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

Danielle Cosme*[1]
Chelsea Helion*[2]
Yoona Kang[3]
David M. Lydon-Staley[1,4,5]
Bruce P. Doré[6]
Ovidia Stanoi[7]
Jeesung Ahn[8]
Mia Jovanova[1]
Amanda L. McGowan[9]
Zachary M. Boyd[10]
Peter J. Mucha[11]
Dani S. Bassett[4,12-16]
Kevin N. Ochsner[7]
Emily B. Falk[1,8,17-18]

[1] Annenberg School for Communication, University of Pennsylvania, USA
[2] Department of Psychology and Neuroscience, Temple University, USA
[3] Department of Psychology, Rutgers University–Camden, USA
[4] Department of Bioengineering, University of Pennsylvania, USA
[5] Leonard Davis Institute of Health Economics, University of Pennsylvania, USA
[6] Desautels Faculty of Management, McGill University, Canada
[7] Department of Psychology, Columbia University, USA
[8] Department of Psychology, University of Pennsylvania, USA
[9] Department of Psychology, Concordia University, Canada
[10] Department of Mathematics, Brigham Young University, USA
[11] Department of Mathematics, Dartmouth College, USA
[12] Department of Electrical & Systems Engineering, University of Pennsylvania, USA
[13] Department of Neurology, University of Pennsylvania, USA
[14] Department of Psychiatry, University of Pennsylvania, USA
[15] Department of Physics & Astronomy, University of Pennsylvania, USA
[16] The Santa Fe Institute, USA
[17] Wharton Marketing Department, University of Pennsylvania, USA
[18] Wharton Operations, Information and Decisions Department, University of Pennsylvania, USA

Abstract

It is critical to support healthy development of alcohol-related habits, particularly in contexts with heightened risk such as college campuses. Mindfulness-based strategies are frequently used in interventions to reduce substance use in clinical populations, but their utility as a preventative strategy among emerging adults is less clear. 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 in a sample of college students. Students completed a mindful attention task towards alcohol in an fMRI scanner followed by a 28-day, smartphone-based, experience sampling intervention. We leveraged functional neuroimaging and machine learning to develop a neural measure (signature) of mindful attention that enabled us to examine moment-to-moment fluctuations and individual differences in effective implementation 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, the mindful attention intervention increased mindful responses to alcohol and decreased lagged alcohol consumption through two distinct pathways: mindful responses directly influenced alcohol consumption and indirectly influenced it by reducing cravings for alcohol. Moreover, individuals who more strongly expressed the mindful attention signature benefitted the most from the intervention. Broadly, our study highlights how mindful attention can reduce alcohol consumption among emerging adults in college via a scalable smartphone-based intervention.

Keywords: Mindfulness, emotion regulation, intervention, alcohol, college

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 (Duncan et al., 1997), 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, and we map the associated neural pathways of effectiveness. 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 and its mechanisms 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; Pagnini et al., 2016), 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 preventative 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 substance 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 preventative 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

We predict that attending to alcohol mindfully will reduce craving, but how can we tell whether and how well someone is attending to their experience mindfully? Simply instructing individuals to attend mindfully does not guarantee that they are, and even if they are, it does not account for variability in the quality of this attention. We might infer this from their self-reported cravings, but this itself is not a measure of 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 these issues and potential biases inherent in all self-report measures of mental states (Wager et al., 2013), including mindfulness (Grossman & Van Dam, 2011). 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. Applying this approach to mindful attention has the potential to more robustly quantify whether and how well participants are engaging in mindful attention in the moment, as well as generate a more precise individual difference measure of overall ability across the task (versus e.g., mean activity in a single brain region of interest). 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 or examined intervention effectiveness within individuals by exposing them to both intervention and control conditions. Because this approach generates repeated measures within-person for each condition, it can enable more fine-grained assessment of intervention adherence and mechanisms at the individual level.

Toward this goal, participants in the present study completed a 28-day within-person mindful attention intervention and reported how mindfully they attended to alcohol, as well as alcohol craving and consumption multiple times a day. This design allowed us to consider not only the intervention condition as a whole, but also afforded assessment of fluctuations in mindful responses within condition, and to test causal pathways among these variables within individuals (Hsiao et al., 2019). Based on theoretical models (Brewer et al., 2013; Garland et al., 2014), our overarching hypothesis is that mindful attention would decrease craving for alcohol, which would in turn decrease consumption of alcohol (*H3*). However, given craving for alcohol tends to be low in non-clinical populations, in addition to this indirect path, we also examined direct paths between mindful attention and alcohol consumption.

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 (Cosme et al., 2020) and hypothesized that people who on average show increased expression of the mindful attention signature will be most responsive to the intervention (*H4*). This work is novel in linking a neural signature of emotion regulation strategy use to evaluate the effectiveness of a health behavior change intervention using densely sampled within-person measures. Such evidence is important for identifying personalized approaches to public health interventions that target health behavior change (Doré et al., 2016).

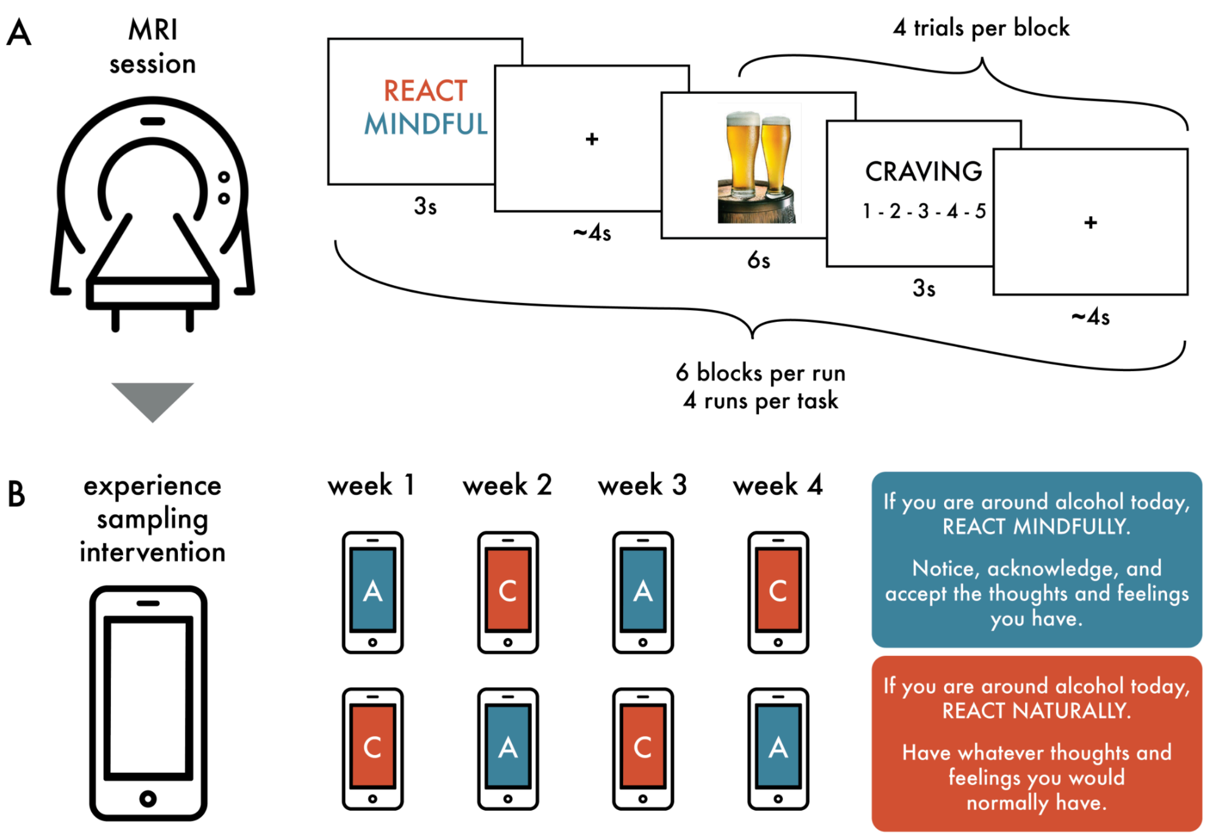
Methods

Study overview

The present study had two phases: an MRI session followed by a 28-day experience sampling intervention (Figure 1). In the context of the MRI session, we tested the *efficacy* (i.e., success in a controlled laboratory setting) 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



Note. (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).

Transparency and openness

This study uses data from a broader project (the Social Health Impact of Network Effects study) that examined how interactions between mind, brain, and community give rise to health and well-being (Cosme et al., 2022; https://osf.io/gkahy). Other publications using these data but focusing on different research questions include: Jovanova et al. (2023), Zhou et al. (2022), (Kang et al., 2022, 2023). In this study, we report how we determined our sample size, all data exclusions, all manipulations, and the measures relevant to this study (all measures are described in Cosme et al., 2022). The hypotheses and analysis plan for the mindful attention signature development and efficacy analyses (H2) were preregistered (https://osf.io/tpyws), whereas the other analyses were not preregistered. We note deviations from our 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://github.com/cnlab/shine-mindfulness-mvpa). The unthresholded mindful attention signature is available on NeuroVault (https://neurovault.org/collections/13816/).

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 $N = 108$ for the broader project. In the project, these 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. Because the present study aims to understand whether, how, and for whom mindful attention is an effective regulation strategy to reduce alcohol consumption, we focus on the mindful attention group ($n = 38$, $M_{\text{age}} = 20.8$, $SD_{\text{age}} = 1.9$). Because we are conducting within-person analyses with repeated measures, we have 80% power to detect task condition effects on craving ($n_{\text{trials}} = 2193$) of $d = 0.1$ or larger, intervention week effects on alcohol consumption ($n_{\text{observations}} = 340$) of $d = 0.26$ or larger, and intervention week effects on craving ($n_{\text{observations}} = 1460$) of $d = 0.12$ or larger. Between-group comparisons of the intervention effects on alcohol consumption in daily life are reported in Jovanova et al. (2023). We also conducted sensitivity analyses reported in Supplementary Material using data from participants in the perspective-taking group ($n = 34$). Participants were university students who belonged to social groups (e.g., clubs, sports teams, or Greek life organizations) at the University of Pennsylvania ($n_{\text{groups}} = 17$) and Columbia University ($n_{\text{groups}} = 21$). 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). The data used in this study were collected between January 2019 and April 2020.

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; Westbrook et al., 2013). 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/3eyh6). 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 alcohol consumption (number of standard drinks of beer, liquor, and wine) and 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) since the previous survey. Current alcohol craving (1 = Not at all, 100 = Extremely) was assessed four times each day at 8AM, 2PM, 6PM, and 9PM.

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).

To confirm that signature expression was higher on Mindful Attention than Reactivity trials, we applied the signature to the trial-level and used Bayesian multilevel modeling to test the difference between conditions. We regressed trial-level signature expression on the fixed effect task condition using the *brms* package (Bürkner, 2017) in R (R Core Team, 2022). Intercepts and task condition slopes were allowed to vary randomly across people. Signature expression was z-scored and we used a weakly informative prior for the fixed effect parameters, defined as a normal distribution with M = 0 and SD = 1 (Lemoine, 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). Ninety percent credible intervals are used in all analyses due to greater computational stability (Goodrich et al., n.d.) and indicate that based on the observed data, there is a 90% probability that the true parameter value is in the credible interval. In the Supplementary Material, we also report sensitivity analyses including subjective confidence using the mindful attention strategy (rated after the MRI scan) or scores on the Mindful Attention and Awareness

Scale (reported before the scan) as covariates; the results of both models are consistent with those reported in the main manuscript indicating that expression of the mindful attention signature is distinct from subjective confidence and self-reported trait mindfulness.

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 potential mechanisms through which the mindful attention intervention might impact alcohol consumption and the degree to which individual differences in mindful attention signature expression moderated these relationships using moderated multilevel sequential mediation. We expected that: the intervention (X) would increase mindful responses to alcohol (M1), more mindful responses to alcohol would decrease craving (M2), and less craving would be associated with decreased alcohol consumption (Y). In addition to this sequential indirect path, we estimated all nested simple indirect and direct paths, and included mindful attention signature as a moderator of these paths. To do so, we fit three models using brms (Bürkner, 2017) in R (R Core Team, 2022), which allowed the random effects to correlate across models. In the first model (X → M1), mindful responses were regressed on intervention (active or control), signature expression, and their interaction; the slope of intervention was allowed to vary randomly across people. In the second model (M1 → M2), craving was regressed on intervention, mindful responses, signature expression, and the two-way interactions between signature expression and intervention and mindful responses; the slopes of intervention and mindful responses were allowed to vary randomly across people. In the third model (M2 → Y), alcohol consumption was regressed on intervention, mindful responses, craving, signature expression, and the two-way interactions between signature expression and intervention, mindful responses, and craving; the slopes of intervention, mindful responses, and craving were allowed to vary randomly across people. Mindful responses, craving, and alcohol consumption were within-person centered and standardized such that they reflect changes from a person's average in *SD* units. Given that the number of standard drinks consumed is a meaningful unit, alcohol consumption values were not standardized. In the craving models, craving was lagged so that we examined the relationship between craving at a previous time point (e.g., reported at 2PM) and alcohol consumption at the next time point (e.g., retrospectively reported at 6PM). The same modeling parameters (e.g., priors) as in the trial-level analyses were used here.

Results

Descriptive statistics

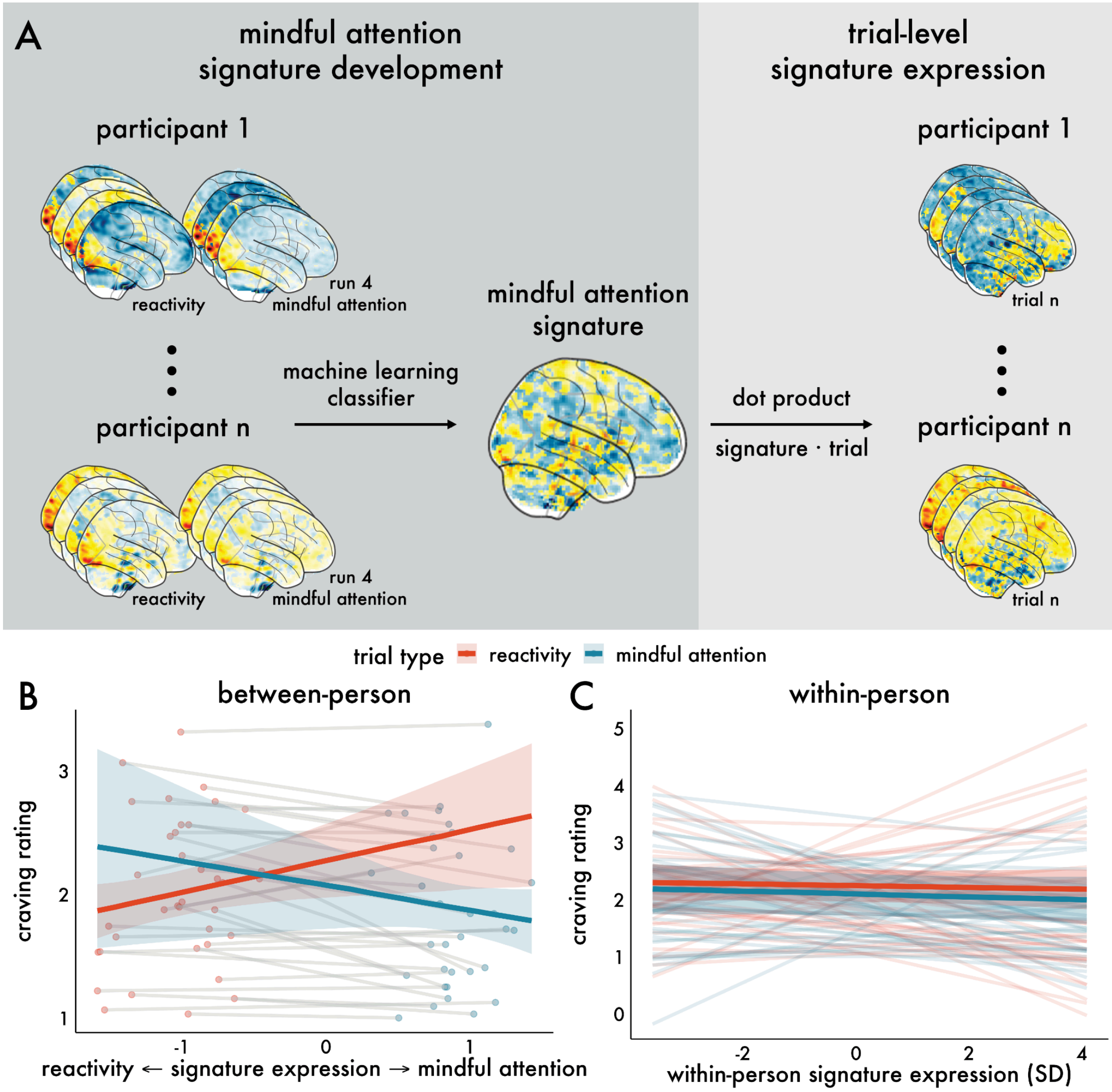
During the laboratory task, participants reported relatively low cravings for alcohol on average when reacting naturally (*M* = 2.0, *SD* = 1.1) and when attending mindfully (*M* = 1.9, *SD* = 1.0). In daily life, participants reported low cravings for alcohol on active intervention weeks (*M* = 12.4, *SD* = 18.3) and control (*M* = 11.9, *SD* = 17.4). On active intervention weeks, participants reported attending to alcohol more mindfully (*M* = 62.5, *SD* = 24.2) than on control weeks (*M* = 43.1, *SD* = 29.9). As reported in Jovanova et al. (2023), participants tended to consume alcohol less frequently on active intervention days (*M* = 22.3% of days, *SD* = 15.6%, *range* = 0-57.1%) than on control days (*M* = 26.3% of days, *SD* = 21.1%, *range* = 0-100%), but drank similar amounts on active intervention days (*M* = 2.9 standard drinks, *SD* = 2.7, *range* = 0-16) and control days (*M* = 3.0 standard drinks, *SD* = 2.4, *range* = 0-12) when consuming alcohol. Across conditions, participants drank 5.3 standard drinks per week (*SD* = 7.0, *range* = 0 - 45).

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 as expected that signature expression was higher on Mindful Attention trials compared to Reactivity trials (β_{diff} = 0.85, 90% CrI [0.79, 0.91) 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. Supplementary analyses also indicate that expression of the mindful attention signature is distinct from subjective confidence employing mindful attention and self-reported trait mindfulness, as they are not strongly related either at the trial- or person-level. Together, these findings indicate expression of this neural signature is a valid measure of mindful attention that is distinct from subjective measures of mindfulness and can be applied to trial-level data to measure fluctuations and individual differences in mindful attention.

Figure 2

Overview of the analytic process and results from the efficacy analyses (H2)



Note. (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 raw 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 raw individual slopes across trials within each condition (thin red and blue lines). Error bands reflect 90% credible intervals.

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, 90% CrI [-0.21, -0.03]).

H2: Individual differences in expression of the mindful attention signature are 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 on Reactivity trials ($b_{reactivity}$ = 0.25, 90% CrI [0.03, 0.48]), whereas on Mindful Attention trials, they tended to report weaker cravings ($b_{interaction}$ = -0.45, 90% CrI [-0.84, -0.06]; $b_{simple\ slope}$ = -0.20, 90% CrI [-0.51, 0.12]). How strongly participants expressed the mindful signature compared to their average (i.e., within-person expression) was not associated with cravings on Reactivity trials ($b_{reactivity}$ = -0.01, 90% CrI [-0.06, 0.03]) or Mindful Attention trials ($b_{interaction}$ = -0.01, 90% CrI [-0.08, 0.06]; $b_{simple\ slope}$ = -0.03, 90% CrI [-0.08, 0.03]). Results are visualized in Figure 2B-C. Supplementary analyses including subjective confidence employing mindful attention and self-reported trait mindfulness indicated that while subjective confidence was associated with lower cravings on Mindful Attention trials, trait mindfulness was not related to cravings on either trial type (Supplementary Tables S2-3). Across both models, including subjective measures of mindfulness did not appreciably alter the results reported here (Figures S2-3), further supporting the notion that the mindful attention signature and subjective measures of mindfulness contain distinct and complementary information.

Effectiveness: experience sampling intervention analyses

H3: Indirect effects of the intervention on alcohol consumption through mindful responses and craving

Extending the findings from the laboratory task, we assessed the effectiveness of the mindful attention intervention in daily life. Using multilevel sequential mediation modeling, we tested the hypothesis that there would be a sequential indirect effect of the intervention on alcohol consumption through mindful responses and craving. That is, we expected that: the intervention would increase mindful responses to alcohol, more mindful responses to alcohol would decrease craving, and less craving would be associated with decreased alcohol consumption. Consistent with these hypotheses: 1) compared to control weeks, active intervention weeks increased self-reported mindful attention to alcohol (*a1* path; β = 0.48, 90% CrI [0.29, 0.67]), 2) more mindful responses to alcohol were associated with lower craving for alcohol (*b1* path; β = -0.29, 90% CrI [-0.45, -0.11]), and 3) lower craving for alcohol was associated with lower alcohol consumption (*b2* path; *b* = 0.62, 90% CrI [0.41, 0.82]). Linking these paths, we observed the hypothesized sequential indirect effect of the intervention on alcohol consumption through these paths (a1**b1***b2* = -0.08, 90% CrI [-0.16, -0.02]).

Because non-clinical samples tend to have lower craving for alcohol, we also tested whether there was an indirect effect of the intervention on alcohol consumption directly through mindful responses to alcohol. We observed that more mindful responses to alcohol were directly associated with lower alcohol consumption (*b3* path; b = -0.51, 90% CrI [-0.78, -0.21]). We also observed an indirect effect of the intervention on alcohol consumption through mindful responses alone ($a1*b3$= -0.23, 90% CrI [-0.40, -0.06]). For completeness, we also tested whether there was a direct effect of the intervention on craving (*a2* path; β =0.03, 90% CrI [-0.27, 0.34]) or an indirect effect of the intervention on alcohol consumption through craving alone, but did not observe strong evidence for either of these paths ($a2*b2$ = 0.02, 90% CrI [-0.17, 0.22]). All paths are visualized in Figure 3.

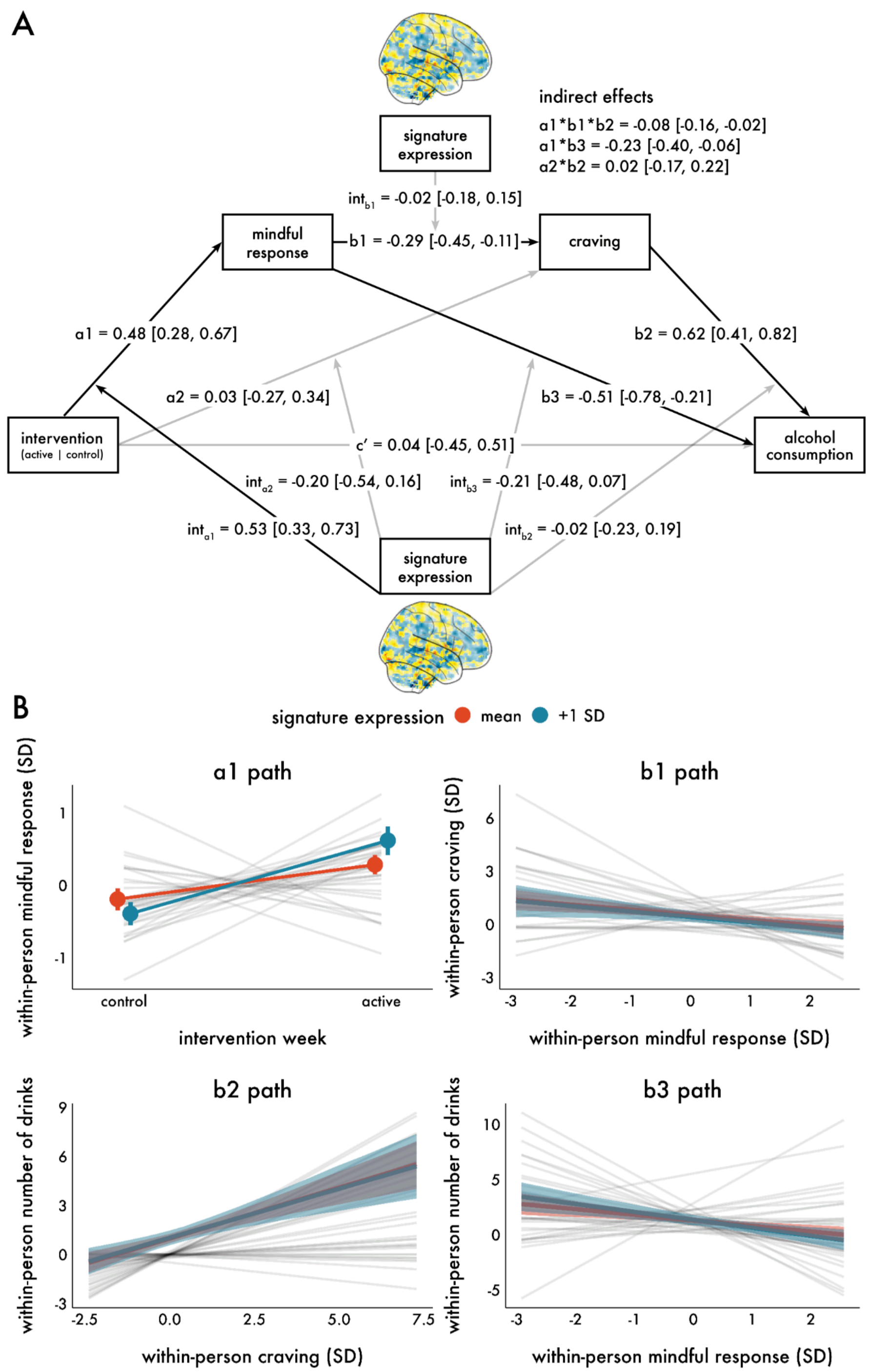
Individual differences in intervention effectiveness

H4: Mindful attention signature expression moderates intervention effects

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 relationships tested in *H3*. Consistent with the notion that mindful attention signature expression is indexing effective deployment of mindful attention, people who more strongly expressed the mindful attention signature in the laboratory showed a stronger effect of the intervention on mindful responses to alcohol (*a1* path; $\beta_{interaction}$ = 0.53, 90% CrI [0.33, 0.73]). People with greater signature expression also showed directionally stronger intervention-related decreases in craving (*a2* path; $\beta_{interaction}$ = -0.20, 90% CrI [-0.54, 0.16]) and stronger negative relationships between mindful responses to alcohol and alcohol consumption (*b3* path; $b_{interaction}$ = -0.21, 90% CrI [-0.48, 0.07]) but these effects were weaker. We did not observe evidence of moderation for either the relationship between mindful responses and craving (*b1* path; $\beta_{interaction}$ = -0.02, 90% CrI [-0.18, 0.15) or between craving and alcohol consumption (*b2* path; $b_{interaction}$ = -0.02, 90% CrI [-0.23, 0.19]). These results are visualized in Figure 3.

Figure 3

Results from the effectiveness and individual differences analyses



Note. (A) Results from the moderated sequential mediation model showing evidence of a sequential indirect effect of the intervention (active versus control weeks) on alcohol consumption through mindful responses to alcohol and craving for alcohol. That is, the mindful attention intervention increased mindful responses (*a1 path*); more mindful responses were associated with decreased craving (*b1*); and lower craving for alcohol was associated with reduced alcohol consumption (*b2*). These results also show an additional indirect effect of the intervention on alcohol consumption through mindful responses to alcohol alone. Furthermore, individual differences in the mindful attention signature expression during the laboratory task moderated intervention-related increases in mindful responses to alcohol. Black arrows indicate paths with 90% credible intervals not including zero, whereas gray arrows indicate credible intervals including zero. (B) Panels visualize the model predicted relationships of interest from the mediation model as a function of individual differences in mindful attention signature expression. 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 the top left panel represent raw individual differences between control and active weeks, and gray lines in the other panels represent raw individual relationships. Error bars and bands reflect 90% credible intervals. c′ = direct effect; int = interaction. Mindful responses, craving, and signature expression variables are standardized; alcohol consumption units are the number of standard drinks.

Discussion

The present study investigated the effects of mindful attention on brain responses, craving reduction, and alcohol consumption. We leveraged functional neuroimaging and machine learning to develop a neural measure of mindful attention that enabled us to examine moment-to-moment fluctuations and individual differences in effective implementation of mindful attention. We found that greater expression of this mindful attention 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 and decreased alcohol consumption through two distinct pathways: mindful responses directly influenced alcohol consumption and indirectly influenced it by reducing cravings for alcohol. Moreover, individuals who more strongly expressed the mindful attention signature—reflecting greater ability to use this strategy in the laboratory—benefitted the most from the intervention. Compared to people with weaker expression of the signature, they reported responding more mindfully to alcohol on intervention weeks. Together, our findings extend theoretical models of how mindfulness impacts alcohol use in emerging adults without alcohol use disorders. More broadly, they also highlight the promise of a relatively scalable mindful attention intervention to reduce alcohol consumption, and the use of neural signatures to test 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 reducing alcohol craving in controlled settings even in the absence of strong cravings, and requires little training (Ngnoumen, 2017).

Effectiveness in daily life

Using an experience sampling intervention design to examine the effectiveness of the mindful attention intervention in daily life, we observed two distinct pathways through which the intervention increased mindful responses to alcohol and reduced alcohol consumption. We found an indirect effect in which mindful responses to alcohol reduced cravings and lower cravings were in turn associated with consuming less alcohol. This is consistent with prior studies demonstrating negative indirect relationships between trait mindfulness and alcohol consumption via craving in individuals who engage in hazardous drinking (Skrzynski et al., 2024; Szeto et al., 2019). In addition to the indirect path from mindful responses to alcohol consumption, there was a direct path (i.e., not through craving) between mindful responses to alcohol and alcohol consumption. Together, this demonstrates that there are multiple pathways through which mindful attention can reduce alcohol consumption among college students without substance use disorders who do not strongly crave alcohol. 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). Furthermore, it demonstrates the utility of mindful attention as an effective emotion regulation strategy among non-clinical populations in preventative contexts.

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 operationalized the ability to attend mindfully as expression of a neural signature of mindful attention and found that individuals with stronger signature expression in the laboratory were also those who benefited most from the intervention by responding more mindfully to alcohol during intervention weeks. 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.

Measuring emotion regulation using neural signatures

A critical barrier to studying emotion regulation is the lack of sensitive and specific indicators of regulation strategy use that can be used to index whether and how well someone is regulating their emotions. Building on prior work developing neural signatures of psychological states from multivariate patterns of brain activity (Chang et al., 2015; 2022; Cosme et al., 2020; Koban et al., 2023; Schneck et al., 2023; Wager et al., 2013; Woo et al., 2017), we created a neural signature of mindful attention that enabled more fine-grained assessment of momentary fluctuations and individual differences in mindful attention. Individual differences in signature expression were related to both cravings in the laboratory and intervention effectiveness in daily life, highlighting the potential utility of this approach to generate indices of emotion regulation ability. Notably, the mindful attention signature was not correlated with subjective confidence employing mindful attention or trait mindfulness, demonstrating the importance of considering both objective and subjective indicators of regulatory ability. Finally, given recent reports calling into question the usefulness of “traditional” functional brain metrics (e.g., mean activity in brain regions of interest) as biomarkers given high within-person variability (Elliott et al., 2020; Flournoy et al., 2024), our results add to the mounting evidence that multivariate neural signatures representing psychological processes may be more promising candidates (Kragel et al., 2021).

Limitations and constraints on generality

Despite notable strengths, such as approaching links between mindfulness, craving and alcohol use across multiple levels of analysis, that included fMRI and experience sampling, testing a within-person intervention, and preregistering the study, there are several limitations that should be noted. First, we focused on college students because they are at risk for alcohol-related negative consequences and could benefit from preventative interventions that help them develop healthy habits related to alcohol. However, this means that our findings may not generalize beyond this population, which tends to be wealthier, whiter, and more highly educated than the general population (Henrich et al., 2010), future work is needed in more diverse populations. Despite a wide range of drinking behavior in our sample, 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). Future work should examine how any demand effect may be reduced by introducing regulatory choice, that is, letting participants opt into mindful attention as a regulatory strategy on a subset of trials (Cosme et al., 2018).

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 used functional neuroimaging and machine learning to develop a predictive model of mindful attention that enabled us to measure momentary fluctuations and individual differences in mindful attention. Mindful attention reduced cravings for alcohol in the laboratory and decreased alcohol consumption in daily life directly and indirectly through reduced cravings. Moreover, individuals who more strongly engaged the mindful attention brain signature—indicating greater ability to attend to alcohol mindfully at baseline—benefited the most from the intervention. Together, these findings suggest that mindful attention can be an effective, preventative strategy for reducing alcohol consumption when successfully implemented. Furthermore, it highlights the potential of scalable, smartphone-based interventions that remind individuals to regulate their responses to alcohol (Jovanova et al., 2023).

Acknowledgements

We thank our participants and the Social Health Impact of Network Effects team without whom this work would not have been possible.

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 45% women and 54% men (1% of names could not be classified) across all authors from non-software references; 37% women and 61% men (2% of names could not be classified) 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.

Funding

This research was sponsored by the Army Research Office and was accomplished under Grant Number W911NF-18-1-0244. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Office or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein. Additional support to researchers individually as follows: DML and ALM acknowledge support from the National Institute on Drug Abuse (K01 DA047417) and the Brain & Behavior Research Foundation. DSB acknowledges support from the John D. and Catherine T. MacArthur Foundation, the SwartzFoundation, the Paul G. Allen Family Foundation, the Alfred P. Sloan Foundation and the NSF (PHY-1554488; IIS-1926757). DC and EBF acknowledge support from Hopelab. YK acknowledges support from the Mind and Life Institute. EBF acknowledges support from the National Cancer Institute, R01 CA229305-01A1. BPD acknowledges support from the Social Sciences and Humanities Research Council of Canada (Insight Grant 435-2021-0511), the Natural Sciences and Engineering Research Council of Canada (Discovery Grant RGPIN-2021-03438), Defence Research and Development Canada, and the Canada First Research Excellence Fund, awarded to the Healthy Brains Healthy Lives Initiative at McGill University.

References

Berkman, E. T., & Falk, E. B. (2013). Beyond Brain Mapping: Using Neural Measures to Predict Real-World Outcomes. *Current Directions in Psychological Science*, *22*(1), 45–50. https://doi.org/10.1177/0963721412469394

Bertolero, M. A., Dworkin, J. D., David, S. U., Lloreda, C. L., Srivastava, P., Stiso, J., Zhou, D., Dzirasa, K., Fair, D. A., Kaczkurkin, A. N., Marlin, B. J., Shohamy, D., Uddin, L. Q., Zurn, P., & Bassett, D. S. (2020). Racial and ethnic imbalance in neuroscience reference lists and intersections with gender (p. 2020.10.12.336230). bioRxiv. https://doi.org/10.1101/2020.10.12.336230

Bishop, S. R., Lau, M., Shapiro, S., Carlson, L., Anderson, N. D., Carmody, J., Segal, Z. V., Abbey, S., Speca, M., Velting, D., & Devins, G. (2004). Mindfulness: A proposed operational definition. *Clinical Psychology: Science and Practice*, *11*(3), 230–241. https://doi.org/10.1093/clipsy.bph077

Bonanno, G. A., & Burton, C. L. (2013). Regulatory Flexibility: An Individual Differences Perspective on Coping and Emotion Regulation. *Perspect. Psychol. Sci.*, *8*(6), 591–612. https://doi.org/10.1177/1745691613504116

Brewer, J. A., Elwafi, H. M., & Davis, J. H. (2013). Craving to quit: Psychological models and neurobiological mechanisms of mindfulness training as treatment for addictions. *Psychol. Addict. Behav.*, *27*(2), 366–379. https://doi.org/10.1037/a0028490

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *J. Stat. Softw.*, *80*, 1–28.

Byrne, S. P., Haber, P., Baillie, A., Costa, D. S. J., Fogliati, V., & Morley, K. (2019). Systematic Reviews of Mindfulness and Acceptance and Commitment Therapy for Alcohol Use Disorder: Should we be using Third Wave Therapies? *Alcohol Alcohol*, *54*(2), 159–166. https://doi.org/10.1093/alcalc/agy089

Caplar, N., Tacchella, S., & Birrer, S. (2017). Quantitative evaluation of gender bias in astronomical publications from citation counts. Nature Astronomy, 1(6), Article 6. https://doi.org/10.1038/s41550-017-0141

Chang, L. J., Gianaros, P. J., Manuck, S. B., Krishnan, A., & Wager, T. D. (2015). A Sensitive and Specific Neural Signature for Picture-Induced Negative Affect. *PLOS Biol*, *13*(6), e1002180. https://doi.org/10.1371/journal.pbio.1002180

Chang, L. J., Li, X., Nguyen, K., Ranger, M., Begunova, Y., Chen, P.-H. A., Castrellon, J. J., Samanez-Larkin, G. R., Zald, D. H., Fareri, D. S., Delgado, M. R., & Tomova, L. (2022). *A neural signature of reward* (p. 2022.08.23.504939). bioRxiv. https://doi.org/10.1101/2022.08.23.504939

Chang, L., Sam, Jolly, E., Cheong, J. H., Burnashev, A., Chen, A., & Frey, S. (2019). *cosanlab/nltools: 0.3.14* (0.3.14) [Computer software]. http://doi.org/10.5281/zenodo.3251172

Charness, G., Gneezy, U., & Kuhn, M. A. (2012). Experimental methods: Between-subject and within-subject design. *J. Econ. Behav. Organ.*, *81*(1), 1–8. https://doi.org/10.1016/j.jebo.2011.08.009

Chatterjee, P., & Werner, R. M. (2021). Gender Disparity in Citations in High-Impact Journal Articles. JAMA Network Open, 4(7), e2114509. https://doi.org/10.1001/jamanetworkopen.2021.14509

Chiesa, A., & Serretti, A. (2014). Are Mindfulness-Based Interventions Effective for Substance

Use Disorders? A Systematic Review of the Evidence. *Substance Use & Misuse*, *49*(5), 492–512. https://doi.org/10.3109/10826084.2013.770027

Christensen, T. C., Barrett, L. F., Bliss-Moreau, E., Lebo, K., & Christensen, T. C. (2003). A practical guide to experience-sampling procedures. *J. Happiness Stud.*, *4*(1), 53–78. https://doi.org/10.1023/a:1023609306024

Cosme, D., Kang, Y., Tartak, J. C., Ahn, J., Corbani, F. E., Cooper, N., Doré, B., He, X., Helion, C., Jovanova, M., Lomax, S., Mahadevan, A. S., McGowan, A. L., Paul, A. (Ally) M., Pei, R., Resnick, A., Stanoi, O., Zhang, T. (Sky), Zhang, Y., … Falk, E. (2022). *Study protocol: Social Health Impact of Network Effects (SHINE) Study*. PsyArXiv. https://doi.org/10.31234/osf.io/cj2nx

Cosme, D., Mobasser, A., Zeithamova, D., Berkman, E. T., & Pfeifer, J. H. (2018). Choosing to regulate: Does choice enhance craving regulation? *Social Cognitive and Affective Neuroscience*, *13*(3), 300–309. https://doi.org/10.1093/scan/nsy010

Cosme, D., Zeithamova, D., Stice, E., & Berkman, E. T. (2020). Multivariate neural signatures for health neuroscience: Assessing spontaneous regulation during food choice. *Soc. Cogn. Affect. Neurosci.*, *15*(10), 1120–1134. https://doi.org/10.1093/scan/nsaa002

Dahl, C. J., Lutz, A., & Davidson, R. J. (2015). Reconstructing and deconstructing the self: Cognitive mechanisms in meditation practice. *Trends Cogn. Sci.*, *19*(9), 515–523. https://doi.org/10.1016/j.tics.2015.07.001

Dion, M. L., Sumner, J. L., & Mitchell, S. M. (2018). Gendered Citation Patterns across Political Science and Social Science Methodology Fields. Political Analysis, 26(3), 312–327. https://doi.org/10.1017/pan.2018.12

Doré, B. P., Silvers, J. A., & Ochsner, K. N. (2016). Toward a Personalized Science of Emotion Regulation. *Soc. Personal. Psychol. Compass*, *10*(4), 171–187. https://doi.org/10.1111/spc3.12240

Duncan, S. C., Alpert, A., Duncan, T. E., & Hops, H. (1997). Adolescent alcohol use development and young adult outcomes. *Drug and Alcohol Dependence*, *49*(1), 39–48. https://doi.org/10.1016/S0376-8716(97)00137-3

Dworkin, J. D., Linn, K. A., Teich, E. G., Zurn, P., Shinohara, R. T., & Bassett, D. S. (2020). The extent and drivers of gender imbalance in neuroscience reference lists. Nature Neuroscience, 23(8), Article 8. https://doi.org/10.1038/s41593-020-0658-y

Elliott, M. L., Knodt, A. R., Ireland, D., Morris, M. L., Poulton, R., Ramrakha, S., Sison, M. L., Moffitt, T. E., Caspi, A., & Hariri, A. R. (2020). What Is the Test-Retest Reliability of Common Task-Functional MRI Measures? New Empirical Evidence and a Meta-Analysis. *Psychological Science*, *31*(7), 792–806. https://doi.org/10.1177/0956797620916786

Elwafi, H. M., Witkiewitz, K., Mallik, S., Thornhill, T. A., & Brewer, J. A. (2013). Mindfulness training for smoking cessation: Moderation of the relationship between craving and cigarette use. *Drug and Alcohol Dependence*, *130*(0), 222–229. https://doi.org/10.1016/j.drugalcdep.2012.11.015

Flournoy, J. C., Bryce, N. V., Dennison, M. J., Rodman, A. M., McNeilly, E. A., Lurie, L. A., Bitran, D., Reid-Russell, A., Vidal Bustamante, C. M., Madhyastha, T., & McLaughlin, K. A. (2024). A precision neuroscience approach to estimating reliability of neural responses during emotion processing: Implications for task-fMRI. *NeuroImage*, *285*, 120503. https://doi.org/10.1016/j.neuroimage.2023.120503

Fulvio, J. M., Akinnola, I., & Postle, B. R. (2021). Gender (Im)balance in Citation Practices in

Cognitive Neuroscience. Journal of Cognitive Neuroscience, 33(1), 3–7. https://doi.org/10.1162/jocn_a_01643

Gál, É., Ștefan, S., & Cristea, I. A. (2021). The efficacy of mindfulness meditation apps in enhancing users' well-being and mental health related outcomes: A meta-analysis of randomized controlled trials. *Journal of Affective Disorders*, *279*, 131–142. https://doi.org/10.1016/j.jad.2020.09.134

Garland, E., Froeliger, B., & Howard, M. (2014). Mindfulness Training Targets Neurocognitive Mechanisms of Addiction at the Attention-Appraisal-Emotion Interface. *Frontiers in Psychiatry*, *4*. https://www.frontiersin.org/articles/10.3389/fpsyt.2013.00173

Garrison, K. A., Pal, P., O'Malley, S. S., Pittman, B. P., Gueorguieva, R., Rojiani, R., Scheinost, D., Dallery, J., & Brewer, J. A. (2020). Craving to Quit: A randomized controlled trial of smartphone app-based mindfulness training for smoking cessation. *Nicotine Tob. Res.*, *22*(3), 324–331. https://doi.org/10.1093/ntr/nty126

Goldberg, S. B., Riordan, K. M., Sun, S., & Davidson, R. J. (2022). The Empirical Status of Mindfulness-Based Interventions: A Systematic Review of 44 Meta-Analyses of Randomized Controlled Trials. *Perspect. Psychol. Sci.*, *17*(1), 108–130. https://doi.org/10.1177/1745691620968771

Goodrich, B., Gabry, J., Ali, I., & Brilleman, S. (n.d.). *Posterior uncertainty intervals—Posterior_interval.stanreg*. Retrieved February 5, 2024, from https://mc-stan.org/rstanarm/reference/posterior_interval.stanreg.html#default-90-intervals

Gorgolewski, K. J., Auer, T., Calhoun, V. D., Craddock, R. C., Das, S., Duff, E. P., Flandin, G., Ghosh, S. S., Glatard, T., Halchenko, Y. O., Handwerker, D. A., Hanke, M., Keator, D., Li, X., Michael, Z., Maumet, C., Nichols, B. N., Nichols, T. E., Pellman, J., … Poldrack, R. A. (2016). The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments. *Scientific Data*, *3*(1), Article 1. https://doi.org/10.1038/sdata.2016.44

Gotham, H. J., Sher, K. J., & Wood, P. K. (1997). Predicting stability and change in frequency of intoxication from the college years to beyond: Individual-difference and role transition variables. *J. Abnorm. Psychol.*, *106*(4), 619–629. https://doi.org/10.1037//0021-843x.106.4.619

Grossman, P., & Van Dam, N. T. (2011). Mindfulness, by any other name…: Trials and tribulations of sati in western psychology and science. *Contemporary Buddhism*, *12*(1), 219–239. https://doi.org/10.1080/14639947.2011.564841

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, *33*(2–3), 61–83. https://doi.org/10.1017/S0140525X0999152X

Heron, K. E., & Smyth, J. M. (2010). Ecological momentary interventions: Incorporating mobile technology into psychosocial and health behaviour treatments. *British Journal of Health Psychology*, *15*(1), 1–39. https://doi.org/10.1348/135910709X466063

Hsiao, Y.-Y., Tofighi, D., Kruger, E. S., Lee Van Horn, M., MacKinnon, D. P., & Witkiewitz, K. (2019). The (Lack of) Replication of Self-Reported Mindfulness as a Mechanism of Change in Mindfulness-Based Relapse Prevention for Substance Use Disorders. *Mindfulness*, *10*(4), 724–736. https://doi.org/10.1007/s12671-018-1023-z

Jernigan, D. H., & Trangenstein, P. J. (2020). What's next for WHO's global strategy to reduce the harmful use of alcohol? *Bull. World Health Organ.*, *98*(3), 222–223.

https://doi.org/10.2471/BLT.19.241737
Jovanova, M., Cosme, D., Doré, B., Kang, Y., Stanoi, O., Cooper, N., Helion, C., Lomax, S., McGowan, A. L., Boyd, Z. M., Bassett, D. S., Mucha, P. J., Ochsner, K. N., Lydon-Staley, D. M., & Falk, E. B. (2023). Psychological distance intervention reminders reduce alcohol consumption frequency in daily life. *Scientific Reports*, *13*(1), Article 1. https://doi.org/10.1038/s41598-023-38478-y
Jovanova, M., Cosme, D., Doré, B., Kang, Y., Stanoi, O., Cooper, N., Helion, C., Lomax, S., McGowan, P., Amanda L., Boyd, Z. M., & al., E. (2022). *Psychological distance intervention reminders reduce alcohol consumption frequency in daily life*. https://doi.org/10.31234/osf.io/yw7s3
Kabat-Zinn, J. (2009). *Wherever You Go, There You Are: Mindfulness Meditation in Everyday Life*. Hachette Books.
Kang, Y., Ahn, J., Cosme, D., Mwilambwe-Tshilobo, L., McGowan, A., Zhou, D., Boyd, Z. M., Jovanova, M., Stanoi, O., Mucha, P. J., Ochsner, K. N., Bassett, D. S., Lydon-Staley, D., & Falk, E. B. (2023). Frontoparietal functional connectivity moderates the link between time spent on social media and subsequent negative affect in daily life. *Scientific Reports*, *13*(1), Article 1. https://doi.org/10.1038/s41598-023-46040-z
Kang, Y., Cosme, D., Lydon-Staley, D., Ahn, J., Jovanova, M., Corbani, F., Lomax, S., Stanoi, O., Strecher, V., Mucha, P. J., Ochsner, K., Bassett, D. S., & Falk, E. B. (2022). Purpose in life, neural alcohol cue reactivity and daily alcohol use in social drinkers. *Addiction*, *117*(12), 3049–3057. https://doi.org/10.1111/add.16012
Karyadi, K. A., VanderVeen, J. D., & Cyders, M. A. (2014). A meta-analysis of the relationship between trait mindfulness and substance use behaviors. *Drug Alcohol Depend.*, *143*, 1–10. https://doi.org/10.1016/j.drugalcdep.2014.07.014
Koban, L., Wager, T. D., & Kober, H. (2023). A neuromarker for drug and food craving distinguishes drug users from non-users. *Nature Neuroscience*, *26*(2), 316–325. https://doi.org/10.1038/s41593-022-01228-w
Kober, H., Brewer, J. A., Height, K. L., & Sinha, R. (2017). Neural stress reactivity relates to smoking outcomes and differentiates between mindfulness and cognitive-behavioral treatments. *Neuroimage*, *151*, 4–13. https://doi.org/10.1016/j.neuroimage.2016.09.042
Kober, H., Buhle, J., Weber, J., Ochsner, K. N., & Wager, T. D. (2019). Let it be: Mindful acceptance down-regulates pain and negative emotion. *Soc. Cogn. Affect. Neurosci.*, *14*(11), 1147–1158. https://doi.org/10.1093/scan/nsz104
Kobylińska, D., & Kusev, P. (2019). Flexible Emotion Regulation: How Situational Demands and Individual Differences Influence the Effectiveness of Regulatory Strategies. *Front. Psychol.*, *10*, 72. https://doi.org/10.3389/fpsyg.2019.00072
Könen, T., & Karbach, J. (2021). Analyzing Individual Differences in Intervention-Related Changes. *Advances in Methods and Practices in Psychological Science*, *4*(1), 2515245920979172.
Kragel, P. A., Han, X., Kraynak, T. E., Gianaros, P. J., & Wager, T. D. (2021). Functional MRI Can Be Highly Reliable, but It Depends on What You Measure: A Commentary on Elliott et al. (2020). *Psychological Science*, *32*(4), 622–626. https://doi.org/10.1177/0956797621989730
Lemoine, N. P. (2019). Moving beyond noninformative priors: Why and how to choose weakly informative priors in Bayesian analyses. *Oikos*, *128*(7), 912–928. https://doi.org/10.1111/oik.05985

Li, W., Howard, M. O., Garland, E. L., McGovern, P., & Lazar, M. (2017). Mindfulness treatment for substance misuse: A systematic review and meta-analysis. *J. Subst. Abuse Treat.*, *75*, 62–96. https://doi.org/10.1016/j.jsat.2017.01.008

López-Caneda, E., & Carbia, C. (2018). The Galician Beverage Picture Set (GBPS): A standardized database of alcohol and non-alcohol images. *Drug and Alcohol Dependence*, *184*, 42–47. https://doi.org/10.1016/j.drugalcdep.2017.11.022

Maliniak, D., Powers, R., & Walter, B. F. (2013). The Gender Citation Gap in International Relations. International Organization, 67(4), 889–922. https://doi.org/10.1017/S0020818313000209

Mitchell, S. M., Lange, S., & Brus, H. (2013). Gendered Citation Patterns in International Relations Journals. International Studies Perspectives, 14(4), 485–492. https://doi.org/10.1111/insp.12026

Naqvi, N. H., Ochsner, K. N., Kober, H., Kuerbis, A., Feng, T., Wall, M., & Morgenstern, J. (2015). Cognitive Regulation of Craving in Alcohol Dependent and Social Drinkers. *Alcoholism, Clinical and Experimental Research*, *39*(2), 343–349. https://doi.org/10.1111/acer.12637

Ngnoumen, E. J. L., Christelle T. (2017). Mindfulness. In *Positive Psychology*. Routledge.

NIAAA. (2022). *College Drinking | National Institute on Alcohol Abuse and Alcoholism (NIAAA)*. https://www.niaaa.nih.gov/publications/brochures-and-fact-sheets/college-drinking

Nook, E. C., Satpute, A. B., & Ochsner, K. N. (2021). Emotion Naming Impedes Both Cognitive Reappraisal and Mindful Acceptance Strategies of Emotion Regulation. *Affective Science*, *2*(2), 187–198. https://doi.org/10.1007/s42761-021-00036-y

Pagnini, F., Bercovitz, K., & Langer, E. (2016). Perceived control and mindfulness: Implications for clinical practice. *Journal of Psychotherapy Integration*, *26*(2), 91–102. https://doi.org/10.1037/int0000035

Peirce, J. W. (2007). PsychoPy—Psychophysics software in Python. *Journal of Neuroscience Methods*, *162*(1), 8–13. https://doi.org/10.1016/j.jneumeth.2006.11.017

R Core Team. (2022). *R* (3.3.6) [Computer software]. http://www.R-project.org

Rissman, J., Gazzaley, A., & D'Esposito, M. (2004). Measuring functional connectivity during distinct stages of a cognitive task. *NeuroImage*, *23*(2), 752–763. https://doi.org/10.1016/j.neuroimage.2004.06.035

Roberts, S. O., Bareket-Shavit, C., Dollins, F. A., Goldie, P. D., & Mortenson, E. (2020). Racial Inequality in Psychological Research: Trends of the Past and Recommendations for the Future. Perspectives on Psychological Science, 15(6), 1295–1309. https://doi.org/10.1177/1745691620927709

Sala, M., Roos, C. R., Brewer, J. A., & Garrison, K. A. (2021). Awareness, affect, and craving during smoking cessation: An experience sampling study. *Health Psychol.*, *40*(9), 578–586. https://doi.org/10.1037/hea0001105

Schneck, N., Herzog, S., Lu, J., Yttredahl, A., Ogden, R. T., Galfalvy, H., Burke, A., Stanley, B., Mann, J. J., & Ochsner, K. N. (2023). The Temporal Dynamics of Emotion Regulation in Subjects With Major Depression and Healthy Control Subjects. *Biological Psychiatry*, *93*(3), 260–267. https://doi.org/10.1016/j.biopsych.2022.09.002

Suzuki, S., Mell, M. M., O'Malley, S. S., Krystal, J. H., Anticevic, A., & Kober, H. (2020). Regulation of Craving and Negative Emotion in Alcohol Use Disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, *5*(2), 239–250.

https://doi.org/10.1016/j.bpsc.2019.10.005

Tapper, K. (2018). Mindfulness and craving: Effects and mechanisms. *Clin. Psychol. Rev.*, *59*, 101–117. https://doi.org/10.1016/j.cpr.2017.11.003

Van Dam, N. T., van Vugt, M. K., Vago, D. R., Schmalzl, L., Saron, C. D., Olendzki, A., Meissner, T., Lazar, S. W., Kerr, C. E., Gorchov, J., Fox, K. C. R., Field, B. A., Britton, W. B., Brefczynski-Lewis, J. A., & Meyer, D. E. (2018). Mind the Hype: A Critical Evaluation and Prescriptive Agenda for Research on Mindfulness and Meditation. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *13*(1), 36–61. https://doi.org/10.1177/1745691617709589

Varela, A., & Pritchard, M. E. (2011). Peer influence: Use of alcohol, tobacco, and prescription medications. *J Am. Coll. Health*, *59*(8), 751–756. https://doi.org/10.1080/07448481.2010.544346

Wager, T. D., Atlas, L. Y., Lindquist, M. A., Roy, M., Woo, C.-W., & Kross, E. (2013). An fMRI-Based Neurologic Signature of Physical Pain. *New England Journal of Medicine*, *368*(15), 1388–1397. https://doi.org/10.1056/NEJMoa1204471

Wang, X., Dworkin, J., Zhou, D., Stiso, J., Falk, E., Zurn, P., Bassett, D., & Lydon-Staley, D. M. (2020). Gendered Citation Practices in the Field of Communication. PsyArXiv. https://doi.org/10.31234/osf.io/ywrcq

Weng, H. Y., Lewis-Peacock, J. A., Hecht, F. M., Uncapher, M. R., Ziegler, D. A., Farb, N. A. S., Goldman, V., Skinner, S., Duncan, L. G., Chao, M. T., & Gazzaley, A. (2020). Focus on the Breath: Brain Decoding Reveals Internal States of Attention During Meditation. *Frontiers in Human Neuroscience*, *14*. https://www.frontiersin.org/articles/10.3389/fnhum.2020.00336

Westbrook, C., Creswell, J. D., Tabibnia, G., Julson, E., Kober, H., & Tindle, H. A. (2013). Mindful attention reduces neural and self-reported cue-induced craving in smokers. *Social Cognitive and Affective Neuroscience*, *8*(1), 73–84. https://doi.org/10.1093/scan/nsr076

Witkiewitz, K., Bowen, S., Douglas, H., & Hsu, S. H. (2013). Mindfulness-based relapse prevention for substance craving. *Addict. Behav.*, *38*(2), 1563–1571. https://doi.org/10.1016/j.addbeh.2012.04.001

Woo, C.-W., Chang, L. J., Lindquist, M. A., & Wager, T. D. (2017). Building better biomarkers: Brain models in translational neuroimaging. *Nature Neuroscience*, *20*(3), 365–377. https://doi.org/10.1038/nn.4478

Zhou, D., Bertolero, M., Stiso, J., Cornblath, E., Teich, E., Blevins, A. S., Oudyk, K., Michael, C., Urai, A., Matelsky, J., Virtualmario, Camp, C., Castillo, R. A., Saxe, R., Dworkin, J., & Bassett, D. (2022). Gender diversity statement and code notebook v1.1.1. Zenodo. https://doi.org/10.5281/zenodo.4104748

Supplementary Material

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

Danielle Cosme*
Chelsea Helion*
Yoona Kang
David M. Lydon-Staley
Bruce P. Doré
Ovidia Stanoi
Jeesung Ahn
Mia Jovanova
Amanda L. McGowan
Zachary M. Boyd
Peter J. Mucha
Dani S. Bassett
Kevin N. Ochsner
Emily B. Falk

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.

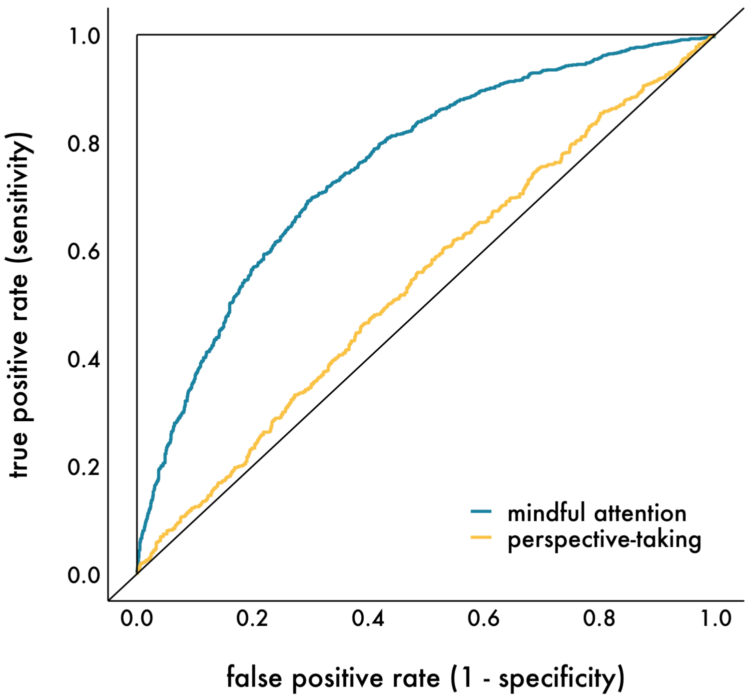
Mindful signature attention: discriminant validity

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 significantly 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



Note. 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 individual differences in subjective confidence were related to 1) individual differences in average signature expression on mindful attention trials and 2) expression of the mindful attention signature during the MRI task, and 3) whether conditioning the associations between signature expression (within- and between-person) and craving ratings on individual differences in subjective confidence (i.e., "controlling" for subjective confidence) affected the magnitude of the associations. Subjective confidence scores were Z-scored to facilitate interpretation. Subjective confidence and average signature expression on mindful attention trials were not substantially correlated ($r(31) = .03$, 95% CI [-.32, .37], $t = 0.16$, $p = .871$). In trial-level analyses, 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 ($\beta = 0.04$, 90% CrI [-0.81, 0.81]) or Reactivity ($\beta = 0.06$, 90% CrI [-0.86, 0.93]) 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 and its interaction with task condition. The results reported in Table S2 and Figure S2 show that confidence ratings were associated with decreased cravings on Mindful Attention trials, but including confidence ratings in the model did not appreciably alter the strength of the relationships between signature expression (within- and between-person) and craving.

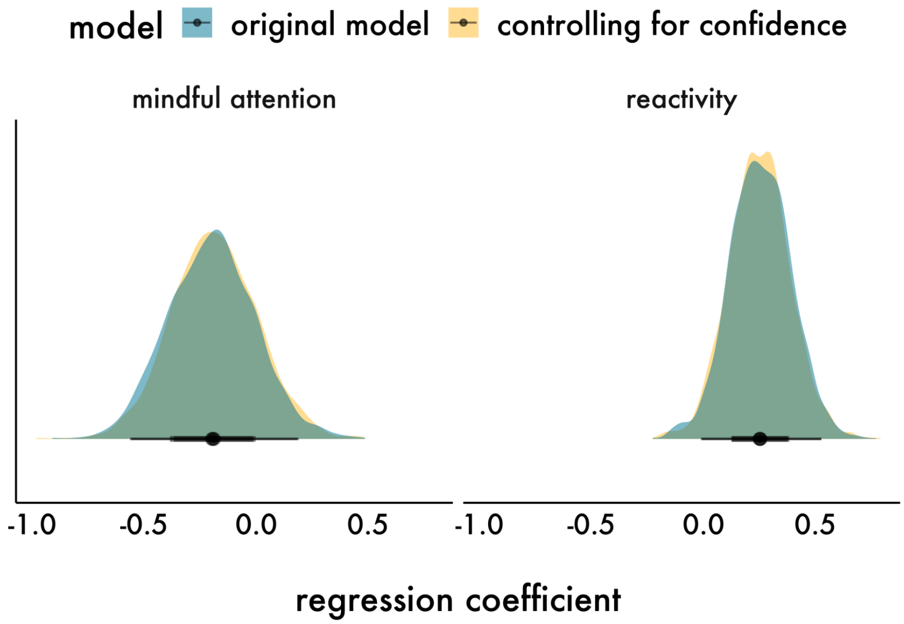
Table S2

Confidence rating results from the craving model

Term	*b* [90% CrI]
Intercept (reactivity)	2.30 [2.00, 2.60]
Task condition (mindful attention)	-0.21 [-0.60, 0.18]
Signature expression (between)	0.25 [0.03, 0.47]
Signature expression (within)	-0.01 [-0.06, 0.04]
Confidence rating	-0.02 [-0.21, 0.16]
Task condition (mindful attention) x signature expression (between)	-0.44 [-0.79, -0.07]
Task condition (mindful attention) x signature expression (within)	-0.02 [-0.10, 0.06]
Task condition (mindful attention) x confidence rating	-0.12 [-0.20, -0.03]

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



Note. 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.

Mindful Attention Awareness Scale (MAAS) analyses

Prior to the MRI scan, participants completed the Mindful Attention Awareness Scale (Brown & Ryan, 2003). In the following analyses, we explored the degree to which individual differences in trait mindfulness were related to 1) individual differences in average signature expression on mindful attention trials and 2) expression of the mindful attention signature during the MRI task, and 3) whether conditioning the associations between signature expression (within- and between-person) and craving ratings on individual differences in trait mindfulness (i.e., "controlling" for trait mindfulness) affected the magnitude of the associations. Trait mindfulness scores were Z-scored to facilitate interpretation. Trait mindfulness and average signature expression on mindful attention trials were not substantially correlated ($r(32) = .08$, 95% CI [-.26, .41], $t = 0.47$, $p = .540$). In trial-level analyses, 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 trait mindfulness was strongly related to signature expression on either Mindful Attention ($\beta = 0.13$, 90% CrI [-0.96, 1.24]) or Reactivity ($\beta = 0.46$, 90% CrI [-0.40, 1.22]) trials. This null finding indicates that trait mindfulness 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 trait mindfulness scores by regressing trial-level craving on the fixed effects of within- and between-person signature expression, task condition, and their separate interactions, and MAAS scores and its interaction with task condition. The results reported in Table S3 and Figure S3 show that trait mindfulness was not related to cravings, and controlling for trait mindfulness did not appreciably alter the strength of the relationships between signature expression (within- and between-person) and craving.

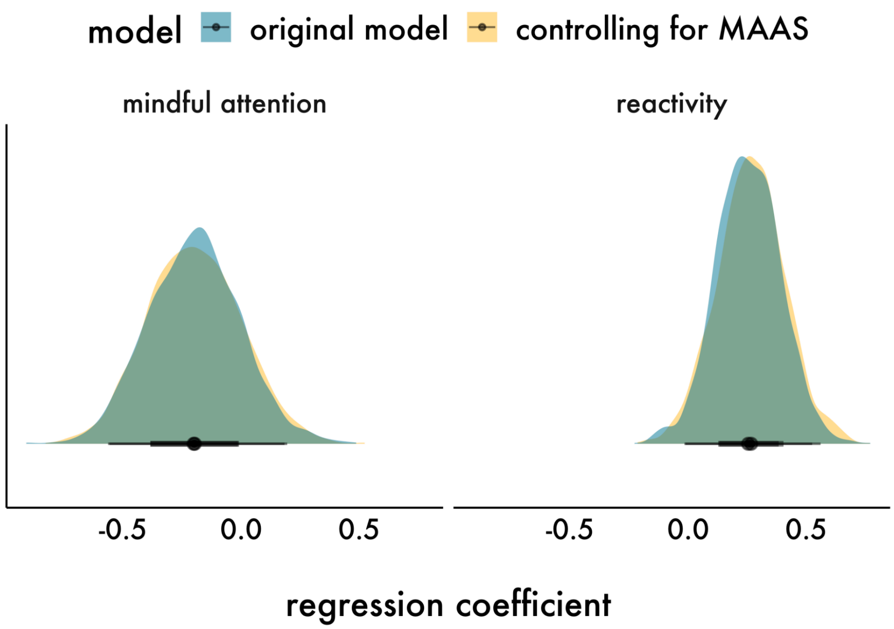
Table S3

Results from the craving model

Term	*b* [90% CrI]
Intercept (reactivity)	2.28 [1.97, 2.61]
Task condition (mindful attention)	-0.21 [-0.61, 0.18]
Signature expression (between)	0.27 [0.03, 0.50]
Signature expression (within)	-0.02 [-0.07, 0.04]
Trait mindfulness	-0.05 [-0.23, 0.12]
Task condition (mindful attention) x signature expression (between)	-0.46 [-0.85, -0.05]
Task condition (mindful attention) x signature expression (within)	-0.01 [-0.09, 0.06]
Task condition (mindful attention) x trait mindfulness	0.00 [-0.09, 0.10]

Figure S3

Posterior distributions of the association between trial-level cravings and between-person mindful attention signature expression for Mindful Attention and Reactivity trials separately



Note. This visualization compares the posterior distributions in the original model reported in the main manuscript (in blue) and the supplementary model controlling for trait mindfulness scores on the MAAS scale (in yellow). The distributions are largely overlapping, suggesting that the strength of the associations are not substantially different when controlling for trait mindfulness.

References

Brown, K.W. & Ryan, R.M. (2003). The benefits of being present: Mindfulness and its role in psychological well-being. *Journal of Personality and Social Psychology*, *84*, 822-848.

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *J. Stat. Softw.*, *80*, 1–28.

Corbin, N., Todd, N., Friston, K. J., & Callaghan, M. F. (2018). Accurate modeling of temporal correlations in rapidly sampled fMRI time series. *Human Brain Mapping*, *39*(10), 3884–3897. https://doi.org/10.1002/hbm.24218

Cosme, D., Flournoy, J. C., & Vijayakumar, N. (2018). *auto-motion-fmriprep: A tool for automated assessment of motion artifacts* (v1.0) [Computer software]. http://doi.org/10.5281/zenodo.1412131

Cosme, D., Kang, Y., Tartak, J. C., Ahn, J., Corbani, F. E., Cooper, N., Doré, B., He, X., Helion, C., Jovanova, M., Lomax, S., Mahadevan, A. S., McGowan, A. L., Paul, A. (Ally) M., Pei, R., Resnick, A., Stanoi, O., Zhang, T. (Sky), Zhang, Y., … Falk, E. (2022). *Study protocol: Social Health Impact of Network Effects (SHINE) Study*. PsyArXiv. https://doi.org/10.31234/osf.io/cj2nx

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J. D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., & Gorgolewski, K. J. (2019). fMRIPrep: A robust preprocessing pipeline for functional MRI. *Nature Methods*, *16*(1), Article 1. https://doi.org/10.1038/s41592-018-0235-4

Fischl, B. (2012). FreeSurfer. *NeuroImage*, *62*(2), 774–781. https://doi.org/10.1016/j.neuroimage.2012.01.021

Gorgolewski, K., Burns, C., Madison, C., Clark, D., Halchenko, Y., Waskom, M., & Ghosh, S. (2011). Nipype: A Flexible, Lightweight and Extensible Neuroimaging Data Processing Framework in Python. *Frontiers in Neuroinformatics*, *5*. https://www.frontiersin.org/articles/10.3389/fninf.2011.00013

Gorgolewski, K. J., & Poldrack, R. A. (2016). A Practical Guide for Improving Transparency and Reproducibility in Neuroimaging Research. *PLOS Biology*, *14*(7), e1002506. https://doi.org/10.1371/journal.pbio.1002506

Halchenko, Y., Goncalves, M., Castello, M. V. di O., Ghosh, S., Hanke, M., Salo, T., Dae, Kent, J., pvelasco, Amlien, I., Brett, M., Tilley, S., Markiewicz, C., Lukas, D. C., Gorgolewski, C., Kim, S., Stadler, J., Kaczmarzyk, J., lee, john, … Kahn, A. (2020). *Nipy/heudiconv v0.8.0* [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.3760062

R Core Team. (2022). *R* (3.3.6) [Computer software]. http://www.R-project.org