**Measuring self-regulation in the field:**

**Reliability and Validity of smartphone-based cognitive-motivational experiments in alcohol use order**

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**Abstract**

Experimental measures of self-regulation are thought for long to play an integral role in our scientific understanding of loss of control behaviors, for example in addiction. Yet, experimental task measures cannot be easily deployed where addictive behaviors actually occur—in people’s real lives outside of the laboratory. Moreover, self-regulation tasks have recently come under criticism for their poor test–retest reliability and lacking tests of construct validity. Together, these two disadvantages might explain why ecological validity of task-based self-regulation measures—their ability to predict real-life behavior—is low. To overcome this problem, we assessed the reliability and construct validity of four smartphone-based tasks designed to measure different aspects of self-regulation by drawing upon measures of cognitive control and decision-making in a large (N=488 sample of psychiatric patients with alcohol use disorder and associated comorbidities. We show that task parameters have moderate to good reliability, which is further improved to good to excellent when separate measurements sessions were modeled jointly. We show that the data is described for by four factors, which cover one cognitive control factor separately from two to three distinct aspects of decision-making. This work indicates that self-regulation can be measured experimentally with sufficient reliability and validity in addiction. This represents a critical milestone towards longitudinal experimental studies in the field in addiction research but also in psychiatry and psychology more generally.

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**Introduction**

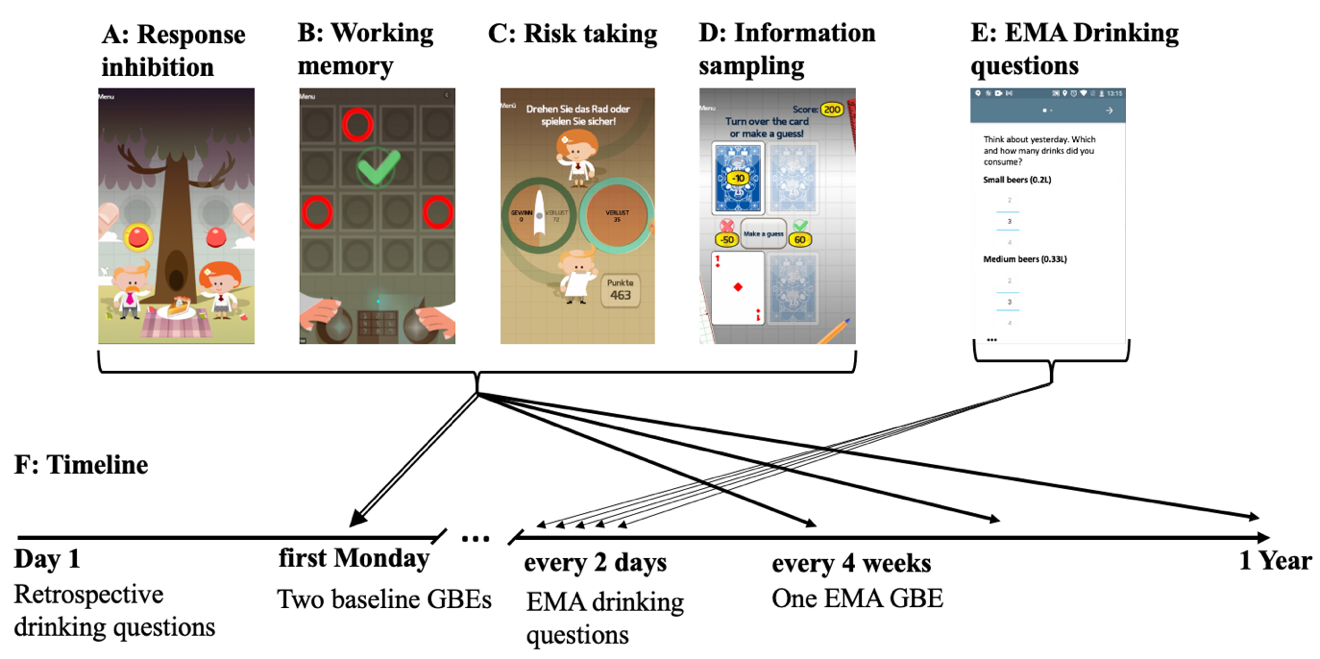
Self-regulation—the ability to control behavior in service of long term-goals—is related to a range of important outcomes, including wealth, health, and public safety (Moffit et al, 2011). As a consequence, interest in self-regulation has increased across research domains, including economics, psychology, cognitive neuroscience, and psychiatry (Nigg, 2017). Researcher have used different methodologies to study self-regulation, ranging from surveys, to neural measures and experimental tasks (Eisenberg et al., 2019).

Experimental tasks play an especially important role in researching self-regulation. Self-regulation is an umbrella term encompassing a range of distinct capacities. Tasks can be specifically designed to isolate distinct cognitive-motivational processes of self-regulation, such as working memory, inhibition, and decision making, that may not be easily revealed by surveys (Falk and Heckman, 2009). Moreover, tasks can be used to manipulate brain activity experimentally. This effort could ultimately lead to an improved mechanistic understanding of self-regulation and its failures. Clinically, this proposal feeds the promise of targeted, mechanism-based treatments for conditions characterized by deficient self-regulation (e.g., addiction).

Although tasks may excel at measuring the processes underlying self-regulation, research linking task measures to real-life outcomes has so far been less successful than survey-based research. For example, in a recent study, Eisenberg et al. (2019) assessed the ecological validity of 22 surveys and 37 task measures of self-regulation. While surveys modestly predicted real-world outcomes related to self-regulation, tasks showed largely no relationship to real-world outcomes. This finding mirrors a more widely held opinion that experimental tasks lack “realism” and generalizability (Falk and Heckman, 2009).

Here, we argue that tasks do not inherently lack real-world relevance, but that shortcomings regarding their psychometric properties can explain their “lack of realism”. Specifically, it has recently been shown that task measures largely show low test-retest reliability (Enkavi et al., 2019; Hedge et al., 2018). Test-retest reliability is an important psychometric quality, which refers to the consistency in measuring between-participant differences. It is especially important when relating one measurement to another (e.g., task-based self-regulation to drinking in addiction)—because (low) reliability limits the observed correlation between two outcomes (Spearman, 1904). For example, would working memory and drinking *actually* have a high correlation of .8, but working memory would only be measured with a low reliability of .3, the observed correlation between the two measures would mathematically decrease to .44. Indeed, task measures of self-regulation were shown to suffer from low test-retest reliability (Enkavi et al., 2019; Hedge et al., 2018). Thus, it is possible that the failure to link task measures to real-life outcomes simply results from the tasks’ low reliability. Further, the theoretical assumption that tasks are particularly well suited to assess distinct cognitive-motivational processes of self-regulation requires empirical investigations of construct validity.

As opposed to surveys, it is difficult to deploy tasks when self-regulation actually matters—outside the laboratory in people’s real lives (Zech et al., 2022, accepted manuscript). Most tasks were designed to run on laboratory computers, requiring specialized software and sometimes specialized hardware, that most people do not have at home. This makes it difficult to link task measures to “in-the moment” self-regulation failures, which happen comparably rarely (e.g., binge drinking) and usually take place in specific environments outside the laboratory (e.g., in the bar). Thus, laboratory studies substantially limit researchers access to state-dependent dynamics in conjunction with cognitive-motivational experimental task data.

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**Figure 1.** Illustration of study timeline and smartphone-based tasks from a customized version of the Great Brain Experiment (GBE) app used in this study. All tasks were translated to German. Panel A shows the stop signal task, Panel B the working memory task, Panel C the risk taking task, Panel D shows the information sampling task, Panel E the EMA drinking questions, and Panel F the study timeline

Here, we show that these shortcomings of experimental tasks can be overcome by moving task measures to mobile platforms such as smartphones and when analytically exploiting rich longitudinal data generated by mobile data collection. We tested the reliability and construct validity of four smartphone-based tasks in a large (*N* = 488) sample of participants suffering from mild to moderate alcohol use disorder. The tasks were designed to capture four components of self-regulation—working memory (McNab et al., 2015), inhibition (Smittenaar et al., 2015), risk-taking (Rutledge et al., 2014), and information sampling (Hunt et al., 2016; see Figure 1). Foreshadowing our results, test-retest reliability was initially moderate to good and could be improved to good to excellent levels when modelling longitudinal data from two sessions jointly (Brown et al., 2020; Waltmann et al., 2022). Analysis of construct validity revealed a separate cognitive control factor as well as two/three distinct aspect of decision-making emphasizing the ability of tasks to measures separate ingredients of self-regulation.

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**Results**

***Reliability.***To allow us to test the tasks’ test-retest reliability, participants completed each task two times in the field. Reliability was assessed using intra class coefficients (ICCs), which compare the variance of interest—the between-participant variance—with the total variance (including systematic within-session variance, e.g. repetition effects). To assess whether reliability could be improved by making use of longitudinal data, we compared two approaches to analyzing task data: In the first *separate modeling* approach, we first calculated task scores for each session separately and then calculated test–retest reliability based on the resulting scores. A problem of this commonly used approach is that it does not take into account the dependency of data within participants. This leads to excessive within-participant variance which depresses reliability (Brown et al., 2020; Waltmann et al., 2022). To overcome this problem, we next analyzed the data in a *joint modeling* approach. Here we modeled data from both sessions jointly using hierarchical mixed models. These models take into account the dependency of data within participants, thereby regularizing scores by moving sessions scores towards the participant means. Waltmann et al. (2022) recently showed that this method of analyzing task data can yield both higher and more accurate reliability estimates than the *separate modeling* approach.

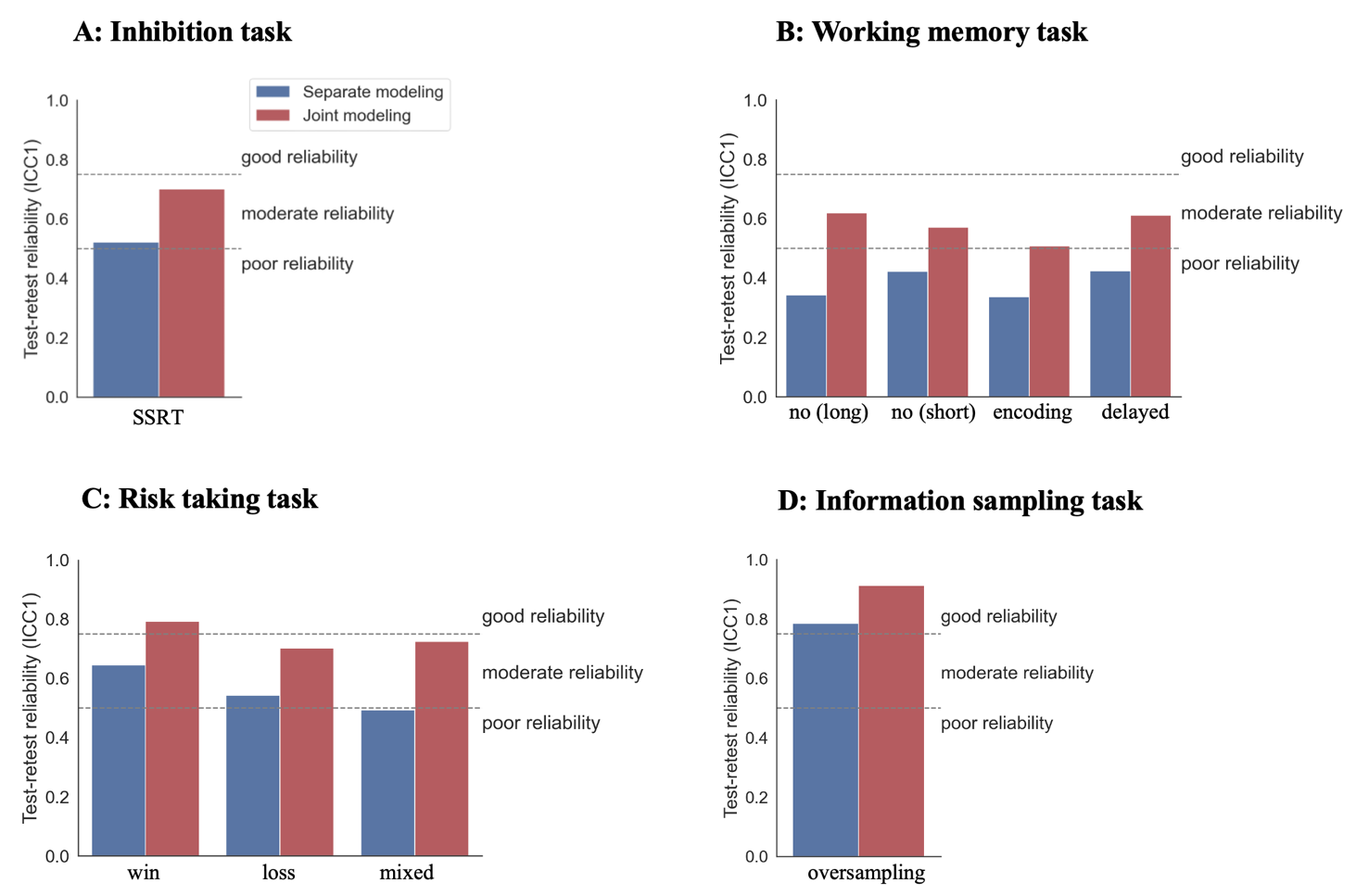
*Split-half reliability.* For the risk taking task, split-half reliabilities for the win and loss gambles were adequate (*rsb win session 1* = .84; *rsb\_win session 2* = .91; *rsb loss session1* = .77; *r\_sb\_loss\_session\_2* = .82) but lower for mixed gambles (*rsb\_mixed\_session\_1* = .67; *r\_sb\_mixed\_session\_2* = .71). For the information sampling task, split-half reliabilities were adequate (*r\_sb\_session\_1*  = .86; *r\_sb\_session\_2*  = .86). Split-half reliabilities for the working memory task and for the inhibition task could not be analyzed due reasons inherent to their adaptive task design (see methods section).

*Test-retest reliability.*Test-retest reliability increased for all tasks, when calculating scores based on the joint compared to the separate modeling approach (see Table 1 and Figure 2). The inhibition task had moderate reliability when scores were calculated based on separate modeling (ICC1 = .52), but good reliability when scores were calculated based on joint modeling (ICC1 = .70). The working memory task had poor reliability in all conditions when scores were calculated based on separate modeling (ICC1s < .43), but reliability increased to moderate levels when scores were calculated based on joint modeling (ICC1 ranging from .51 to .61).

The risk taking task had moderate reliability in all conditions when scores were calculated based on separate modeling (ICC1s ranging from .49 to .65). Reliability increased to moderate to good reliability when scores were calculated based on joint modeling (ICC1s ranging from .70 to .79). Finally, the information sampling task had good reliability when scores were calculated based on separate modeling (ICC1 = .78), which further improved when scores were calculated based on joint modeling (ICC1 = .91).

**Table 1.** Test-retest reliabilities (ICCs) for the different task measures and analysis approaches. Note that for the prediction method, only ICC1s could be calculated.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Aggregation | | Prediction |
| Task measure | ICC(1) | ICC(2) | ICC(1) |
| **Response inhibition task** |  |  |  |
| SSRT | .52 | .53 | .70 |
| **Working memory task** |  |  |  |
| No distractor (long) | .34 | .34 | .61 |
| No distractor (short) | .42 | .2 | .57 |
| Encoding distractor | .34 | .34 | .51 |
| Delayed distractor | .42 | .43 | .61 |
| **Risk taking task** |  |  |  |
| Win | .65 | .65 | .79 |
| Loss | .54 | .55 | .70 |
| Mixed | .49 | .50 | .72 |
| **Information sampling task** |  |  |  |
| Oversampling | .78 | .78 | .91 |

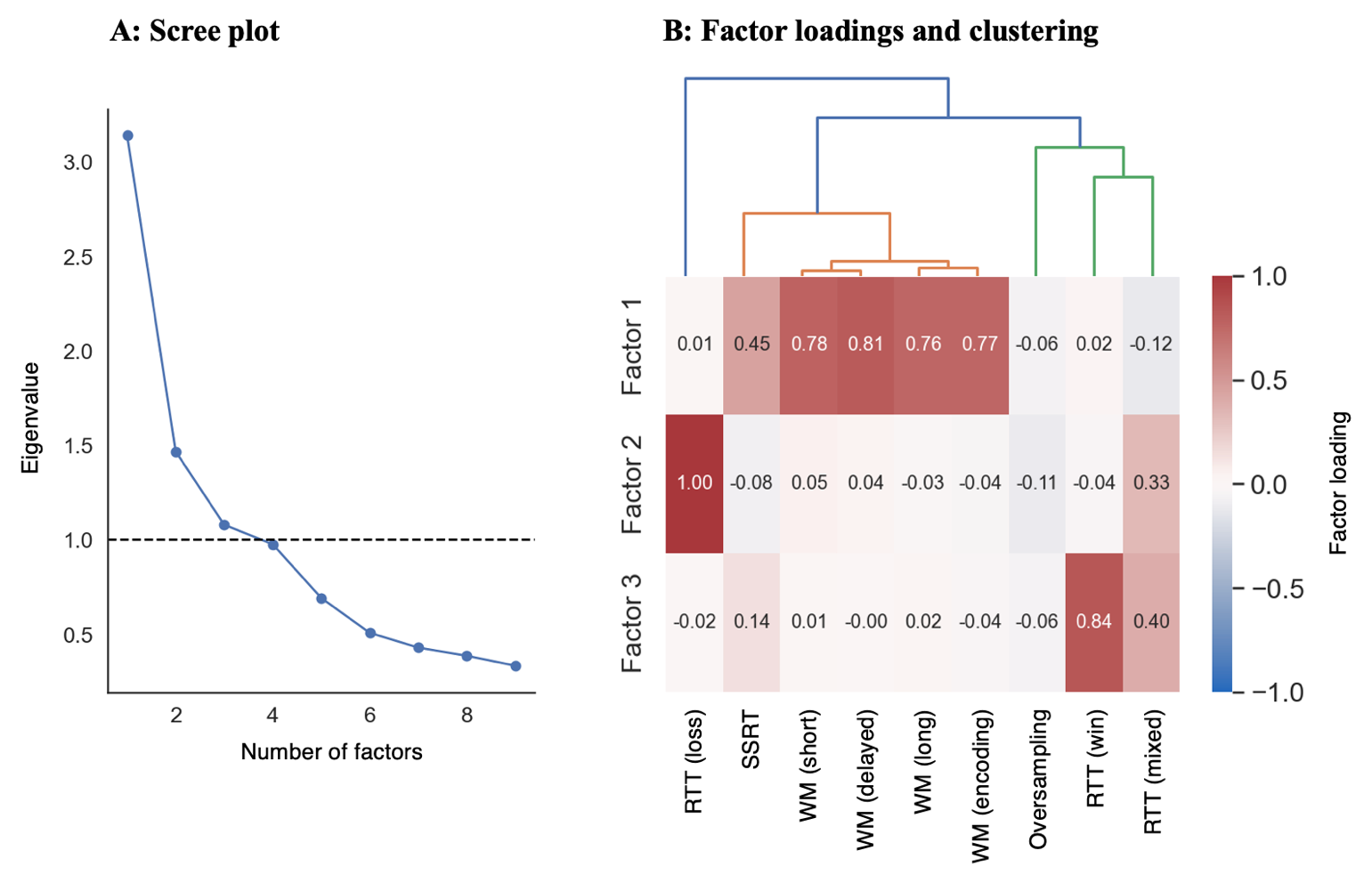
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**Figure 2.** Test-retest reliabilities (ICC1s) for the four tasks split by score calculation approach (blue: based on separate modeling; red: based on joint modeling).

***Construct validity.*** To assess the tasks discriminant and convergent validity, we used exploratory factor analysis. Factor analysis seeks to reduce the dimensionality of measurements, thus revealing whether several measurements outcomes can be described by fewer underlying factors (Eisenberg et al., 2019). This allows researchers to assess whether theoretical constructs (such as self-control) are also present in a given dataset. Crucially, the factor structure of measurement outcomes can differ depending on the population (Knekta et al., 2019) and little is known about how measures of self-regulation are related in participants suffering from addiction. As the extent to which a factor can represent underlying measurements also depends on measurements reliability, we conducted our factor analysis based on the average jointly modeled scores from both sessions—which had the highest reliability estimates.

A scree plot indicated that the data was best represented by three factors (see Figure 3). Factor loadings further indicated that the first factor represented measures related to cognitive control, with the different working memory conditions showing factor loadings of .77 to .81 and the inhibition task a factor loading of .45. The second factor mostly represented risk taking for losses (factor loading of 1.00) and the third factor risk taking for wins (factor loading of .84). Risk taking for mixed gambles loaded equally on factor 2 (factor loading of .33) and factor 3 (factor loading of .39) and oversampling loaded on none of the factors (all loadings < .12; see Figure 3).

Together the factor loadings indicated one cognitive control dimension and potentially several decision making dimensions. However, some measures, such as risk taking for mixed gambles did not clearly load on one distinct factor but were spread over several factors. To further categorize the data, we therefore conducted a hierarchical clustering analysis based on the factor loadings. Rather than showing to which extent a measurement can be represented by each individual factor, cluster analyses can show which variables load similarly on one or several factors (Eisenberg et al., 2019). Hierarchical clustering constructs a relational tree depending on how much each variable loads on each factor (see Figure 3). Depending on where the tree is cut, different clustering solutions can be determined. The clusters that emerged from this analysis mirrored the factor analysis in that a large cognitive control cluster consisting of the working memory and inhibition task emerged. In addition, the analysis revealed two to three decision making clusters consisting of one risk taking for losses cluster and one risk taking for gains cluster which further split into one risk taking for gains and mixed gambles cluster and one oversampling cluster. All in all the clustering is consistent with theory predicting a cognitive control dimension of self-regulation which is separate from risk taking and a risk taking dimension that is split in risk taking for gains and risk taking for losses.

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**Figure 3.** Panel A shows the scree plot used to determine the number of factors best representing the data. Panel B shows the factor loadings and the hierarchical clustering.

**Discussion**

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**Materials and Methods**

**General procedure.** This study was part of a larger German research consortium on addiction at three sites (Technical University Dresden, Charité Berlin, and Central Institute of Health Mannheim), in which a smartphone-based longitudinal Ecological Momentary Assessment (EMA) of up to one year was performed with a range of subjective reports. In addition to subjective reports, patients performed four cognitive-motivational tasks on the smartphone once per month. These tasks were taken from the Great Brain Experiment (GBE) app (Brown et al., 2014, see below for details). Before starting the EMA study, patients underwent extensive clinical and neurocognitive assessments (see Heinz et al., 2020). During this assessment appointment, which was either conducted inside the laboratory or online via video chat, the app for running the EMA study (Movisens app; movisens GmbH, Germany; Reichert et al., 2021) as well as a customized version of the GBE app for assessment of the four cognitive-motivational tasks (see below) were installed either on participants’ own phone or on a study phone. On the first Monday following the assessment, participants completed each smartphone task twice. Participants also participated in multiple subprojects of the consortium (see Heinz et al., 2020), which are not subject to the present study.

**Participants.** The study procedure was approved by the review boards of the local ethics committee at Heidelberg University (2018-621N-MA), Charité – Universitätsmedizin Berlin (EA1/212/18), and Technical University Dresden (EK 459112018). All participants gave written consent before participating in the study. For study inclusion at all three sites, participants had to fulfill criteria of mild to moderate Alcohol Use Disorder (AUD). According to DSM V, mild to moderate AUD was defined as the presence of at least two AUD criteria. Participants were recruited through flyers and advertisements. Telephone screenings were conducted before study inclusion/exclusion. Exclusion criteria were: clinical indication for detoxification treatment, insufficient knowledge of the German language, seeking a therapeutic intervention, MRI contraindications, medical history of DSM-5 bipolar disorder, psychotic disorder, schizophrenia or schizophrenic spectrum disorder, or current use of drugs or medication nor substance dependence thereof other than alcohol, nicotine, or cannabis, as well as medical history of severe head injury, or other severe central nervous system disorders. As pre-registered (Zech et al., 2021), data from 300 participants was analyzed for the present study. Participants age ranged from 17 to 65 years (*M* = 37.9, *SD* = 13.0) and 113 participants (37.7%) reported to be female. Participants AUD criteria ranged from 2 to 9 (*M* = 3.93, *SD* = 1.51).

**Working memory task.** During the working memory task (WMT, McNab et al., 2015) participants were asked to remember the positions of two up to 12 red circles presented on a 4 x 4 grid (see Fig. 1B). The task involved four conditions: In the ‘*long no distractor’* conditioncircles were presented for two seconds (encoding phase), then disappeared for one second (maintenance phase), before participants had to tap on their no-longer visible locations. In the ‘short *no-distractor’* condition, patterns were presented for one instead of two seconds. In the ‘*encoding-distractor’* condition, two yellow distractors were presented together with the red circles during the encoding phase. In the ‘*delayed-distractor’* condition, the same two yellow distractors were presented but during the maintenance phase. Each 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 for once. If they failed again the condition was terminated. A maximum of eight trials was completed for each condition.

**Risk taking task**. During the risk taking task (RTT; Rutledge et al., 2014), participants repeatedly chose between a certain outcome and a gamble, with 50/50 probabilities of the two outcomes (see Fig. 1C). The task involved three conditions: In the ‘*gain’* conditionparticipants chose between either a certain gain or to gamble for a larger gain against 0 points. In the ‘*loss’* conditionparticipants chose between either a certain loss or to gamble for 0 points against a larger loss. In the ‘*mixed’* condition, participants chose between a certain amount of 0 points or to gamble for a gain against a loss amount. Each condition consisted of ten 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 (for details, see Rutledge et al., 2014, supplementary materials). The task also involved current mood ratings (“How happy are you at this moment?”; rating line with endpoints “very happy” and “very unhappy”) which were presented after every two to three trials but are not subject to the currently reported reliability analysis.

**Information sampling task.**During the information sampling task (Hunt et al., 2016) participants were presented with four playing cards in rows of two and had to choose the row with the largest sum of card values (see Fig. 1D). Each of the 21 trials began with all cards face 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 chose 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.

**Reliability.** The first goal of this study was to assess the smartphone tasks’ reliability. Where possible—we first assessed the tasks’ split-half reliability—or the consistency with which a task measures its construct within one measurement session. Next, we assessed the tasks’ test–retest reliability—or the consistency with which a task measures its construct between two measurement sessions. While assessing the tasks’ test–retest reliability, we compared two approaches of analyzing task data—the more traditional *aggregation* approach, and an alternative *prediction* approach, which has recently been shown to improve reliability in other cognitive tasks (for details, see below; Brown, 2020; Haines, 2021; Waltmann et al., 2021). Finally, we also explored the effect of retest-period on test–retest reliability.

***Aggregation vs. prediction approaches****.* For each task, we compared two approaches of analyzing task data: The first approach, which we subsequently call *aggregation*, is traditionally used to analyze task data. In this approach, summary scores are first created by aggregating data for each session of each participant. Next, these summary scores are used for inference, for example to calculate test-retest reliabilities. According to Haines et al. (2021), one problem of this approach is that it assumes that scores are estimated without measurement error. This, in turn, leads to ignoring uncertainty during inference, which, for example, can attenuate test-retest reliability. A second problem is that this method assumes that person-level parameters are distributed uniformly across an interval that spans beyond a reasonable range of task scores. This is because, knowledge about scores from other participants or scores from other sessions of the same participant is not integrated in estimating individual session scores. Prior research shows that integrating such information into individual score estimation yields more reliable scores (Efron & Morris, 1977; Gelman, 2006; Williams et al., 2020; as cited in Haines et al., 2021).

The alternative analysis approach, which we subsequently call *prediction*, overcomes both problems of the aggregation approach. Instead of first calculating summary scores and using them in a second step for inference, the prediction approach performs inference directly based on all available trial-level data. This allows it to carry, firstly, within-session uncertainty into the inference step and, secondly, to use information from other participants and sessions in each individual session score estimation. Both of these aspect improved test-retest reliability in previous work. We implemented this approach using hierarchical mixed models specifically designed to model each task’s outcome measure (for details see supplementary materials). Hierarchical mixed models allow to analyze data at the trial-level while still accounting for the participant and session structure of the data. We validated that mixed model based scores did not substantially differ from aggregation-based scores when modelled for each session separately (see supplementary materials).

***Reliability assessment.*** Firstly, split-half reliability was assessed based on Spearman-Brown-corrected correlations within each session (based on odd-even splits). Note that for the working memory task and for the SSRT, split-half reliabilities could not be computed because these tasks are adaptive. Therefore, splitting the task into two halves is not appropriate (Draheim et al., 2020). Qualitative interpretations of split-half reliabilities are given in line with Nunnally and Bernstein (1994; split-half reliabilities above .8 were labelled as adequate). Secondly, test-retest reliability was calculated based on intra-class correlation coefficients (ICCs) based on data from the first two measurement sessions. To calculate ICCs directly from mixed models, we followed the method recently described by Brown et al. (2020), which calculates reliabilities based on variance components extracted from mixed models. Waltmann et al. (2021) recently showed that this method yields more conservative and more accurate reliabilities than alternative methods (e.g. first predicting sessions scores and calculating reliabilities based on these predictions). To investigate whether increased retest-periods lead to decreased reliability, we also calculated test-retest reliabilities for longer retest-periods of one to six months. Qualitative interpretations of test-retest reliabilities are given in accordance with Koo and Li (2016): ICCs less than .5 were being interpreted as “poor”, ICCs between .5 and .75 as “moderate”, ICCs between .75 and .9 as “good”, and ICCs above .9 as “excellent”.

**Factor and clustering analysis**.Exploratory factor analysis was conducted using maximum likelihood estimation followed by oblimin rotation, which rotates factors without enforcing orthogonality. Before conducting this analysis stop signal reaction times, the outcome measure of the inhibition, task reversed, so they could be interpreted in the same direction as working memory tasks. This analysis was implemented using the factor\_analyzer package (Python 3.5). The optimal number of factors was determined using a scree plot (see Figure 3). The hierarchical clustering analysis was conducted using the SciPy package (Python 3.5). The analysis was conducted using Euclidean distances to generate a hierarchical tree. As there were no implicit heights at which to cut this tree, the cut height was determined based on theoretical considerations.

**Acknowledgments**

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**Figure 3.** Factor loadings and clusters