# Ecological Momentary Assessment and Personalized Networks in Cognitive Bias Modification Studies on Addiction: Advances and Challenges

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**Abstract**

Adding cognitive bias modification (CBM) to treatment as usual for alcohol use disorders has been found to reduce relapse rates. However, CBM has not yielded effects as a stand-alone intervention. One possible reason may be that this is due to CBM effects being underpinned by inferential rather than associative mental mechanisms. This change in perspective has led to a proposed improved version of CBM: Inference-based ABC training. In ABC training, participants learn to relate the antecedents (A) of their addiction behavior to alternative behaviors (B) and to their expected consequences (C) in relation to their long-term goals. Mechanisms triggering and maintaining addiction, such as those targeted during ABC training, can differ between people. Ecological Momentary Assessment (EMA) and derived personalized statistics, including models depicting relationships between variables (i.e., personalized networks), are therefore promising tools to help to optimally personalize this training. In this paper, we (1) explain the theoretical background and first implementations of ABC training; (2) present novel approaches to personalize treatment based on EMA; (3) propose ways forward to integrate improved CBM approaches and EMA to potentially advance addiction treatment; and (4) discuss promises and challenges of these proposed new approaches.

*Keywords:* Cognitive Bias Modification, ABC training, Ecological Momentary Assessment, Personalized Network, Addiction

In this paper, we discuss the current state of affairs of Cognitive Bias Modification (CBM) in addiction in relation to the network theory of psychopathology and intense time-series measurements or Ecological Momentary Assessment (EMA). We argue that EMA may help in personalizing new varieties of CBM that are based on recent insights regarding the cognitive mechanisms underlying the effects of CBM. We exemplify this approach in reference to inference-based ABC training, a novel intervention in which participants see relevant antecedent contexts ("As") and train behavioral alternatives to addictive behaviors ("Bs") in light of the expected consequences ("Cs") that are instrumental to their goals.

## Cognitive Bias Modification in Addiction

Cognitive bias modification (CBM) refers to varieties of computerized training paradigms that aim to alter cognitive biases that may play a role in maintaining addictive behaviors. Cognitive biases in addiction are specific inclinations in the cognitive processing of addiction-related cues and are typically assessed with computerized tasks in which responses to addiction-related versus control-stimuli are compared. Several biases have been distinguished for addiction-related stimuli, including attentional biases, memory biases, and biased action tendencies or “approach biases” (for a review see R. W. Wiers et al., 2013; in press). In the years following the seminal work in anxiety (MacLeod et al., 2002; Mathews & Mackintosh, 2000), first attempts were made to change cognitive biases in addiction, including attentional biases (Field & Eastwood, 2005; T. Schoenmakers et al., 2007), approach biases (e.g., R. W. Wiers et al., 2010) and memory biases (e.g., Houben et al., 2010, 2011).

It is important to note that all these early studies were designed as experimental psychopathology (EPP) studies; that is to say, their primary purpose was to test the causal role of a putative construct (the cognitive bias) by manipulating it in healthy volunteers, in order to examine effects on disorder-relevant behaviors. In the field of addiction, for example, this behavior involved craving for a drink or the amount of alcohol consumed during a taste-test directly after the manipulation. These studies concern the first stage of the experimental medicine approach to intervention development: to test the causal status of (mental) constructs related to the disorder-related behavior. Note that, once the first stage is successfully completed, the interventions can be tested in clinical samples, which constitutes the next stage of intervention development (Sheeran et al., 2017).

Importantly, in the first EPP studies, the intervention typically involved healthy volunteers being trained in two directions, to either temporarily increase the bias toward alcohol stimuli or to temporarily decrease the bias, to study effects on disorder-related behaviors (craving, drinking). In later randomized controlled trials (RCTs) in clinical samples, clients were randomized over an experimental condition targeting a decrease in the bias or a control condition. The control condition was either sham-training in the form of continued assessment, no training, or a sham-training thought to have little or no effects on the bias under investigation (e.g., Schoenmakers et al., 2010; R. W. Wiers et al., 2011).

This essential distinction between two different types of studies was not considered in the first meta-analysis of CBM in addiction (Cristea et al., 2016), which combined many EPP studies with the few first clinical RCTs and concluded that CBM may change the targeted cognitive bias, but has no clinical effects (although finding clinical effects was not aimed for in the large majority of included EPP studies in healthy volunteers, see R. W. Wiers et al., 2018). In the EPP-studies, healthy volunteers were included (typically college students), who had no intention to change their drinking behavior, but who participated for course credit, reward and/or free beer (often a taste-test including alcoholic and non-alcoholic drinks was used in which alcohol consumption was measured as a dependent variable, e.g., Field et al., 2007; Schoenmakers et al., 2007 for attentional bias and R. W. Wiers et al., 2010 for approach bias). In these studies, the purpose was to examine the effects of a successful manipulation of the bias for alcohol (either temporarily increased or decreased) on drinking behavior (do people who are trained away from alcohol drink less than people trained toward alcohol). Hence, no clinical outcomes were included, as this is not the aim of the first stage of intervention development (which is establishing the causal relationship). Therefore, studies of these different phases of intervention development should not be combined in a meta-analysis (see Sheeran et al., 2017 and R.W. Wiers et al., 2018 for the elaborate argument).

A later meta-analysis did make this crucial distinction in studies of different phases of intervention development and included only clinical studies of CBM (where participants had the goal to reduce or stop the addictive behavior). This meta-analysis found both an effect of CBM on the targeted bias and on abstinence, but not on other alcohol use measures (Boffo et al., 2019). This may seem contradictory at first sight, but it is related to different treatment goals and related outcomes: In clinical RCTs with inpatients, the treatment goal is almost invariably abstinence, and the related outcome duration of abstinence (e.g., Schoenmakers et al., 2010) or percentage of patients who have remained abstinent one year after treatment discharge (e.g., R.W. Wiers et al., 2011; Eberl et al., 2013; Rinck et al., 2018; Salemink et al., 2021). In studies with outpatients (e.g., Heitmann et al., 2021) or online volunteers who wish to change their drinking, the goal is often to reduce rather than to quit drinking (e.g., Jones et al, 2018; R.W. Wiers et al., 2015), and in these studies, reduction in use is the logical outcome measure (for which no effect was found).

Since then, several large clinical RCTs have found that CBM reduces likelihood of relapse when added to treatment (defined as either remaining abstinent or resuming use). These reductions in relapse rates one year after treatment discharge ranged from 4 to 13% (Eberl et al., 2013; Manning et al., 2022; Rinck et al., 2018; Salemink et al., 2021; R. W. Wiers et al., 2011). Note that all these studies tested add-on effects of changing approach bias for alcohol, and the Rinck et al. (2018) paper also tested effects of attentional retraining, which produced a similar effect-size. The Manning et al. (2022) study, which found the lowest reduction in relapse rates, differed in two respects compared to papers that found a stronger effect on relapse rates (8-13% reduction, Eberl et al., 2013; Rinck et al., 2018; Salemink et al., 2021; R. W. Wiers et al., 2011): Training was done during detox (in all other studies after detox) and a 90% training regime was used throughout the training (hence, patients were trained to push away most alcohol stimuli, but there were still catch trials in which alcohol was pulled), while in all other studies each training session started with a brief assessment block (50-50, pushing and pulling alcohol), followed by a 100% pushing alcohol block, in the experimental condition.

Notably, the small but clinically significant reduction in relapse rates of about 8-10% one year after treatment discharge has been observed only for on-site CBM (e.g., in the clinic), as add-on to regular abstinence-oriented treatment. However, several studies found no differential effect for stand-alone versions of CBM in online interventions aimed at reduced use (Jones et al., 2018; Van Deursen, 2019; R. W. Wiers et al., 2015). It is as yet unclear to what extent the consistent negative findings for online interventions are related to the different goals of the participants compared to on-site CBM (reduced use vs. abstinence) or to the lack of a therapeutic context (and possibly related positive expectations of treatment outcome). Interestingly, there is one study in which an effect was found in an online intervention in the context of smoking cessation which verified that participants indeed made a quit attempt before they were allowed to do the training (Elfeddali et al., 2016), and found improved abstinence in heavy smokers. This suggests that an abstinence goal might be necessary for clinical effects of CBM. There is also one study that did not find the now often-replicated add-on effect of CBM to the treatment of addiction (Heitmann et al., 2021). This result could be related to (1) heterogeneity in the treatment goals of these participants with some participants aiming for reduction and others for abstinence, (2) heterogeneity in the involved substances (alcohol and cannabis), (3) the fact that a gamified version of attentional retraining was used. Also note that in the largest RCT including attentional retraining as add-on to the clinical treatment of AUD, this did yield a convincing effect of a 12% reduction in relapse compared with sham-training (Rinck et al., 2018, see Supplements Table 1). To conclude, the bigger picture is that CBM has been found to improve treatment outcomes rather consistently when added to clinical treatment but not as a stand-alone online intervention. We now turn to current insights about the (neuro-) cognitive mechanisms underlying CBM effects.

## (Neuro-) Cognitive Mechanisms Underlying CBM

Over the past decade, there has been much discussion about the (neuro-) cognitive mechanisms of CBM. First, studies were conducted to explain CBM effects at the neuro-cognitive level. These studies implied that reduction in neural reactivity (e.g., cue-evoked activity in the medial prefrontal cortex and amygdala) may be a key factor underlying the therapeutic effectiveness of CBM training (Martínez-Maldonado et al., 2020; C. E. Wiers, Ludwig, et al., 2015; C. E. Wiers, Stelzel, et al., 2015). One interesting finding was that amygdala cue-reactivity decreased for alcohol pictures after training, but also that cue-reactivity to non-alcoholic alternatives increased and this was correlated with a decrease in subjective craving for alcohol (C. E. Wiers, Stelzel, et al., 2015). A review that involved 13 studies on CBM and neuroimaging concluded that CBM has the potential to change certain neuropathological mechanisms, especially in the fronto-amygdalar system (for details see C. E. Wiers & Wiers, 2017). In line with the aim of the current paper, we will now shift our focus from explanations of CBM effects at the neural level to the underlying mental mechanisms.

CBM procedures have originally been developed in reference to dual-process theories, which argue that healthy behaviors typically result from goal-directed, belief-based processes whereas harmful (addictive) behaviors may result from the automatic activation of associations between representations in memory (Stacy & Wiers, 2010; R. W. Wiers et al., 2013). From this perspective, when coming into contact with an addictive stimulus, in real life or in memory, activation may spread from stimulus representations to representations of a frequent response to the stimulus such that the stimulus may come to evoke this response. CBM procedures therefore typically target change in this associative network. They utilize conditioning procedures (i.e., procedures that involve repeated pairings) because associations are often assumed to form gradually as the result of frequent pairings (e.g., of a stimulus and a response) (Stacy & Wiers, 2010). For instance, Approach Bias Modification is a CBM procedure that involves the repeated pairing of an addictive stimulus with a(n) (avoidance) response that contrasts with the typical addictive (approach) response.

The efficacy of CBM procedures was ordinarily explained in reference to this associative mechanism. Specifically, by utilizing conditioning techniques, CBM procedures might add new associations to the associative network that replace harmful stimulus-response associations (e.g., Foa & Kozak, 1986) or simply overrule them (Bouton, 2004). In turn, this associative change may promote a reduction in addictive responses to the stimulus.

Notably, recent studies found results in healthy volunteers that do not fit well with these associative explanations of conditioning procedures. First, a recent review of studies in which conditioning procedures in general were used, concluded that there is no good evidence that associative processes underlie conditioning effects (Corneille & Stahl, 2019). Second, a review of studies that tested specific assumptions of associative theories of conditioning effects in the context of approach bias modification (ApBM) procedures concluded that these theories are ill-supported by the bulk of the evidence (Van Dessel et al., 2019). For instance, these theories generally assume that repeated pairings of stimuli and (approach/avoidance) responses directly change mental associations that should translate into stimulus-dependent evaluative behavior. Yet, even in the context of neutral stimuli, ApBM does not always lead to behavioral changes or may even lead to reversed changes (Mertens et al., 2018; Vandenbosch & De Houwer, 2011).

Similarly, as mentioned above, CBM as an add-on training to clinical treatment has a small (and consistent) effect, but does not yield significant improvements as stand-alone training among healthy volunteers (for a review, see R. W. Wiers et al., 2018). This difference also contrasts with assumptions of associative theories of CBM that assume that the CBM procedures directly change mental associations that translate into addictive behavior. Of course, it is important to note that this does not provide definitive evidence against associative explanations, as some associative theories might also incorporate the possibility that specific (e.g., motivational) moderators determine association formation. Studies might be needed that more directly test assumptions of associative theories in the context of (clinical) addiction.

As noted above, associative theorizing in CBM is based on the idea that addictive behavior depends on automatic processes that are independent of personal beliefs or goals (Stacy & Wiers, 2010). This idea accords with the observation that addictive behavior may emerge even when a person reports beliefs or goals that contrast with this behavior (e.g., a smoker may indicate they know that smoking is unhealthy and want to quit smoking). Yet, it is important to realize that this observation does not prove that goal- or belief-independent processes underlie this behavior (Moors et al., 2017). While engaging in addictive behavior may not fit with certain goals and beliefs, it may be a function of other beliefs and goals that may drive behavior in a specific context. For instance, a person who indicates that they want to quit smoking may still smoke when feeling stressed if they expect that this behavior may have the (short-term) benefit to relieve stress. Similarly, this behavior may fit with the goal to reduce entropy or disorder in the mental system (see Parr et al., 2022, for more elaborate explanation in reference to predictive coding principles).

Per these ideas, in recent years, it has been argued that all behaviors (except reflexes), including habitual behavior, are mediated by goal-directed and context-dependent inferential processes (Van Dessel et al., 2022). From this perspective, the mental system supports propositional representations and is geared to make (automatic) inferences (i.e., to activate propositional information based on its compatibility with other propositional information). These inferences are goal-directed (i.e., evoked by the contextual activation of a wanted outcome) and directly underlie behavior. In this inferential account, (addictive) behavior is goal-driven and sensitive to changes in goal properties (inferences about reward contingencies; Kruglanski & Szumowska, 2020; Moors et al., 2017) instead of being driven by mere automatic stimulus-response compulsive mental associations as suggested by associative accounts (Hogarth, 2020). Specifically, addictive behavior may result from the contextual activation of representations of wanted outcomes (goals) and consequent (automatic) inferences. For instance, an activated goal (e.g., to reduce stress) may evoke inferences about the actions available in this context to achieve this goal and an inferred match between an (addictive) action and the wanted outcome may translate into this behavior. In accordance with recent theorizing in cognitive science (e.g., in the context of predictive processing theories: Parr et al., 2022), these inferences may be automatic (e.g., they are evoked in the absence of awareness) and occur in reference to a person's network of beliefs that have been established throughout their life.

This inferential perspective on addiction has recently been applied to explain CBM effects. From this perspective, CBM effects depend on the extent to which participants learn to apply relevant inferences during the training (e.g., they learn to infer that they want to and can avoid substance use by repetitively avoiding the substance). In accordance, recent studies have established that ApBM effects are moderated by factors that should impact inferential (but not associative) processes. For instance, effects depend on beliefs about the implications of learned relations (Van Dessel et al., 2019), the verbal instruction used in the training (Van Dessel et al., 2015), and awareness of stimulus-action contingencies (Van Dessel et al., 2016, 2020). While these studies involved social stimuli such as faces rather than addictive stimuli, these findings support inferential explanations of CBM procedures in general which may extend to addictive stimuli. Results of recent ApBM studies that included addictive (alcohol-related or food-related) stimuli and that pitted predictions of associative and inferential theories against one another also support these findings (Van Dessel et al., 2018; 2023; see below).

According to the inferential account, CBM can be effective for addiction when it leads to changes in the addiction-related inferences people make. Specifically, during CBM people may practice inferences about the contingencies between stimuli (e.g., alcohol), responses (e.g., avoidance), and outcomes (e.g., positive effects). Under specific circumstances, these practiced inferences may generalize to other contexts and consequently influence addictive behavior. This contrasts with an associative explanation according to which CBM replaces one association (e.g., alcohol-approach) with another association (e.g., alcohol-avoid).

In this sense, CBM interventions might be more effective if they are designed to more directly target (the automatization of) inferences that can transfer to real-life. A key assumption of the inferential account is that inferences that underlie (addictive) behavior are activated in reference to goals. From this perspective, it was argued that including relevant consequences in ApBM should improve effectiveness. In accordance, a training to consistently avoid unhealthy foods (typical ApBM) proved less effective than a training in which participants were free to make approach or avoidance actions to unhealthy foods, but that included health-related consequences to foster the inference that approaching unhealthy foods has unwanted consequences (Van Dessel et al., 2018). While the approach to target the automatic application of propositional information (i.e., to target automatic inferences) in risk situations is novel, it fits well with dominant (cognitive behavioral) therapy approaches in which change in beliefs (i.e., propositional information) is targeted, and with recent theories that have specified in detail how automatic inferential processes can be targeted (e.g., in reference to fundamental biological principles such as entropy reduction and the maintenance of homeostasis: Friston, 2010; Parr et al., 2022). This new perspective on CBM might therefore provide important insights to implement more effective CBM procedures that suit a broader population (e.g., problematic drinkers outside of the clinical setting), which will be discussed in the next section.

## Improvements of Current CBM

ABC training is a novel type of CBM that has been proposed on the basis of emerging insights into the cognitive underpinnings of CBM effects, and specifically of approach bias modification (ApBM, R. W. Wiers et al., 2020). As described above, the inferential account is better supported by the evidence from previous studies (compared with the associative account) and postulates that ApBM functions by evoking (repeated) inferences about the contingencies between stimuli (e.g., substance cue), responses (e.g., avoidance), and outcomes (e.g., positive consequences) that may foster a reduction in addictive behaviors (Van Dessel et al., 2019; R. W. Wiers et al., 2020).

From this perspective, three adaptations have been put forward in ABC training, that is, to include personally relevant As, Bs, and Cs. A stands for “antecedent”, meaning the personally relevant contextual cues that can trigger or activate addictive behaviors. B stands for alternative “behaviors” that might take the place of addictive behaviors. Finally, C stands for relevant “consequences” of the behavioral choices which should be associated with the goals of the participants/patients. Thus, ABC training targets inferential learning by training alternative behaviors (e.g., going for a walk) in reference to relevant consequences (e.g., relaxing after work) in personally relevant risk situations (e.g., when feeling stressed).

Recent studies have provided initial evidence for the potential effectiveness of the three adaptations in ABC training. First, Köpetz et al. (2017) found that providing personalized alternative behaviors can improve the effectiveness of CBM in smokers. When behavioral alternatives were personalized in compliance with personal goals (e.g., jogging to reduce stress), an increase was shown in the accessibility of the alternative activity relative to smoking, with a lexical decision task. Similar results were found in a follow-up study (Wen et al., 2021). This is important, because previous CBM studies in smoking used visually matched control pictures (e.g., a picture of a hand holding a pen rather than a cigarette), which is not motivationally relevant (unless somebody wants to write in situations where they would typically smoke). Related, the fact that the most consistent findings of add-on effects of ApBM are as an add-on to the treatment of AUD, may be because the non-alcoholic drinks used as contrast category are universally relevant: When you don't want to drink alcohol, a non-alcoholic drink is often a good alternative.

Second, presenting the consequences of behavioral choices in CBM can also improve its effectiveness. As explained above, a recent study found that showing the consequences of healthy eating in CBM improved CBM outcomes compared to regular CBM without consequences (Van Dessel et al., 2018). Note that this relevance of consequences for ApBM effects might explain the different effects of clinical RCTs (where the consequences of drinking and abstinence are highlighted) and EPP studies in healthy volunteers (where the goal-driven processes are normally masked or not highlighted), in addition to the earlier highlighted differences (participants are healthy volunteers not participating with the goal to change behavior). Third and finally, the study by Van Dessel et al. (2018) also involved participants completing the ApBM task in a simulated real-life context (which also improved

CBM effects), highlighting the importance of providing personalized and real-life antecedent cues. There are also two as-yet unpublished studies that integrated the A, B and C, and found improved effectiveness of this ABC training compared with CBM. In one study in healthy volunteers partaking in an alcohol abstinence challenge, participants who received ABC training showed higher odds to stay abstinent during the challenge (Pan et al., 2022). In another (online) study with volunteers with self-reported hazardous alcohol drinking, participants who received ABC training showed more beneficial changes in outcome expectancies of drinking alcohol (Van Dessel et al., 2023).

Importantly, the ABC training that is currently under investigation is a very preliminary type of training that is still highly generic. For instance, the training only involves a couple of contexts, behavioral choices, and virtual consequences to choose from and is implemented in an environment with a basic avatar. This approach is probably sub-optimal given that, in inferential theorizing, behavior change requires targeting relevant inferences within a person's individual network of beliefs (Van Dessel et al., 2022). State-of-the-art approaches and technologies might be introduced to further improve the efficacy of ABC training (or other types of CBM), for example, by implementing training in a virtual reality (VR) setting to improve the immersiveness and reduce boredom. Note that while ABC-training is a novel variety of CBM, it is closely related to CBT and to implementation intentions and related methods (e.g., Oettingen, 2012), but the major difference is that ABC-training, like other forms of CBM, involves systematic computerized training that targets the automatization of relevant inferences. New methodological approaches like personalized networks (which can investigate complex interactions triggering and maintaining addiction behavior) and ecological momentary assessment (EMA, discussed next) can also be adopted to investigate the antecedents and consequences of addictive behavior, to improve (and personalize) CBM and to investigate the effects of CBM.

## EMA, Personalized Feedback and Personalized Networks in Addiction

According to the network theory of psychopathology, mental disorders are caused and maintained by the complex dynamic interactions between psychological symptoms, social, behavioral, cognitive, affective, and environmental factors (Borsboom, 2017). Addiction is no exception, as addiction symptoms interact with symptoms from other disorders, for example, depressive and anxious symptomatology may increase substance use and in turn be increased by it, potentially giving rise to self-maintaining feedback loops. Interaction with different people, environments, and situations, can also influence substance craving and substance use both directly and through their interaction with psychological symptoms. Thus, different factors may interact in a complex fashion to trigger and maintain addiction. Such complex interactions can be estimated using network analysis, which results in networks graphing the relationships between different variables while controlling for all other variables in the model. Between-subjects networks estimated from cross-sectional data have been recently applied to addiction (Anker et al., 2017; Huth et al., 2022; Kroon et al., 2023; Rhemtulla et al., 2016). For example, an exploratory network analysis of cannabis use disorder (CUD) symptoms in women suggested that a mood disorder was associated with experiencing cannabis craving and withdrawal, which in turn was associated with experiencing other CUD symptoms such as failing to reduce or quit use (Kroon et al., 2023).

Despite its value, cross-sectional network analysis is unable to (1) capture the within-subject relationships between substance use and possible influencing factors over time and (2) estimate individual differences in addiction mechanisms. For example, with between-subject networks we can investigate whether, on average, people who are more likely to feel socially anxious are also more likely to drink alcohol to cope; however, we cannot investigate whether in a specific client social anxiety is a predictor of drinking in their daily life, or whether a different factor such as depressed mood is most relevant. Since addiction is characterized by heterogeneity in triggering and maintaining factors (Carroll, 2021; Litten et al., 2015; Volkow, 2020), understanding personalized mechanisms is a promising approach to improving treatment. However, modeling personalized mechanisms over time requires intensive time-series data. These data can be collected through ecological momentary assessment (EMA; Shiffman et al., 2008), also called experience sampling method (ESM). With EMA, clients are asked to answer questions, for example on substance use, psychological symptoms, and other factors, possibly multiple times per day for a number of consecutive days (commonly using smartphones). EMA has been applied to addiction research for over a decade (Shiffman, 2009). For example, it has been used to study daily life substance use predictors and consequences (Wray et al., 2014), the relationship between craving and use at different time intervals (Serre et al., 2015), and substance use motives (Votaw & Witkiewitz, 2021).

Importantly, different factors influencing substance use at the momentary level have been mostly studied in isolation, and the complex interactions between them have not been consistently investigated. Time-series network analysis can be applied to EMA data to estimate the within-person relationships between different factors at the same time point (contemporaneous network) and over time (temporal network), while controlling for all other variables in the model and, in the contemporaneous network, while also controlling for the temporal effects (Burger et al., 2022; Epskamp, van Borkulo, et al., 2018; Epskamp, Waldorp, et al., 2018). This potentially allows to detect mediation pathways and feedback loops happening within one person at faster (e.g., within seconds or minutes in the contemporaneous network) and slower (e.g., every three hours in the temporal network) time scales. Time-series network analysis can be used to estimate the average mechanisms of multiple people (multilevel network analysis), or the mechanisms specific to one person (personalized, idiographic, or N=1 network analysis) (Epskamp, Waldorp, et al., 2018). To date, we are aware of only one study applying time-series network analysis to EMA data in addiction (Lydon-Staley et al., 2021). These authors used multilevel and idiographic network analyses to study the interactions between withdrawal symptoms and the spreading of symptom activation in the networks during different smoking cessation interventions. Interestingly, this study found a large amount of heterogeneity between people, which may affect treatment outcomes and could be investigated to personalize treatment.

More recently, first attempts have been undertaken to explore EMA to improve substance use treatment. First of all, it has been suggested that EMA monitoring in itself could increase awareness of one's substance use resulting in helpful effects on substance use, which is sometimes observed but findings are mixed (Gass et al., 2021). Moreover, specific responses to EMA items have been used to trigger just-in-time interventions to prevent substance use, manage cravings, or cope with relapse in mobile health interventions (for a recent review, see Carreiro et al., 2020). This is often done in the form of personalized text messages, for example, a text to encourage the participant to refrain from substance use can be sent when craving is reported. Machine learning has also been applied to EMA to predict drinking episodes. For example, a machine learning algorithm has been developed to predict drinking episodes in at-risk drinkers (Walters et al., 2021), based on which intervention messages can be delivered.

Although promising, these applications of EMA in addiction interventions did not use EMA to investigate the complex mechanisms that trigger and maintain addiction in each client and did not integrate such knowledge into treatment. Knowledge about individual mechanisms can be gained through estimating idiographic network models graphing the relationships between addiction behavior, factors precipitating and sustaining such behavior, and consequences of the behavior. For example, while in one individual, negative affect and craving may predict substance use, in another person, positive affect may predict use. In the context of just-in-time interventions, this information could be used to personalize triggers for treatment messages. In the context of addiction therapy, personalized networks could be used as part of personalized monitoring and feedback procedures to start a collaborative discussion between the therapist and client. This could result in (1) increased motivation of the client to stop or diminish the addictive behavior, (2) increased self-awareness and understanding of addiction mechanisms in the client, and (3) improved collaborative choice of personalized treatment targets.

Giving personalized feedback is not a new concept in the field of addiction interventions. Personalized feedback in the form of normative feedback, which compares substance use in the participant to their peers, has been used as a stand-alone or add-on intervention, especially in the context of university and college students (Saxton et al., 2021). Self-directed personalized normative feedback showed short-term efficacy with small effect sizes in addressing alcohol use, but further research is needed to investigate whether this may be more effective when used in specific contexts, for example as the start of more intensive treatment (Saxton et al., 2021). Often, mobile health interventions also include personalized feedback about substance use goals based on time-intensive monitoring of substance use (Carreiro et al., 2020). For example, self-monitoring and personalized feedback on substance use and its consequences have been used in a smartphone application for excessive alcohol use reduction (Crane et al., 2018). Additionally, personalized feedback based on retrospective surveys has been used in motivational interviewing (Lee et al., 2013). However, interventions that systematically integrate personalized feedback on complex dynamic mechanisms have not been tested yet in addiction treatment. First examples of how this could be done are available in the context of depression (Riese et al., 2021). Importantly, EMA-derived feedback on dynamic mechanisms can include personalized networks (Riese et al., 2021; von Klipstein et al., 2022) but also more simple inferential statistics such as client-specific correlations between substance use and influencing factors (Piccirillo et al., 2022) and descriptive statistics such as trends of the variables over time (Bringmann et al., 2021).

While the network theory of psychopathology proposes that addiction involves a network of interacting symptoms and influencing factors, this does not mean that network analysis must be the only strategy to investigate and understand such interactions. Other statistics derived from EMA data can also give insights into dynamic mechanisms, and network analysis theory can even be used as a conceptual clinical tool in itself, as personalized networks can be drawn jointly by client and therapist using perceived causal relations (Frewen et al., 2013; Klintwall et al., 2021), which could subsequently be tested, for example as a behavioral experiment in cognitive behavioral therapy (CBT). In conclusion, understanding the complex dynamic mechanisms triggering and maintaining addiction in each different client would cover a gap in the current literature and may prove useful for personalizing and thus improving interventions.

## Integrating EMA, Personalized Feedback and Personalized Networks with Cognitive Training

Recent developments in theory and research have identified three promising directions that may result in improvements in addiction interventions: (1) the shift from traditional CBM to ABC training, (2) the shift from a categorical understanding of addiction to a network theory of addiction, and (3) the study of individual dynamic mechanisms and their application to personalize treatment. In this section, we illustrate possibilities to integrate these three directions in future research.

ABC training is based on the inferential account, according to which participants/patients may change their addictive behavior after applying the causal relationships between antecedents (i.e., triggers of addiction behaviors), behaviors (i.e., addiction and alternative behaviors) and consequences of the behaviors (negative and positive) in their behavioral choices. In current ABC training, clients choose at baseline which antecedents, alternative behaviors, and related consequences are relevant to their daily life and long-term goals. The training then targets automatization of inferences that they will choose alternative behaviors in risk situations in light of the relevant consequences.

EMA-derived statistics, including personalized network models, could be used to better understand which antecedents predict the addictive behavior in a client. For example, a client may be aware that they are more likely to drink when feeling stressed, but unaware that they also drink more when feeling happy. Before the ABC training, the client can be asked to collect EMA data (for example five times per day for three weeks) about substance use and its possible antecedents. This can be followed by a personalized network analysis, which can be discussed with the client, including a discussion of which antecedents could best be included in their training. Contemporaneous associations depicting interactions at the same time point could be particularly helpful to this aim, as they would allow us to investigate what usually happens in the moment when the participant drinks. In addition, temporal networks could be used to detect antecedents that predict addictive behaviors at longer time intervals (e.g., across intervals of 3 hours).

A personalized network approach could potentially also allow us to detect associations between multiple antecedents, for example, for one person, being at home could be associated with feeling sad, which could in turn be associated with alcohol use; at the same time being at the bar could be associated with feeling happy and, consequently, with alcohol use. Based on this information, more complex situations that contain combinations of multiple relevant antecedents could be used during ABC training, possibly improving similarity to real-life situations, which may be of crucial importance to foster changes in inferential networks that generalize to these situations.

Personalized networks could also be used to visualize the consequences of addiction and alternative behaviors. For example, a contemporaneous network could show that when a client smokes more cannabis, they also have more concentration problems. Since contemporaneous networks usually do not allow estimating the direction of a relationship, the information given in the contemporaneous network could be used as a starting point for discussion in the therapy room, where the direction of the relationship could be explained based on client's experiences and previous research. For example, it is likely that smoking leads to lower average levels of concentration (compared to non-smokers), and these are temporarily remediated when smoking, which gives the illusion of helping to concentrate. Temporal networks, that allow us to estimate the direction of the relationships between variables, could also be useful to detect possible consequences that happen at longer time intervals (from one measurement point to the next). However, these usually depict relationships between variables over hours, depending on EMA data collection frequency. Some consequences of addiction behaviors may be positive within this relatively short-term time frame, while some negative effects may develop over longer periods of time. For example, a client may feel more relaxed three hours after drinking alcohol. If such positive short-term effects are present in the networks, the therapist could discuss this with the client and use this information to explain that alternative behaviors resulting in similar short-term benefits can be chosen and practiced during ABC training. To complement the discussion, the therapist could ask the client to draw in the network the long-term negative effects of substance use and the long-term positive effects of the alternative behaviors that are relevant to the long-term goals of the client. Using this or similar approaches, the choice of alternative behaviors and long-term goals for the ABC training could be further improved.

Another important concept within ABC training is motivation to change, which has been suggested to be necessary for ABC training, and more generally for cognitive training interventions, to be effective (R. W. Wiers et al., 2020). EMA monitoring and personalized feedback could be useful to increase motivation to change, as they could make clients more aware of the magnitude of their addiction and related problems. Moreover, these techniques may also allow one to believe more in the intervention's effectiveness, which is likely crucial to achieving change in (active) inferences and resulting behavior (Van Dessel et al., 2022).

To go a step further, motivational interviewing, EMA monitoring and feedback, and ABC training could be used together. After some weeks of EMA monitoring, data-driven personalized feedback could be shared with the client during a motivational interviewing session, where the therapist could aim to (1) increase motivation, and (2) choose the antecedents, alternative behaviors, and consequences for ABC training in a collaborative effort with the client and discuss the personalized statistics. This may also help the clients to better understand their own addiction mechanisms, possibly strengthening the learning of causal relations that is then automatized during ABC training and improving self-efficacy with regards to ABC training. Figure 1 depicts how discussion with a counselor or therapist together with EMA and personalized feedback such as personalized networks could be used in preparation for ABC training. In the future, there may also be possibilities for full automatization using smart chatbots (e.g., He et al., 2022).

EMA monitoring and feedback could also be used after the ABC training is completed, to monitor its effects. For example, EMA could be used to observe whether the participant puts alternative behaviors into practice. If not, additional ABC training sessions could be administered, or alternative treatment strategies may be applied. Similarly, EMA data collected after the ABC intervention could also be used to give personalized feedback to clients. For example, personalized networks could be estimated to show whether alternative behaviors are associated with positive consequences such as stress reduction, which may motivate the client to continue applying alternative behaviors. Network analysis applied to

EMA data before, during, and after ABC training could also give valuable insights regarding the change in complex addiction mechanisms possibly caused by ABC, which would be valuable from a research perspective even if not directly used as part of the intervention itself.

If clients struggle with maintaining the alternative behaviors, EMA could also be used to trigger personalized just-in-time messages encouraging the client to put the alternative behaviors into practice. For example, if personalized statistics and further client-therapist discussion identified anxiety as one of the triggers of substance use, messages for this specific client could be sent after they report feeling anxious, possibly when no substance use has occurred yet. We could therefore imagine integrating personalized EMA monitoring and feedback (including personalized networks) and just-in-time interventions with ABC training. While only providing a message in the heat of the moment is unlikely to help clients to change behavior if the addiction behavior is already the chosen way to cope, just-in-time messages as an add-on to ABC training may provide useful because ABC training involves practicing alternative behaviors.

We must also remember that, although promising, the application of EMA and personalized statistics, such as personalized networks, to ABC training is not without challenges. In most clinical applications, due to time-constraints and participants' effort, it may not be feasible to collect more than around 100 time points per person before starting the intervention. This means that, when estimating complex models such as networks including many variables in one person, low statistical power is to be expected, based on simulation studies (Mansueto et al., 2022). To address this problem, the number of variables included in the network should be limited based on previous research, hypotheses, theory, or knowledge about the specific client. Other possible solutions can be to use the personalized networks in combination with simpler descriptive and inferential statistics (for example those used in Piccirillo et al., 2022) which do not suffer from the same power problems, or in combination with therapist's and client's knowledge. For example, instead of using only relevant antecedents resulting from personalized networks to personalize ABC training, the participant should also be allowed to add additional antecedents based on their experience. Data from similar clients could also be used to increase power when estimating personalized models, for example, average within-subject networks of similar clients could be used as a prior for N=1 network estimation in a Bayesian framework. Additionally, a theory-driven approach to model specification could be integrated with a data-driven approach (e.g., Burger et al., 2022), possibly improving feasibility of idiographic models in intervention settings. It should also be considered that different choices regarding which variables to measure and include in the personalized models, and which preprocessing steps and statistical analyses to perform on the EMA data, may result in different therapeutic recommendations (Bastiaansen et al., 2020). Identifying consistent strategies to formulate clinically relevant hypotheses for each client, test these, and further discuss and interpret these in collaboration with clients, may bring forward solutions to this problem.

Another limitation to consider is that for EMA variables with low variance, we will probably find no connections in the personalized network, even if these may still be important for addiction. For example, if a person feels anxious at almost every time point, we will likely find no association between this feeling and substance use, but this does not exclude that anxiety plays a role in motivating substance use. To solve this problem, other EMA-derived statistics may be used with personalized networks. A constant high level of anxiety will be visible in a simple plot of anxiety over time and this information could be used to ask the participant whether anxiety may also be an antecedent of substance use. The perceived causal relationship approach could also be used to draw possible relationships in the network. This approach may be even more valuable taking into consideration the different timescales at which addiction mechanisms unfold. When relevant mechanisms happen at time intervals that are challenging to capture in a brief pre-ABC EMA monitoring period of a couple of weeks, network theory could be used as a clinical tool by drawing perceived causal relationships. Of note, antecedents used in ABC training are typically momentary antecedents that co-occur with substance use or predict substance at very short time intervals, so EMA may be particularly suitable to study these.

Additional challenges of time-series networks are that the statistical models most readily available to obtain personalized networks, such as the graphical vector autoregressive model (Epskamp, Waldorp, et al., 2018), assume stationarity and equal time intervals. For a review of these and more methodological challenges of time-series networks and future developments to overcome them see Bringmann et al., (2022).

## Conclusions

Integrating EMA monitoring, personalized feedback on addiction mechanisms, and personalized networks with targeted personalized cognitive training (like ABC training) could prove a promising way forward to improve addiction treatment. However, whether EMA and personalized models improve effectiveness of CBM is currently an open question. To answer this question, research is needed that tests whether EMA-derived information and personalized network approaches add something above simple recollection and retrospective self-report in choosing antecedents, alternative behaviors and consequences for ABC training. Also, future research should test whether ABC training (integrated with EMA and personalized feedback) yields additional value compared to traditional therapeutic approaches.

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**Figure 1**

*Integration of Novel Approaches (e.g., EMA, Personalized Networks) with Counselor/Therapist Discussion to Inform ABC Training*