Daily fluctuations in delay discounting and smartphone-based multimodal measures track nighttime drinking in alcohol use disorder: A 28-day monitoring study

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Abstract

Background and Aims:
Alcohol use disorder (AUD) involves day-to-day fluctuations in cognitive, psychological, and contextual factors that are difficult to fully capture using retrospective or cross-sectional assessment alone. Computational markers, such as discounting rate, ambiguity tolerance, and risk preference, may provide useful indicators of day-level drinking risk, but have rarely been assessed repeatedly in real-world settings or examined together with daily app-based self-reports and passive smartphone-derived measures. This study examined whether these multimodal day-level measures were associated with same-day nighttime drinking, focusing on whether within-person changes in computational markers remained associated with drinking after accounting for concurrent self-reported and contextual measures.

Design:
A 28-day longitudinal observational study using repeated smartphone-based assessments and passive sensing.

Setting:
Daily-life smartphone-based monitoring of community-recruited participants in the Republic of Korea.

Participants:
The final analytic sample included 143 adults meeting DSM-5 criteria for AUD.

Measurements:
The primary outcome was same-day nighttime drinking, assessed using daily app-based self-reports. Daily predictors covered three domains. App-based self-reports included mood, alcohol craving, meal intake, and sleep-related variables. Computational predictors were derived from delay discounting and choice under risk and ambiguity tasks. Passive smartphone-derived predictors included time spent at home, calls, steps, and foreground app use. Generalized linear mixed-effects models examined associations between nighttime drinking and multimodal predictors decomposed into within-person and between-person components.

Findings:
A multimodal model integrating computational parameters, daily app-based self-reports, and passive smartphone-derived measures showed the highest explanatory power for same-day nighttime drinking (marginal $R^2 = 0.22$). In this final model, higher within-person delay discounting [log(k)], alcohol craving, and positive mood, as well as lower meal intake and percent time at home, were associated with a higher likelihood of nighttime drinking. At the between-person level, only lower average meal intake was associated with a higher likelihood of nighttime drinking. Within-person fluctuations in log(k) were largely uncorrelated with other day-level predictors and showed no clear next-day association.

Conclusions:
Associations with same-day nighttime drinking were observed primarily at the within-person level, suggesting that day-level changes may be more informative than stable individual

differences. Within-person increases in delay discounting remained associated with nighttime drinking after accounting for other modalities, suggesting that multimodal monitoring may help identify periods of elevated drinking risk.

Keywords: alcohol use disorder; delay discounting; multimodal monitoring; computational psychiatry; within-person variability; generalized linear mixed model

INTRODUCTION

Alcohol use disorder (AUD) is a major contributor to global morbidity and mortality (1). AUD is characterized by dynamic fluctuations in drinking behavior that unfold over days and weeks (2,3). These fluctuations are shaped by cognitive, psychological, and contextual factors, which may vary in both magnitude and timing across individuals and situations (3,4). Capturing these dynamic processes is critical for understanding how alcohol use unfolds in daily life. Yet fluctuating risk states may be difficult to detect through retrospective or cross-sectional assessment alone (3,5,6).

To address this, ecological momentary assessment (EMA) and daily diary methods have been widely used to track within-person fluctuations in psychological states, including mood, craving, and sleep, and to examine their associations with substance use in naturalistic settings (3,4,6). In addition, passive smartphone-derived measures, which are broadly referred to as digital phenotyping, can capture complementary information about behavioral and contextual changes in daily life (5,7–9). However, these approaches primarily capture subjective states that participants can consciously report or behavioral patterns that are expressed externally, and may not directly access latent cognitive processes that also contribute to drinking risk.

In this context, prior work has focused on latent cognitive processes relevant to substance use disorders, as indexed by computational markers derived from decision-making tasks. These markers include delay discounting, risk preference, and ambiguity tolerance (10,11). Delay discounting, or the tendency to prefer smaller immediate rewards over larger delayed rewards, has been consistently associated with greater addiction severity and substance use (12–15). Decision-making under uncertainty has also been linked to addiction vulnerability. In particular, greater tolerance for ambiguity has been associated with elevated relapse risk in opioid and nicotine use disorders (16,17). These findings suggest that computational markers can capture latent cognitive mechanisms relevant to substance use vulnerability. However, most prior work has been cross-sectional, despite evidence that drinking risk fluctuates dynamically over time (3). It remains important to determine whether these computational markers vary meaningfully from day to day and track real-world changes in drinking-related states (18,19).

However, only a small number of studies have used repeated assessments to examine within-person changes in computational markers (16,17,20). A key reason such studies have been difficult to conduct is that traditional tasks used to estimate computational markers are often lengthy and repetitive, reducing participant motivation and lowering data quality, especially in clinical populations (21). To minimize participant burden and enable frequent assessments, adaptive design optimization (ADO) offers a machine-learning-based approach that shortens tasks to as few as 20-30 trials while maintaining reliable parameter estimation (22,23). ADO thus makes it feasible to assess computational markers daily in longitudinal designs.

If computational markers do fluctuate meaningfully from day to day, a further question is whether these fluctuations provide information about drinking risk beyond that captured by self-report or contextual measures alone. Examining computational markers in combination with daily app-based self-reports and passive smartphone-derived measures may help address this question while providing a more comprehensive account of how drinking risk unfolds in daily life. Although some studies have examined daily fluctuations in cognitive control alongside self-

reported states (24), relatively few longitudinal alcohol studies have integrated these modalities within the same design, particularly alongside repeatedly assessed computational parameters.

To address these challenges, we conducted a 28-day longitudinal monitoring study among adults meeting DSM-5 criteria for alcohol use disorder, combining daily decision-making tasks, daily app-based self-reports, and passive smartphone sensing. Participants completed two well-established decision-making tasks daily, both administered via ADO. These included the delay discounting task (25), indexing temporal impulsivity in preference for smaller immediate over larger delayed rewards (12,13), and the choice under risk and ambiguity task (26), which assesses risk and ambiguity preferences. Participants also completed daily app-based self-reports, while passive smartphone sensing data, including GPS location, phone call logs, step counts, and app usage were continuously collected throughout the study period (7).

Rather than treating drinking risk as a static trait, we conceptualized same-day nighttime drinking as a dynamic outcome that fluctuates over time and may be associated with time-varying changes across cognitive, psychological, and behavioral domains. We aimed to examine whether day-level computational parameters, daily app-based self-reports, and passive smartphone-derived measures were jointly associated with same-day nighttime drinking among adults meeting DSM-5 criteria for alcohol use disorder. More specifically, we expected within-person changes in computational markers would be associated with same-day drinking even after accounting for concurrent self-reported and contextual measures.

METHODS

Participants

We recruited 213 participants (46.7% male; age $M = 33.24$, $SD = 9.45$) through online advertisements, all of whom reported experiencing emotional, social, or functional problems related to alcohol use. Before enrollment, all participants underwent a clinical interview with a board-certified psychiatrist. AUD diagnosis and severity (mild, moderate, or severe) were determined based on DSM-5 criteria based on this interview.

Participants were enrolled into two cohorts based on whether they underwent additional laboratory assessments. One cohort participated only in the 28-day mobile app study (app-only group; initially n = 143), whereas the other completed the same app protocol as part of a broader research protocol that also included neuroimaging and cognitive assessments (comprehensive assessment group; n = 70). These additional laboratory data were not used in the present analyses. All procedures were approved by the Institutional Review Board of Seoul National University (2302/002-002). All participants provided written informed consent. Data were collected from July 2023 to September 2024. No formal a priori sample size calculation was conducted for the present analysis. Of the 213 recruited participants, 143 were included in the final analytic sample after excluding those who dropped out, did not meet DSM-5 diagnostic criteria for AUD, or lacked usable data for the multimodal analyses (app-only group, n = 100; comprehensive assessment group, n = 43; Figure S1).

Procedure

All participants completed a baseline questionnaire in person on the day the app was installed, before beginning app use. Two mobile apps were installed on participants' smartphones for data collection. The *Harujjan* app delivered nightly psychological surveys on daily experiences and drinking behavior and collected passive smartphone sensing data throughout the 28-day study period. The *Cocomo* app delivered two decision-making tasks each day. After the 28-day study period, participants returned for a follow-up visit to complete a post-study survey (Figure 1).

Measures

Baseline psychological questionnaires

Participants completed baseline psychological questionnaires during their initial visit, including the Korean version of the Alcohol Use Disorders Identification Test (AUDIT-K) (27), Beck Anxiety Inventory (BAI) (28), Beck Depression Inventory (BDI) (29), and the Barratt Impulsiveness Scale 11-revised (BIS-11-R) (30).

Daily app-based self-report

Daily self-report data were collected using the *Harujjan* mobile app. Participants were instructed to complete brief self-reports assessing affective states (mood, general interest), daily functioning variables (meal amount, sleep duration, sleep satisfaction, sleep disturbance), and alcohol-related outcomes (daily alcohol consumption, craving) before going to bed each day. Along with drinking, participants also provided contextual information about the episode, such as the type and amount of alcohol consumed, the time and duration of the drinking episode, drinking companions, location, and drinking motives (Figure 2A). To account for alcohol use occurring after the initial nightly report, participants could update the previous day's entry by the following day when necessary. In the primary analyses, self-report records were assigned to the calendar day to which they referred, rather than to the submission date.

Daily app-based self-report measures included in the model were constructed as follows. Mood was defined as the mean of the mood and general interest ratings, reflecting overall positive emotional state. Alcohol craving was indexed using the daily craving rating. The meal index was defined as the sum of meal amounts across breakfast, lunch, and dinner. Sleep disturbance was indexed using the daily sleep disturbance rating.

Computational parameters from daily decision-making tasks

Participants completed two brief decision-making tasks each day within the *Cocomo* mobile application. The delay discounting task (25) measured temporal discounting tendencies (Figure 2B), and the choice under risk and ambiguity task assessed risk preference and ambiguity tolerance (Figure 2C) (26). These tasks yielded daily estimates of key computational parameters, including the delay discounting rate (k), risk preference (α), and ambiguity tolerance ($1-\beta$).

Because the application followed a Coordinated Universal Time (UTC)-based server schedule, the daily reset occurred at 09:00 Korea Standard Time (KST) rather than 00:00 KST. To align task data with participants' local calendar day and the intended once-daily assessment schedule, task records completed before 09:00 KST were excluded prior to analysis. This affected 5.8% of delay discounting records and 5.8% of choice under risk and ambiguity records. Detailed modeling and estimation procedures are provided in the *Computational modeling* section.

Passive smartphone-derived measures

Participants' smartphones provided four types of passive smartphone sensing: GPS location, phone call logs, step counts, and app usage. These data were passively recorded through the sensing functions enabled by installing the *Harujjan* application and collected continuously throughout the 28-day study period.

% Time at home. Location data consisted of latitude–longitude coordinates with timestamps. From these data, we derived daily indices capturing mobility patterns. Points of interest (PoIs) were identified using the DPLocate framework (31), and the most visited PoI was classified as each participant's home location (32). Percentage of time at home was calculated as the proportion of timestamped GPS records assigned to the home PoI on a given day.

Foreground time. Passive smartphone logs recorded which applications were active in the foreground and the duration of each foreground app-use episode. Foreground time was calculated as the cumulative duration of foreground app activity for each participant-day.

Steps. Smartphone step logs were used to calculate the total number of steps recorded for each participant-day.

Calls. Phone call logs were used to calculate the total number of incoming and outgoing calls for each participant-day.

Computational modeling

Adaptive Design Optimization (ADO)

We estimated computational parameters for both the delay discounting and choice under risk and ambiguity tasks using ADO. ADO is a machine learning–based active-learning method that selects the most informative stimulus on each trial based on the participant's previous responses. After each choice, the posterior distribution over model parameters was updated using grid-based Bayesian inference with uniform priors, and the next trial's design variables (e.g., receipt delay, reward amount, winning probability, reward amounts, ambiguity level) were chosen to maximize expected information gain. All procedures were implemented using the Python package ADOpy (33).

Delay discounting task

Choices in the delay discounting task were modeled using a hyperbolic discounting model (34). Subjective values (V) for the larger-later (LL) and smaller-sooner (SS) options were computed as a function of reward amount (R) and receipt delay (t). Choice probabilities were generated using a softmax rule based on the difference in subjective value between the two options.

$$D(t) = \frac{1}{1 + kt}$$

$$V_{LL} = R_{LL} \cdot D(t_{LL}), \qquad V_{SS} = R_{SS} \cdot D(t_{SS})$$

$$P(LL \text{ over } SS) = \frac{1}{1 + \exp[-\tau(V_{LL} - V_{SS})]}$$

The parameter k represents the discounting rate, with higher values indicating stronger preference for immediate rewards. The parameter τ is an inverse-temperature parameter reflecting choice consistency. Each daily session consisted of 20 trials.

Choice under risk and ambiguity task

Choices in the choice under risk and ambiguity task were modeled using a power-utility function combined with a linear ambiguity-discounting component (26). Subjective values were computed for the fixed option (U_F), which offered reward R_F with a known probability of 0.5, and for the variable option (U_V), whose value depended on reward amount (R_V), winning probability (p_V) on risk trials, and ambiguity level (A_V) on ambiguous trials. Choice probabilities were generated using a softmax rule.

$$U_F = 0.5 \cdot (R_F)^{\alpha}$$

$$U_V = \left[p_V - \beta\left(\frac{A_V}{2}\right)\right] \cdot (R_V)^{\alpha}$$

$$P(V \text{ over } F) = \frac{1}{1 + \exp[-\gamma(U_V - U_F)]}$$

The parameter α reflects risk sensitivity, $1 - \beta$ reflects ambiguity such that higher values indicate greater tolerance for unknown probabilities, and γ is an inverse-temperature capturing choice consistency. Each daily session consisted of 30 trials**.**

Analytical approach

Modeling of same-day nighttime drinking

To examine associations between day-level factors and same-day nighttime drinking, we used a generalized linear mixed-effects model. Nighttime drinking was defined as a binary outcome (drinking vs. no drinking) based on participants' evening self-report of whether they had consumed alcohol that day. Because daily observations were nested within participants

across the 28-day period, we included subject-level random intercepts. A logit link was used because the outcome was binary.

To distinguish within-person fluctuations from stable between-person differences, each daily predictor was decomposed into within-person and between-person components (35,36). The between-person component was defined as each participant's mean across all available study days and was grand-mean centered before standardization. The within-person component was defined as the deviation of each daily value from that participant's mean. To facilitate comparison across predictors, both components were standardized by dividing them by the total standard deviation of the corresponding raw variable before being entered into the model.

To examine the temporal specificity of these associations, we additionally fit a lagged GLMM predicting next-day nighttime drinking from today's within-person predictor values, with same-day nighttime drinking included as a covariate. Only consecutive day-pairs were included in this analysis.

The final model can be expressed as follows:

$$logit\big(P(Y_{it}=1)\big) = \beta_0 + \sum_k \beta_{Wk} X_{kit}^{(W)} + \sum_k \beta_{Bk} X_{ki}^{(B)} + \beta_A AUDIT_i + u_i$$

where Y_{it} indicates whether participant i reported nighttime drinking on day t, $X_{kit}^{(W)}$ and $X_{ki}^{(B)}$ denote the within-person and between-person components of predictor k, respectively, k indexes all predictors included across the three modalities, and u_i is a subject-level random intercept corresponding to $(1 \mid \text{subject})$.

We implemented the model using the *glmer* function from the lme4 package in R (37). Predictor variables were organized into three categories: (1) Daily app-based self-reports, (2) Computational parameters derived from decision-making tasks, and (3) Passive smartphone-derived measures. Baseline AUDIT-K score was included as a covariate to account for between-person differences in alcohol-related problem severity. Because the analyses were conducted at the day level, participant-days with missing values on variables required for a given model were excluded from that analysis, and missing observations were not imputed. Variable-level data availability in the final analytic sample is reported in Supplementary Table S1.

We compared a series of candidate models representing all possible combinations of the three data modalities. Specifically, models were tested for each modality alone, for all pairwise combinations, and for the full multimodal combination including all three modalities. To evaluate model performance, we used marginal R^2 (38).

To assess the robustness of the final model, we conducted three sensitivity analyses. First, to examine whether the DSM-5 AUD diagnostic criterion affected the findings, we repeated the final multimodal model in the broader sample of 168 participants available before excluding those who did not meet DSM-5 diagnostic criteria for AUD. Second, we repeated the final model among participants with at least 70% adherence to both daily self-report and decision-making

task assessments. Third, we repeated the final multimodal model after excluding participant-days for which the daily self-report record was submitted or updated more than one day after the calendar day to which it referred. All models were fitted with the bobyqa optimizer.

Code availability

The underlying code for this study is not publicly available but may be made available to qualified researchers on reasonable request from the corresponding author.

Data availability

The datasets generated and analyzed during the current study are not publicly available due to privacy and ethical restrictions, as they include sensitive longitudinal self-report and passive smartphone sensing data. The data are available from the corresponding author on reasonable request.

Analysis plan pre-registration

No formal analysis plan was pre-registered.

RESULTS

Participant characteristics

A total of 143 participants were included in the final analytic sample (43.4% male; age: M = 33.35, SD = 8.44; Table 1). In cohort comparisons, the comprehensive assessment group was older and had more years of education than the app-only group, whereas there was no clear evidence of cohort differences in gender, marital status, AUDIT-K, BIS-11-R, BAI, or BDI scores (Table S2). Based on DSM-5 criterion counts, 60 (42.0%) met criteria for mild, 53 (37.1%) for moderate, and 30 (21.0%) for severe AUD (Figure S1B). Across the 28-day study period, participants completed a median of 18 assessment days (interquartile range: 11.5–23), yielding 2,441 participant-days included in the final multimodal model. Nighttime drinking was reported on 436 of 2,441 participant-days (17.9%).

Daily-level associations with nighttime drinking

Among the candidate models, the model integrating daily app-based self-reports, computational parameters, and passive smartphone-derived measures showed the highest marginal R^2 of 0.22 (Table S3). In this final integrated model, at the within-person level, higher delay discounting (log(k)), higher alcohol craving, more positive mood, lower meal intake, and lower percent time at home were associated with a higher likelihood of nighttime drinking. At the between-person level, only lower average meal intake was associated with a higher likelihood of nighttime drinking. Baseline AUDIT-K score, included as a covariate, was also positively associated with nighttime drinking (Figure 3; Table S4). The same pattern of significant predictors and effect directions was reproduced across the broader-sample analysis

before DSM-based exclusion, the ≥70% adherence analysis, and the timestamp-based analysis excluding delayed self-report records (Figures S2–S4).

To further illustrate this within-person association, we fitted a separate single-predictor generalized linear mixed-effects model including only within-person deviations in log(k) and a subject-level random intercept. Higher within-person log(k) was associated with a higher likelihood of same-day nighttime drinking ($\beta = 0.34$, 95% CI [0.10, 0.58], $p = .006$; Figure 4A). Notably, within-person fluctuations in log(k) showed minimal correlation with other within-person predictors, including alcohol craving, mood, and percent time at home, with correlations close to zero (Figure S5). This suggests that daily variation in log(k) captured information largely distinct from these other day-level predictors.

To examine the temporal specificity of these associations, we fit lagged generalized linear mixed-effects models predicting next-day drinking from today's predictor values while including same-day nighttime drinking as a covariate. There was no clear evidence that today's within-person predictors were associated with next-day nighttime drinking (Figure S6).

DISCUSSION

The present study examined whether daily computational parameters, daily app-based self-reports, and passive smartphone-derived measures were jointly associated with same-day nighttime drinking in adults meeting DSM-5 criteria for AUD. Among the candidate models, the multimodal model integrating all three data modalities showed the highest explanatory power (marginal $R^2 = 0.22$). Associations with same-day nighttime drinking were observed primarily at the within-person level, indicating that day-level deviations from an individual's own average were more consistently linked to drinking than stable between-person differences. Within-person associations were observed across multiple domains: higher delay discounting [log(k)], higher alcohol craving, more positive mood, lower meal intake, and lower percent time at home were each associated with a higher likelihood of nighttime drinking. Among these predictors, within-person log(k) was associated with same-day drinking even after accounting for concurrent self-reported and contextual measures in the full model, suggesting that day-level variation in delay discounting may capture information about drinking risk that is not already available from other modalities.

Prior research has consistently shown that individuals with AUD exhibit steeper delay discounting compared with controls (12,15), and that the degree of discounting is associated with treatment outcomes (13). This literature has predominantly focused on who discounts more steeply. The present findings suggest that delay discounting also varies meaningfully within individuals from day to day and that these within-person fluctuations are informative about same-day drinking behavior. On days when individuals discounted delayed rewards more steeply than usual, they were more likely to drink that night. This association is notable in two respects. Within-person fluctuations in log(k) showed minimal correlation with other within-person predictors, indicating that log(k) captures a dimension of day-level variation that is largely independent of self-reported psychological states and contextual indicators. Furthermore, when the same model was tested with one-day-lagged predictors, there was no clear evidence of next-day associations for log(k) or any other within-person variable, suggesting that the association may reflect a same-day state rather than a carryover process.

These findings indicate that the window of elevated risk may be narrow and that repeated assessment of delay discounting may offer information about day-level vulnerability that is not available from daily app-based self-reports or passive sensing alone.

The absence of a significant between-person effect of log(k) may seem unexpected given the well-established cross-sectional association between delay discounting and addiction severity. One possible factor is that the analytic sample was restricted to individuals meeting DSM-5 criteria for AUD and did not include a non-AUD comparison group. As a result, between-person differences in average discounting may have been less pronounced than in studies contrasting clinical and healthy control groups (39). In samples with restricted between-person variance, within-person fluctuations may become the primary source of meaningful variation.

Neither risk preference (α) nor ambiguity tolerance (1−β) showed clear evidence of association with same-day nighttime drinking. Prior work has linked greater ambiguity tolerance to relapse vulnerability in opioid and nicotine use disorders, particularly among patients who continue substance use despite uncertainty about negative consequences (16,17). However, those studies examined relapse, defined as a categorical transition from abstinence to use, among patients who had initiated outpatient treatment, whereas the present study modeled daily drinking episodes in community-recruited adults who met DSM-5 criteria for AUD and were not necessarily seeking abstinence. It is also possible that delay discounting is more proximally relevant to daily drinking decisions, which involve a concrete tradeoff between immediate reward and delayed consequences, than are risk or ambiguity preferences, which may be more relevant under conditions of explicit uncertainty about outcomes.

Daily self-reported psychological and behavioral states were also associated with same-day nighttime drinking. Higher craving, more positive mood, and lower meal intake showed significant within-person associations. These findings are consistent with prior EMA work linking day-level fluctuations in craving and affective states to alcohol consumption in naturalistic settings (3,6). The within-person association between more positive mood and nighttime drinking is consistent with prior EMA and daily-diary evidence linking daily positive affect to alcohol use (40). Because mood and drinking were assessed in the same nightly report, however, the current design cannot determine whether positive mood preceded drinking or reflected the affective context of drinking days, such as socially rewarding settings in which positive mood and alcohol use co-occurred. Meal intake was the only predictor that also showed a significant between-person effect, suggesting that lower average food consumption may reflect a more stable behavioral pattern associated with elevated drinking risk.

Among the passive smartphone-derived measures, spending less time at home was the only variable significantly associated with same-day nighttime drinking in the full model. This pattern may reflect greater exposure to contexts in which drinking opportunities are available, consistent with prior work integrating geospatial data with EMA and smartphone sensing approaches (41). Foreground time, steps, and calls were not significantly associated with nighttime drinking after accounting for the other modalities. One possibility is that these passive measures capture behavioral patterns that are only indirectly related to drinking risk, such as contextual factors associated with social activity or location. At the day level, these signals may

have provided limited incremental information once more proximal self-report and computational measures were included in the model.

Several limitations should be considered. First, because participants were community-recruited adults meeting DSM-5 criteria for AUD and were not necessarily seeking treatment, the findings may not generalize to treatment-seeking or more clinically severe AUD populations. Second, although daily assessments captured short-term variability, the observational design precludes causal inference about the temporal ordering of discounting and drinking. Furthermore, because the analysis plan was not pre-registered, the findings should be interpreted as exploratory and hypothesis-generating rather than confirmatory.

Despite these limitations, the present findings have implications for understanding alcohol use in daily life. The observation that associations with nighttime drinking were concentrated at the within-person level, with no clear evidence of lagged associations, suggests that the relevant risk window may be narrow and that monitoring approaches may benefit from detecting day-level changes rather than assessing stable traits. That within-person log(k) was associated with same-day drinking independently of self-reported states and contextual measures suggests that brief, repeated computational assessments may add information to multimodal monitoring systems. More broadly, integrating computational markers with daily app-based self-reports and passive sensing may help identify within-person states of elevated drinking risk and inform future efforts to design timely, individualized interventions in real-world settings (42).

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TABLE

Table 1. Demographic and clinical characteristics of participants (N = 143)

Variable	Mean ± SD or n (%)
Age (years)	33.35 ± 8.44
Education (years)	15.23 ± 2.81
Gender (Male/Female)	62 (43.4%) / 81 (56.6%)
Marital Status (Unmarried)	108 (75.5%)
AUDIT-K	20.20 ± 6.48
BAI	15.36 ± 15.59
BDI	26.90 ± 17.98
BIS-11-R	64.55 ± 10.26

Note. Values are presented as mean ± SD for continuous variables and n (%) for categorical variables. Gender values are presented as male/female. Marital status indicates the number and percentage of unmarried participants. AUDIT-K = Korean version of the Alcohol Use Disorders Identification Test; BAI = Beck Anxiety Inventory; BDI = Beck Depression Inventory; BIS-11-R = Barratt Impulsiveness Scale-11-Revised.

FIGURES

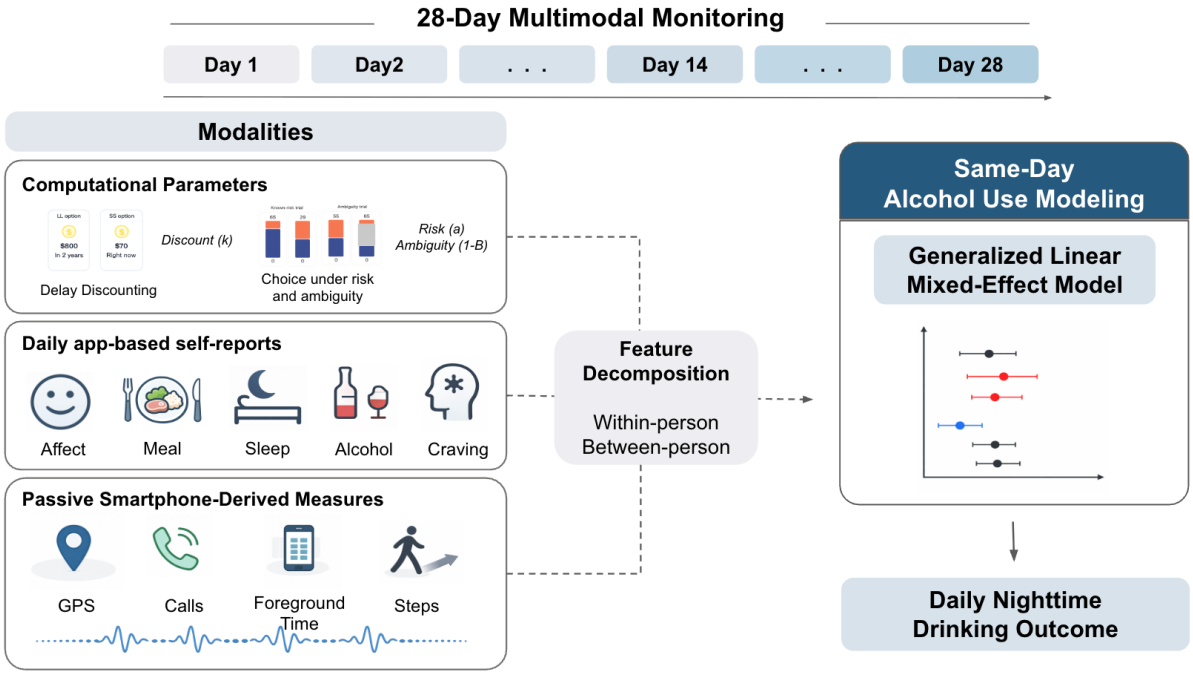

Figure 1. Overview of the study design and analytic framework. Over the 28-day study period, multimodal data were collected from computational parameters, daily app-based self-reports, and passive smartphone-derived measures. These features were decomposed into within- and between-person components and included in a generalized linear mixed-effects model to predict same-day nighttime drinking.

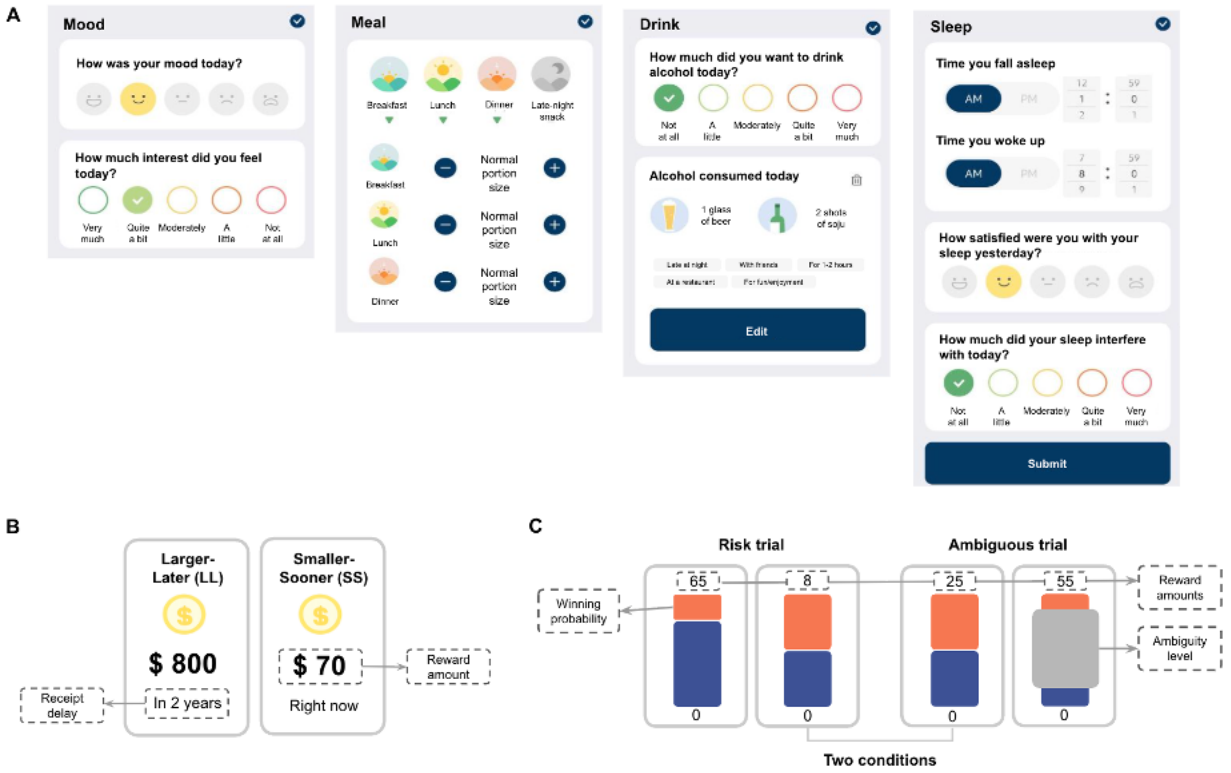

Figure 2. Mobile app interface and decision-making tasks. **(A)** Exemplar screens from the daily self-report module. **(B)** Delay discounting task. Participants chose between two reward options, one offering a larger, later (LL) reward and the other offering a smaller, sooner (SS) reward. Dashed boxes indicate the task features treated as design variables and adaptively optimized by adaptive design optimization (ADO) on each trial (e.g., receipt delay and reward amount). **(C)** Choice under risk and ambiguity task. Participants chose between options under either risk or ambiguity. In ambiguity trials, part of the probability information was occluded by a gray box, such that the exact winning probability was not fully known. Red and blue areas indicated the probabilities of winning and losing, respectively; the winning reward was shown above the box, and the losing outcome (fixed at 0) was shown below the blue area. Dashed boxes indicate the task features treated as design variables and adaptively optimized by ADO on each trial (e.g., winning probability, reward amounts, and ambiguity level).

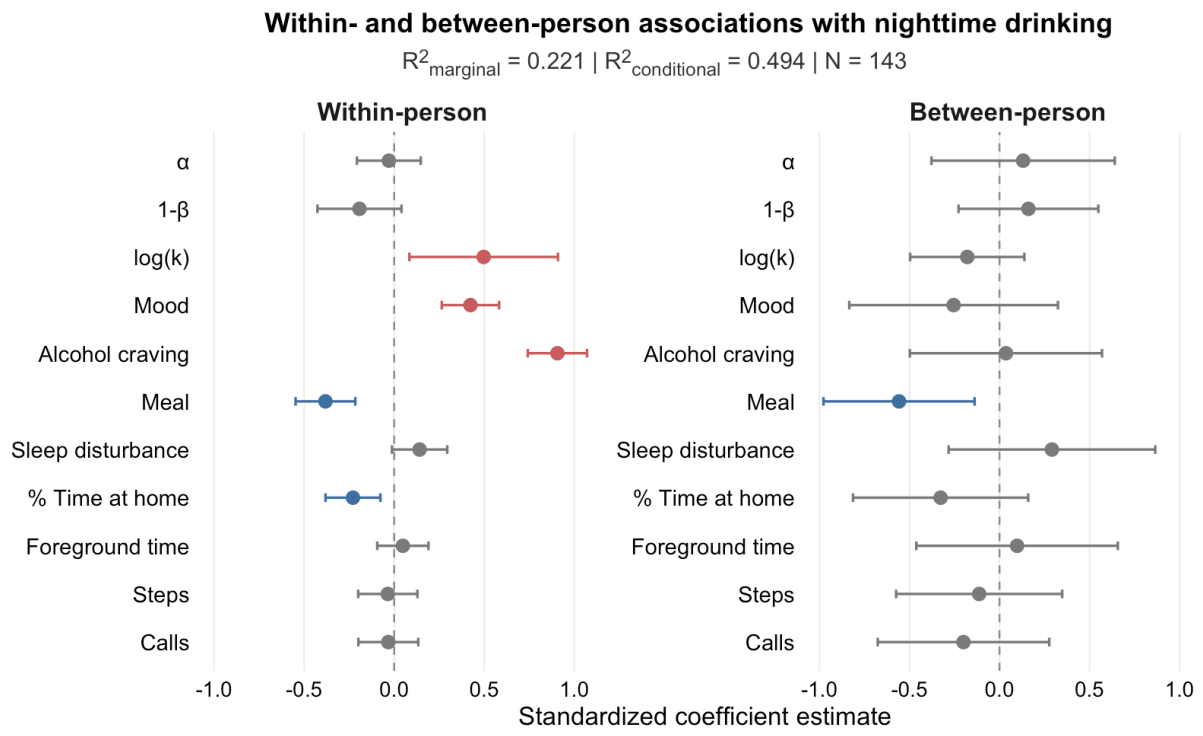

Figure 3. Standardized within-person and between-person coefficient estimates from the final integrated model predicting same-day nighttime drinking (N = 143). Points represent coefficient estimates, and error bars indicate 95% confidence intervals.

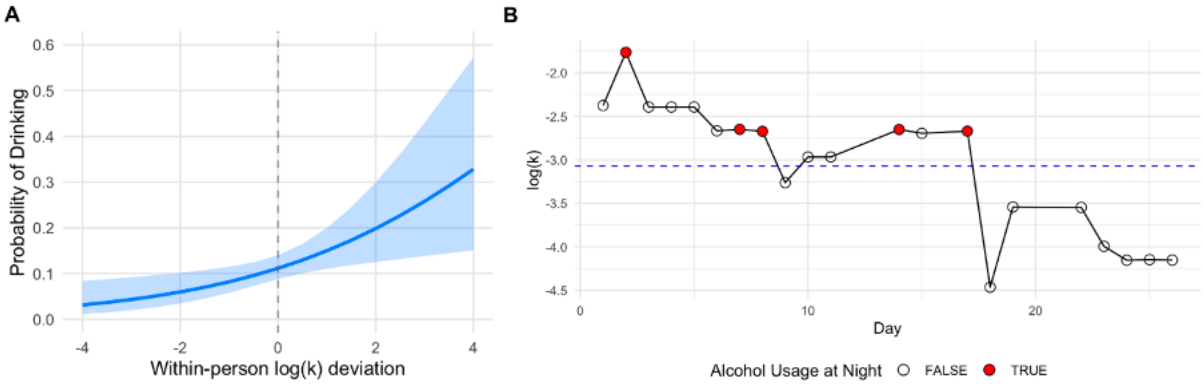

Figure 4. (A) Predicted probability of same-day nighttime drinking as a function of within-person deviations in log(k), estimated from a separate single-predictor generalized linear mixed-effects model including within-person log(k) deviation and a subject-level random intercept. **(B)** Daily fluctuations in the delay discounting parameter log(k) across 28 days for one exemplar participant. Each point indicates the log(k) value estimated for that day, with red dots denoting days on which nighttime alcohol consumption was reported. The dashed blue line represents the participant's mean log(k) across the study period. This panel provides a representative example of day-to-day variability in log(k) and its temporal alignment with reported nighttime alcohol use.

AUTHOR CONTRIBUTIONS

Hyeonmin Lee: Data curation; Formal analysis; Investigation; Methodology; Visualization; Writing – original draft; Writing – review & editing.
Manjae Kwon: Data curation; Formal analysis; Methodology; Investigation; Writing – original draft; Writing – review & editing.
Jeung-Hyun Lee: Formal analysis; Methodology; Writing – review & editing.
Mina Kwon: Investigation; Data curation.
Suyeon Song: Investigation; Data curation.
Deokjong Lee: Conceptualization; Methodology; Funding acquisition; Writing – review & editing.
Jung-Seok Choi: Conceptualization; Methodology; Funding acquisition; Writing – review & editing.
Young-Chul Jung: Conceptualization; Funding acquisition; Supervision; Writing – review & editing.
Woo-Young Ahn: Conceptualization; Funding acquisition; Methodology; Supervision; Writing – review & editing.

DECLARATION OF INTERESTS

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None.

Competing interests: non-financial:
None.

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