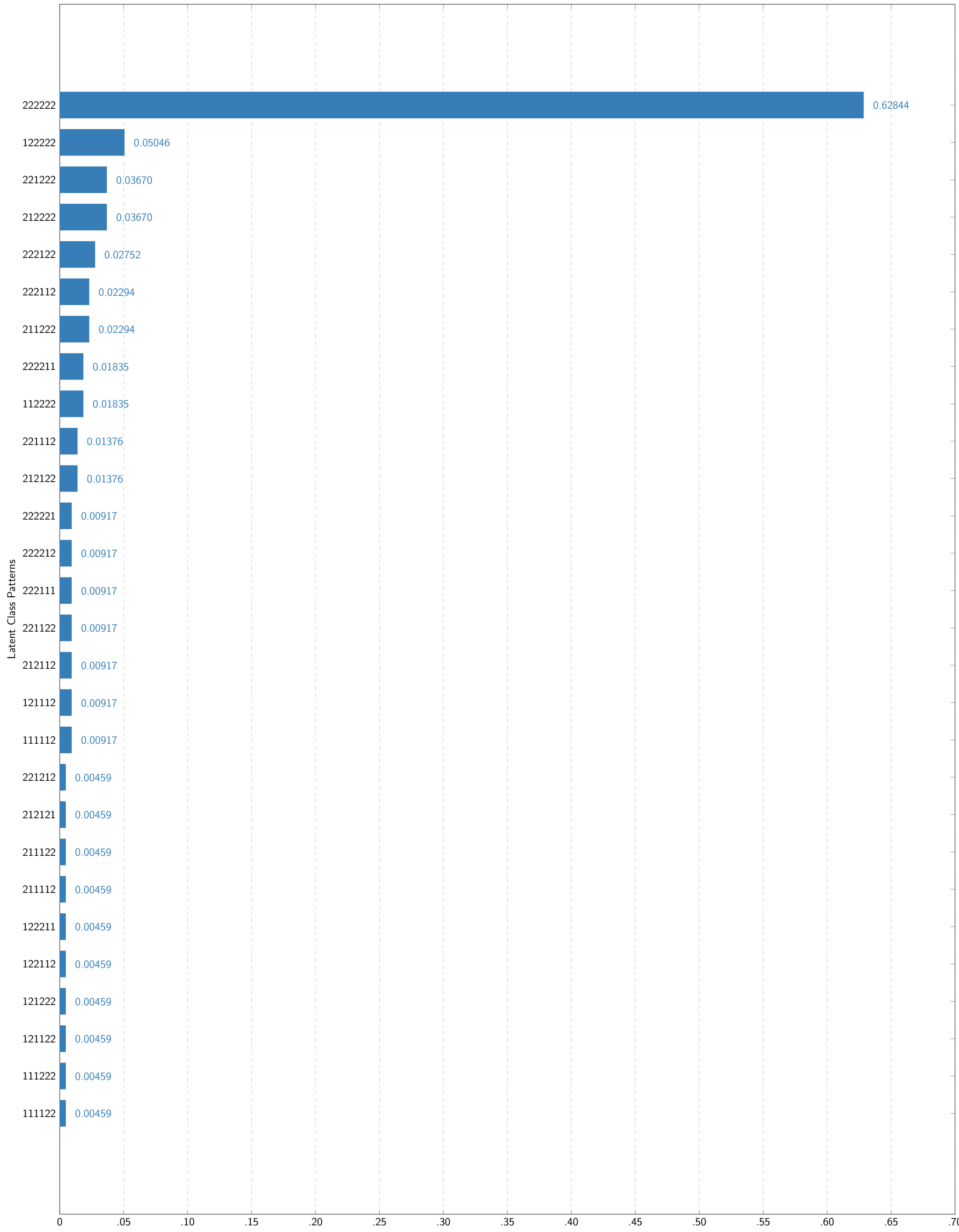


Figure 7

Final Class Proportions for the Latent Class Patterns



Note: 1 = High Trait HED. 2 = State HED. Latent class patterns with proportions of zero were omitted for ease of presentation.