

Fluctuations in Real-Life Drinking in Alcohol Use Disorder: A 1-Year Longitudinal Study Using Gamified Tasks of Decision Making and Cognitive Control

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ABSTRACT

BACKGROUND: Alcohol use disorder (AUD) is a major contributor to global disability and mortality. Cross-sectional studies have linked AUD to reduced cognitive control and heightened risky decision making. However, the temporal direction of these effects remains unknown: are cognitive-behavioral alterations a consequence or a precursor of changes in drinking?

METHODS: We deployed a battery of smartphone-based, gamified tasks in a 1-year longitudinal ecological momentary assessment study of 603 participants diagnosed with mostly mild-to-moderate AUD. Tasks measured cognitive control (working memory, response inhibition) and decision making (risk-taking, information sampling). Participants completed tasks monthly and reported alcohol consumption every 2 days.

RESULTS: We found that monthly fluctuations in aspects of decision making predicted subsequent consumption. Specifically, participants shifted to higher monthly alcohol consumption when their risk-taking was higher in a mixed gambling context and lower in a loss context in the preceding month. Furthermore, when information sampling biases decreased, participants consumed more alcohol in the subsequent month. This temporal direction—that within-subject fluctuations in task outcomes preceded changes in monthly drinking—was specific, was not observed vice versa, and survived correction for autocorrelation in drinking, indicating risky decision making as a precursor to subsequent drinking. Fluctuations in cognitive control and risk-taking in a win context were not associated with fluctuations in drinking.

CONCLUSIONS: Our findings offer novel insights into the cognitive-behavioral forces driving changes in alcohol consumption in AUD: specific alterations in decision making precede changes in consumption. These findings suggest that smartphone-based gamified tasks show promise in identifying periods of heightened risk, paving the way for mechanism-based, real-time interventions in AUD.

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Alcohol use disorder (AUD) is a leading contributor to global death and disability (1). AUD is related to biased assessment of risks in decision making and difficulties in following goals (i.e., cognitive control) in cross-sectional studies (2–9). Decision making and cognitive control cannot be examined through interviews or self-reports; instead, they require experimental tasks (10–12). Because experimental tasks cannot be easily deployed outside the laboratory, the mechanisms that drive changes in real-life alcohol use remain largely unknown (13). Thus, task-based research has not yet provided a mechanistic understanding of the temporal dynamics of alcohol use (14): are cognitive-behavioral alterations a consequence or a precursor of changes in drinking?

Previous research relied mostly on cross-sectional laboratory studies or studies with large follow-up intervals (2,3,6,9,15–21). These studies cannot examine intraindividual changes between occasional and excessive alcohol use, which takes place in real-life settings over weeks to months (20,22). The prediction of changes in alcohol use may be crucial to develop earlier interventions, especially for those with mild-to-moderate AUD, who are at risk of progressing to a more severe AUD (22). Task measures may be particularly useful in predicting such changes because they tap into mechanisms putatively underlying substance use (20,23), which likely also fluctuate substantially over time (24–27). However, testing whether such fluctuations in task measures

can predict changes in real-life alcohol use requires the use of specifically designed longitudinal studies.

Most experimental tasks were designed to run in the laboratory (20). This hinders their real-life deployment when changes in alcohol use occur. Consequently, to our knowledge, so far no study has connected intraindividual fluctuations in decision making to alcohol consumption, and few studies have connected fluctuations in cognitive control to fluctuations in alcohol consumption (28,29).

To address real-life fluctuations, mobile, smartphone-based versions of experimental tasks were developed (20). Unlike traditional laboratory-based tasks, these tasks are often short in duration. Designing tasks as games (30–32) has been discussed as a means to enhance participant motivation and compliance. We recently showed that, despite their very short duration (approximately 5 minutes), a set of gamified smartphone-based tasks (31) provides valid and reliable measurements of cognitive control and decision making in real-life settings (27).

Here, we deployed this battery of 4 gamified smartphone-based tasks in a unique 1-year longitudinal design to predict changes in real-life drinking behavior. The tasks were chosen to measure different functions of cognitive control and decision making. Cognitive control was assessed with a working memory task (33) and a response inhibition task (34). Decreased cognitive control has previously been linked to AUD and increased substance use (2–5,7). Decision making was tested with a risk-taking task (35) and an information-sampling task (36). Biased risk preferences have previously been linked to addictive behavior (15,21,37). To detect intraindividual fluctuations, we deployed these tasks in a large ($N = 603$) sample of participants diagnosed with mostly mild-to-moderate AUD in combination with daily self-reported alcohol consumption over 1 year. To tap into changes in consumption over clinically relevant time frames, we focused on monthly fluctuations [rather than fluctuations over shorter periods, which are largely driven by circadian or weekday effects, e.g., (22)]. This preregistered study is the first to deploy smartphone-based tasks longitudinally to predict real-life substance use in participants with mild-to-moderate AUD.

METHODS AND MATERIALS

General Procedure

This ecological momentary assessment (EMA) study of up to 1 year was part of a larger German research consortium on substance use disorder (SUD) at 3 sites (Dresden, Berlin, and Mannheim in Germany). Before the EMA study, individuals underwent extensive clinical and neurocognitive assessments (38), during which the EMA app (39) and a customized Great Brain Experiment (31) app running the 4 tasks were installed on participants' own phones or a study phone. During the EMA study, participants completed tasks every 4 weeks on a weekday and at a time they indicated was least likely to coincide with alcohol consumption. Gamification was implemented via game-like visual design (Figure 1A) and score-based performance feedback. The order of tasks remained constant throughout the experiment (order: inhibition task, working memory task, information sampling task, and

risk-taking task). Alcohol consumption was reported every 2 days at noon. The study procedure was approved by local ethics committees at Heidelberg University (2018-621N-MA), Charité Universitätsmedizin Berlin (EA1/212/18), and Technical University Dresden (EK 459112018). All participants provided written informed consent and were compensated monetarily in proportion to the number of completed task sessions and EMA forms. The study protocol, sample size, hypotheses, and data analysis plans were preregistered (<https://osf.io/9ze2u/>).

Participants

Participants were included if they fulfilled at least 2 DSM-5 AUD criteria and were recruited through flyers and other advertisements. Telephone screenings were conducted before study inclusion. Exclusion criteria are provided in the Supplement.

Although we preregistered discovery and hold-out samples separately, the complete sample ($N = 603$) became available during manuscript preparation. Therefore, we tested all hypotheses on the full sample for greater precision and power; these analyses are thus preregistered but are no longer confirmatory in the originally planned hold-out sense. Nevertheless, to probe robustness across subsamples, we conducted 1000 random splits, which showed the reported effects to be consistent in direction but also indicated that subsamples of approximately 300 were in many cases underpowered to detect these effects (Figure S7). Consistent with this observation, our effects were significant in the initial but not the hold-out subsample, although when probing differences between samples directly, none of the reported effects differed between the 2 samples (see the Supplement).

Participants' ages ranged from 16 to 65 years (mean = 37.32, $SD = 12.64$), and 232 participants (38.5%) reported being female. The number of fulfilled AUD criteria ranged from 2 to 10 (mean = 4.09, $SD = 1.67$). Comorbid diagnoses were assessed via the Structured Clinical Interview for DSM. Tobacco and cannabis use disorder criteria were assessed dimensionally and ranged from 0 to 9 (mean = 1.20, $SD = 1.92$) and from 0 to 10 (mean = 0.40, $SD = 1.34$), respectively. Lifetime major depressive disorder was present in 32.3% of participants, any anxiety disorder in 8.1%, and attention-deficit/hyperactivity disorder in 4.1%. Exposure to medication known to interact with the central nervous system was an exclusion criterion in this study (for details, see the Supplement).

Of the 603 participants included, 218 dropped out before the end of the study (however, these participants were still included in the analysis). Monthly task and self-report data were available for 82.4% of the expected sessions (sessions before study completion or study dropout). In total, 4464 sessions were analyzed.

EMA Self-Reports

Every 2 days, participants reported how much alcohol they had consumed in previous 2 days. They selected items from a list of 19 alcoholic drinks (e.g., small beer, large beer, bottle of wine; the full list is provided in Table S3) and indicated the quantity of each. Based on these responses and the amounts of alcohol per drink specified in Table S3, their daily alcohol consumption

A Tasks and questionnaires



B Sample and timeline

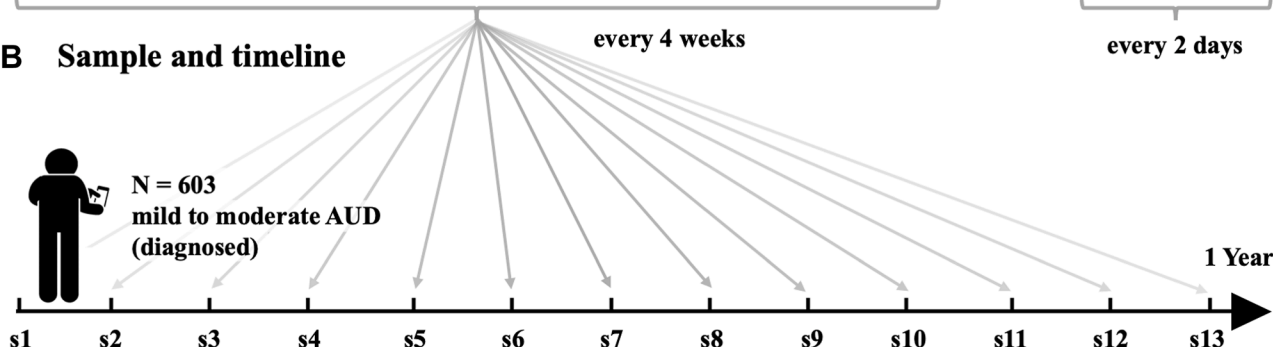


Figure 1. Illustration of smartphone-based tasks, questionnaires, and study timeline. **(A)** The task battery consisted of 4 tasks: a response inhibition task, a working memory task, a risk-taking task, and an information sampling task. Alcohol consumption was measured using questionnaires. **(B)** $N = 603$ participants with mostly mild to moderate alcohol use disorder (AUD) completed each task every 4 weeks (s1–s13, 7.4 times on average) and questionnaires every 2 days for a period of 1 year.

in standard drinks (12 g of alcohol) was calculated. Participants consumed an average of 36 g of alcohol per day ($SD = 48$ g) and 63 g per drinking day ($SD = 48$ g).

Inhibition Task

In each trial of this stop-signal task (34) (Figure 1), a fruit fell from a tree past 1 of 2 circles, and participants tapped to collect it (Go trials; response window 500–800 ms after onset). In 12 of 32 trials (37.5%), the fruit turned brown, signaling that it was rotten and should not be collected (stop trials). The stop-signal delay (the time until the fruit turned brown) started at 350 ms and followed a staircase procedure (41), increasing by 50 ms after each successful stop and decreasing by 50 ms after each failed stop.

Working Memory Task

Participants reproduced the positions of 2 to 12 red circles presented on a 4×4 grid (33) (Figure 1). Due to a ceiling effect in the working memory capacity (WMC) task, we estimated WMC based on the most difficult delayed distractor condition (substituting other conditions did not change any results; see the Supplement). First, red circles were presented for 2 seconds (encoding phase). Next, a distractor pattern of yellow circles was presented for 2 seconds, after which participants were asked to reproduce the initial pattern. Each session

started with 3 circles. The complexity increased by one circle after each correct trial, and trials were terminated after failing to reproduce a given complexity level twice.

Risk-Taking Task

Participants repeatedly chose between a certain outcome and an equiprobable gamble across 3 conditions (35) (Figure 1): a certain gain versus a larger gain against 0 (gain; 11 trials), a certain loss versus 0 against a larger loss (loss; 11 trials), and 0 versus a gain against a loss (mixed; 8 trials; here, percentage gambles index loss aversion). In each trial, a certain amount was first randomly chosen with replacement from a fixed list of outcomes (35,40).

Information Sampling Task

Across 21 trials, participants chose which of 2 rows of face-down cards had the larger sum (36) (Figure 1). They could pay to reveal cards one at a time at an increasing cost (0, 10, 15, and 20 points) before guessing, or guess immediately at no cost (winning 60 or losing 50 points for correct or incorrect guesses). Card values were drawn with replacement from a discrete uniform distribution (1–10).

Hierarchical Modeling of Monthly Task Scores

We followed the procedure outlined in (27) and modeled all participants and all sessions jointly in a hierarchical model.

Similar to other work (41–46), we showed that hierarchical modeling improves the test–retest reliability (27) of the working memory task from 0.36 to 0.64; of the stop signal task from 0.51 to 0.70; of the win, loss, and mixed conditions of the risk-taking task from 0.65, 0.57, and 0.52 to 0.80, 0.73, and 0.75; and of the information sampling task from 0.78 to 0.91 (27).

Preregistered Confirmatory Hypotheses

Six specific, confirmatory hypotheses on the relationship between intraindividual fluctuations in task measures and subsequent changes in real-life alcohol consumption were preregistered (<https://osf.io/9ze2u/>). Derived from previous cross-sectional research (5), we expected a negative relation between fluctuations in inhibition and subsequent changes in real-life alcohol consumption, such that participants consumed less alcohol when their ability to inhibit automatic responses was higher than usual (H1). Based on previous cross-sectional research (15,47), we formed 3 separate hypotheses for the risk-taking task, focusing separately on risk-taking in the context of gains, losses, and in combinations of gains and losses. Specifically, we expected that fluctuations in risky decision making in the context of gains and mixed contexts were positively related to subsequent changes in alcohol consumption (H2 and H4), but that fluctuations in risk-taking in the context of losses were negatively related to alcohol consumption (H3). We further expected that when participants made more careful decisions by revealing more cards in the information sampling task, they subsequently consumed less alcohol (H5). Finally, and in line with previous research (48), we predicted that between-participant differences in WMC buffered these intraindividual effects, such that the hypothesized within-subject relationships were less expressed in participants with high WMC (H6). For an overview of all hypotheses, see Table 1. Note that because each hypothesis concerns a distinct cognitive process with its own direction-specific, theory-derived prediction, each was

evaluated against its own null rather than as one test within a single combined hypothesis (49). For completeness, we also report multiple-testing-corrected analyses in the Supplement, which confirmed each of our confirmatory findings.

Modeling of Changes in Alcohol Use

Data were analyzed using the following preregistered (<https://osf.io/9ze2u/>) linear mixed model. The preregistered model includes stress effects, which will be reported elsewhere. As preregistered, we centered all variables to their participant-specific means to examine within-participant effects, except for WMC, which was centered on the sample mean to examine between-participant effects.

Alcohol consumption $\sim$ (SSRT + RTG + RTL + ISB + stress) $\times$ WMC + RTM + (RTM + ISB | participant) (1).

Monthly aggregated alcohol consumption was defined as the median daily drinking over the month following each task session. We chose the median over the mean because daily drinking was highly skewed, with many low- or no-consumption days and occasional high-consumption days; the median thus captures typical-day drinking, whereas the tail is captured by separate preregistered binge-drinking analyses reported elsewhere. We confirmed this approach by showing that the monthly mean, but not the median, consumption is significantly correlated with binge-drinking frequency (see the Supplement).

SSRT refers to stop-signal reaction times from the inhibition task. RTG, RTL, and RTM refer to risk-taking in the context of gains, losses, and mixed gambles, respectively, from the risk-taking task. ISB refers to information sampling bias from the information sampling task, defined as the number of additional cards turned over relative to the optimal number. Stress refers to (mean) aggregated self-reported stress. We used this model to perform 6 preregistered, confirmatory tests for the hypotheses reported above. All further tests reported below (reverse-lagged, autoregressive, hurdle, and subsample analyses) are sensitivity or exploratory analyses.

Table 1. Preregistered Hypothesis Tests

Preregistered Hypothesis	<i>b</i>	<i>p</i> Value
H1. Fluctuations in Inhibition Relate Negatively to Drinking	−0.00	.546
H2. Fluctuations in Risk-Taking (Gain Trials) Relate Positively to Drinking	−0.13	.411
H3. Fluctuations in Risk-Taking (Loss Trials) Relate Negatively to Drinking	−0.34	.045*
H4. Fluctuations in Risk-Taking (Mixed Trials) Relate Positively to Drinking	0.49	.036*
H5. Fluctuations in Information Sampling Relate Negatively to Drinking	−0.33	.046*
H6. Differences in WMC Moderate the Effects of:		
Inhibition	0.01	.471
Risk-taking (gain)	−1.84	.159
Risk-taking (loss)	−0.11	.938
Information sampling	2.04	.111

As preregistered, we found that monthly fluctuations in risky decision making and information sampling predicted fluctuations in real-life drinking in subsequent months. Effect sizes are in daily standard drinks (12 g of alcohol per drink).

**p* < .05.

WMC, working memory capacity.

RESULTS

Intraindividual Fluctuations in Decision Making but Not Cognitive Control Predict Changes in Real-Life Drinking

The preregistered model did not reveal any significant association between monthly fluctuations in response inhibition and subsequent real-life drinking (H1) or between risk-taking in the gain domain and drinking (H2).

However, the model revealed the hypothesized (H3) negative association between fluctuations in risk-taking in loss trials and changes in subsequent drinking. Participants consumed less alcohol during months in which they made more risky decisions compared to months in which they made fewer risky decisions in the loss trials of the risk-taking task ($b = -0.34$, $t = -2.00$, $p = .045$) (Figure 2A).

The model also revealed the hypothesized (H4) positive association between fluctuations in risk-taking in mixed trials and changes in subsequent drinking. Participants consumed more alcohol in months in which they made more risky decisions compared to months in which they made fewer risky

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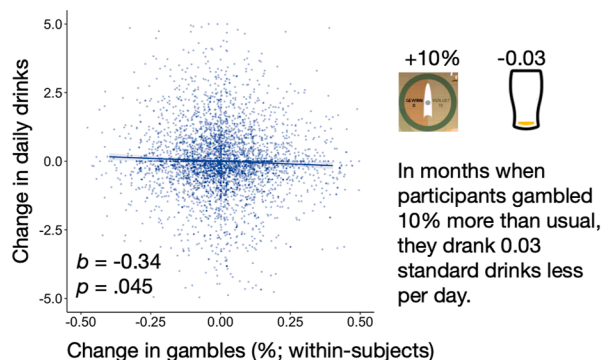
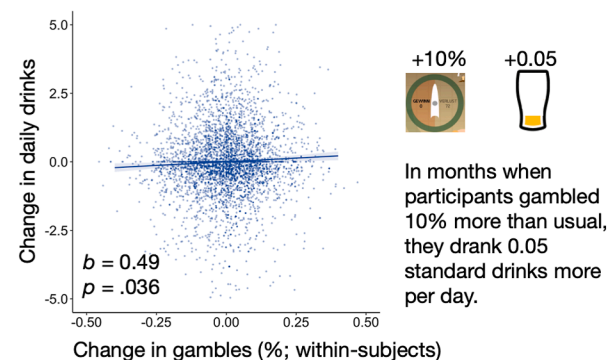
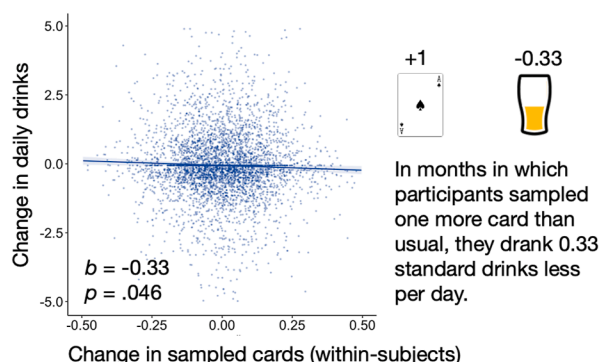
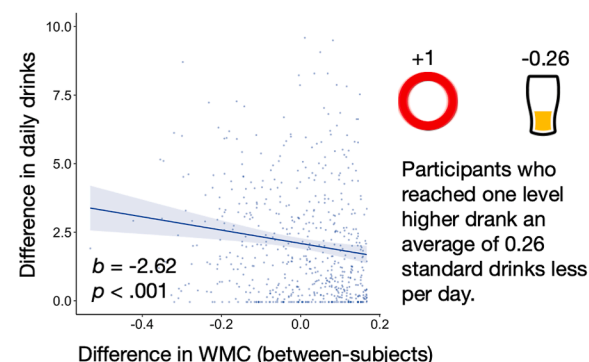
A Risk taking (loss trials)**B Risk taking (mixed trials)****C Information sampling****D Working memory**

Figure 2. Results of preregistered hypotheses (main effects). **(A)** Within-participant fluctuations in percent gambles (in loss trials) are negatively associated with within-participant fluctuations in subsequent monthly drinking. **(B)** Within-participant fluctuations in percent gambles (in mixed trials) are positively associated with within-participant fluctuations in subsequent monthly drinking. **(C)** Within-participant fluctuations in information sampling are negatively associated with within-participant fluctuations in subsequent monthly drinking. **(D)** Between-participant differences in working memory capacity (WMC) are negatively associated with between-participant differences in drinking. Drinks refer to standard drinks (drinks containing 12 g of alcohol). In **(A–C)** both the x- and y-axis show participant-mean centered values to better visualize the within-participant effects of interest. Change in daily drinks refers to change in average daily drinks per month.

decisions in the mixed trials of the risk-taking task ($b = 0.49$, $t = 2.11$, $p = .036$) (Figure 2B).

The model also revealed the hypothesized (H5) negative association between fluctuations in information sampling and drinking. Participants consumed less alcohol in the month after they turned over more cards in the information sampling task compared to the months after they turned over fewer cards ($b = -0.33$, $t = -2.00$, $p = .046$) (Figure 2C). Although information sampling was highly correlated with a computational model-derived sampling preference parameter, fluctuations in information sampling were not associated with fluctuations in drinking (see the Supplement).

As expected, between-participant differences in WMC were negatively related to average alcohol consumption, as participants with higher WMC consumed less alcohol than those participants with lower WMC ($b = -2.62$, $t = -3.42$, $p < .001$) (Figure 2D). However, none of the hypothesized interactions of WMC with other variables (see Table 1, H6) were significant.

Together, our pattern of results suggests that intraindividual fluctuations in decision making (i.e., risk-taking and information sampling), but not fluctuations in cognitive control, can

predict within-participant changes in real-life drinking behavior.

Alcohol Consumption Does Not Predict Task Outcomes

To test whether alcohol consumption affected subsequent task measures, we explored the relationship between alcohol consumption in the months preceding task measures and subsequent task measures. This did not reveal any significant association between drinking behavior and task measures (all $ps > .1$) (Table S1).

Robustness Checks

Because monthly drinking was serially correlated ($\phi \approx 0.27$), we reestimated the primary model including first-order autoregression, which confirmed the effects reported above. To probe the effect of dropout on our main findings, we ran pattern mixture models (50) comparing findings between participants who did and did not drop out of the study. These models did not reveal any significant interactions (Table S4).

We additionally predicted permanent dropout and intermittently missing sessions from the preceding month's task scores, alcohol consumption, and self-reported stress. Task scores and alcohol consumption predicted neither dropout nor intermittent missingness; stress showed a small association with subsequent dropout (odds ratio = 1.13, $p = .049$) (Tables S5 and S6). Therefore, we reran our primary model using stabilized inverse-probability-of-censoring weights for dropout. Weighted estimates were virtually identical to the unweighted estimates (Table S7), indicating that informative dropout did not bias our findings. This study was partially conducted during the COVID-19 pandemic, and an analysis published elsewhere indicated that COVID-19-related lockdowns influenced drinking patterns in the current dataset (22). However, a supplementary analysis of our own data revealed no significant effects of COVID-19-related lockdowns on our main effects of interest. Because the drinking data in our study were highly zero-inflated (Figure S1), we reanalyzed our data using log-linked gamma hurdle models. The loss-trial risk-taking effect was robust, with a very high probability of direction (PD = 98.3%) and a credible interval (CI) excluding 0 ($b = -11.23$, 95% CI $[-21.41$ to $-0.82]$, PD = 98.3%). The mixed-trial risk-taking and information-sampling effects were directionally consistent with the primary analysis and had high probabilities of direction (PD = 95.8% and 92.7%), but their 95% CIs included 0 ($b = 11.63$, 95% CI $[-1.49$ to $24.59]$ and $b = -7.18$, 95% CI $[-16.91$ to $2.50]$), indicating greater uncertainty under this specification. Additional checks of behavioral data quality and task effects can be found in the [Supplement](#).

DISCUSSION

In this study, we found that fluctuations in several measures of decision making, but not cognitive control, predicted drinking in the subsequent month. When participants took more risks in a mixed gambling task, took fewer risks in a loss-framed gambling task, and made less careful choices in an information sampling task, they reported more alcohol use in the subsequent month. We did not find associations when predicting task outcomes from earlier alcohol consumption. This provides the first evidence for a specific temporal direction in which fluctuations in distinct measures of decision making precede changes in drinking.

Although, to our knowledge, we are the first to show that intraindividual fluctuations in decision making precede monthly fluctuations in alcohol consumption in AUD, the direction of these fluctuations is in line with existing cross-sectional research [for an overview, see (21)]. For example, Bernhardt *et al.* (15) found that patients with AUD showed significantly lower loss aversion (directly related to higher risk-taking in mixed trials) and decreased risky decision making when gambling in a loss context compared with controls. However, it is important to note that such cross-sectional findings do not necessarily generalize to within-participant fluctuations (50), and no study has, so far, reported that fluctuations in risky decision making precede fluctuations in alcohol consumption. Although our finding that fluctuations in information sampling precede fluctuations in alcohol consumption does not, to our knowledge, have a direct empirical precedent in the AUD literature, it aligns well with prominent

theories of SUD that characterize substance use as impulsive behaviors initiated without sufficient deliberation or information gathering (51). Somewhat related to this finding, Konova *et al.* (23) found that weekly fluctuations in ambiguity tolerance, or the ability to cope with little information about risks, predicted consumption in opioid use disorder, giving further evidence that dynamics in decision making might play an important role in SUD.

Together, our findings imply that smartphone-based decision-making tasks could eventually be deployed to predict changes in real-life alcohol use and implement future just-in-time interventions. For example, high-risk drinkers could receive notifications when their risk-taking scores exceed a threshold and could then be presented with either automated interventions or asked to seek in-person help. Our findings address recent criticisms suggesting that tasks lack realism compared with self-report questionnaires (52), which is often attributed to tasks' poor psychometric properties, particularly low retest reliability or temporal stability (24–26,52). In an earlier report, we showed that our tasks are indeed reliable (27). Here, we show that when these tasks were deployed in a longitudinal design, within-subject temporal variance in task measures was meaningfully related to real-life drinking.

Our study had several strengths. We were the first to deploy cognitive tasks to study monthly changes in real-life alcohol consumption in participants diagnosed with AUD. The long study period of 1 year was unique in EMA research on AUD (53). Thus, it allowed us to focus on monthly changes in typical drinking rather than capturing higher-frequency fluctuations that might be influenced by contextual factors such as weekday-related drinking patterns (22). The large sample of 603 participants, moreover, allowed for sufficient power to detect within-subject drinking-task relations, which are, based on between-subject studies, often small (52). The focus on participants diagnosed with mostly mild-to-moderate AUD fills an important gap in the literature, as studies on real-world alcohol consumption often focus on convenience samples rather than diagnosed individuals who are most affected by changes in alcohol consumption (53). Finally, the use of short, gamified tasks suggests a path toward clinical applicability, as they allow for repeated assessment of decision making in naturalistic settings with minimal participant burden.

However, our study is also limited in several ways. First, we did not find that intraindividual fluctuations in response inhibition, a major component of cognitive control, were related to subsequent drinking. One explanation could be that measures of cognitive control do not fluctuate over time. However, an earlier analysis of the tasks revealed both lower measurement error and lower retest reliability of the inhibition task, suggesting it may fluctuate substantially even at shorter time-scales (27). Other studies that focus on moderators of cognitive control also point toward its short-term malleability (54–56). Thus, it is possible that meaningful fluctuations in cognitive control may occur at higher frequencies than were sampled in our study. Indeed, 3 studies that found the expected relationship focused on high sampling frequencies [several samples per day, (20,28,57–59)]. However, these studies only found the expected relationship when focusing on specific samples, sampling schemes, or means of aggregation. Specifically, Emery *et al.* (29) found that only nighttime,

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but not daytime, cognitive control predicted subsequent drinking. Jones *et al.* (28) did not find a direct relationship between cognitive control and subsequent drinking but found that deterioration of cognitive control during the day predicted subsequent drinking. This suggests that the sampling frequency and sampling scheme used in this study might not have been ideal to connect fluctuations in cognitive control to fluctuations in drinking. Second, although we show that it is possible to connect fluctuations in task measures to fluctuations in alcohol consumption in AUD, the current effect sizes are likely too small to be clinically relevant already. While effect sizes are in line with studies that connect tasks and real-world outcomes cross-sectionally (56) and should be seen in light of the overall low consumption of our participants (36 g/day on average), future studies will have to overcome known limitations of tasks, such as their limited sensitivity to within-sample variance (25), and establish optimal sampling frequencies and sampling designs to further increase power and effect sizes. Third, although our findings are in line with existing empirical studies and theoretical predictions, the mechanisms underlying our effects remain speculative. The computational models employed in our study revealed that information sampling correlated highly with a sampling preference parameter derived from a specifically designed computational model. However, intraindividual fluctuations in this parameter were not associated with fluctuations in drinking, so additional modeling effort is required to determine the mechanisms underlying the behavioral outcomes reported here. Future studies could also integrate neurobiological markers to further elucidate the neurocognitive mechanisms underlying task effects. Fourth, although a potential strength of our study is the use of short, gamified tasks, which might have enhanced adherence over the 1-year period, we did not actually compare the performance of these tasks to nongamified equivalents. Fifth, the intensive nature of our study entails a substantial amount of missing data. Sensitivity analyses (pattern-mixture models, missingness prediction models, and inverse-probability-of-censoring weighting) indicated that our findings were robust to dropout related to measured variables, including a weak association between stress and subsequent dropout. However, we cannot rule out that missingness was additionally influenced by unmeasured variables. Finally, although our reverse-lagged models and models including autocorrelation indicate a temporally specific effect in which fluctuations in task outcomes precede fluctuations in drinking, the study design does not allow us to infer any causal relationship between the variables.

Conclusions

Using gamified smartphone-based tasks to predict changes in real-life drinking over 1 year, we found that monthly fluctuations in several decision-making measures predicted subsequent drinking. Our findings demonstrate how longitudinal smartphone-based gamified tasks may help predict changes in real-life alcohol use. This indicates the possibility of future targeted and potentially just-in-time interventions for people with AUD.

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The data that support the findings of this study, as well as all materials and analysis scripts needed to replicate our results, have been deposited in the Open Science Framework (<https://osf.io/9ze2u/>).

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ARTICLE INFORMATION

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