Predicting Alcohol Lapses: A 100-Day Ecological Momentary Assessment Study on 3-Hour Interval Predictors in Individuals with Alcohol Use Disorder Undergoing Treatment

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Abstract

Background: Alcohol Use Disorder (AUD) poses significant public health challenges, particularly due to the complex interplay of various physiological, psychological, and contextual factors contributing to lapses. This study explores the predictive relationships between these factors and lapses in individuals undergoing treatment for AUD over an extended period using Ecological Momentary Assessment (EMA).

Methods: An Intensive Repeated and Continuous Measures in Naturalistic Settings Case-study design was conducted. Six participants recruited from an addiction care facility in the Netherlands completed multiple questionnaires per day over 100 days, providing self-reported measures of craving, affect, stress, coping skills, and lapses. Additionally, participants were monitored using an E4 wristband to measure cardiovascular activity, electrodermal activity, and movement. Multilevel Modelling and Time-Series Analysis were used to investigate the predictive relationships of these factors, on lapses three hours later with a focus on both group-level trends and individual variability.

Results: The belief in the effectiveness of one's coping skills was found to be the most robust predictor of lapses three hours later, suggesting that higher self-efficacy reduces the likelihood of lapsing. Craving, negative affect, availability of alcohol, and permission to drink were identified as significant predictors of lapses with a 3-hour lag in the SEM analysis. Positive affect, coping skills, and perceived availability of alcohol were also found to covary with each other.

Conclusion: This study highlights the importance of the belief in the effectiveness of one´s coping skills and the complexity of relationships between variables that predict lapses in the long-term AUD recovery process. Despite the study's limitations, such as a small sample size and low model fit indices, the results underscore the importance of personalized interventions and continuous support in sustaining long-term sobriety for individuals with AUD. Hence, future research with larger and more diverse populations is needed to validate and extend these results, enhancing the robustness and applicability of interventions for AUD.

Keywords: Alcohol Use Disorder, Ecological Momentary Assessment, Alcohol Lapse Prediction, Coping Skills, Craving Dynamics

Predicting Alcohol Lapses: A 100-Day Ecological Momentary Assessment Study on 3-Hour Interval Predictors in Individuals with Alcohol Use Disorder Undergoing Treatment

"First you take a drink, then the drink takes a drink, then the drink takes you" – F. Scott Fitzgerald.

From ancient rituals to modern-day societal norms, alcohol has long held a prominent place in human culture. What used to be a tool for societal rituals in ancient civilizations is now the leading cause of mortality as well as morbidity (Lindenmeyer, 2022). According to the World Health Organization (WHO), roughly 5.3% of all deaths result from harmful use of alcohol every year (Park & Kim, 2020). In young people, this figure rises to approximately 13.5% (WHO, 2021). Additionally, a substantial body of evidence suggests an association between alcohol misuse and various mental health and behavioural disorders, contributing significantly to the burden of morbidity (WHO, 2022). Even though some individuals seek sobriety, an estimated 80% of all individuals addicted to alcohol or other drugs will experience lapses (Sinha, 2011). Hence identifying and analysing factors related to lapses is a crucial step for creating effective interventions and fostering sustainable long-time sobriety (Álvarez-Jiménez et al., 2009; Hendershot et al., 2011; Sun et al., 2023).

Alcohol Use Disorder (AUD) is a chronic relapsing brain disease characterized by an impaired ability to stop or control alcohol use despite adverse social, occupational, or health consequences (American Psychiatric Association, 2013; Koob & Volkow, 2010). Diagnosed based on criteria outlined in the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* (DSM-5), AUD includes a range of symptoms such as craving, loss of control over drinking, withdrawal symptoms, and a persistent desire or unsuccessful efforts to cut down or control alcohol use (APA, 2013).

The development of AUD can be compared to that of an ice floe. It oftentimes starts unnoticed as a social or recreational activity, similar to how many people initially engage in activities like trying new foods, experimenting with hobbies, or socializing with friends. In its early stages, alcohol consumption may be occasional, moderate, and primarily for enjoyment or relaxation purposes. It can be perceived as a way to unwind after a long day, celebrate special occasions, or enhance social interactions. In many instances, it is also reinforced by positive feedback from the social environment and pleasant emotions. However, as alcohol use continues and potentially escalates over time, some individuals may find themselves experiencing negative

consequences or developing an alcohol dependence, leading to addiction or AUD. This dependence also oftentimes passes unnoticed until physiological or behavioural negative consequences occur (Lindenmeyer, 2022).

Excessive alcohol consumption is harmful for numerous reasons, significantly impacting physical health, mental well-being, social relationships, and overall quality of life. From a physical health perspective, chronic alcohol consumption is known to damage vital organs, particularly the liver (Testino, 2013), contributing to cardiovascular issues, and raising the risk of various cancers (Lindenmeyer, 2022). Thus, alcohol consumption exacerbates mental health disorders like depression and anxiety while impairing cognitive functions such as memory and decision-making (Gurling et al., 1984; Schuckit, 2009), leading to strained relationships and conflicts with family and friends (Lindenmeyer, 2022). In the vocational domain, alcohol use can reduce productivity, potentially leading to job loss and financial instability (Anderson et al., 2012). The additional financial burden of alcohol consumption, coupled with the risks of accidents and legal issues, can thus result in long-lasting consequences, including fines and imprisonment (Gurling et al., 1984).

Quitting alcohol poses significant challenges due to a combination of factors. Firstly, alcohol enjoys a high level of social acceptance and availability, making it deeply ingrained in societal norms and rituals (Alaniz and Wilkes 1998; Hastings et al. 2005; McKee et al. 2011). Additionally, AUD includes physiological dependence, with withdrawal symptoms that can be severe and even life-threatening, setting it apart as the only drug where withdrawal can end deadly (Waldee & Phan, 2019). Moreover, even after successful sobriety, alcohol presents numerous lapse triggers, from commonplace activities like a trip to the supermarket to ubiquitous advertisements on the TV that may induce cravings (Lindenmeyer, 2022). Furthermore, social events often revolve around alcohol consumption, making it difficult for individuals to stay sober in social settings (Lindenmeyer, 2022). These multifaceted challenges underscore the complexity of quitting alcohol and highlight the importance of comprehensive support and intervention strategies in achieving long-term sobriety (Longabaugh et al., 1998).

Individuals with AUD who decide to seek treatment oftentimes experience relapse, or frequent lapses throughout their abstinence journey (Witkiewitz & Villarroel, 2009). In the context of drinking resumption, the terms "lapse" and "relapse" describe different experiences related to drinking after a period of abstinence. Understanding the distinction between these

terms is important for effective management and recovery. Whilst a lapse is a brief, isolated incident of alcohol use after a period of sobriety, a relapse encompasses a return to a pattern of problematic drinking after a period of abstinence, signifying a more sustained and significant return to alcohol use. Hence, the key difference is that a relapse involves prolonged or repeated instances of drinking where an individual resumes their previous levels of alcohol consumption or worse and may lose control over their drinking and return to behaviours associated with AUD. A lapse however is a single instance or very short period of drinking. The individual often recognizes the lapse and feels remorse or guilt and attempts to return to sobriety immediately after the lapse (Steckler et al., 2013).

Given the nuanced distinction between lapses and relapses, it becomes crucial to understand the underlying factors that can trigger these events. Various factors contribute to both lapses and relapses in individuals with AUD, and these can be broadly categorized into psychological, physiological, and contextual influences. Psychological factors include the experience of negative affect (Witkiewitz & Villarroel, 2009), stress (Brady, 1999), craving (DeMartini et al., 2020, and the belief in the effectiveness of one´s coping skills (Sjöberg & Samsonowitz, 1985). Physiological factors, serving as precursors to lapses include increased cardiovascular activity (Segerstrom & Nes, 2007), electrodermal activity (Dawson et al., 2007), and movement (Rosenbaum et al., 2014). Lastly, contextual factors such as social activity (Zheng et al., 2015), the availability of alcohol and the permission to drink or not to drink (Shiffman et al., 1996), influence the likelihood of lapses.

According to Russell and Carroll (1999), *negative affect* refers to unpleasant emotions such as anxiety, depression, and irritability. Thus, based on the affective processing model of negative reinforcement, negative affect is a key factor in the development and maintenance of alcohol addiction, as individuals may turn to alcohol as a means of coping with unpleasant emotions (Witkiewitz & Villarroel, 2009). Therefore, monitoring negative affect in real-time can provide valuable information about an individual's risk of lapsing (van Lier et al. 2017). By detecting increases in negative affect, clinicians can intervene and provide support to prevent lapses.

Stress, defined as a state of mental or emotional strain caused by adverse or challenging circumstances (Lazarus, 1990), is widely recognized as a significant trigger for alcohol cravings and subsequent lapses (Brady, 1999). The affective processing model of negative reinforcement

highlights the critical role of stress in real-time craving monitoring research, as it directly influences the urge to consume alcohol (van Lier et al., 2017). In individuals with alcohol addiction, heightened stress levels can intensify cravings, making them more vulnerable to lapses. Therefore, real-time stress monitoring can be a valuable tool in identifying periods of increased risk, allowing clinicians to intervene promptly and offer the necessary support to prevent lapses (Battalio et al., 2021).

A further variable to be investigated is *alcohol craving*. Craving is a psychological and neurobiological phenomenon that is associated with addictive behaviours in a subset of patients (Cooney et al., 1997), involving a powerful urge or desire to consume alcohol, often triggered by external cues or internal emotional states (Anton, 1999). Even though the role of craving is subject to debate in the literature (van Lier et al., 2022), most scholars assert a causal role for craving in the context of addiction (Baker et al., 2004; Larimer et al., 1999; Reis, 2012; Robinson & Berridge, 1993; Tiffany & Conklin, 2000; Verheul et al., 1999). Whilst some research posits that there is no significant relationship (Cooney et al., 1997, Holt et al., 2012, Krahn et al., 2005), other studies establish a significant correlation between craving and lapses (DeMartini et al., 2020; Higley et al., 2011; Miller et al., 1996; Waters et al., 2020. Hence, craving is a further variable in this study.

The belief in the effectiveness of one's coping mechanisms is a significant psychological factor that can play a crucial role in alcohol lapse. This belief, often referred to as self-efficacy, is rooted in the individual's confidence in their ability to cope with challenging situations, triggers, or stressors without resorting to alcohol consumption (Rychtarik et al., 1992). Individuals with high self-efficacy in managing life stressors and avoiding alcohol use are more likely to resist the temptation to lapse. Conversely, those with lower self-efficacy may struggle to navigate these challenges, increasing the risk of returning to alcohol use. The influence of self-efficacy on lapses is consistent with social cognitive theory, which emphasizes the importance of personal beliefs and expectations in shaping behaviour. High self-efficacy empowers individuals to face challenges, employ adaptive coping strategies, and view lapses as manageable setbacks rather than definitive failures (Van Zundert et al., 2009). As such, interventions that strengthen self-efficacy play a vital role in promoting sustained recovery from AUD (Sjöberg & Samsonowitz, 1985).

Physiological precursors to alcohol lapses include *electrodermal activity (EDA)*, which refers to the electrical properties of the skin that are influenced by sweat gland activity, which is modulated by the sympathetic nervous system. EDA is widely recognized as a sensitive measure of emotional and physiological arousal (Dawson et al., 2007). In the context of AUD, elevated EDA levels can indicate heightened stress or anxiety, which are known triggers for alcohol craving and consumption (Baker et al., 2004). By monitoring EDA in real-time, the study aims to identify moments of increased physiological arousal that may precede the resumption of drinking. This approach allows for timely interventions by clinicians to address stress or anxiety, potentially preventing a return to alcohol use. Previous research has demonstrated the utility of EDA in predicting lapses in various substance use disorders (Trull & Ebner-Priemer, 2013).

Cardiovascular activity (CVA), measured as heart rate (HR), provides critical insights into the autonomic nervous system's functioning. Elevated HR is often associated with stress, anxiety, and substance craving (Segerstrom & Nes, 2007). In individuals with AUD, fluctuations in CVA can reflect underlying emotional and physiological states that contribute to alcohol cravings and lapses (Kim et al., 2018). Hence, by continuously monitoring cardiovascular metrics, our study seeks to capture these fluctuations and their temporal relationship with alcohol use behaviours. This data-driven approach enables us to identify periods of increased cardiovascular stress that may signal a heightened risk of resumption, facilitating proactive support to maintain abstinence.

Movement data, typically captured via accelerometers in wearable devices like the E4 wristband (van Lier et al., 2020), offers valuable information about an individual's physical activity and rest patterns. In the context of AUD, changes in movement patterns can be indicative of agitation, restlessness, or altered routines, which may correlate with increased stress or craving (Rosenbaum et al., 2014). For instance, periods of increased movement might signal attempts to cope with craving or stress, while reduced activity could reflect depressive states or withdrawal symptoms (Woodruff et al., 2022; Kim & Hodgins, 2018; Segerstrom & Nes, 2007). Our study leverages movement data to identify such patterns and to correct for confounding in EDA and HR measures. Thus, their association with the resumption of alcohol use was measured. By analysing these data alongside self-reported variables, we aim to build a comprehensive picture of the physical and behavioural precursors of drinking (van Lier et al., 2022).

In terms of contextual factors*, social activity* serves a multifaceted role in the context of addiction, acting as both distractors and sources of support. Research by Hinojosa et al. (2015) suggests that engaging in social activities can function as an effective protective factor, diverting attention away from craving triggers by swiftly capturing attentional resources, and redirecting focus from the originally directed task. However, social activity can also serve as a risk factor for alcohol cravings. Thereby, the availability of alcohol and whether drinking alcohol is permitted in social contexts can serve as contextual factors that foster craving due to social activity (Shiffman et al., 1996).

The *availability of alcohol* is a critical contextual factor that influences the likelihood of lapses among individuals with AUD. Studies have shown that increased access to alcohol significantly raises the risk of lapses, as the presence of alcohol in the environment can act as a powerful cue that triggers craving and undermines self-control (Shiffman et al., 1996). According to Marlatt and George (1984), the mere availability of alcohol can weaken an individual's resolve to abstain. Environments where alcohol is readily accessible, such as social events or certain public spaces, are particularly high risk for individuals recovering from AUD (Larimer et al., 1999). By limiting exposure to these environments or restricting access to alcohol, the risk of lapses can be mitigated (DiClemente et al., 2007).

Permission to drink, whether granted internally by the individual or externally by others, is another contextual factor that influences the likelihood of lapses (Shiffman et al., 1996). When individuals perceive that they have permission, whether it be self-permission arising from rationalizations or social permission from peers, it can erode their commitment to sobriety and lead to a lapse (Larimer et al., 1999). This permission can also be influenced by social cues, such as seeing others drink, or by cultural norms that downplay the risks of occasional drinking (Lindenmeyer, 2022).

The Present Study

Van Lier et al. (2022) conducted a longitudinal study that aimed to investigate the within-person association between self-reported craving and lapses, as well as the association between heightened physiological activity and self-reported craving during a 100-day monitoring period of individuals recovering from AUD in their daily lives. The study engaged in a cross-lagged design by examining how contextual factors, recorded at an earlier time, are related to later experiences of craving. The goal was to understand whether changes in physiological states or

specific contextual conditions can serve as early indicators or predictors of later alcohol cravings and lapses, thus providing a potential window for timely interventions. While cravings did not significantly affect lapses, there was high variability in individual experiences of alcohol craving, with heightened physiological activity and stress being key factors. This underscores the importance of personalized approaches in addiction treatment, considering physiological, psychological, and contextual factors.

Furthermore, it is of paramount importance to identify factors contributing to lapses in alcohol-dependent individuals. Firstly, understanding the complex interplay of physiological, psychological, and contextual factors that contribute to lapses can inform the development of personalized interventions tailored to individual needs (Álvarez-Jiménez et al., 2009; Hendershot et al., 2011; Sun et al., 2023). Such interventions could serve as early warning systems to provide timely alerts to both individuals and healthcare providers, allowing for proactive intervention before a full lapse occurs (Helmich et al., 2021), such as JITAIs (Nahum-Shani et al., 2018). This individualized approach is crucial, as the study highlighted the substantial variability in the association between lapses and craving across individuals (van Lier et al., 2022). Secondly, recognizing the diverse and individualized nature of alcohol-craving experiences can help treatment providers and researchers move beyond aggregated data and develop targeted strategies to support individuals in recognizing and managing high-risk situations (van Lier et al., 2022). Thirdly, by identifying and addressing the specific precursors and triggers of craving and lapses, it may be possible to enhance the effectiveness of interventions and improve long-term treatment outcomes for individuals recovering from AUD (Álvarez-Jiménez et al., 2009). Therefore, a comprehensive understanding of the factors contributing to lapses is essential for the development of effective, personalized interventions and the advancement of alcohol addiction treatment and management (Hendershot et al., 2011).

Hence, as the question as to what led to those lapses is still pending, this research will follow an exploratory approach aiming to identify variables that may have led to lapses in the participants. The objective of the following thesis will therefore be to identify variables that precede lapses in the participants.

Rationale for Experience Sampling Methodology

The adoption of the Ecological Momentary Assessment (EMA) and the Experience Sampling Method (ESM) has become imperative in addiction research, as underscored by studies

such as Van Lier (2022) and Serre et al. (2015). These methodologies offer a compelling rationale for the need to acquire real-time, ecologically valid data, especially in capturing the dynamic nature of craving and social activities.

Mobile technologies, such as smartphones, introduced a new era in research methodologies, allowing for the collection of data in naturalistic settings. EMA, a rapidly expanding approach in clinical psychology, behavioural neurosciences, and addiction research, presents a solution to methodological barriers that traditionally characterized clinical studies (Myin-Germeys & Kuppens, 2021). EMA, inclusive of ESM, utilizes various recording methods, with signal-contingent recording standing out as an experience sampling procedure. This method, repeated over a short time frame, captures the rapid fluctuations of variables like craving and social activities, providing a comprehensive understanding of their dynamic nature (Serre et al., 2015).

ESM also allows for the measurement of variables that are time-limited in nature and hold possible biases associated with retrospective reporting, such as alcohol craving, as highlighted by Serre et al. (2015). EMA addresses this limitation by allowing researchers to collect real-time data in daily life, offering strong ecological validity. The feasibility and validity of EMA have been demonstrated across various types of addiction, emphasizing its adaptability and applicability in exploring craving as influenced by diverse environmental determinants (Myin-Germeys & Kuppens, 2021).

Variables and Research Questions

In the main study, variables were investigated and ranked according to their classification into physiological, psychological, and contextual factors. Physiological variables included EDA, CVA, and bodily movement. Psychological variables comprised self-reported craving, negative affect, stress, and belief in the effectiveness of coping skills. And contextual variables encompassed lapses, social activity, availability of alcohol, and permission to drink.

Building upon the gap of knowledge regarding the factors that led to lapses in the sample, established in the introduction, the research question seeks to delve deeper into triggers preceding alcohol lapses:

"What physiological, psychological, and contextual factors precede lapses three hours later during a 100-day observation period in individuals seeking treatment for Alcohol Use Disorder?"

A second research question aims to investigate how the potential predictors interact by asking:

"How do physiological, psychological, and contextual factors covary with each other to influence lapses during a 100-day observation period in individuals who are seeking treatment for Alcohol Use Disorder?"

Methods

Study Design

The following research was part of a larger study named "An ideographic study into physiology, alcohol craving and lapses during one hundred days of daily life monitoring" and adopted an observational approach utilizing an intensive repeated and continuous measure in naturalistic settings case-study design conducted by van Lier et al. (2022). Participants were subjected to continuous monitoring through a wearable biosensor (Empatica's E4 wristband) while responding to a series of questions on a smartphone app every three hours. Ethical approval was guaranteed by the BMS Ethics Committee from the University of Twente (request number 240050). The initial study received Ethical Approval from the Medical Ethical Committee Twente (registration number: NL58392.044.16).

The study utilized a longitudinal ESM, which captures moment-to-moment variations in reported variables (Myin-Germeys & Kuppens, 2021). Time-contingent recording prompted participants to report experiences at specific times throughout the day, with an additional end-of-day questionnaire on craving moments and alcohol use (van Lier et al., 2022). Participants received prompts on their mobile phones at predetermined times, enhancing ecological validity by collecting real-time data in natural environments (Bolger & Laurenceau, 2013). Alongside self-report questions, participants wore a biosensor wristband to measure EDA, HR, and movement linked to cognitive craving (Carter and Tiffany, 1999). Participants activated the E4 wristband upon waking, downloaded the data, and charged it overnight. The monitoring spanned 100 days, aligning with findings that the risk of lapsing significantly decreases after this period (Kirshenbaum et al., 2009).

Participants

In the initial study by van Lier et al. (2022), the sample consisted of individuals who were (a) older than 18 (b) diagnosed with a moderate or severe AUD according to the DSM-5 (c) currently in or willing to be enrolled in the "alcholdebaas" online or face-to-face treatment phase

(d) aiming to reach abstinence or drinking less. In the case of drinking less, this aim had to include at least two days a week of not drinking at all, and (e) being in possession of a personal mobile phone. Detailed inclusion and exclusion criteria for participants can be found in the original study by van Lier et al. (2022). Additionally, this study focused on a subset of 6 participants from the original sample who (f) specifically experienced lapses during the observation period.

Participants joined the study after establishing their primary treatment goal of abstinence, typically around six weeks into treatment when cravings were expected to begin. Further information regarding the participant selection can be found in the Article by van Lier et al. (2022).

Materials

Participants were given an E4 Biosensor and had to possess a smartphone on which they received the questionnaires. Respondents were requested to provide informed consent before taking part in the survey and were then required to set clear abstinence goals.

Measures

Lapse. Participants had two opportunities to report lapses during the study. The first registration cue took place at the end of each day regarding activities following cravings, and retrospectively in the morning for the prior day. This option accommodated situations where a participant might have been unable to respond the previous day due to intoxication or being asleep. If a participant acknowledged drinking during the morning registration and was asked about the number of alcoholic units consumed, this information was not utilized in the study.

Self-Reported Craving. Following Ooteman et al. (2006), craving was measured with a single item on a 0-10 Likert scale, where 0 denoted an absence of craving, and 10 signified high levels of craving. Participants were asked, "How strong is your craving currently?". Initially, prior to the reactivity reflection session, the question specified, "How strong is your alcohol craving currently?" However, based on input from experienced experts, the use of the word "alcohol" was eliminated from the questions to avoid potentially triggering additional craving with the word.

Electrodermal Activity. EDA measures were determined by measuring skin conductance (SC) with an E4 wristband which used electrodes. The selected parameter to measure EDA was total amplitude. The decision to use Total Amplitude was based on its

incorporation of both the number of skin conductance responses and their amplitudes, two commonly employed measures in EDA data analysis. To derive the total amplitude from the SC, classical trough-to-peak analysis (TTP) was employed, with a set threshold for skin conductance response (SCR) amplitude at 0.01 μS (Boucsein, 2012). Ledalab was used for data analysis, utilizing the default settings for filtering, and smoothing (Benedek & Kaernbach, 2010). The amplitude of an SCR was calculated as the difference in conductance between response onset and response peak. These individual amplitudes were summed to determine the total amplitude per minute. Consequently, the total amplitude was a composite measure considering both the number of SCRs and the amplitude of each SCR. The total amplitude per minute was then averaged over the three hours leading up to the conclusion of the potential question administration period.

Cardiovascular Activity. CVA was determined by measuring mean HR due to its relevance as an indicator of CVA with the same E4 wristband as for EDA. The E4 wristband thus utilized a photoplethysmogram (PPG) to capture blood volume pulse (BVP) for CVA measurements. Instantaneous HR was derived by dividing the mean PP interval per minute by 60 seconds. HR was preferred over the PP interval since it is a more widely recognized transformation of the PP interval. The mean HR per minute was once again averaged over the three hours preceding the potential conclusion of the question administration period.

Movement. A MEMS-type 3-axis accelerometer in the E4 wristband measured movement in three dimensions. Data were sampled at 32 Hertz, and force was calculated from spatial data. The standard deviation of the force was calculated for the three-hour period leading up to the potential conclusion of the question administration. Standard deviation was opted for over the mean due to the substantial time intervals in this study. While the mean movement is anticipated to remain relatively constant over an hour, the standard deviation of force captures these fluctuations more effectively.

Other Self-Reported Measures. Various other self-reported measures were gathered, each structured as single-item constructs on a 0 to 10 Likert scale, unless specified otherwise. These measures included (1) negative affect, which was administered on a valence-arousal scale, a two-dimensional scale with valence on the x-axis (ranging from negative to positive) and arousal on the y-axis (ranging from low to high energy). Both scales were combined into a single variable by standardizing the valence and arousal scores. The standardized scores were then

combined to create a composite Negative Affect score. The composite score was calculated by averaging the standardized valence and arousal scores, ensuring that both the intensity and quality of the negative affect were captured in the overall assessment. (2) stress, accessed on a 0 to 10 Likert Scale, (3) social activity, categorized into five possible social activities, namely "no social activity/work," "friend/family," "terrace/restaurant," "party," and "other," where other activities included hobby-related or religious activities. (4) availability, measured through a yes or no question. (5) permission to drink, accessed through a yes or no question. And (6) own belief in the effectiveness of one´s coping skills, rated on a scale of 0 to 10.

Procedure

The data collection took place from 2016 to 2017. Demographic variables were accessed, and participants were asked to fill out a questionnaire at the beginning and end of each day, thus multiple questions throughout the day, and one at the end of each week. Detailed design choices can be found in the original study by van Lier et al. (2022). Missing data at night-time and structurally throughout the day was categorized as sleeping and later coded as missing. The self-report questionnaires collected throughout the day were administered at 7, 10, 13, 16, 19, 22, 1 and 4 o'clock. Participants had a period of 59 minutes to respond to the questions and were provided a cumulative micro incentive of max 1 euro a day per finished questionnaire. Participants with a fixed sleep rhythm were expected to answer solely 5 questionnaires a day. Additional questions regarding craving moments were administered at each end of the day to lower the participant burden (van Lier et al., 2017).

Table 1

Schedule of the Assessment Prompts

Assessment Type	Time	Description
Self-Report EMA Questionnaire	01:00 04:00 07:00 10:00 13:00 16:00 19:00 22:00	Assessment of self-reported negative affect, stress, social activity, availability of alcohol, permission to drink, and the belief in the effectiveness of one´s coping skills.

Assessment Type	Time	Description
Lapse Registration	Beginning and end of each day	Additional Question in the EMA Questionnaire to access self-reported lapses.
Cravings Registration	At the end of each day	Additional Questions in the EMA Questionnaire to access craving moments throughout the day.

Note. Each Questionnaire had a window of one hour and expired after 59 minutes. Missing data at night-time and structurally throughout the day were categorized as sleeping. Physiological Markers were measured continuously on an E4 wristband.

Data Analysis

All analyses were performed on the Statistical Software R version 4.4.0 (R Core Team, 2023). After setting the working directory, several packages were loaded for data manipulation to answer the research questions, including "tidyverse" (version 2.0.0, for general data manipulation and visualization), "dplyr" (version 1.1.4, for data wrangling), "nlme" (version 3.1.164, for linear and nonlinear mixed-effects models), "lme4" (version 1.1.35.3, for fitting linear and generalized linear mixed-effects models), psych (version 2.4.3, for psychological research and factor analysis), "car" (version 3.1.2, for regression analysis, model diagnostics, and data manipulation), "ggplot2" (version 3.5.1, for data visualization), "lavaan" (version 0.6.17, for SEM), and "semPlot" (version 1.1.6, for visualizing the results of the SEM) (Myin-Germeys & Kuppens, 2021; It, 2023). The datasets of the six participants who lapsed were loaded, each containing data collected every three hours for different participants. These datasets were cleaned to remove duplicates based on the time variable and combined into one dataset. The variables were standardized to facilitate group-level analysis. To ensure the predictive value of the variables measured throughout the day to predict lapses measured at the end of each day, for each independent variable, the mean value was calculated, standardized, and lagged three hours (one timepoint prior to the dependent variable) backwards. Lapses were not lagged, averaged, or standardized, as they were only measured at one timepoint each day.

Descriptive Statistics. First, descriptive statistics were computed for all variables, including a heatmap to display lapses of participants over time, providing a visual representation of the frequency and distribution of lapses across the observation period. This approach allows for easy identification of patterns or trends in lapses among the participants (Shiffman et al.,

1996). Additionally, time series plots were created to map each variable over time for each participant, enabling the visualization of the development of physiological, psychological, and contextual factors on an individual level over time (Chatfield & Xing, 2019).

Structural Equation Modelling. The primary analysis was structural equation modelling (SEM) and conducted using SEM with the "lavaan" package to examine the relationships between various psychological and behavioural factors and lapses. The SEM model included three hours lagged effects of craving, negative affect, stress, availability, feeling encouraged, coping skills, social activities, mean CVA, mean EDA, and mean movement rate, on lapses, as well as covariances among the predictors.

The results were interpreted using p-values to determine the statistical significance of the relationships between variables. A p-value threshold of 0.05 was used to assess significance, meaning that any p-value higher than 0.05 indicated a poor fit.

Furthermore, a model fit measure was applied to evaluate how well the statistical model represented the data and to determine whether the selected model was a good fit for the observed data using several fit indices. The chi-square test of model fit was employed to compare the observed and expected results, where a p-value less than 0.05 indicates a good fit as the null hypothesis can be rejected. Other fit indices included the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), where values above 0.90 are generally considered indicative of a good fit, and the Root Mean Square Error of Approximation (RMSEA), with values less than 0.06 indicating a good fit (Hu & Bentler, 1999). The Standardized Root Mean Square Residual (SRMR) was also used, with values less than 0.08 considered acceptable (Kline, 2023).

Lastly, residuals were checked to control how well the selected model fits the data. Residuals were checked using the standardized residuals, which represent the differences between the observed values and the values predicted by the model. Standardized residuals greater than ± 2.58 ($p < 0.01$) were flagged as potential areas of poor fit, indicating where the model might not be accurately capturing the data (Byrne, 2013).

Factor Analysis. Due to the low model fit of the SEM model, further analyses were conducted to explore whether the model fit could be improved by identifying latent factors among the independent variables. The purpose of conducting EFA and CFA was to refine the SEM by potentially improving model fit through the identification and validation of latent

factors. By reducing the number of observed variables to a smaller number of latent factors, it was anticipated that the SEM might better capture the underlying structure of the data.

Specifically, Exploratory Factor Analysis (EFA) was employed to uncover potential underlying dimensions within the independent variables, which might not have been apparent in the initial model. It thus allowed for the exploration of whether a more parsimonious structure could be identified among the independent variables. EFA was used to determine if the observed variables could be grouped into underlying latent factors, thereby simplifying the model and potentially improving fit by reducing the complexity and multicollinearity among the predictors. Principal axis factoring was chosen due to the non-normality of observations, addressing skewness and kurtosis in the data (Fabrigar et al., 1999). Direct Oblimin rotation was applied to facilitate the interpretability of the factors, considering potential correlations between them. The appropriateness of factor analysis was confirmed by consulting both Scree plots and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, as well as Bartlett's test of sphericity. Factors were retained based on eigenvalues greater than one and the scree plot, with the factor loadings and communalities examined to ensure a meaningful interpretation of the factors (Tabachnick & Fidell, 2013).

To validate the factor structure identified in the EFA, Confirmatory Factor Analysis (CFA) was subsequently performed. This allowed us to confirm whether the two-factor structure, identified in the EFA, provided a better representation of the data. Based on the results from the EFA, the CFA model was specified with two latent factors and their respective observed indicators (Fabrigar et al., 1999). For this purpose, the dependent variable, lapse, was left out of the analysis, as the focus was on finding latent factors among all independent variables. As defined by Cohen (1988), a regression path was established if the correlation between two factors exceeded a medium level of 0.30. The model fit was evaluated using several fit indices: Chi-square ($\chi 2$), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The criteria for acceptable model fit were CFI > 0.95, TLI > 0.95, RMSEA < 0.05, and SRMR < 0.08 (Blunch, 2008; Byrne, 2013). However, obtaining a statistically significant $\chi 2$ is common in social research due to its sensitivity to large numbers of observations. Both EFA and CFA were conducted using the "psych" package in R (Byrne, 2013).

Generalized Linear Mixed-Effects Model. Furthermore, a Generalized Linear Mixed-Effects Model (GLMER) was employed using the "lme4" package in R to examine the relationship between the predictors and lapses, as well as to identify relevant interactions, while accounting for the hierarchical structure of the data, and for the dependency of observations within participants, recognizing that measurements taken from the same individual are likely to be more similar to each other than to those taken from different individuals. This nested structure allows for the modelling of both fixed effects, which are consistent across all individuals, and random effects, which vary among individuals (Pinheiro & Bates, 2000).

GLMER conducts a backward stepwise selection of fixed effects in a generalized linear mixed-effects model, starting with interaction terms before removing them to evaluate the main effects. Main effects that are part of significant interaction terms are retained, regardless of their individual significance as main effects. The random effect of participant ID was included to account for within-subject correlations. The GLMER was fitted using the binomial family with a logit link function, treating lapses as the dependent variable and the standardized predictors as independent variables (Bates et al., 2015). Model convergence was assessed using the optimizer "bobyqa" with a maximum of 10,000 iterations (Powell, 2009). Fixed effects were reported with their estimates, standard errors, z-values, and significance levels (Bates et al., 2015).

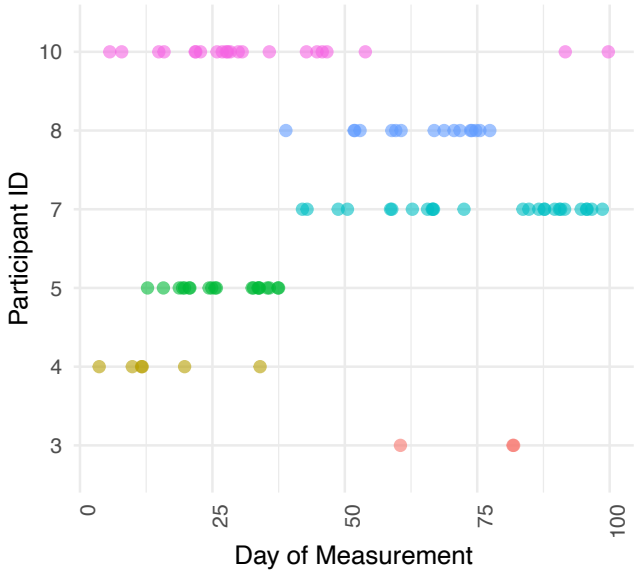
Results

Descriptive Statistics

Participants filled out between 106 and 327 Questionnaires in total, with a mean of 294.67 Questionnaires. The total number of lapses ranged between 3 and 28 lapses, with an average of 16.5 lapses per person. Craving occurred between 20 and 161 times with an average of 82.67 times per participant. Over time the perceived craving, social activity and the availability of alcohol decreased, whilst CVA, EDA, and negative affect, increased for most participants. Movement, perceived permission to drink and the belief in the effectiveness of one´s coping mechanisms remained steady. Stress increased for half of the participants and decreased for the other half. Noteworthy is also, the two individuals who lapsed the most, started lapsing in the second half of the trial, where they also reported a decrease in perceived stress and craving, as well as an increase in the belief in the effectiveness of their coping mechanisms (see Appendix B).

Figure 1

Time Series Plot of Recorded Lapses over Time by Each Participant



Note. Time measured in days. Each dot represents one lapse.

Structural Equation Modelling

The SEM analysis revealed several predictors of lapses. Higher craving levels ($\beta = 0.054$, $p < .001$), negative affect ($\beta = 0.019$, $p = .002$), and the availability of alcohol ($\beta = 0.037$, $p < .001$) were positively associated with lapses. Conversely, increased belief in one´s coping skills ($\beta = -0.028$, $p = .007$) was negatively associated with lapses, indicating that higher belief in one´s coping skills decreases the likelihood of lapsing.

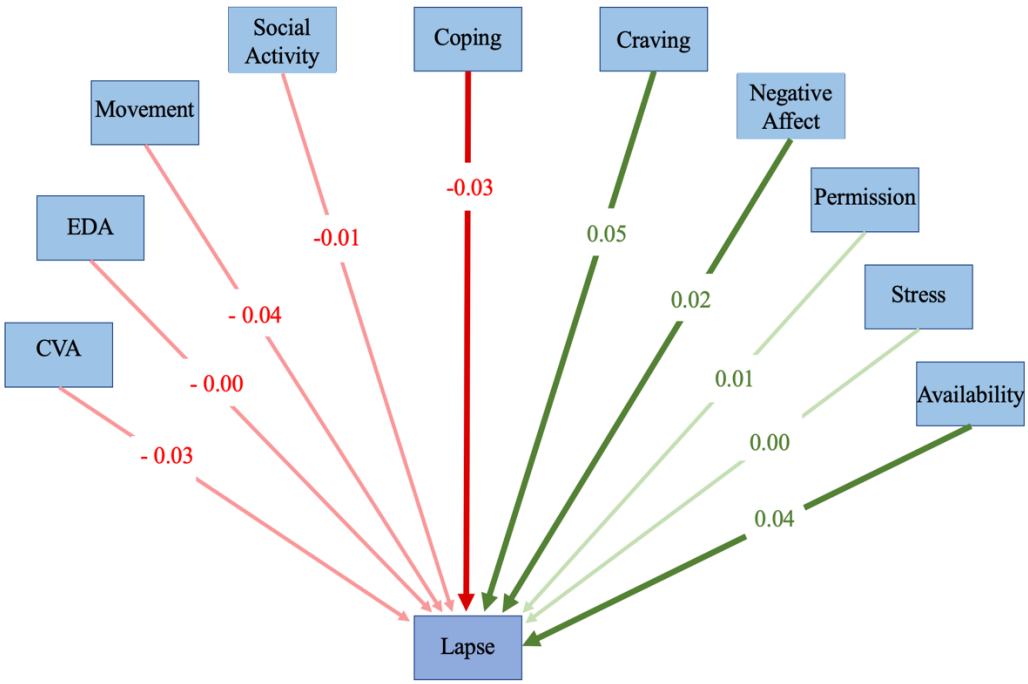
Significant covariances were observed that provide further insight into the relationships between key predictors and lapses. Firstly, higher craving levels were associated with higher levels of stress (covariance = 0.349, $z = 9.725$, $p < .001$) and availability of alcohol (covariance = 0.193, $z = 5.761$, $p < .001$). This suggests that individuals experiencing higher cravings may also be dealing with more stress and greater access to alcohol, contributing to their risk of lapses, and vice versa. Additionally, higher craving was associated with lower levels of coping (covariance = -0.416, $z = -13.129$, $p < .001$), indicating that those with intense cravings might struggle more with implementing effective coping strategies, which can also be interpreted bidirectionally. Moreover, higher negative affect was associated with higher stress levels (covariance = -0.359, $z = -8.161$, $p < .001$), lower availability of alcohol (covariance = -0.379, $z = -8.676$, $p < .001$), and increased use of coping strategies (covariance = 0.107, $z = 3.048$, $p < .001$). These relationships suggest that individuals with higher negative affect might face more stress and have less access

to alcohol, while also being more inclined to use coping strategies and reverse. Furthermore, the perceived availability of alcohol was associated with increased stress (covariance = 0.163, z = 4.815, p < .001) and reduced coping (covariance = -0.225, z = -7.772, p < .001). This indicates that environments with more accessible alcohol might exacerbate stress and hinder coping efforts. Lastly, better coping skills were negatively correlated with craving (covariance = -0.416, z = -13.129, p < .001) and stress (covariance = -0.196, z = -6.722, p < .001), highlighting that individuals who are better at coping tend to experience less craving and stress and vice versa.

However, the model fit indices suggested that the model fit was below acceptable thresholds, indicating a need for refinement (CFI = 0.824; TLI = 0.623; RMSEA = 0.086 (90% CI: 0.076 – 0.096); SRMR: 0.067). This indicates that the overall model may not adequately represent the data.

Figure 2

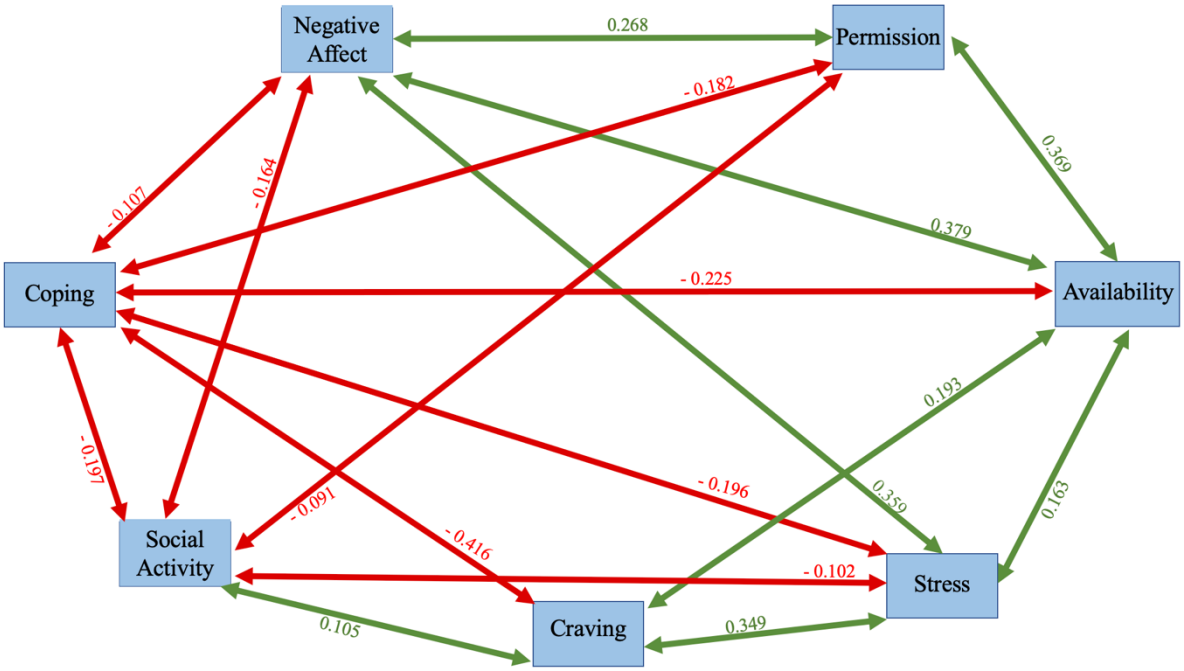
Predictors of Lapses



Note. β –Values as predictive estimates. Thick lines equal significance (P < .001).

Figure 3

Covariance Estimates Derived from the Structural Equation Modelling



Note. Covariance estimates between variables. Only significant covariances (P < .001).

Factor Analysis

The KMO measure indicated sampling adequacy (KMO = 0.83), and Bartlett's test of sphericity was significant ($\chi2(55) = 31309.25$, $p < 0.001$), justifying the use of factor analysis. Two factors were retained based on eigenvalues greater than one and the scree plot. The first factor explained 23% of the variance, and the second factor explained 18% of the variance. Factor loadings for the retained factors were as follows: The first factor encompassed psychological and contextual factors, including craving (MR1: 0.98; MR2: 0.11), negative affect (MR1: -0.09; MR2: -0.09), stress (MR1: 0.41; MR2: -0.02), availability of alcohol (MR1: 0.93; 0.07), the permission to drink (MR1: 0.11; -0.11), coping mechanisms (MR1: -0.68; MR2: -0.08), and social activities (MR1: 0.13; MR2: 0.06), whilst the second factor encompassed the physiological factors. CVA (MR1: 0.07; MR2: 0.99), EDA (MR1: 0.02; MR2: 0.16), and movement (MR1: -0.07; MR2: -0.97).

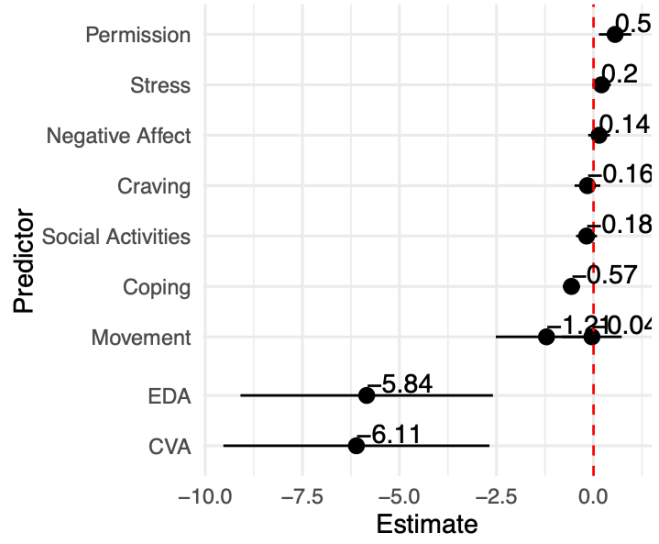
The CFA results supported the two-factor model identified in the EFA. The fit indices indicated an acceptable model fit: $\chi2(8) = 27.29$, $p < 0.001$, CFI = 0.998, TLI = 0.996, RMSEA = 0.033 (90% CI [0.020, 0.046]), SRMR = 0.027. The standardized factor loadings were all significant and ranged from 0.378 to 0.994, supporting the convergent validity of the factors.

Generalized Linear Mixed-Effects Models

The GLMER analysis revealed that coping was significantly negatively associated with lapse (Estimate = -0.569, SE = 0.220, z = -2.591, p = 0.009). Suggesting that higher levels of coping are linked to a reduced likelihood of experiencing a lapse. This finding aligns with the bivariate correlations, which showed a significant negative correlation between coping and lapses (correlation = -0.174, $p < 0.05$), confirming that individuals who engage more in coping strategies are less likely to lapse. Other predictors, including craving, negative affect, stress, availability of alcohol, permission to drink, social activities, CVA, movement, and EDA, did not show significant associations with lapses. Despite these predictors having notable bivariate correlations with lapses (e.g., craving: correlation = 0.078; Stress: correlation = 0.090), their effects were not significant in the multivariate context of the GLMER model. This may indicate that the influence of these factors is more complex and possibly mediated by or interacting with other variables. The model fit indices indicated a well-fitted model: AIC = 150.3, BIC = 202.8, and deviance = 126.3. The random effect of participant ID was negligible, indicating minimal between-subject variability in the likelihood of lapses, which suggests that the fixed effects accounted for most of the variance in the outcome.

Figure 4

Fixed Effects of the GLMER Model



Note. Variables are person-mean centred, standardized, and lagged forward by three hours.

Discussion

This study investigated factors predicting lapses in 6 individuals undergoing treatment for AUD during a 100-day period using EMA. By examining various psychological, physiological,

and contextual factors, the research aimed to uncover patterns and interactions that could help predict if timely lagged lapses are likely to occur. Understanding these predictors is crucial for developing more effective treatment strategies that can address the complexities of AUD and support individuals in maintaining long-term sobriety. Thus, analysing covariances provided a deeper understanding of how the co-occurrence or interaction between factors could exacerbate or mitigate the risk of subsequent lapses. Multilevel Modelling and Time-Series Analysis were the preferred methods of exploration. The study thereby attempted to capture how different factors influence each other and, ultimately, the risk of lapsing and to evaluate predictive effects over time and access both predictive effects as well as covariance.

Key Findings

Coping and Lapse

Through a comprehensive analysis, several critical insights emerged, shedding light on both the pathways that contribute to the risk of subsequent lapsing. Whilst both analyses yielded different findings, they converged on key insights. Firstly, both analyses found a significant negative association between the belief in the effectiveness of one´s coping skills and lapses, indicating that individuals who believe in their ability to manage stressors without resorting to alcohol are less likely to lapse. This finding aligns with the social cognitive theory, which emphasizes the importance of self-efficacy in behaviour change (Van Zundert et al., 2009). Enhancing coping skills through therapeutic interventions like Cognitive-Behavioural Therapy (CBT) (Karademas & Thomadakis, 2021) and Motivational Enhancement Therapy (MET) could be an effective strategy for sustaining long-term sobriety by increasing self-efficacy (Miller & Rollnick, 2002; Hemrage et al., 2023).

Craving, Negative Affect, and Lapse

In the following, one must be careful in interpreting the findings of the SEM analysis due to low model fit indices. However, SEM analysis additionally found significant effects of craving, negative affect, the availability of alcohol, and the permission to drink. The positive association between craving and lapse supports the role of craving in the lapsing process, aligning with existing literature that identifies craving as a significant predictor of lapses (Baker et al., 2004; Larimer et al., 1999). Similarly, the link between negative affect and lapses supports the affective processing model of negative reinforcement, which posits that individuals with AUD may use alcohol to mitigate unpleasant emotions (Witkiewitz & Villarroel, 2009). These

findings suggest that interventions aimed at managing cravings and negative emotions could be beneficial in preventing lapsing.

The scatterplots reinforce these findings, showing significant fluctuations in craving and negative affect over time, with individual differences in these experiences. Specifically, the plot of craving over time highlights its episodic nature, indicating that targeted interventions during peak craving times could be beneficial. Similarly, the variability in negative affect suggests that emotional regulation strategies should be personalized (Shiffman & Waters, 2004).

Covariance between Positive Affect and Coping

Additionally, intercorrelations were measured to determine whether some of these variables are related to one another. It was found that positive affect decreased the perceived alcohol use availability and increased coping skills. A possible explanation for this finding could be that positive affect enhances an individual's sense of control and self-efficacy (Bandura & Wessels, 1997), reducing the likelihood of perceiving alcohol as readily available or necessary for coping. This relationship is supported by research indicating that individuals with higher positive affect often experience a greater sense of self-efficacy and control over their behaviours and environment (Labrague et al., 2018; Schwarzer et al., 1997). Furthermore, this relationship may also be bidirectional, as according to the self-determination theory, each successful instance of refraining from alcohol activates the brain's reward system, fostering a sense of empowerment. This heightened sense of well-being, in turn, strengthens the individual's resilience against future lapses (Richards et al., 2020). Thus, as the sample consists of individuals who are in treatment for their AUD, a further explanation could be that they are already trained in the use of their coping skills, and positive emotions reinforce their ability to implement these skills effectively. According to research by Karademas and Thomadakis (2021), individuals with enhanced self-efficacy are more likely to employ effective coping strategies, particularly when experiencing positive emotions.

Covariance between Stress, Perceived Availability and Coping

Moreover, increased stress levels were correlated with increased perceived availability of alcohol and lower coping skills, indicating that individuals felt more inclined to drink and thereby perceived their surroundings in a more alcohol-favourable manner. A possible explanation for this finding might be that some individuals who suffer from AUD may be more likely to perceive alcohol-related cues when in a bad mood (Lindenmeyer, 2022). In line with

this, Brandon et al. (2007) posit that individuals are also less likely to employ their coping skills when they are experiencing high levels of stress, as stress can impair cognitive functions and the ability to access coping strategies. The scatterplot for stress (see Figure 10, Appendix B) further supports this, showing a trend where higher stress levels correspond with lower coping scores, indicating that stress indeed hampers the use of coping strategies. However, this trend could also be interpreted vice versa, as a decline in the belief of one´s coping mechanisms might lead to increased levels of stress and perceived availability of alcohol (Corbin et al., 2013).

Covariance between Perceived Availability and Permission to Drink

Furthermore, increased perceived availability was also correlated with increased permission to drink, social activity, and coping. A possible explanation could be that individuals in social settings where alcohol is present may feel more socially accepted or encouraged to drink, leading to an increased perception of permission to drink. This social acceptance might also create opportunities for practising coping skills, particularly if their treatment includes strategies for managing social pressures and alcohol availability (Marlatt & George, 1984). The scatterplot for the availability of alcohol illustrates this relationship, showing that as alcohol becomes more accessible, permission to drink and social activities also increase, highlighting the complex interplay between environmental and social factors (see Figures 12 & 13, Appendix B).

Implications

Overall, the findings of this research may not fully generalize to broader populations, as both major analyses conducted in this study, the SEM model and the GLMER model yielded different results and obtained low model fit measures as both models were moderate to highly overfitted, leading to inconsistent results. Nonetheless, the results obtained provide a basis for considering implications for the treatment and prevention of AUD. These insights highlight the necessity of personalized interventions, environmental modifications, stress and emotional regulation, comprehensive treatment approaches, Just-in-Time Adaptive Interventions (JITAIs), and policy measures to enhance the efficacy of lapse prevention efforts.

The findings of this research suggest several implications for the treatment and prevention of AUD. Firstly, the significant negative predictive effect of coping skills on lapses underscores the importance of enhancing coping mechanisms in therapeutic interventions (Magill & Ray, 2009; Deas & Thomas, 2001). This finding aligns with the notion that individuals who believe in their ability to manage stressors without resorting to alcohol are less

likely to lapse. Thus, the influence of coping mechanisms and, by extension, self-efficacy continues to be significant over an extended period, rather than being confined solely to the early stages of recovery. While standard therapeutic interventions such as CBT and MET focus on building self-efficacy to sustain initial sobriety (Karademas & Thomadakis, 2021; Miller & Rollnick, 2002; Hemrage et al., 2023), this study reveals that self-efficacy remains a vital protective factor beyond the early stages of recovery. Treatment strategies should be adapted to include continuous support for developing and maintaining self-efficacy, ensuring that individuals are equipped to manage stressors and potential relapse triggers throughout their recovery journey, such as regular booster sessions or therapeutic support aimed at reinforcing coping mechanisms and self-efficacy, thereby reducing the risk of lapses over the extended course of recovery (Marlatt & Donovan, 2005).

Moreover, the less robust, but significant associations found between craving, negative affect, availability of alcohol, and permission to drink with lapses indicate a predictive effect on lapses. The positive association between craving and lapse underscores the pivotal role of craving in the lapsing process, aligning with existing literature that identifies craving as a significant predictor of lapses (Baker et al., 2004; Larimer et al., 1999). Interventions aimed at managing cravings and negative emotions are critical. Emotion regulation strategies that address negative affect may prevent lapses by mitigating the desire to use alcohol as a coping mechanism for unpleasant emotions (Witkiewitz & Villarroel, 2009).

Furthermore, policy measures that regulate alcohol availability and promote alcohol-free environments can be effective in reducing lapsing rates. Public health campaigns that educate about the risks of alcohol and promote sober lifestyles can also contribute to lower lapse rates (DiClemente et al., 2007). Integrating addiction treatment with general healthcare services ensures comprehensive care, addressing co-occurring mental health issues alongside AUD, which can improve overall treatment outcomes (Kelly & Daley, 2013).

Limitations

One significant limitation involves the scope of the factor analysis, which focused solely on the independent variables. The dependent variable, lapses, was intentionally excluded from the EFA and CFA to allow for a clearer understanding of the latent structures among the predictors. While this approach helped to identify potential underlying factors, it also means that the direct relationship between these factors and lapses requires further investigation in future

research by providing a more consolidated view of how these grouped variables interact to influence lapse risk, potentially enhancing the accuracy and efficacy of predictive models for lapses. Integrating these factors into intervention strategies may allow for more targeted and effective approaches to relapse prevention, focusing on the most influential dimensions of behaviour and physiology (Fabrigar et al., 1999).

The study's small sample size (N = 6) presents another limitation, impacting the generalizability of the findings. A small sample size can lead to less reliable results and may not capture the full variability of the population. This limitation underscores the need for larger, more diverse samples in future research to validate and extend these findings (Hackshaw, 2008). Studies with larger sample sizes can provide more robust evidence and improve the generalizability of the results to broader populations.

A further limitation is the reliance on technology for data collection which poses significant challenges. One participant withdrew from the initial study due to difficulties with the technology, highlighting the potential barriers to using advanced data collection methods. Additionally, technological issues impacted the collection of physiological data, with incomplete data in the scatterplots for EDA and movement, and significant gaps in HR data for some participants (see Figures 6-8, Appendix B). Ensuring user-friendly interfaces and providing adequate technical support are crucial for future studies to mitigate these issues (Convery & Cox, 2012; Calear & Christensen, 2010). Improving the usability of technological tools can enhance participant retention, data quality, and the accuracy of physiological measurements.

Moreover, the relatively low occurrence of cravings in the initial study, as well as the zero inflation in the scatterplot of craving over time (see Figure 5, Appendix B) is inconsistent with previous research, which typically reports higher rates of craving among individuals with AUD (Tiffany & Wray, 2012). This discrepancy may have influenced the study's findings, as craving is considered a critical factor in understanding lapse dynamics (Higley et al., 2011). The absence of cravings could also be traced back to a measurement issue in capturing cravings. This would also explain the lack of predictive effects of the physiological predictors, as the absence of predictive effects of physiological markers is contrary to the literature (Iacono et al., 1996). Hence, future research should explore this inconsistency and aim to ensure more representative measurements of craving and physiological data to better understand their role in lapses.

The negligible random effect of participant ID is another noteworthy limitation, indicating minimal between-subject variability in the likelihood of lapses. This suggests that the fixed effects, such as coping and craving, are sufficiently capturing most of the variability in lapses, leaving little room for individual differences. This homogeneity might reflect specific characteristics of the sample, or the nature of the variables measured, raising questions about the generalizability of these findings (Browne & Goldstein, 2010; Snijders & Bosker, 2011). The minimal variability may be a result of the small and homogenous sample size used in this study. Future studies should explore whether this minimal variability is observed in larger, more diverse samples, or if it is specific to this particular group of participants.

One further limitation stemming from the observation of the GLMER analysis is the presence of strong estimates for some physiological predictors, which, despite their apparent strength, were not statistically significant. This highlights a potential limitation of the current model, where certain predictors exhibit strong effects that might not be reliable. This discrepancy underscores the importance of interpreting these results with caution and suggests that further research with a larger sample size or different model specifications may be necessary to confirm these effects (Gelman, 2007).

Lastly, the SEM analysis revealed low model fit indices, indicating that the model may not adequately represent the underlying data structure. Poor model fit suggests that the relationships between variables might not be accurately captured, potentially leading to biased estimates and conclusions, such as model misspecification, longitudinal measurement invariance and possible confounders (Hooper, Coughlan, & Mullen, 2008). Future studies should refine the model and consider alternative statistical approaches to improve model fit and ensure more reliable results.

Strengths

Despite the massive limitations, the research possessed several strengths. First, the study collected a substantial amount of data over a 100-day period, with measurements taken every three hours. This extensive data collection provides a rich dataset, allowing for detailed analyses and more nuanced insights into the patterns and predictors of lapses. The high frequency of data points enhances the ability to detect subtle changes and trends over time, which is crucial for understanding the dynamics of lapses (Csikszentmihalyi & Larson, 2014).

Moreover, the study incorporated a wide range of variables, including physiological, psychological, and contextual factors. This comprehensive approach enables a holistic analysis of the lapsing process, capturing the complexity and multifaceted nature of AUD. The inclusion of diverse variables allows for a more detailed examination of how different factors interact and contribute to lapses (Bickel & Marsch, 2001).

Thus, by integrating several physiological, psychological, and contextual factors, over time, the study provides a holistic view of the lapsing process. This integrative approach contributes to a deeper understanding of the multifaceted nature of AUD and highlights the importance of considering multiple dimensions in treatment and prevention efforts (Halvorson et al., 2022).

Overall, the use of ESM and wearable biosensors enabled the capture of real-time data in naturalistic settings for an extended period. This methodological strength enhances the ecological validity of the findings, as it allows for the assessment of participants' experiences and physiological states in their everyday environments. Real-time data capture reduces recall bias and provides a more accurate representation of the factors influencing lapses (Shiffman, Stone, & Hufford, 2008).

The study's focus on individual variability in the lapsing process aligns with contemporary perspectives on addiction treatment, which emphasize the need for personalized interventions. By highlighting individual differences, the study underscores the importance of tailoring treatment plans to the specific needs and circumstances of each person with AUD. This personalized approach can improve treatment outcomes and support sustained recovery (McKay, 2009).

Lastly, the intensive repeated measures design, conducted in naturalistic settings, allows for the examination of time variations and the impact of different times of the day and days of the week on the risk of lapsing. This design provides valuable insights into temporal patterns and can inform the timing of interventions to maximize their effectiveness (Bolger & Laurenceau, 2013).

Directions for Future Research

The current study has provided valuable insights into the multifaceted nature of AUD and its treatment. However, there are several areas where future research could further enhance our understanding and effectiveness of interventions.

One promising direction for future research is the development and implementation of Just in Time Early Interventions (JITAIs). They utilize real-time data to provide timely and personalized interventions that can effectively address lapse triggers as they occur. By leveraging mobile health technologies and wearable sensors, JITAIs can dynamically adapt to the changing needs and contexts of individuals with AUD. This approach has the potential to significantly improve treatment outcomes by offering immediate support during critical moments (Nahum-Shani et al., 2017; Heron & Smyth, 2010). Given the findings of this study, JITAIs could be particularly effective in targeting periods of low belief in the effectiveness of one´s coping mechanisms. For instance, the scatterplots showing coping over time suggest that this factor is episodic and varies greatly between individuals (see Figure 14, Appendix B). JITAIs could provide personalized interventions during times or moments of low coping, thereby helping to prevent lapses. Research supports the efficacy of JITAIs in managing coping as well as cravings and negative affect through real-time data collection and intervention, as evidenced in studies of other substance use disorders (Carpenter et al., 2020; Frumkin et al., 2021).

Additionally, JITAIs could integrate strategies to manage environmental factors, such as the perceived availability of alcohol. Real-time data could be used to monitor an individual's exposure to alcohol-related cues and deliver interventions that promote coping strategies and reduce permission to drink. The integration of coping strategies and real-time support could help individuals manage stress and negative emotions more effectively, reducing the likelihood of lapses (Shiffman et al., 2014). The dynamic tailoring of interventions based on immediate data allows for a more responsive and effective approach to addiction treatment (Nahum-Shani et al., 2017; Bolger & Laurenceau, 2013).

Moreover, while the associations found between craving, negative affect, availability of alcohol, and permission to drink with lapses were significant, they were less robust compared to other factors. This suggests that the predictive effect of these variables on lapses might vary over time. For instance, negative affect might play a more critical role in the early stages of recovery but may lose its influence as time progresses (Marlatt & Donovan, 2005). Yet, since this study did not specifically investigate time-varying effects, this remains an area for future research. Future studies could explore how these predictors' influence on lapses evolves over different phases of recovery, providing a more nuanced understanding of the lapsing process (Shiffmann & Waters, 2004; Witkiewitz & Marlatt, 2007).

Given the limitations of the small sample size in the current study, future research should aim to include larger and more diverse populations. Longitudinal studies with extended follow-up periods can provide more robust and generalizable findings. These studies should also consider the inclusion of diverse demographic groups to better understand the variability in lapse dynamics and treatment responses across different populations (Creswell, 2013), enhancing the external validity of the findings and supporting the development of tailored interventions for various subgroups within the AUD population (Kazdin, 2022).

To address the limitation of unaccounted autocorrelation in the current study, future research should incorporate advanced statistical methods that correct for autoregressive processes. Techniques such as time-series analysis and hierarchical linear modelling with autoregressive terms can provide more accurate estimates of the relationships between variables over time (Jebb et al., 2015; Faraway, 2016). By accounting for the temporal dependencies in the data, these methods will help in understanding the true predictive effects of various factors on lapses.

Given the technological challenges encountered in the current study, future research should focus on evaluating the usability of digital tools and their impact on participant engagement. User-centred design approaches can be employed to develop more intuitive and user-friendly interfaces for data collection devices. Additionally, studies should investigate the factors that influence participant retention and adherence to technology-based interventions, aiming to enhance the overall experience and effectiveness of digital health solutions (Baker et al., 2014; Calear & Christensen, 2010).

Additionally, integrating Time-Varying Effect Modelling (TVEM) could address the temporal complexities of the variables researched here. TVEM models non-linear and non-parametric changes over time, offering a more flexible and precise analysis of how these relationships change throughout an individual's treatment or recovery process (Stull et al., 2023). This approach could lead to a better understanding of recovery dynamics, which would help to improve treatment strategies by matching the changing needs of individuals with AUD.

Conclusion

This study examined factors predicting lapses in six individuals undergoing treatment for AUD over a 100-day period using EMA. The primary objective was to identify which continuously measured factors predicted lapses over time and how these variables covary with

each other. Multilevel modelling and time-series analysis were employed to assess both predictive and interactive effects. The results revealed a significant negative association between the belief in the effectiveness of one's coping skills and lapses, indicating that self-efficacy plays a crucial role in lapse prevention. SEM analysis highlighted the significant effects of craving, negative affect, the availability of alcohol, and the permission to drink on lapses, aligning with existing literature that emphasizes the importance of these factors in the lapsing process (Baker et al., 2004; Witkiewitz & Villarroel, 2009). Intercorrelations showed that positive affect, coping skills, and the perceived availability of alcohol, are correlated suggesting that they influence one another in the context of long-term AUD recovery. Despite these findings, the study faced limitations including small sample size, technological challenges, and low model fit indices, impacting the generalizability and consistency of the results. Future research should incorporate larger samples, advanced statistical methods like TVEM and the development of JITAIs to address these limitations and further enhance the understanding and treatment of AUD. Overall, this study underscores the necessity for personalized interventions, environmental modifications, and real-time adaptive support to effectively prevent lapses and support long-term sobriety in individuals with AUD.

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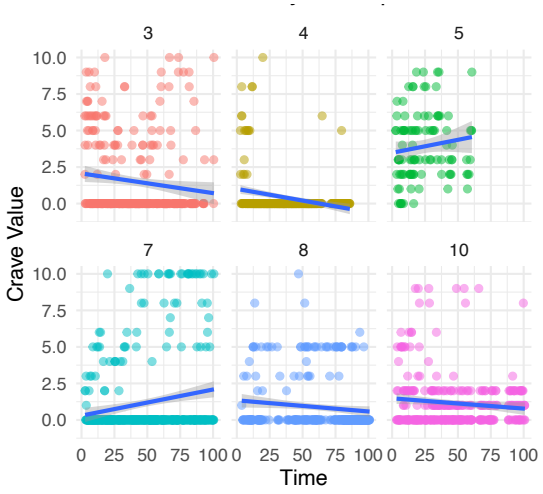
Appendix A: Use of Artificial Intelligence Statement

During the preparation of this work, the author used the tools ChatGPT and Grammarly to refine codes for statistical analyses and for copy-editing, including minor revisions for conciseness and clarity of writing. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

Appendix B: Development over Time of each Variable and Participant

Figure 5

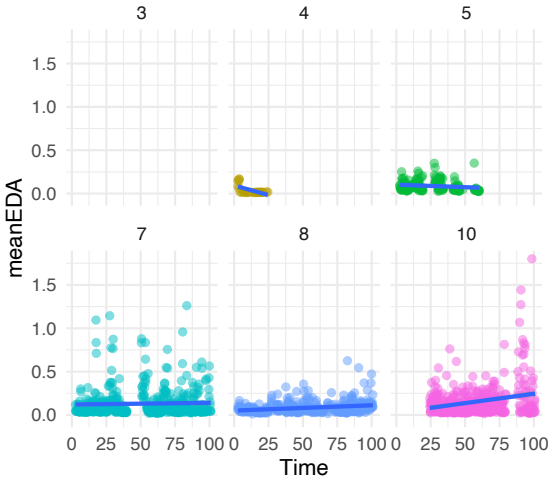
Scatterplot of Level of Craving and Mean Craving over time for each Participant



Note. Slopes generated in means per day. Raw craving score. Shaded areas around the regression line represent the standard error.

Figure 6

Electrodermal Activity over Time by Participant



Note. Slopes generated in means per day. Raw EDA score. Shaded areas around the regression line represent the standard error.

Figure 7

Cardiovascular Activity over Time by Participant

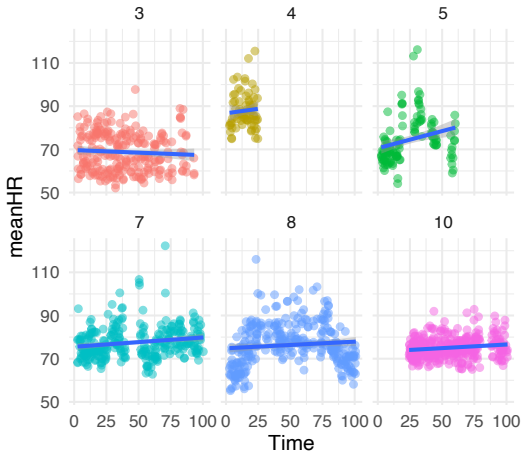
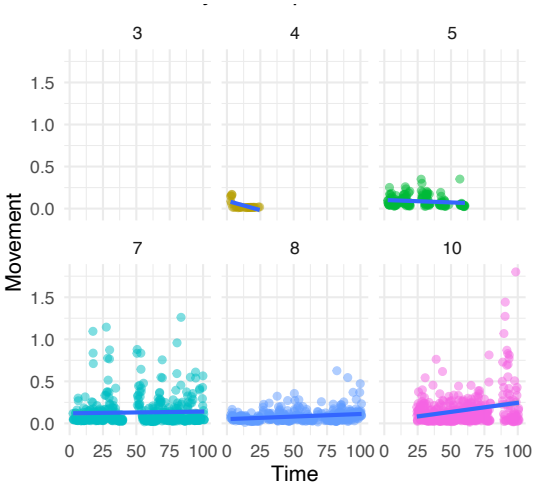


Figure 8

Movement over Time by Participant

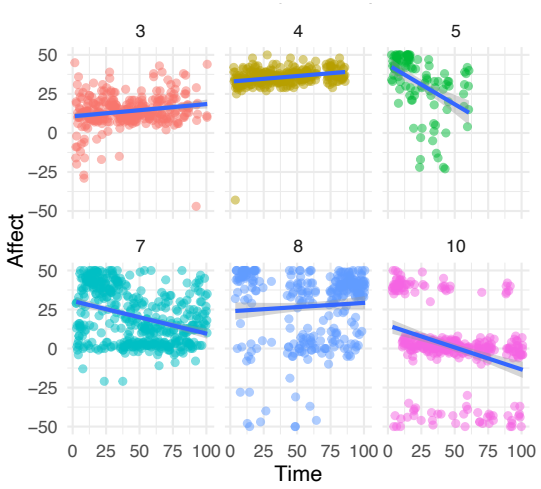


Note. Slopes generated in means per day. Raw movement score. Shaded areas around the regression line represent the standard error.

Note. Slopes generated in means per day. Raw CVA score. Shaded areas around the regression line represent the standard error.

Figure 9

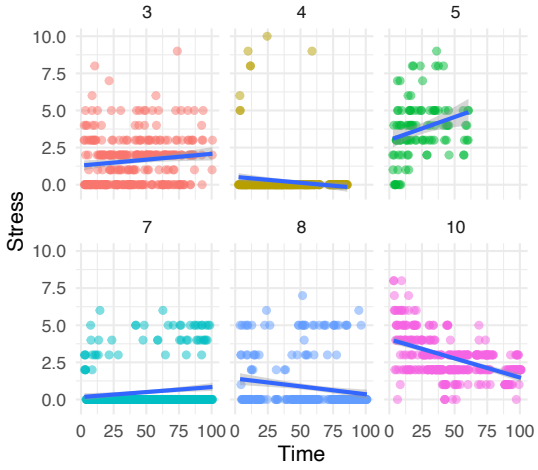
Negative Affect over Time by Participant



Note. Slopes generated in means per day. Raw negative affect score. Shaded areas around the regression line represent the standard error.

Figure 10

Stress over Time by Each Participant



Note. Slopes generated in means per Ddy. Raw stress score. Shaded areas around the regression line represent the standard error.

Figure 11

Social Activity over Time by Participant

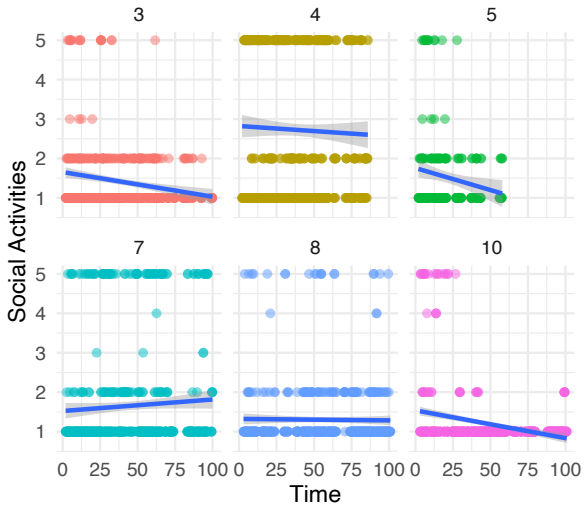
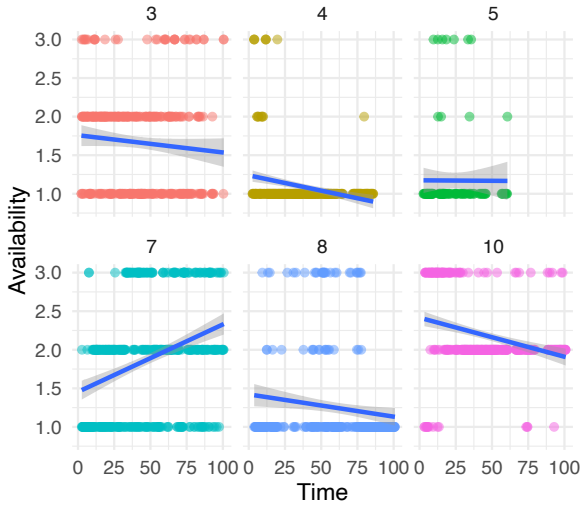


Figure 12

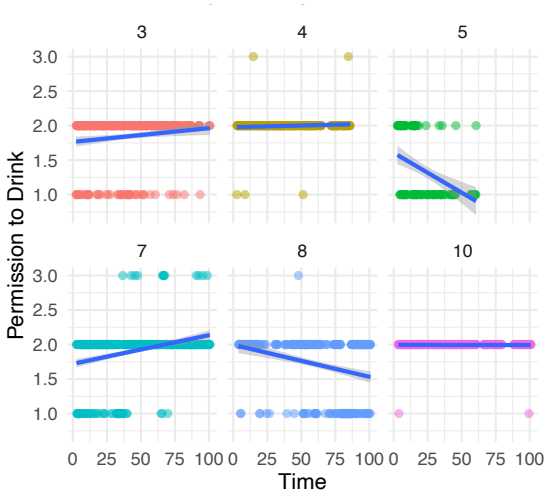
Availability of Alcohol over Time by Participant



Note. Slopes generated in means per day. Raw social activity score. Shaded areas around the regression line represent the standard error.

Figure 13

Permission to Drink over Time by Each Participant

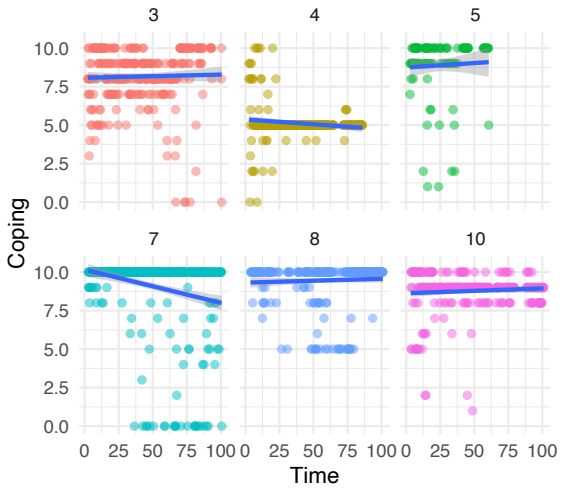


Note. Slopes generated in means per day. Raw perceived permission to drink score. Shaded areas around the regression line represent the standard error.

Note. Slopes generated in means per day. Raw perceived availability of alcohol score. Shaded areas around the regression line represent the standard error.

Figure 14

Belief in the Effectiveness of one's own Coping Skills over Time by each Participant



Note. Slopes generated in means per day. Raw belief in the effectiveness of own coping skills score. Shaded areas around the regression line represent the standard error.

Appendix C: Covariances

Table 2

Covariances Between Variables (N = 6)

		Estimate	SE	z-value	P(>|z|)
Craving	Mood	-0.037	0.041	-0.899	0.369
Mood	Stress	0.349	0.036	9.725	0.000
Mood	Availability	0.193	0.033	5.761	0.000
Stress	Availability	-0.416	0.032	-13.129	0.000
Stress	Permission	-0.359	0.044	-8.161	0.000
Availability	Permission	0.052	0.039	1.326	0.185
Availability	Coping	-0.225	0.029	-7.772	0.000
Availability	Social	-0.102	0.033	-3.043	0.002
Permission	Coping	-0.196	0.029	-6.722	0.000
Permission	Social	0.091	0.038	2.388	0.017
Coping	Social	-0.182	0.033	-5.457	0.000
Coping	Lapse	0.105	0.036	2.965	0.003
Social	Lapse	-0.197	0.031	-6.403	0.000
Craving	Mood	-0.037	0.041	-0.899	0.369
Mood	Stress	0.349	0.036	9.725	0.000
Mood	Availability	0.193	0.033	5.761	0.000

Note. P-values > 0.05 are considered significant.