Mindful attention to alcohol can reduce cravings in the moment and consumption in daily life

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Abstract

It is critical to support healthy development of alcohol-related habits, particularly in contexts with heightened risk such as college campuses. Combining multivariate neuroimaging, intervention, and experience sampling methodologies, we tested the degree to which mindful attention reduces alcohol cravings in the laboratory and consumption in daily life. College students completed a mindful attention task towards alcohol in an fMRI scanner followed by a 28-day, smartphone-based, experience sampling intervention. Using machine learning, we created a brain signature of mindful attention. In the laboratory, mindfully attending to alcohol decreased craving, particularly among people who more strongly expressed the mindful attention signature. In daily life, mindful attention to alcohol reduced alcohol consumption. Individuals who more strongly expressed the mindful attention brain signature in the laboratory benefited the most from the intervention. Broadly, our study highlights how mindful attention can reduce alcohol consumption via a scalable smartphone-based intervention.

Keywords: Mindfulness, self-regulation, intervention, alcohol, college, prevention, neural signature, emotion regulation

Statement of Relevance

Over-consumption of alcohol can be harmful to an individual's health, well-being, and social relationships. In this work, we found that mindful attention reduced craving for alcohol in the laboratory, and that a mindful attention intervention reduced drinking behavior in daily life when individuals attended to alcohol mindfully. By using machine learning and neuroimaging techniques, we developed a neural signature of mindful attention that indexes momentary fluctuations and individual differences in mindful attention across both laboratory and real-world contexts. As one of the primary risk factors for developing an alcohol-use disorder is beginning to drink at a younger age, identifying effective strategies for reducing alcohol craving and drinking frequency among emerging adults is of interest to psychologists, clinicians, public health researchers, and the general public.

In popular culture, college life is often depicted as a series of unending parties, with frequent binge drinking and comparatively few long term consequences. Indeed, alcohol use in college is highly normative in many Western countries (Gotham et al., 1997)—the majority of American college students report drinking in the past month and a quarter of these students engaged in binge drinking (NIAAA, 2022). However, alcohol consumption in college is associated with a host of negative consequences, including academic problems, physical injury, assault, and even death (NIAAA, 2022). Individuals with alcohol use disorder are at highest risk for negative alcohol-related consequences, but even minimal alcohol consumption is associated with negative health outcomes (Jernigan & Trangenstein, 2020). Given the extent to which adolescents and young adults are at risk for developing alcohol-related problems (Sancho et al., 2018), identifying scalable strategies to encourage the development of healthy behaviors in alcohol-related contexts is critical. Here, we test the degree to which a smartphone-based intervention encouraging participants to mindfully attend to alcohol reduces alcohol craving and consumption. We take a multimodal approach, combining experimental intervention, functional magnetic resonance imaging (fMRI), and experience sampling methodologies. This approach allows us to examine the mindful attention intervention from three angles: 1) *efficacy*—performance under controlled conditions, 2) *effectiveness*—performance under "real-world" conditions, and 3) *individual differences*—identification of individuals for whom the intervention works most successfully.

Mindful attention as an emotion regulation strategy to reduce craving

In scientific contexts, mindfulness is often defined as the directed and nonjudgmental awareness of the present moment (Kabat-Zinn, 2009; Van Dam et al., 2018), and comprises multiple cognitive and behavioral components (Bishop et al., 2004). Here, we focus on the element of mindfulness that involves cultivating awareness and acceptance of one's thoughts and reactions to stimuli (Dahl et al., 2015), with a particular emphasis on attending to stimuli in a distanced manner. Since the term *mindfulness* is used to describe various concepts—for example, an attention state, psychological trait, and meditation practice (Van Dam et al., 2018)—we use the term *mindful attention* to describe the specific emotion regulation strategy examined in the present work. Mindful attention can shape emotional responses both prior to and during initial stages of exposure to emotion-eliciting stimuli. Notably, mindful attention can reduce negative affect, pain, and craving in individuals who do not practice mindfulness meditation (Kober et al., 2019; Nook et al., 2021; Westbrook et al., 2013), highlighting its potential as a scalable intervention strategy in young adults. Related to substance use specifically, mindfulness (both trait and training) has been associated with decreased appetitive craving (Brewer et al., 2013; Karyadi et al., 2014; Kober et al., 2017; Tapper, 2018; Westbrook et al., 2013). Although this and other evidence suggests that mindfulness training reduces craving and consumption (Byrne et al., 2019; Chiesa & Serretti, 2014; Elwafi et al., 2013; Goldberg et al., 2022; Li et al., 2017; Witkiewitz et al., 2013), it is unclear *how* mindful attention may regulate cravings in the moment, and whether these findings generalize to preventive contexts in populations without substance-use disorders, such as college students without alcohol use disorders. As such, our first goal was to examine the *efficacy* of mindful attention to reduce craving in a laboratory context in which alcohol-related cues are decontextualized, and college students are fully sober and alone (i.e., not under peer influence; Naqvi et al., 2015;

Varela & Pritchard, 2011). We hypothesized that mindful attention would reduce craving (relative to reacting naturally) for alcohol stimuli in a laboratory context (*H1*).

A neural signature approach to measuring momentary fluctuations and individual differences in mindful attention

In order to characterize fluctuations in the quality of mindful attention from moment to moment, and individual differences in the ability to use this strategy, we leveraged neuroscience methods with the goal of creating a sensitive and specific measure of mindful attention (Weng et al., 2020). We adopted a neural signature approach (Woo et al., 2017) to overcome potential biases inherent in all self-report measures of mental states, including mindfulness (Grossman & Van Dam, 2011; Wager et al., 2013). This approach has been successfully used to create neural signatures of psychological states, such as pain (Wager et al., 2013), negative affect (Chang et al., 2015), reward (Chang et al., 2022), craving (Koban et al., 2023), craving regulation (Cosme et al., 2020) and emotion regulation (Schneck et al., 2023), that can accurately predict how strongly a given state is being engaged at any given moment. We hypothesized that people who more strongly express the mindful attention signature on average (i.e., between-person expression) will also have lower craving ratings on average (*H2a*), and that trials with greater signature expression compared to one's average (i.e., within-person expression) will be associated with lower craving ratings on a trial-by-trial basis (*H2b*).

Mindful attention interventions in daily life

Our second goal was to examine the *effectiveness* of mindful attention outside of the lab to reduce alcohol consumption in daily life. We do so using an experience sampling intervention (Heron & Smyth, 2010), which simultaneously deploys an intervention and collects repeated-measures data in daily life (Christensen et al., 2003). The majority of experience sampling interventions have thus far focused on cigarette smoking and reported mixed evidence regarding the effectiveness of mindfulness interventions to reduce craving and consumption (Garrison et al., 2020; Sala et al., 2021). Numerous studies have observed positive effects of smartphone-based mindfulness training on mental health (e.g., depression, anxiety) using pre-post designs (see Gál et al., 2021 for a meta-analysis), but fewer studies have examined dynamic relationships between mindful attention and substance use in an intervention context. Toward this goal, we had three interrelated research hypotheses for the mindful attention intervention: 1) Compared to control weeks, active intervention weeks will increase participants' self-reported mindful attention to alcohol (*H3a)*; 2) More mindful responses to alcohol will be associated with reduced alcohol consumption (*H3b*); 3) There will be an indirect effect of intervention-related change in alcohol consumption through greater self-reported mindful attention to alcohol (*H3c*).

Linking efficacy in the lab to effectiveness in the real-world

A primary challenge to intervention development is the vast heterogeneity in how people respond (Könen & Karbach, 2021). Therefore, our final goal was to explore the degree to which intervention-related changes in drinking behavior were moderated by *individual differences* in effective implementation of mindful attention in the laboratory by adopting a brain-as-predictor approach (Berkman & Falk, 2013). We employed average expression of the mindful attention signature as an individual difference measure of effective implementation and hypothesized that people who on average show increased expression of the mindful attention signature will be most responsive to the intervention. That is, they will show stronger increases in mindful attention to alcohol on active intervention weeks compared to control weeks (*H4a*), and more negative relationships between mindful attention to alcohol and alcohol consumption (*H4b*). To our knowledge, this work would be the first to link neural signatures of regulation strategy use to to evaluate a health behavior change intervention. Such evidence is important for identifying personalized approaches to public health interventions that target health behavior change (Doré et al., 2016).

Methods

Study Overview

The present study had two phases: an MRI session and a 28-day experience sampling intervention (Figure 1). In the context of the MRI session, we tested the *efficacy* (i.e., success in controlled laboratory settings) of mindful attention to reduce cravings for alcohol in a neuroimaging experiment (Figure 1a). To examine the *effectiveness* of the intervention in daily life, participants completed a smartphone-based experience sampling intervention for 28 days following the brain scan (Figure 1b). We varied whether participants received instruction to respond mindfully versus to react naturally to alcohol on a weekly basis, allowing us to examine within-person changes in alcohol consumption, which we operationalize as the number of drinks per occasion, as a function of the intervention. This approach also enabled us to examine *individual differences* in intervention effectiveness by exploring whether people who were more effective in mindfully attending to alcohol during the laboratory task were also more responsive to the intervention.

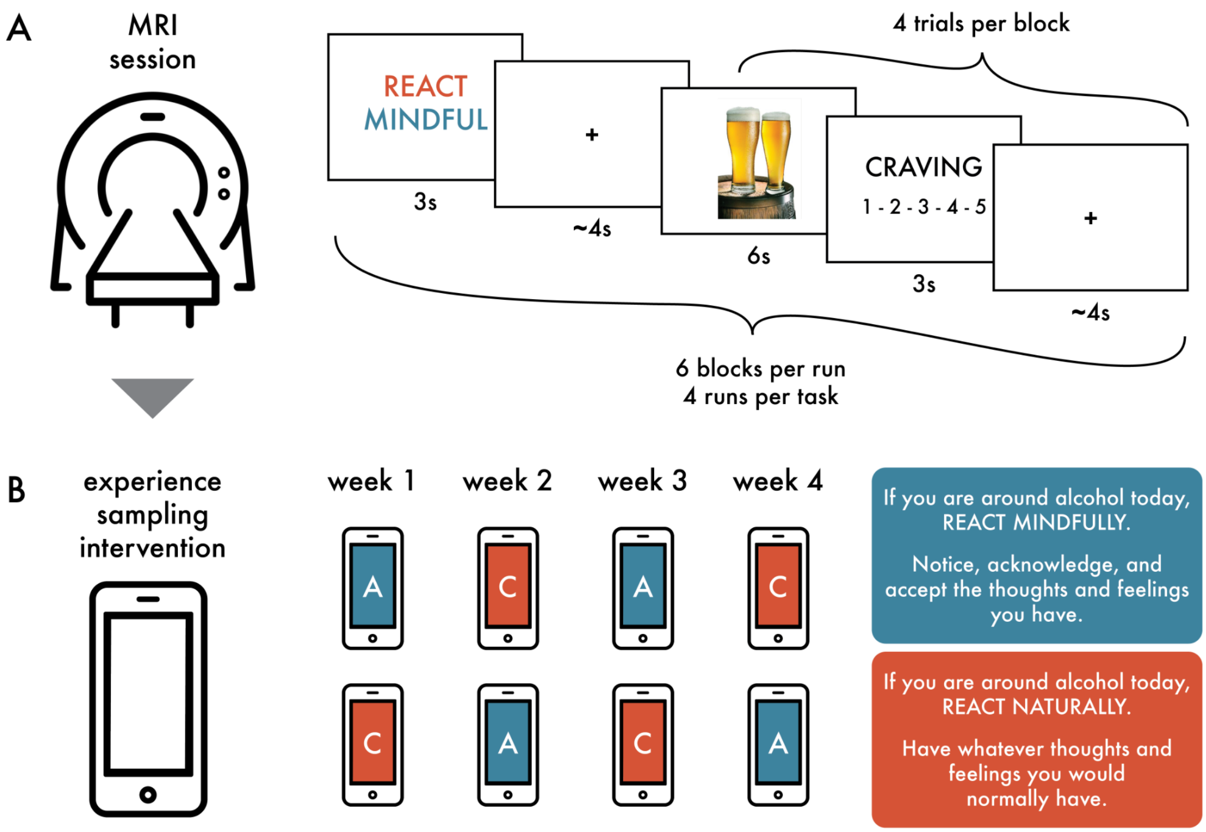

Figure 1. Overview of the study design. (A) In the MRI session, participants completed a cue reactivity and mindful attention regulation task. Prior to the scan, participants were given basic training in implementing mindful attention. At the beginning of each block, participants saw an instruction cue (Reactivity or Mindful Attention) and followed the instruction throughout the 4 trials in the block. After each beverage image, participants rated their craving. Each task run contained 6 blocks, and participants completed 4 task runs. (B) Following the MRI session, participants completed a 28-day experience sampling intervention. Each day participants reported their craving and consumption of alcohol, and how mindfully they responded to alcohol when they encountered it. On counterbalanced, alternating weeks they were reminded to attend mindfully to alcohol (A = active intervention week) or react naturally to alcohol (C = control week).

Open practices statement

The hypotheses and analysis plan for the mindful attention signature development and efficacy analyses (H2) were preregistered (https://osf.io/up6en?view_only=49ce7a0c7ad04ab9942ccd5d42632e52). We note deviations from this preregistered plan here: 1) to preserve the meaningful classification decision boundary (i.e., averages above 0 represent evidence for Mindful Attention, whereas averages below 0 indicate evidence for Reactivity), we did not grand-mean center the between-person signature expression values in trial-level craving analyses, and 2) we used Bayesian multilevel modeling rather frequentist multilevel modeling to facilitate model convergence and enable us to conduct within-person moderated mediation analyses. The data and code needed to reproduce the analyses reported in this study are available in the project repository (https://anonymous.4open.science/r/shine-mindfulness-mvpa-CD01). The unthresholded mindful attention signature is available on NeuroVault (https://neurovault.org/collections/13816/). More information about the broader project (Social Health Impact of Network Effects) that this study was a part of is available on the Open Science Framework (https://osf.io/gkahy/?view_only=49ce7a0c7ad04ab9942ccd5d42632e52).

Participants

This study used a subset of data from a larger project that examined how interactions between mind, brain, and community give rise to health and well-being (Cosme et al., 2022). The target sample size for the study (N = 240) was determined based on the power analysis accompanying the original grant application (W911NF-18-1-0244). However, recruitment was interrupted due to the COVID-19 pandemic, resulting in a final sample of N = 108. In this project, participants were randomly assigned to one of three self-regulation intervention groups: mindful attention, perspective-taking, or control. Participants in the mindful attention group were instructed how to respond to alcohol cues with mindful, non-judgmental attention; participants in the perspective-taking group were instructed how to take the perspective of peers who drink less than themselves; and the control group was not instructed in any form of regulation. The present study focuses on the mindful attention group (n = 38, M_{age} = 20.8, SD_{age} = 1.9), but also uses data from participants in the perspective-taking group (n = 34) in a sensitivity analysis reported in Supplementary Material. Participants were university students who belonged to social groups (e.g., clubs, sports teams, or Greek life organizations) at the University of Pennsylvania (n = 17) and Columbia University (n = 21). Detailed information regarding the recruitment process, participant eligibility, and the intervention randomization process, are described in Cosme et al. (2022).

At the time of data collection, participants in the mindful attention group identified as the following genders: 55.3% women, 34.2% men, 2.6% as additional genders not specified in our response options, and 7.9% did not report. With respect to race and ethnicity, participants reported identifying as the following: 47.4% White, 28.9% Asian, 10.5% more than one race or ethnicity, 2.6% Black or African American, 2.6% Latino/a/x, and 7.9% did not report. Additional socioeconomic demographic information is reported in Supplementary Material. This study was approved by the University of Pennsylvania Institutional Review Board and acknowledged by the Army Research Office's Human Research Protection Office. All participants gave informed consent and were paid for their participation.

Procedure

After being randomized to the mindful attention intervention group, participants completed an MRI session. During this session, they were instructed how to mindfully attend to alcohol and then completed a mindful-attention-to-alcohol-cues task in which they used this regulation strategy while undergoing functional neuroimaging. After the MRI session, participants completed a 28-day experience sampling intervention during which they employed mindful attention when encountering alcohol in their daily lives. Intervention-related results from all participants in the broader project are reported in Jovanova et al. (2023).

Mindful attention

Participants were trained to approach alcohol cues mindfully by, "mentally taking a step back in order to observe the situation and [their] responses in an impartial and non-judgmental manner" (Jovanova et al., 2023). They were also trained to take a step back, and pay attention to and accept their reactions without getting caught up in them. Participants used this strategy both during the MRI alcohol cue task and during the experience sampling intervention.

Mindful attention to alcohol cues laboratory task

Consistent with past work on the regulation of alcohol craving (Naqvi et al., 2015; Suzuki et al., 2020), we used images of alcohol (beer, wine, and liquor) to elicit craving. During the task, participants saw images of alcohol (e.g., bottle of beer) and control images of non-alcoholic beverages (e.g., water bottle) from the Galician Beverage Picture Set (López-Caneda & Carbia, 2018). While viewing the images, participants were instructed to either react naturally ("Reactivity" trials) or regulate their responses using mindful attention ("Mindful Attention" trials). After each image, they rated their craving on a 5-point scale (1 = not at all, 5 = very much). On half of the Reactivity trials, participants saw images of alcoholic beverages; on the other half, they saw control, non-alcoholic beverages. The present study focuses on reactivity to images of alcoholic beverages. On Mindful Attention trials, participants were instructed to attend mindfully to their experience, taking a step back, and accepting their thoughts and feelings in a non-judgemental way. Detailed instructions for the task are provided on OSF (https://osf.io/c4mxw?view_only=49ce7a0c7ad04ab9942ccd5d42632e52). Due to a technical error, three participants are missing behavioral response data collected during Mindful Attention trials; however, the brain data and behavioral data from Reactivity trials from these participants were still used in analyses.

Participants completed 96 trials across four task runs (Figure 1a). This task used a mixed design in which trials were blocked per condition to reduce the burden associated with task-switching. Each block consisted of four trials and each task run consisted of six blocks. Each block (Figure 1) began with a condition cue (3s) followed by four trials, each consisting of an image presentation (6s) and a craving rating (3s); each event was separated by a jittered fixation cross (M = 4.0s, SD = 2.6s). Block order was randomized across participants; that is, participants were assigned one of 9 randomized orders. Stimuli were presented using PsychoPy (Version v3.0.0b11; Peirce, 2007) and participants responded using a five-button box. After the scan session, participants answered questions about the mindful attention strategy they used during the task and rated their level of confidence using this strategy in the post-scan survey.

Experience sampling intervention

After completing the MRI session, participants (N = 37) began a 28-day experience sampling protocol that measured daily craving and consumption of alcohol, among other measures (Figure 1b). On each day for 28 days, participants received two surveys on their smartphones via LifeData (https://www.lifedatacorp.com/). Two daily surveys sent at 8AM and 6PM assessed current alcohol craving (1 = Not at all, 100 = Extremely) and alcohol consumption (number of standard drinks of beer, liquor, and wine) since the previous survey. The evening survey also assessed how effectively participants responded with mindful attention to alcohol ("Since the previous survey (morning or evening), I REACTED MINDFULLY to alcohol;" 1 = Strongly disagree, 100 = Strongly agree).

The experience sampling procedure also served as an intervention by reminding participants of the instructions for how to regulate their responses to alcohol using mindful attention, as they were trained to do at the MRI session. The intervention was delivered on alternating weeks. During active intervention weeks, participants received two prompts a day (2PM and 9PM) reminding them to mindfully attend to alcohol when encountering alcohol ("If you are around alcohol today, REACT MINDFULLY – notice, acknowledge, and accept the thoughts and feelings you have."). During control weeks, participants were instructed to react naturally to alcohol cues ("If you are around alcohol today, REACT NATURALLY – have whatever thoughts and feelings you would normally have"). This approach was adopted in order to assess within-person effects of the intervention. Intervention delivery week order (ACAC or CACA; A = active intervention week, C = control week) was counterbalanced across participants.

Neuroimaging

Scans were acquired using 3 Tesla Siemens Prismas at the University of Pennsylvania Center for Functional Neuroimaging and at the Mortimer B. Zuckerman Mind Brain Behavior Institute at Columbia University. Information about the MRI scan sequences, preprocessing, and first-level modeling is briefly reported in the Supplementary Material.

Mindful attention signature development

Using multivoxel pattern analysis, we trained a machine learning classifier to distinguish mindful attention from natural reactivity to alcohol using distributed patterns of activity across the whole brain. This process enables us to evaluate how effectively participants engage in mindful attention at any given moment when instructed to do so. The input data were participant's average condition effects (i.e., the average across trials for each condition resulting in the following contrasts: Mindful Attention > Rest, Reactivity > Rest) for each task run. This procedure resulted in a maximum of four whole-brain maps per task condition (Mindful attention and Reactivity) per person. The signature was developed in accordance with the procedures used in Cosme et al. (2020). First, we partitioned the data into two sets as follows: 75% of the data was used in the development of the signature (i.e., the development set), and 25% was withheld as a hold out, or "lockbox" set to test potential overfitting. Using the data in the development set, we classified task condition (Mindful Attention versus Reactivity). We used 5-fold cross-validation to assess classification accuracy while controlling for the dependence of runs within person using stratified sampling such that a given participant's data is kept together within each cross-validation fold. Given that the classes were balanced, we used accuracy as the metric. This process yielded a single predictive model that was used in the trial-level craving analyses. We used a logistic classifier with L2 regularization with the default hyperparameters (C = 1.0) implemented in NLTools 0.4.2 (Chang et al., 2019).

Efficacy: trial-level craving analyses

Beta-series modeling. The same first-level modeling procedure used in the mindful attention signature development (described in the Supplementary Material) was used, with the exception that each trial was entered in the model as a separate regressor (rather than grouped by condition) to create a beta-series (Rissman et al., 2004). Because motion artifacts may persist in the beta-series, we calculated the mean global intensity (i.e., the average signal across all voxels in the brain) for each beta map and excluded trials that were more than 3 *SD* from the mean, calculated within-person (*n* = 79 trials, 0.8% of all trials).

Signature expression. To assess the degree to which participants expressed the neural signature, we took the dot product of the mindful attention signature and each trial-level map to generate a single scalar value, which served as our measure of signature expression (Cosme et al., 2020). More positive signature expression values indicate stronger evidence for mindful attention, whereas more negative values indicate weaker evidence (i.e., stronger evidence for reactivity).

Multilevel modeling. To account for the nested nature of the data (a maximum of 96 trials within each of the 37 participants), we used Bayesian multilevel modeling to examine associations between signature expression and trial-level craving ratings. In a single model, we regressed trial-level craving on the fixed effects of signature expression, task condition, and their interaction using the *brms* package (Bürkner, 2017) in R (R Core Team, 2022). We disaggregated within- and between-person effects of signature expression by including a time-varying, person-centered predictor (the “within-person” variable) and an average per person, entered as a person-level predictor (the “between-person” variable). Both the within- and between-person signature expression variables were standardized across people. Intercepts and task condition and the within-person signature expression slopes were allowed to vary randomly across people, and intercepts were allowed to vary randomly across stimuli. We used weakly informative priors for the fixed effect parameters, defined as a normal distribution with *M* = 0 and *SD* = 1 (Lemoine, 2019). In the Supplementary Material, we also report a sensitivity analysis including subjective confidence using the mindful attention strategy (rated after the MRI scan) as a covariate; the results are consistent with those reported in the main manuscript.

Effectiveness and individual differences: experience sampling intervention analyses

Building on the laboratory analyses, we explored how the mindful attention intervention affected alcohol consumption in daily life, and the degree to which individual differences in expression of the mindful attention signature during the task (i.e., during mindful attention trials) moderated effectiveness. We tested whether there was an indirect effect of the intervention (active or control week) on alcohol consumption through mindful responses to alcohol, and the degree to which individual differences in mindful attention signature expression moderated the relationships between A) intervention week on mindful responses and B) mindful responses on alcohol consumption. Models were fit using *brms* (Bürkner, 2017) in R (R Core Team, 2022). Mindful responses and alcohol consumption were within-person centered such that they reflect changes from a person’s average. In the first model, mindful responses were regressed on the fixed effects of intervention week, signature expression, and their interaction; intervention week slopes were allowed to vary randomly across people. In the second model, the number of drinks was regressed on the intervention week, signature expression, mindful responses, and the interaction between signature expression and mindful responses; intervention week and mindful responses were allowed to vary randomly across people. The same modeling parameters (i.e., priors, sampling interactions) as in the trial-level analyses were used here. Additional models including alcohol craving as the mediator are reported in the Supplementary Material.

Results

Mindful attention signature development

To dynamically examine the relationship between fluctuations in mindful attention and craving, we first developed a predictive model, or neural signature, of mindful attention from patterns of brain activity across the whole brain (Figure 2). Average out of sample cross-validation accuracy was significantly greater than 50% (Acc = 0.56, 95% CI [0.50, 0.63]; sensitivity = 0.53, specificity = 0.59), indicating that the classifier was able to decode Reactivity from Mindful Attention better than chance from patterns of activity across the whole brain. Furthermore, we observed similar accuracy (Acc = 0.55) when applying the signature to the holdout ("lockbox") sample, suggesting that this predictive model was not substantially overfit to the data during development. Applying this predictive neural signature to the trial-level data in order to examine moment to moment fluctuations in mindful attention, we found that signature expression was higher on Mindful Attention trials compared to Reactivity trials (b_{diff} = 13.28, 95% CrI [12.14, 14.44]) and correctly decoded task condition with high accuracy (Acc = 0.70, 95% CI [0.68, 0.72]; sensitivity = 0.70, specificity = 0.69). Additional analyses showing evidence of discriminant validity, thereby revealing that the mindful attention signature uniquely predicted mindful attention (compared to another cognitive self-regulation strategy), are reported in the Supplementary Material.

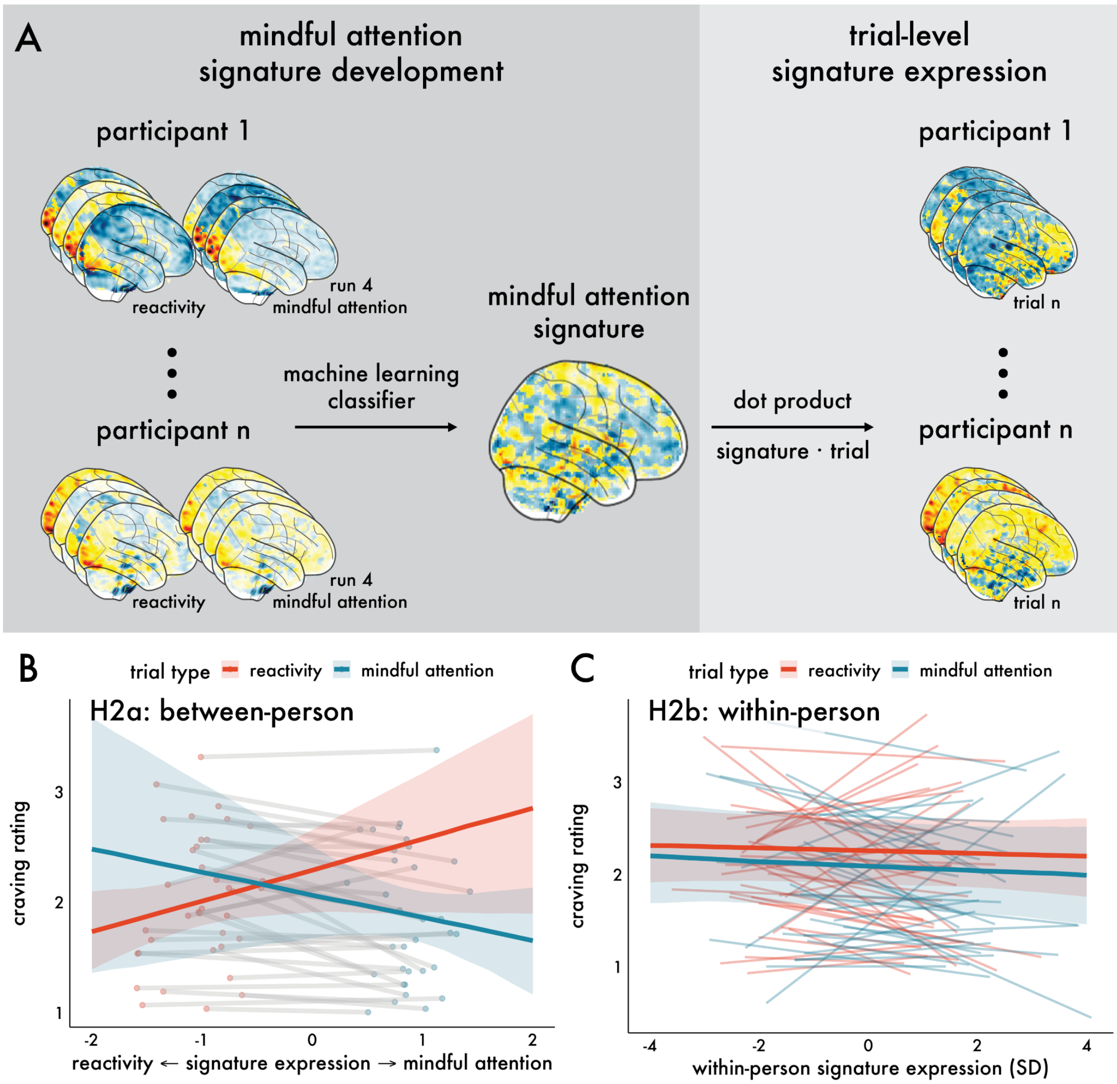

Figure 2. Overview of the analytic process and results from the efficacy analyses (H1-2). (A) First, we used run-level average condition (Reactivity and Mindful Attention) whole-brain maps to train a logistic classifier to decode Reactivity from Mindful Attention trials. This resulted in a predictive model, or mindful attention signature, that we applied to the trial-level data to get continuous predictions. Higher positive pattern expression values indicate stronger evidence for Mindful Attention whereas lower negative values indicate stronger evidence for Reactivity. We disaggregated within-person (i.e., deviations from a person's average) and between-person (i.e., average deviations from the grand mean) pattern expression and examined the degree to which these differences were associated with trial-level cravings in the same model. (B) People who more strongly expressed the mindful attention signature on average (i.e., higher between-person) tended to report higher cravings on Reactivity trials and lower cravings on Mindful Attention trials. The average, fixed effects for each condition (red and blue lines) are overlaid on individual condition averages (red and blue dots connected by gray lines to show the differences between conditions). (C) However, trials in which people more strongly expressed the mindful attention signature compared to their personal average were not strongly associated with lower cravings. The average, fixed effects for each condition (thick red and blue lines) are overlaid on individual slopes across trials within each condition (thin red and blue lines).

Efficacy: trial-level craving analyses

H1: Mindful attention to alcohol cues reduces craving

To test our first hypothesis that mindful attention reduces alcohol craving, we examined relationships between task condition and trial-level cravings. Consistent with this hypothesis, Mindful Attention trials were associated with reduced cravings relative to Reactivity trial (b = -0.12, 95% CrI [-0.23, -0.01]).

H2: Individual differences in expression of the mindful attention signature is associated with reduced craving in the laboratory

Next, we examined how individual differences and moment-to-moment fluctuations in effective implementation of mindful attention—indexed by expression of the mindful attention signature—were related to craving. We hypothesized that people who have greater expression of the mindful attention signature on average (i.e., between-person expression) will also have lower craving ratings on average (*H2a*), and that trials with greater expression of the mindful attention signature compared to one's average (i.e., within-person expression) will be associated with lower craving ratings on a trial-by-trial basis (*H2b*). We found that on Reactivity trials, people who expressed the mindful attention signature more strongly compared to others (i.e., between-person expression) also tended to report stronger cravings ($b_{reactivity}$ = 0.28, 95% CrI [0.00, 0.56]), whereas on Mindful Attention trials, they tended to report weaker cravings ($b_{interaction}$ = -0.49, 95% CrI [-0.97, -0.04]; $b_{simple\ slope}$ = -0.21, 95% CrI [-0.55, 0.18]). Contrary to our hypotheses, trials in which people more strongly expressed the mindful signature compared to their average (i.e., within-person expression) were not associated with weaker cravings ($b_{reactivity}$ = -0.01, 95% CrI [-0.10, 0.08]; $b_{mindful\ attention}$ = -0.03, 95% CrI [-0.09, 0.04]). These results are visualized in Figure 2B-C.

Effectiveness: experience sampling intervention analyses

H3: There is an indirect effect of the intervention on alcohol consumption through increased mindful attention

Extending the findings from the laboratory task, we assessed the effectiveness of the mindful attention intervention in daily life. More specifically, we tested the hypotheses that: active intervention weeks will increase participants' self-reported mindful attention to alcohol (*H3a)*, that more mindful responses to alcohol will be associated with reduced alcohol consumption (*H3b)*, and that there would be an indirect effect of intervention-related change in alcohol consumption through greater self-reported mindful attention to alcohol (*H3c*). Consistent with these hypotheses, compared to control weeks, active intervention weeks increased self-reported mindful attention to alcohol (*a* path; b = 0.48, 95% CrI [0.26, 0.73]), which in turn was associated with lower alcohol consumption than average (*b* path; b = -0.59, 95% CrI [-0.98, -0.17]). Linking these paths, we observed an indirect effect of the intervention on alcohol consumption through increased mindful attention ($a*b$ = -0.26, 95% CrI [-0.52, -0.01]). These results are visualized in Figure 3.

Individual differences in intervention effectiveness

H4: Intervention effects are moderated by mindful attention signature expression

Finally, we tested the degree to which individual differences in effective implementation of mindful attention in the laboratory experiment—indexed by expression of the mindful attention signature—moderated the intervention effects tested in *H3*. We expected that people with stronger signature expression would show greater increases in mindful attention to alcohol on active intervention weeks compared to control weeks (*H4a*), and more negative relationships between mindful attention to alcohol and alcohol consumption (*H4b*). Consistent with these hypotheses, both mediation pathways were moderated by individual differences in mindful attention signature expression. People who more strongly expressed the mindful attention signature in the laboratory showed a stronger effect of the intervention on mindful responses (*a* path; $b_{interaction}$ = 0.41, 95% CrI [0.17, 0.63]), and a more negative relationship between mindful responses and alcohol consumption (*b* path; $b_{interaction}$ = -0.33, 95% CrI [-0.73, 0.08]). These results are visualized in Figure 3.

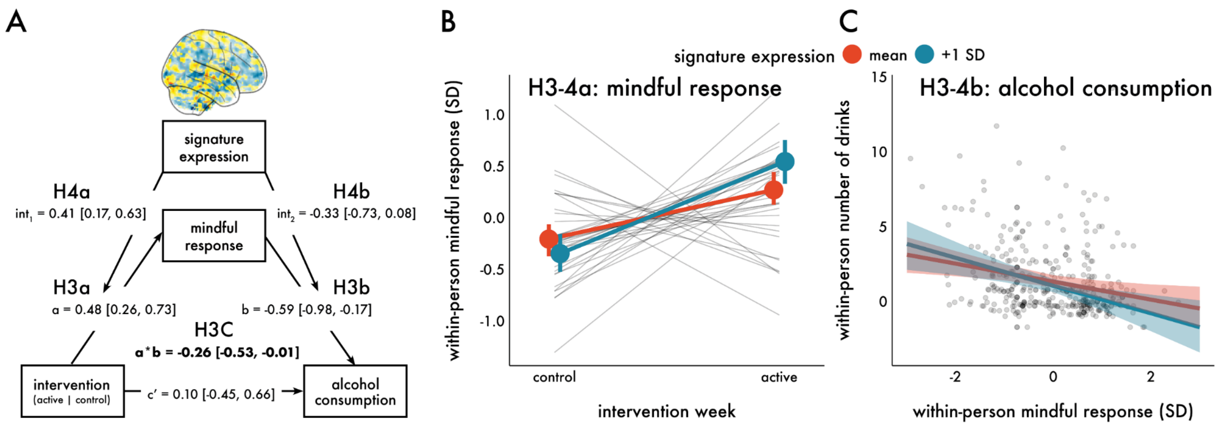

Figure 3. Results from the effectiveness and individual differences analyses (H3-4). (A) Results from the moderated mediation model showing evidence of an indirect effect of the intervention (active versus control weeks) on alcohol consumption through mindful responses to alcohol. That is, the mindful attention intervention increased mindful responses (H3a), which in turn were associated with reduced alcohol consumption (H3b). Furthermore, individual differences in the mind attention signature expression during the laboratory task moderated each of these mediation relationships (H4a-b). That is, people with stronger signature expression showed a (B) stronger increase in mindful responses between active and control weeks and a (C) stronger negative relationship between mindful responses to alcohol and alcohol consumption. In panels (B-C), red lines illustrate relationships at mean mindful attention signature expression and blue lines illustrate relationships at one standard deviation above the mean. Gray lines in panel (B) represent individual differences between control and active weeks; gray points in panel (C) represent individual drinking occasions. c′ = direct effect; int = interaction.

Discussion

Our study investigated the effects of mindful attention on brain responses, craving reduction, and alcohol consumption. To examine moment-to-moment fluctuations and individual differences in effective implementation of mindful attention, we developed a neural measure of mindful attention and found that greater expression of this signature was associated with decreased craving for alcohol in the laboratory. In daily life, we found that the mindful attention intervention increased mindful responses to alcohol, which in turn decreased alcohol consumption. Moreover, individual differences in how strongly individuals expressed the mindful attention signature moderated these relationships. Together, our findings highlight the promise of a relatively scalable mindful attention intervention to reduce alcohol consumption, and use brain measures to identify mechanisms and individual differences in intervention success.

Efficacy in the laboratory

Testing the efficacy of mindful attention as a regulatory strategy under controlled conditions, we found evidence that mindfully attending to alcohol reduced craving. We examined how effectively individuals engaged in mindful attention on average and in the moment by developing a neural signature of mindful attention. Consistent with prior evidence that mindful attention can modulate affective states in individuals who do not meditate (Kober et al., 2019; Nook et al., 2021; Westbrook et al., 2013), we found that people who more strongly engaged this neural signature during mindful attention also reported reduced craving for alcohol. These findings provide promising evidence that mindful attention can be an effective approach for controlling alcohol craving in controlled settings, with little training required.

Effectiveness in daily life

Using an experience sampling intervention design to examine the effectiveness of the mindful attention intervention in daily life, we observed an indirect effect of the intervention on alcohol consumption through self-reported mindful attention to alcohol. That is, the intervention increased perceived mindful attention to alcohol, and this increase in mindful attention was associated with reduced alcohol consumption relative to non-intervention weeks. This pattern of relationships is consistent with prior research showing that mindfulness training and interventions predicted decreased smoking and substance consumption behavior in clinical populations (Bowen et al., 2014; Westbrook et al., 2013). Our work adds evidence linking mindfulness to health-promoting behaviors in real-world contexts, and extends prior research by adopting a within-person approach to the intervention (thereby reducing participant-level variability associated with between-person designs).

Individual differences

Acknowledging that interventions do not work equally well for everyone (Gál et al., 2021), we sought to identify for whom the mindful attention intervention works best. We found that individuals who more strongly expressed the mindful attention neural signature in the laboratory were also those who benefited most from the intervention. These individuals responded more mindfully to alcohol during intervention weeks, and correspondingly, consumed less alcohol when they were responding more mindfully. These findings are consistent with a growing movement emphasizing regulatory flexibility, or the interaction between person, situation, and strategy, in determining whether a strategy will be more or less effective (Bonanno & Burton, 2013; Doré et al., 2016; Kobylińska & Kusev, 2019). The present research identified a method for assessing the fit between an individual and a regulatory strategy: how effectively a person can engage an intermediate neural signature of the regulatory strategy.

Limitations and future directions

There are limitations of our study that are worth noting. First, we focused on college students because they are at risk for alcohol-related negative consequences and could benefit from preventative interventions. However, given that this population tends to be wealthier, more White, and more highly educated than the general population (Henrich, Heine, and Norenzayan 2010), future work is needed in more diverse populations. Despite a wide range of drinking behavior in our sample (drinks per week range = 0 - 45, M = 5.3, SD = 7.0), we did not recruit individuals with alcohol-use disorders. This recruitment strategy may limit the applicability of our findings to individuals with alcohol-use disorder. Finally, we employed a within-person design to enable inferences about individual-level intervention mechanisms. However, this design may have introduced demand effects (Charness et al., 2012).

Conclusion

The aim of this work was to examine how mindful attention impacts alcohol-related craving and consumption under both controlled and real-world conditions. We developed a predictive model of mindful attention to measure momentary fluctuations and individual differences in mindful attention. Overall, mindful attention reduced cravings for alcohol and decreased alcohol consumption, and individuals who more strongly engaged the mindful attention brain signature also benefited the most from the intervention. Together, these findings suggest that mindful attention can be an effective, preventative strategy for reducing alcohol consumption. Furthermore, it highlights the potential of scalable, smartphone-based interventions that remind individuals to regulate their responses to alcohol (Jovanova et al., 2023).

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Positionality statement

In acknowledgement that our identities can influence our approach to science (Roberts et al., 2020) the authors wish to provide the reader with information about our backgrounds. With respect to gender, when the manuscript was drafted, 1 author self-identified as non-binary, 8 authors identified as women, and 5 authors identified as men. With respect to race and ethnicity, 2 authors identified as East Asian, and 12 authors identified as White. With respect to engagement with college students, when this study was conducted, 3 were doctoral students who teach and/or mentor other students, 4 were postdoctoral researchers or research scientists who teach and/or mentor students, and 7 were professors who teach and/or mentor students.

Citation diversity statement

Recent work in several fields of science has identified a bias in citation practices such that papers from women and other minority scholars are under-cited relative to the number of such papers in the field (Bertolero et al., 2020; Caplar et al., 2017; Chatterjee & Werner, 2021; Dion et al., 2018; Dworkin et al., 2020; Fulvio et al., 2021; Maliniak et al., 2013; Mitchell et al., 2013; Wang et al., 2020). Here we sought to proactively consider choosing references that reflect the diversity of the field in thought, form of contribution, gender, race, ethnicity, and other factors. First, we obtained the predicted gender of all authors of each reference (excluding self-citations) by using databases that store the probability of a first name being carried by a woman (Caplar et al., 2017; Dion et al., 2018; Dworkin et al., 2020; Maliniak et al., 2013; Mitchell et al., 2013; Zhou et al., 2022). By this measure, our citations contain 47% women and 52% men across all authors from non-software references; 38% women and 61% men considering only first and last authors from non-software references; and 100% men across software references. This method is limited in that a) names, pronouns, and social media profiles used to construct the databases may not, in every case, be indicative of gender identity and b) it cannot account for intersex, non-binary, or transgender people.

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Supplementary Material

Mindful attention to alcohol can reduce cravings in the moment and consumption in daily life

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Socioeconomic demographics

Household income and highest level of education attained for the sample are reported in Table S1.

Table S1. Sample socioeconomic demographics

Income	Category	%		
	$0 to $9,999	2.6		
	$10,000 to $14,999	0.0		
	$15,000 to $19,999	2.6		
	$20,000 to $34,999	5.3		
	$35,000 to $49,999	5.3		
	$50,000 to $74,999	10.5		
	$75,000 to $99,999	10.5		
	$100,000 to $199,999	23.7		
	$200,000 or more	31.6		
	Not reported	7.9		
Education	**Category**	**Self (%)**	**Mother or Parent 1 (%)**	**Father or Parent 2 (%)**
	Some high school	2.6	2.6	0.0
	High school or GED	78.9	2.6	5.3
	Associate’s or professional degree	2.6	13.2	7.9
	Some college	0.0	0.0	2.6
	Bachelor’s degree	7.9	36.8	23.7
	Master’s degree	0.0	23.7	26.3
	Ph.D or equivalent (M.D., J.D., etc.)	0.0	13.2	26.3
	Not reported	7.9	7.9	7.9

Neuroimaging

Acquisition

Scans were acquired using 3 Tesla Siemens Prismas at the University of Pennsylvania Center for Functional Neuroimaging and at the Mortimer B. Zuckerman Mind Brain Behavior Institute at Columbia University. For each participant, images were acquired using a 64-channel head coil and the present study used the T1-weighted MP-RAGE anatomical scan (TR = 1850ms, TE = 3.91ms, flip angle = 8°, voxel size = 0.9 x 0.9 x 1.0mm, sagittal slices = 160, FOV = 240), T2*-weighted echo-planar sequence (TR = 1000ms, TE = 30ms, flip angle = 62°, voxel size = 3.0 x 3.0 x 3.0mm, axial slices = 42, FOV = 210, multiband acceleration factor = 3), and echo-planar fieldmap (TR = 8000ms, TE = 66ms, flip angle = 90°, voxel size = 3.0 x 3.0 x 3.0mm, axial slices = 42, FOV = 210). DICOM images were converted to NIfTI files in the Brain Imaging Data Structure (Gorgolewski et al., 2016) format using HeuDiConv (Version 0.8.0; Halchenko et al., 2020).

Preprocessing

The neuroimaging data was preprocessed using fMRIPrep (Version 20.0.6; Esteban et al., 2019), which is based on Nipype (Version 1.4.2; Gorgolewski et al., 2011). A detailed description of preprocessing is provided in Cosme et al. (2022). Briefly, anatomical images were segmented and normalized to the Montreal Neurological Institute (MNI) space using FreeSurfer (Fischl, 2012); functional images were susceptibility distortion corrected, realigned, slice-time corrected, and coregistered to the normalized anatomical images. Preprocessed functional data were manually checked for quality to ensure adequate preprocessing, and smoothed using a 6-mm full-width at half maximum smoothing kernel in SPM12.

First-level condition modeling for MVPA analyses

Event-related condition effects were estimated in first-level analyses using a fixed-effects general linear model and a canonical hemodynamic response function. Regressors modeled each experimental condition (Reactivity Alcohol, Reactivity Non-alcohol, Mindful Attention) during image presentation. Additional regressors of no interest were added for the instruction cue and rating periods. Five motion regressors were modeled as covariates of no interest. Realignment parameters were transformed into Euclidean distance for translation and rotation separately; we also included the displacement derivative of each. Another ‘trash’ regressor marked images with motion artifacts (e.g., striping) identified via automated motion assessment (Cosme et al., 2018) and visual inspection. Task runs that contained >10% of volumes classified as containing a motion artifact were excluded from further analyses, resulting in the exclusion of one participant. Data were high-pass filtered at 128 s, and temporal autocorrelation was modeled using FAST (Corbin et al., 2018). The resulting contrast maps for Reactivity > Rest and Mindful Attention > Rest for each run separately (4 per condition per person) were then used to develop the mindful attention signature.

Mindful signature attention: discriminant validity

We used data from another subset of participants from the larger project (N = 34) to test discriminant validity of the mindful attention signature. These participants were randomized to a perspective-taking intervention. Rather than mindfully attending to alcohol, participants in the perspective-taking intervention were trained to adopt the perspective of different peers from their social group when exposed to alcohol cues. They were asked to “try to put yourself in the shoes of [your peer] and consider how they would react to the images based on what you know about them.”

We tested discriminant validity by applying the mindful attention signature to trial-level data from participants in the perspective-taking group and assessing accuracy. If the neural signature is encoding general cognitive processing not specific to mindful attention, then we would expect equivalent performance decoding regulation from reactivity in the perspective-taking group. If performance is much worse in the perspective-taking group, then we can infer that the information contained in the neural signature is unique to mindful attention, and does not reflect more general cognitive processing consistent across regulation strategies. In line with this possibility, we found that decoding accuracy was substantially lower for the perspective-taking group (Acc = 0.53, 95% CI [0.51, 0.56] compared to the mindful attention group (Acc = 0.70, 95% CI [0.68, 0.72]), suggesting that the signature is specific to mindful attention (Figure S1).

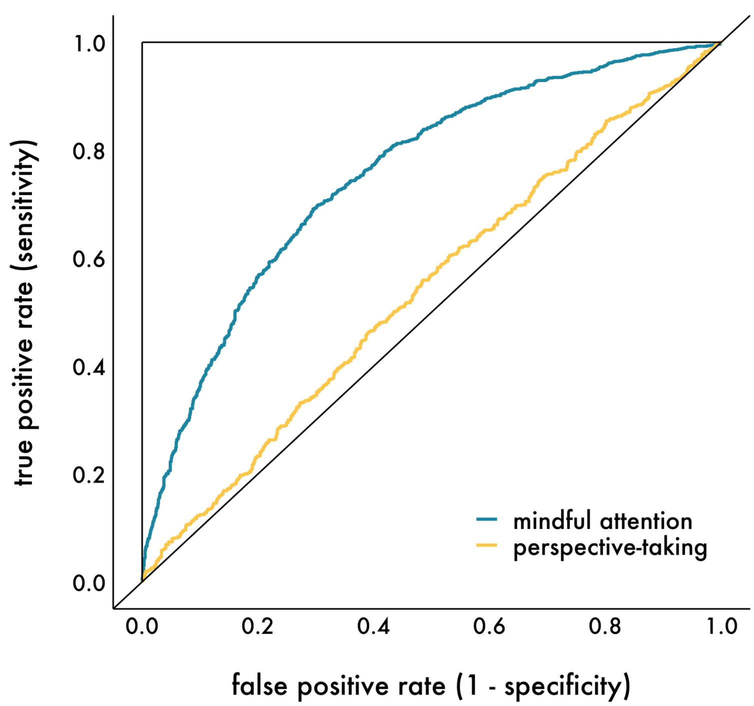

Figure S1. Receiver operating characteristic (ROC) curve showing trial-level prediction accuracy of the mindful attention signature in the mindful attention (blue) and perspective-taking (yellow) groups. The diagonal black line indicates chance classification, whereas the vertical and horizontal black lines indicate perfect classification.

Confidence rating analyses

After the MRI scan, participants rated how confident they were that they correctly followed the instructions to attend to the alcohol cues mindfully (“How successful do you think you were in following the MINDFUL instructions?”). In the following analyses, we explored the degree to which 1) individual differences in confidence were related to expression of the mindful attention signature during the MRI task and 2) conditioning the associations between signature expression (within- and between-person) and craving ratings on individual differences in confidence (i.e., “controlling” for confidence) affected the magnitude of the associations. Models were fit using *brms* (Bürkner 2017) in R (R Core Team, 2022).

Signature expression

Using Bayesian multilevel modeling, we regressed the trial-level mindful attention signature expression on the fixed effects of trial condition, confidence, and their interaction. Intercepts and trial condition slopes were allowed to vary randomly across people. We did not observe evidence that confidence ratings were related to signature expression on either mindful attention (b = 0.04, 95% CrI [-0.81, 0.93]) or reactivity (b = 0.05, 95% CrI [-0.87, 1.01]) trials. This null finding indicates that the subjective perception of how well a person is engaging in mindful attention is not strongly related to the more “objective” measure of mindful attention indicated by the mindful attention brain signature. This observation in turn suggests that each indicator may contain complementary information that can be used to predict cravings.

Craving

We refit the trial-level model reported in the main manuscript while controlling for confidence ratings by regressing trial-level craving on the fixed effects of within- and between-person signature expression, task condition, and their separate interactions, and confidence ratings. The results reported in Table S2 and Figure S2 show that controlling for confidence ratings did not appreciably alter the strength of the relationships between signature expression (within- and between-person) and craving.

Table S2. Results from the craving model

Term	b [95% CrI]
Intercept (reactivity)	2.32 [1.93, 2.73]
Task condition (mindful attention)	-0.20 [-0.71, 0.30]
Signature expression (between)	0.27 [-0.02, 0.56]
Signature expression (within)	-0.01 [-0.07, 0.05]
Confidence rating	-0.07 [-0.30, 0.15]
Task condition (mindful attention) x signature expression (between)	-0.48 [-0.94, -0.01]
Task condition (mindful attention) x signature expression (within)	-0.02 [-0.11, 0.07]

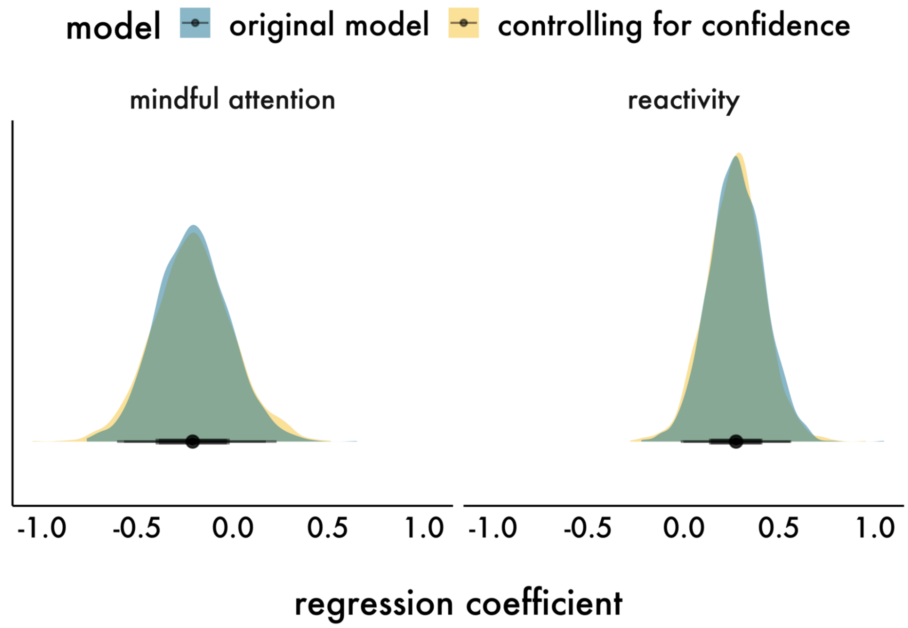

Figure S2. Posterior distributions of the association between trial-level cravings and between-person mindful attention signature expression for mindful attention and reactivity trials separately. This visualization compares the posterior distributions in the original model reported in the main manuscript (in blue) and the supplementary model controlling for confidence ratings (in yellow). The distributions are largely overlapping, suggesting that the strength of the associations are not substantially different when controlling for confidence ratings.

Effectiveness and individual differences: experience sampling intervention analyses with craving

Building on the laboratory analyses, we explored how the mindful attention intervention affected alcohol consumption in daily life, and the degree to which individual differences in expression of the mindful attention signature during the task (i.e., during mindful attention trials) moderated effectiveness. We tested whether there was an indirect effect of the intervention (active or control week) on alcohol consumption through alcohol craving, and the degree to which individual differences in mindful attention signature expression moderated the relationships between A) intervention week on craving, and B) craving on alcohol consumption. Models were fit using *brms* (Bürkner 2017) in R (R Core Team, 2022). Craving and alcohol consumption were within-person centered such that they reflect changes from a person's average. Craving was lagged so that we examined the relationship between craving at a previous timepoint and alcohol consumption at the next. In the first model, craving was regressed on the fixed effects of intervention week, signature expression, and their interaction; intervention week slopes were allowed to vary randomly across people. In the second model, number of drinks was regressed on intervention week, signature expression, craving, and the interaction between signature expression and craving; intervention week and craving were allowed to vary randomly across people. The same modeling parameters (i.e., priors, sampling interactions) as in the trial-level analyses were used here.

Indirect effect of the intervention on alcohol consumption via craving

We did not observe evidence for an indirect effect of the intervention on alcohol consumption through craving (b = 0.01, 95% CrI [-0.02, 0.05]). Active intervention weeks did not significantly affect craving (*a* path; b = 0.04, 95% CrI [-0.06, 0.14]), though stronger cravings were associated with greater alcohol consumption than average (*b* path; b =0.30, 95% CrI [0.19, 0.42]).

Moderation by mindful attention signature expression

We did not observe moderation of either path of the indirect effect. How strongly people expressed the mindful attention signature did not significantly moderate the effect of the intervention on craving (a path; $b_{interaction}$ = -0.06, 95% CrI [-0.16, 0.14]) or the relationship between craving and alcohol consumption (b path; $b_{interaction}$ = 0.06, 95% CrI [-0.07, 0.18]).

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