Gamified smartphone experiments reveal that fluctuations in decision-making precede changes in real-life drinking in alcohol use disorder

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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 one-year longitudinal ecological momentary assessment study of N=288 participants diagnosed with 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 their alcohol consumption daily.

Results. Using both conventional mixed models and specifically designed computational models, we found that monthly fluctuations in risky decision-making predicted subsequent alcohol consumption. Specifically, participants who showed increased risk-taking in a mixed-reward context and decreased information sampling consumed more alcohol in subsequent months. This temporal direction was specific and not observed vice versa, indicating risky decision-making as a precursor of subsequent drinking. Between-participant differences in working memory capacity moderated these effects, with higher capacity mitigating the impact of risky decision-making on drinking.

Discussion. Our findings offer novel insights into the cognitive-behavioral forces driving changes in alcohol consumption in AUD: decision-making alterations precede changes in alcohol consumption, and working memory capacity acts as a protective factor. These findings suggest that smartphone-based gamified tasks can be used to identify periods of heightened risk paving the way for mechanism-based, real-time interventions in AUD.

Introduction

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, and instead require experimental tasks (10–12). As 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?

Existing 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). This 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 deteriorating to 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 specifically designed longitudinal studies.

Experimental tasks were designed to run in the laboratory (20). This hinders their real-life deployment, when changes in alcohol use occur. To our knowledge, only one study has successfully used laboratory-based tasks to connect intraindividual fluctuations in task measures to measures of substance use (23). 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 (28–30) has been discussed to enhance participant motivation and compliance. We recently showed that despite their very short duration (~5 min), a set of gamified smartphone-based tasks (29) provides valid and reliable measurements of cognitive control and decision-making in real-life (27).

Here, we deployed this battery of four gamified smartphone-based tasks in a unique one-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 working memory (31) and a response inhibition task (32). Decreased cognitive control has previously been linked to AUD and increased substance use (2–5,7). Decision-making was tested with a risk-taking (33) and an information-sampling task (34). Biased risk preferences have previously been linked to addictive behavior (21,35,36). To detect intraindividual fluctuations, we deployed these tasks in a large (N = 288) sample of participants diagnosed with mild to moderate alcohol use disorder (AUD) in combination with daily self-reported alcohol consumption over one year. This preregistered study is the first to deploy smartphone-based tasks longitudinally to predict real-life substance use in mild to moderate AUD.

Methods and materials

General procedure. This smartphone-based longitudinal Ecological Momentary Assessment (EMA) of up to one year was part of a larger German research consortium on substance use disorder (SUD) at three sites (Dresden, Berlin, Mannheim; Germany). Before starting the EMA study, individuals underwent extensive clinical and neurocognitive assessments (37). During the assessment appointment, which was either conducted inside the laboratory or online via video chat, the app for running the EMA study *59*) and a customized version of the Great Brain Experiment (GBE, Brown et al., 2014) app for assessment of the four tasks were installed either on participants' own phone or on a study phone. 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 gave written informed consent before participating in the study. Data collection took place between March 2020 and July 2022.

Participants. Included participants fulfilled at least two DSM-5 AUD criteria and were recruited through flyers and other advertisements. Telephone screenings were conducted before study inclusion/exclusion. Exclusion criteria were: indication for detoxification, insufficient German language, treatment seeking, MRI contraindications, medical history of DSM-5 bipolar disorder, psychotic disorder, schizophrenia or schizophrenic spectrum disorder, or current use of drugs or medication or substance dependence thereof other than alcohol, nicotine, or cannabis, as well as a medical history of severe head injury, or other severe central nervous system disorders.

As preregistered (https://osf.io/9ze2u/), we included the first 300 participants (27); data collection of up to n=900 participants is ongoing. Out of the n=300 participants included, 12 were excluded because they only completed baseline tests and did not have any longitudinal EMA data. Therefore, data from 288 participants were analyzed. Participants' ages ranged from 17 to 65 years (M = 38.0, SD = 13.09), and 105 participants (36.5%) reported being female. Participants fulfilled AUD criteria from 2 to 8 (M = 3.93, SD = 1.48).

Of the 288 included participants, 102 dropped out before the end of the study protocol (these participants were still included in the analysis). Monthly task and self-report data was available for 80.1% of the expected sessions (sessions before study completion or study drop out). In total 2224 sessions were analyzed.

EMA self-reports. Every two days, participants were asked how much alcohol they consumed the day before and two days before (“Think about yesterday. What kind and how many alcoholic drinks did you consume?”). They were then presented with a list of 19 alcoholic drinks (e.g., “small beer”, “large beer”, “bottle of wine”, for the complete list, see Table S3) and asked to indicate which drinks and how much of each drink they consumed (“Please first indicate which alcoholic drinks you consumed. In the next step, you can then specify the quantity.”) Based on these responses and the amounts of alcohol per drink specified in Table S3, their daily alcohol consumption in standard drinks (12 grams of alcohol) was calculated.

Inhibition Task. Each trial ((32), Fig. 1). began with two fruits hanging at the top of a tree for one to three seconds (randomly selected from a uniform distribution). Next, one of the fruits fell down and passed over one of two circles, indicating the time during which participants should collect the fruit through tapping (Go-Trials with a response window spanning from 500 to 800 ms after stimulus onset). In 12 of 32 trials (37.5%), the falling fruit turned brown, indicating that it was rotten and should not be collected (stop trials). At the beginning of each session, the delay after which the fruit turned brown (stop signal delay; SSD) was 350ms. This delay changed according to a staircase procedure (39): it increased by 50ms after each successful stop trial and decreased by 50ms after each unsuccessful stop trial.

Working memory task. Participants were asked to remember the positions of two up to 12 red circles presented on a 4 x 4 grid ((31), Fig. 1). As preregistered, we estimate working memory capacity, the variable used in our analyses as the maximum level reached in the in the ‘*long, no distractor’* condition. In this condition, circles were presented for two seconds (encoding phase), and then disappeared for one second (maintenance phase), before participants had to tap on their no-longer visible locations. The condition started with three circles in trial one. If participants failed to respond correctly, two circles were presented in the second trial. If participants failed at this level, the condition was terminated. If a trial was completed correctly, the number of red circles in the corresponding condition increased by one in the next trial. If participants failed in a trial (from level four onwards), the level was repeated once. If they failed again, the condition was terminated. A maximum of eight trials was completed for each condition. The task involved three more conditions, which are described in the supplementary materials.

Risk-taking task. Participants repeatedly chose between a certain outcome and a gamble, with equal probabilities of the two outcomes ((33), Fig. 1). The task involved three conditions: In the '*gain*' condition, participants chose between either a certain gain or to gamble for a larger gain against 0 points. In the '*loss*' condition, participants chose between either a certain loss or gambling for 0 points against a larger loss. In the '*mixed*' condition, participants chose between a certain amount of 0 points or gambling for a gain against a loss amount. The gain and loss conditions had 11 trials, and the mixed condition consisted of 8 trials. In each trial, a certain amount was first randomly chosen with replacement from a fixed list of outcomes. Gamble amounts were then calculated by multiplying the certain amount with a randomly chosen multiplier from another fixed list (33,40).

Information sampling task. Participants were presented with four playing cards in rows of two and had to choose the row with the largest sum of card values ((34), Fig 1). Each of the 21 trials began with all cards facing down. Participants could invest points to turn over one card at a time to sample information with increasing costs for each additional card (zero points for the first card, 10 for the first card, 15 for the third, and 20 for the fourth card). Before turning over a card, participants could also choose to guess, at no cost, which row had the largest value. A choice at this stage would be a gamble (called a guess in the task) at 50/50. Participants won 60 points if this guess was correct and lost 50 points if the guess was incorrect. If turning over one or multiple cards, the costs for information sampling reduced the total win. Card values were sampled randomly with replacement from a discrete uniform distribution with integers ranging from one to 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 modelling improves test-retest reliability (27) of the working memory task from .36 to .64; of the stop signal task from .51 to .70; of the win, loss and mixed condition of the risk-taking task from .65, .57, and .52 to .80, .73, and .75; and of the information sampling task from .78 to .91 (26).

Preregistered hypotheses. Six 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 would consume less alcohol when their ability to inhibit automatic responses was higher than usual (H1). Based on previous cross-sectional research (35,47), we formed three separate hypotheses for the risk-taking task—focusing separately on risk-taking in the context of gains, in the context of losses, and in the context of combinations of gains and losses. Specifically, we expected that fluctuations in risky decision-making in the context of gains and mixed contexts would be positively related to subsequent changes in alcohol consumption (H2, H3) but that fluctuations in risk-taking in the context of losses would be negatively related to alcohol consumption (H4). We further expected that when participants would make more careful decisions by revealing more cards in the information sampling task, they would subsequently consume less alcohol (H5). Finally, and in line with previous research (48), we predicted that between-participant differences in working memory capacity (WMC) would buffer these intraindividual effects such that the hypothesized within-subject relationships would be less expressed in participants with high WMC (H6). For an overview of all hypotheses, see Table 1.

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 working memory capacity (WMC) which was centered to the sample mean to examine between-participant effects.

Alcohol consumption ~

(SSRT + RTG + RTL + ISB + stress) * WMC + RTM +(RTG + RTL + SSRT | participant)

Alcohol consumption refers to (median) aggregated monthly alcohol consumption in the month after each task was completed. We chose the median to aggregate consumption as the distribution of daily drinking within each session of each participant was highly skewed, i.e., on most days, participants drank little, and on some days, they drank a lot.

SSRT refers to stop signal reaction times from inhibition task. RTG, RTL, and RTM refer to risk-taking in the context of gains, losses, and mixed gambles from risk-taking task. ISB refers to information sampling bias from information sampling task. Stress refers to (mean) aggregated self-reported stress. As preregistered, the random structure of the model was determined by first running the maximal model and then removing terms until the model converged (see Table S3). We complemented these primary hypothesis tests with reverse time-lagged analyses (lagging alcohol consumption instead of task measures) to compare the temporal direction of effects.

Computational modeling. A computational model was used to complement the information sampling task analysis (H5) with an analysis that captures the actual decision processes (for model specification, see Fig. 4). The model assumes that participants first determine the value of choosing each row by comparing the rows' expected values. Here, it is assumed that participants substitute the value of hidden cards with their expected value (5.5). The difference in the rows' expected values is then multiplied by a sensitivity parameter (β_1) to determine the value of choosing each row. These choice values are negatively proportional to the choice uncertainty (ω), which is multiplied by the participants' uncertainty sensitivity (β_3) and added to participants' sampling preference (β_2) to determine the value of sampling more cards. Finally, action probabilities are calculated using a softmax function with an inverse temperature parameter (τ) to capture choice stochasticity.

To capture longitudinal fluctuations, the sampling preference (β_2) and uncertainty sensitivity (β_3) parameters were allowed to vary between sessions. Correlation analyses determined that the sampling preference parameter (β_2) was more closely related to the information sampling variable used in the preregistered analysis (session rs > .73; Fig. S1). Consequently, this parameter was chosen as a substitute for the information sampling variable in the preregistered model. Model estimation was performed with hierarchical Bayesian inference using the computational behavioral modeling (cbm) toolbox (for details, see *67*). A recovery analysis (see supplementary analyses) revealed a correlation of r = .912 between behavioral and model simulated information sampling scores.

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 or loss domains and drinking (H2, H3).

The model, however, revealed the hypothesized positive association between fluctuations in risk-taking in mixed trials and changes in subsequent drinking. As hypothesized (H4), participants consumed more alcohol in months in which they made more risky decisions compared to months in which they made fewer risky decisions in the risk-taking task ($b = 1.07$, $t = 2.65$, $p = .008$; Fig. 2A). For illustration, if participants gambled in the risk-taking task 10% more than they usually did, they consumed, on average 0.1 drinks per day more than their usual consumption in the subsequent month.

The model also revealed a significant association between fluctuations in information sampling and drinking. As hypothesized (H5), 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 ($b = -0.90$, $t = -2.39$, $p = .017$; Fig. 2A; Fig. 2B). For illustration, if participants sampled one more card in the information sampling task than they usually did, they consumed, on average 0.6 drinks per day less than their usual consumption in the subsequent month.

We next fitted a computational model including a parameter that captures to what extent participants preferred sampling information rather than guessing *33*). Substituting the information sampling variable in the preregistered analysis with this sampling preference parameter (b2; Fig. 4A), we confirmed the negative relationship between information sampling and drinking behavior uncovered in H5. Specifically, in months when participants had a higher preference for sampling information than their average preference, they drank less ($b = -1.08$, $t = -2.86$, $p = .004$; Fig 4B). This finding was also confirmed in recovery analysis (see supplementary analyses).

This 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 drinking behavior.

The effects of risky decision-making on subsequent alcohol consumption are less expressed in participants with high WMC. Replicating earlier studies (50), we found that between-participant differences in WMC were negatively related to real-life drinking (b = -4.63, t = -3.19, p = .002). We further hypothesized (H6) that WMC would be a protective factor moderating the effects of other task variables on drinking behavior.

This hypothesis was supported by the significant interaction between risk-taking (in the gain condition) and WMC (b = -1.03, t = -2.30, p = .022; Fig. 3A). Simple effects analyses (based on median splits for WMC) revealed that in participants with high WMC there was a negative relationship between risk-taking for gains and drinking behavior (n = 146; b = -1.11, t = -2.04, p = .048); whereas there was no significant effect in participants with low working memory (t = 142; b = 0.60, t = 0.97, p = .333).

The interaction between information sampling and working memory was also significant (b = 0.95, t = 2.60, p = .010; Fig. 3B). Simple effects analyses revealed that in participants with high working memory there was no significant relation between information sampling and drinking behavior (n = 146; b = -0.06, t = -0.12, p = .907), whereas there was a negative relation in participants with low working memory (n = 142; b = -1.65, t = -2.96, p = .003).

These results suggest that between-participant differences in working memory moderate the within-participant relationships between decision-making (risk-taking and information sampling) and 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 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 S2).

Discussion

In this study, we found that fluctuations in decision-making, but not cognitive control, predicted drinking in the subsequent month. When participants took more risks in a mixed gambling task and sampled less information to make choices, they reported more alcohol use in the subsequent month. We did not find associations when predicting task outcomes from earlier alcohol consumption. This provides first evidence for a specific temporal direction of the effect. We also confirmed the finding from the information sampling task in a computational model that was specifically designed to extract decision processes underlying participants' information sampling behavior. Finally, we found that WMC acted as a protective buffer because the influence of decision-making on real-life drinking was decreased in participants with higher WMC.

Only within-subject fluctuations in decision-making—and not in cognitive control—predicted subsequent drinking behavior. This is in line with cross-sectional research reporting higher risk-taking in participants with AUD compared to healthy participants (for a review, see Chen et al., 2020). Our finding of a relationship between risk-taking and drinking specific to mixed trials resonates with existing cross-sectional studies (35,36). Future studies need to determine whether intraindividual fluctuations in risk-taking and information sampling can predict substance use beyond alcohol. Relatedly, one exceptional longitudinal study by Konova et al. (23) found, using a computer-based task, that weekly fluctuations in ambiguity tolerance, the ability to cope with little information about risks, predicted consumption in opioid use disorder.

As hypothesized, we found that inter-individual differences in WMC moderated the within-subject effects of decision-making on drinking. Thus, the influence of risky decision-making was less expressed in participants with higher as compared to lower WMC. Higher WMC could serve as a protective factor that either overrides biases in risky decision-making or inhibits their effect on unwanted behaviors. This supports major theories of cognitive control, which propose WMC to support goals maintenance when other processes, such as automatic behaviors or biased decision-making, could facilitate conflicting behaviors (51). This effect was specifically present in the gain condition of the risk-taking task, which is congruent with recent neural findings that link both risk-taking in the gain domain and WMC with dopamine function (33,52). Existing interventions aiming to improve working memory could help protect individuals with AUD especially when their decision-making bias drives them towards alcohol use (53–55).

We replicated that interindividual differences in WMC relate negatively to interindividual differences in drinking, but 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, implicating 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 (56–58). Thus, it is possible that meaningful fluctuations in cognitive control may occur at higher frequencies than sampled in our study. Indeed, three studies that found this expected relationship focused on high sampling frequencies (several samples per day, (20,59–62)). However, these studies only found the expected relationship when focusing on specific samples, sampling schemes, or means of aggregation. Specifically, Emery et al. (63) found that only nighttime but not daytime cognitive control predicted subsequent drinking. Marhe et al. (61) found the expected relationship between cognitive control and drinking, but only when cognitive control was measured during times of temptation, not when measured at random times. Finally, Jones et al. (59) 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 sampling frequency, sampling schemes, and ways of aggregating data are important factors when studying intraindividual fluctuations especially with higher frequency sampling schemes.

Our findings imply that smartphone-based decision-making tasks could be deployed to predict changes in real-life alcohol use to implement future just-in-time interventions. For example, high-risk drinkers could receive notifications when their risk-taking scores exceed a thresholds and could then be presented either with automated interventions or asked to seek in-person help. Our findings address recent criticisms suggesting that tasks lack realism compared to self-report questionnaires (64), which is often attributed to tasks' poor psychometric properties, particularly low retest reliability or temporal stability (24–26,64). 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. Emphasizing the relevance of good test retest reliability, we predicted intraindividual changes in alcohol use primarily from tasks that had the highest levels of reliability (27).

Using gamified smartphone-based tasks to predict changes in real-life drinking over one year, we found that monthly fluctuations in decision-making predicted subsequent drinking. This finding was corroborated by detailed computational modeling of choice behavior. Moreover, interindividual differences in WMC buffered the effects of decision-making such that drinking in individuals with higher WMC was less affected by more risky decision-making as compared to individuals with lower cognitive control. Our findings demonstrate how longitudinal smartphone-based gamified tasks can 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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Data and materials availability: 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 Open Science Framework (https://osf.io/9ze2u/).

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Table 1. Preregistered hypothesis tests. As preregistered, we found that monthly fluctuations in risky decision making and information sampling predicted fluctuations in real-life drinking in subsequent months. We also found that inter-individual differences in working memory capacity (WMC) moderated these effects, so that the effects were less expressed in participants with overall better WMC. Effect sizes are in daily standard drinks (12 g of alcohol per drink). $^{*}p < .05$, $^{**}p < .01$.

Preregistered hypothesis	b	*p*
H1. Fluctuations in inhibition relate negatively to drinking.	-0.01	.981
H2. Fluctuations in risk-taking (gain trials) relate positively to drinking.	-0.25	.568
H3. Fluctuations in risk-taking (loss trials) relate negatively to drinking.	-0.56	.180
H4. Fluctuations in risk-taking (mixed trials) relate positively to drinking.	**1.07**	**.008****
H5. Fluctuations in information sampling relate negatively to drinking.	**-0.90**	**.017***
H6. Differences in WMC moderate the effects of:		
Inhibition	-0.42	.245
Risk-taking (gain)	**-1.03**	**.022***
Risk-taking (loss)	0.56	.169
Information sampling	**0.95**	**.010****

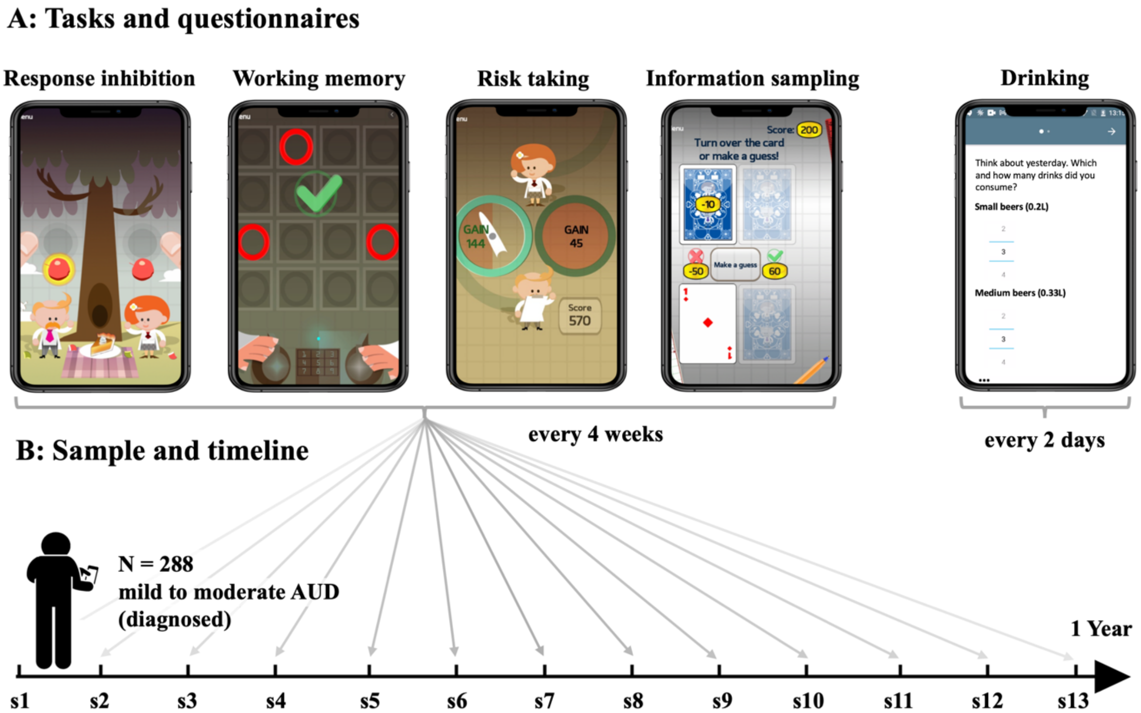

Figure 1. Illustration of smartphone-based tasks, questionnaires, and study timeline. The task battery consisted of four tasks (A): a response inhibition task, a working memory task, a risk-taking task, and an information sampling task. Alcohol consumption was measured using questionnaires. (B) N = 288 participants with mild to moderate AUD completed each task every four weeks (s1-s13, 7.7 times on average, 1 – 13) and questionnaires every two days for a period of one year.

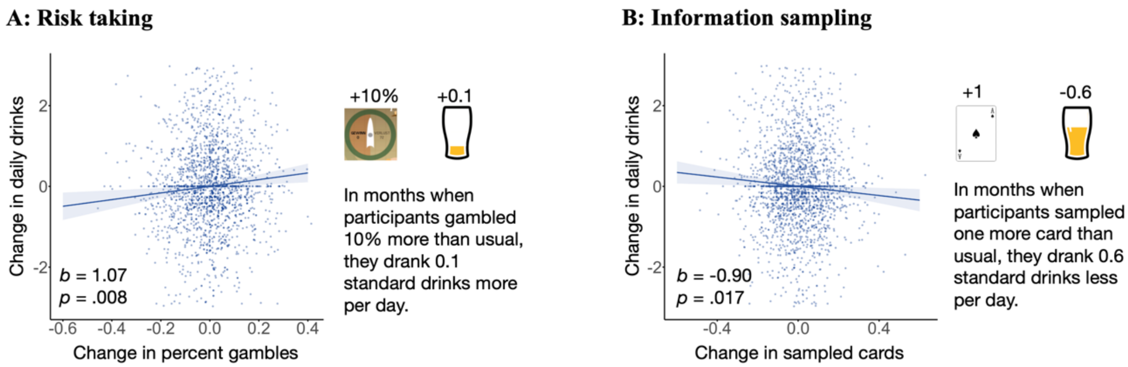

Figure 2. Results of preregistered hypotheses (main effects). A: Within-participant fluctuations in percent gambles (in mixed trials) are positively associated with within-participant fluctuations in subsequent monthly drinking. B: Within-participant fluctuations in information sampling are negatively associated with within-participant fluctuations in subsequent monthly drinking. Drinks refer to standard drinks (drinks containing 12 g of alcohol). Both the x- and y-axes 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.

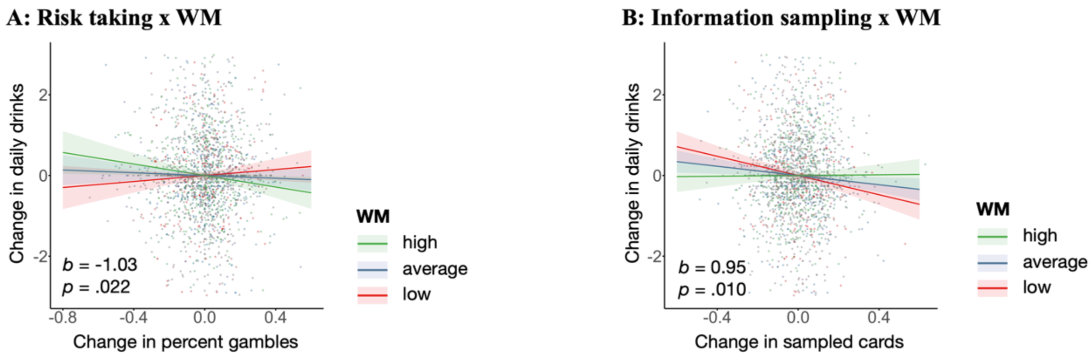

Figure 3. Results of preregistered hypotheses (interaction effects only). A: The positive relationship between fluctuations in risky decision-making in gain trials (percent gambles) is more expressed in participants with low WMC, compared to participants with high WMC. B: The negative relationship between fluctuations in information sampling is more expressed in participants with low working memory (WM) compared to participants with high WM. Betas and p-values refer to the interaction effects. Change in daily drinks refers to change in average daily drinks per month.

A: Computational model specification

1. Value of choosing
$$\begin{cases} V(choose\ A) = \beta_1(V(row\ A) - V(row\ B)) \\ V(choose\ B) = \beta_1(V(row\ B) - V(row\ A)) \end{cases}$$

2. Choice uncertainty
$$\omega = -\left(\frac{1}{1 + e^{V(choose\ B) - V(choose\ A)}} - .5\right)^2$$

3. Value of sampling
$$V(sample) = \boldsymbol{\beta_2} + \beta_3\omega$$

4. Action probability
$$p(C = o) = \frac{e^{\frac{V(o)}{\tau}}}{\sum_i e^{\frac{V(i)}{\tau}}}$$

B: Sampling preference (β_2)

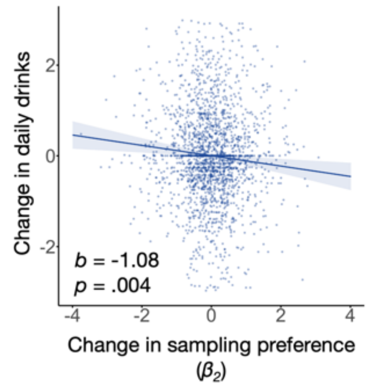

Figure 4. Details and results of the computational modeling analysis. A: 1) According to the model, participants first assess the value of choosing each row by comparing the expected values of the rows (weighed by parameter *β1*). 2) The difference between row values determines the participant's choice uncertainty (ω) which is negatively proportional to the value of choosing each row. 3) The value of sampling is determined by combining the choice uncertainty with the sampling preference parameter (*β2*) and uncertainty sensitivity parameter (*β3*). 4) Action probabilities are calculated using a softmax function with an inverse temperature parameter (τ) to capture choice stochasticity. B: Extracting monthly sampling preferences from this model revealed that fluctuations in the sampling preference are negatively related to drinking behavior. Change in daily drinks refers to change in average daily drinks per month.