Study protocol: Social Health Impact of Network Effects (SHINE) Study

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Abstract

Humans are a fundamentally social species whose well-being depends on how we connect with and relate to one another. As such, scientific understanding of factors that promote health and well-being requires insight into causal factors present at multiple levels of analysis, ranging from brain networks that dynamically reconfigure across situations to social networks that allow behaviors to spread from person to person. The Social Health Impacts of Network Effects (SHINE) study takes a multilevel approach to investigate how interactions between the mind, brain, and community give rise to well-being. The SHINE protocol assesses multiple health and psychological variables, with particular emphasis on alcohol use, how alcohol-related behavior can be modified via self-regulation, and how thoughts, feelings, and behaviors unfold in the context of social networks. An overarching aim is to derive generalizable principles about relationships that promote well-being by applying multilayer mathematical models and explanatory approaches such as network control theory. The SHINE study includes data from 711 college students recruited from social groups at two universities in the northeastern United States of America, prior to and during the COVID-19 pandemic. Participants completed at least one of the following study components: baseline self-reported questionnaires and social network characterization, self-regulation intervention assignment (mindful attention or perspective taking), functional and structural neuroimaging, ecological momentary assessment, and longitudinal follow-ups including questionnaires and social network characterization. The SHINE dataset enables integration across modalities, levels of analysis, and timescales to understand young adults' well-being and health-related decision making. Our goal is to further our understanding of how individuals can change their thoughts, feelings, and behaviors, and of how these changes unfold in the context of social networks.

Keywords: mindfulness, perspective-taking, social influence, intervention, longitudinal data

Background

A fundamental part of being human is our need to connect to and interact with other members of our social groups and networks (Allen et al., 2021; Baumeister & Leary, 1995; Clark & Lemay Jr., 2010). Through connection to other people, we gain greater access to resources, receive aid and support, and form lasting friendships. These social ties are so important that both mental and physical health suffer when they are lacking or dysfunctional (Cohen, 1989; Gariépy et al., 2016; Kent de Grey et al., 2018; Rueger et al., 2016). Scientific understanding of factors that promote well-being therefore requires insight into the causal factors that support our social lives at multiple levels of analysis, ranging from brain networks that dynamically reconfigure across situations to the structure of the social networks that shape how behaviors unfold across time. The Social Health Impacts of Network Effects (SHINE) study seeks to address this issue by combining the study of brain networks and social networks in order to understand how they contribute to health and well-being—with a particular focus on alcohol consumption and mental well-being—and to identify generalizable principles that systematically map the relations between neural, behavioral, and social network variables.

We focus on alcohol use because it presents a pressing problem for public health and is a useful test case for studying mind-brain-community connections. In the United States of America (USA), the majority of young adults drink alcohol and binge-drinking is a significant problem, especially on college campuses. According to the 2020 National Survey on Drug Use and Health, 51.5% of 18-25 year olds consumed alcohol in the past month and both binge drinking and heavy alcohol use were highest among the 18-25 year old age group—31.4% and 8.6%, respectively (Substance Abuse and Mental Health Services Administration, 2021). Alcohol use and abuse has significant negative effects on individuals and society; it is a leading risk factor for death and disability globally (Griswold et al., 2018). Given that approximately 40% of 18-24 year olds are enrolled in college in the USA (National Center for Education Statistics, 2022), college campuses are critical points of contact for scalable health interventions to reduce alcohol consumption. The etiology of alcohol use is multifaceted (Sher et al., 2005) and includes psychological factors, such as the ability and propensity to regulate cravings; biological factors, including brain systems that influence reward and regulation; and social factors, such as social norms and peer influence. Therefore, the SHINE study takes a multilevel approach to investigate how interactions among the mind, brain, and community give rise to alcohol use, how alcohol-related behavior can be modified via self-regulation interventions, and how behavior unfolds in the context of social networks.

Beyond our initial focus on drinking alcohol as a target behavior, our interdisciplinary team is also interested in multiple, complementary factors that contribute to health and well-being. Therefore, this study also measures a range of other variables relevant to a more holistic view of well-being, including additional health behaviors and measures of mental well-being. In doing so, this project aims to derive generalizable principles about relationships within and between people across time, by applying multilayer mathematical models and explanatory approaches such as network control theory.

Self-regulation

Although there are many factors that contribute to alcohol use and other behaviors linked to well-being, the SHINE study focuses on various means of self-regulation. To regulate our thoughts, feelings, and behaviors, various strategies can be used to change the way we attend to, think about, and/or behave towards a given stimulus (Duckworth et al., 2018; Gross & Thompson, 2007; Werner et al., 2022). In the SHINE study, we are particularly interested in different self-regulation strategies that can be broadly and flexibly applied to control responses to everyday stimuli and events that might trigger cravings to consume unhealthy substances, such as alcohol and/or other maladaptive emotional responses during daily life.

Mindful attention

Rooted in ancient Buddhist traditions, mindfulness has been described and defined in different ways (Van Dam et al., 2018). Modern western scientific contexts frequently define mindfulness as awareness of and attention to present moment experience with a non-judgemental and accepting attitude (Langer, 2014). Attending to stimuli in this way can create psychological distance (Trope & Liberman, 2010) from one's initial reactions. In the context of everyday life, where we regularly face health-relevant choices, mindful attention could help create mental space that enables individuals to make healthy choices (Kang et al., 2017). Because the term "mindfulness" is used variously to refer to a range of concepts (including an attentional state, a psychological trait, and training interventions; Van Dam et al., 2018), we refer to the component we target in the SHINE study more specifically as "mindful attention." Mindful attention is thought to facilitate psychological distancing through "defusion" or "decentering" from one's emotional experience (Kang et al., 2013). Studies that examine mindful attention as an emotion regulation strategy have shown that it can reduce negative affect (Nook et al., 2021; Westbrook et al., 2013), pain (Kober et al., 2019), and nicotine cravings (Westbrook et al., 2013). These studies also indicate that mindful attention is an effective emotion regulation strategy for individuals who do not practice meditation (Kober et al., 2019; Nook et al., 2021; Norris et al., 2018; Westbrook et al., 2013), highlighting its potential utility as an intervention target in everyday life. In the context of substance use, both trait mindfulness (Karyadi et al., 2014) and mindfulness training (Brewer et al., 2012; Kober et al., 2017; Tapper, 2018; Westbrook et al., 2013) have been associated with decreased cravings for food, alcohol, and smoking, and various mindfulness-based interventions have been developed to reduce substance use (Chiesa & Serretti, 2014; Goldberg et al., 2022; Kober, 2014; Li et al., 2017; Witkiewitz et al., 2013).

Although it is clear that mindful attention can change behavior and experience, the underlying brain network dynamics through which it accomplishes these changes remain unclear. Furthermore, much of the research on mindfulness in the context of substance use has been conducted in populations with substance use disorders, and less is known about its efficacy for reducing alcohol craving and consumption as a preventative measure in non-clinical samples, such as healthy college students.

Perspective-taking

The second self-regulation strategy featured in the SHINE study involves taking the perspective of another person. Perspective taking has long been of interest to researchers who study social cognition and the ability to mentalize—to think about mental states—more generally (Frith & Frith, 2012). Only recently, however, has it begun to be leveraged as a self-regulation strategy whereby simulating how another person would respond to a stimulus can lead you to experience that simulated reaction as your own. For example, when people take the perspective of a highly reactive vs. stoic individual, their subsequent reactivity to aversive stimuli changes (Gilead et al., 2016).

This finding dovetails with related work on social influence and norms—which may or may not involve explicit mentalizing—suggesting that drawing attention to peer attitudes can shift neural and affective reactions to food (Martin et al., 2018; Nook & Zaki, 2015), artwork (Welborn et al., 2016), faces (Klucharev et al., 2009; Zaki et al., 2011), and products (Cascio et al., 2015), and relate to the adoption of healthy behavior (Pandey et al., 2021). A large body of research highlights the power of social norm interventions to change behaviors (Paluck & Shepherd, 2012; Prentice & Paluck, 2020), including alcohol use (Schroeder & Prentice, 1998).

Here, we sought to combine these two literatures, by leveraging perspective-taking as a means of explicitly simulating the impact of social norms on craving for alcohol. Building on recent work that demonstrates the ability of perspective-taking interventions to promote healthy eating and exercise (Rennie et al., 2016), we test whether taking the perspectives of peers who drink less (more) than oneself might decrease (increase) cue-induced craving and consumption of alcohol. Importantly, this strategy may be particularly effective during developmental periods when individuals are highly attuned to the behaviors and attitudes of their peers (Nelson et al., 2016), such as during adolescence and early adulthood.

Quantifying the effects of self-regulation strategies

This project examines the degree to which mindful attention and perspective-taking alter alcohol craving and consumption in three ways. First, we assess the efficacy of these strategies in a controlled laboratory setting by having participants employ them during an alcohol cue-reactivity task, while being scanned in a magnetic resonance imaging (MRI) machine. This approach allows us to identify the cognitive and neural factors that underlie mindful attention and perspective-taking implementation in the moment. We also collect resting-state brain scans which assess effects relevant to self-regulation in a task-free environment. Second, we test the effectiveness of using these strategies in daily life with ecological momentary assessments via a mobile phone application (app). After the fMRI session, participants receive reminders on their phones to one of the self-regulation strategies (mindful attention, perspective-taking) or a control strategy (react naturally) when they encounter alcohol throughout the day. They also report alcohol craving and consumption, as well as other measures several times per day. Finally, we examine the lasting impact of these interventions with longitudinal follow-up assessments at 6 and 12 months after initial training.

Social context

Individual behavior (Klucharev et al., 2009; Martin et al., 2018; Nook & Zaki, 2015; Rimal & Lapinski, 2015) and brain activity (Berns et al., 2010; Campbell-Meiklejohn et al., 2010; Klucharev et al., 2009; Nook & Zaki, 2015) are influenced by the norms, attitudes, and behaviors of others connected to the individual by social ties. Therefore considering a person's social context is critical for understanding their behavior. One way of investigating social context is through mapping a person's social network. This level of analysis is increasingly incorporated in neuroscientific studies (Falk & Bassett, 2017). Various social network properties (e.g., homophily, centrality, communities, size, density) are related to differences in processing within brain systems involved in navigating the social world. That is, social network structures shape the types of social interactions that people have and are shaped by individual differences in the tendency to use the brain in particular ways, such as when processing faces (Parkinson et al., 2017; Zerubavel et al., 2015), naturalistic stimuli (Baek, Hyon, López, Du, et al., 2022; Baek, Hyon, López, Finn, et al., 2022; Hyon, Kleinbaum, et al., 2020; Parkinson et al., 2018), and health messages (Pandey et al., 2021; Pegors et al., 2017), when at rest (Bickart et al., 2012; Hyon, Youm, et al., 2020), and when engaging in social tasks (O'Donnell et al., 2017; Schmälzle et al., 2017). Furthermore, a variety of behaviors related to health and well-being (Zhang & Centola, 2019), including body mass (de la Haye et al., 2011), smoking (Christakis & Fowler, 2008), alcohol consumption (Rosenquist et al., 2010), happiness (Fowler & Christakis, 2008), and loneliness (Cacioppo et al., 2009), are correlated with distance in social networks. Collectively, these findings highlight the importance of considering social networks for understanding health and well-being.

Assessing social context in the SHINE study

Social context is considered in multiple ways in the SHINE study. First, we examine the social network structure of campus groups that individuals belong to, as well as participants' ego-centric networks, which map the broader social ties of an individual. Second, as described above in the perspective-taking section, each participant takes the perspective of specific others who are connected to the participant by social ties; they do so in the MRI alcohol cue-reactivity task in order to regulate their responses to alcohol. Finally, participants passively view the faces of others in their campus group to whom they are connected by social ties while in the MRI scanner. These levels of analysis will enable us to investigate how individuals affect and are affected by their broader social networks, how taking the perspective of others can be used as a regulatory strategy, and how individuals' brains spontaneously react to faces of those to whom they are socially connected. By integrating across these levels, we will examine how an individual's structural position within a social network and the composition of individuals who surround them affect their peer perceptions and influence their ability to implement regulatory strategies, as well as how this influence might propagate through the social network.

Mathematical modeling

The multilevel, multimodal nature of the SHINE study creates unique opportunities to conceptually integrate and mathematically model the data. Although the study lends itself to numerous modeling approaches, it was designed with two central modeling frameworks in mind: multilayer networks and network control theory.

Network analysis and multilayer networks

The neural, cognitive, behavioral, and social data collected in this study—spanning mind, brain, and community—can be modeled as a multilayer network (Bianconi, 2018). Compared to the traditional single-layer graph typically studied in social network analysis and network science, multilayer networks combine different types of information and networks into a more general data structure. Numerous methods of social network analysis and network science have been extended to multilayer networks; for example, multilayer variants of community detection can provide important insights about how the objects represented as nodes cluster in importantly different ways in different connection modalities (see e.g., Bassett et al., 2011; Cranmer et al., 2015; Mucha et al., 2010; Puxeddu et al., 2021). This capability allows us to represent each dimension of variation (within a single session, across sessions, and between subjects), as well as the interlayer couplings that constitute the interactions within and between individuals, as a single data structure. For complex behaviors like alcohol consumption, the integration of different data types can account for factors that are not traditionally captured in single-layer network models but which may alter the critical points for observed dynamics. In this study, intra-individual models of brain connectivity and extra-individual models of the spread of drinking behaviors within a social network will be used to build a first-principles understanding of the processes that govern how individuals respond to alcohol-related and social cues, in order to identify optimal points for intervention within each network. For instance, intra-individual alterations in reward-related neurocircuitry may give rise to differences between individuals that govern how they use alcohol in response to environmental cues (e.g., seeing a peer drink).

Network control theory

One approach to understanding how complex systems work is to perturb the system and observe how it is affected. Network Control Theory (NCT) is an emerging framework that can be used to explain how these perturbations impact a connected system. This theory posits that alterations in the activation of a single node in a network can lead to system-wide effects (Kim & Bassett, 2020; Lydon-Staley et al., 2021; Towlson et al., 2018), with the exact pattern of the effects being dependent on how the nodes are structured within the network. NCT has been successfully applied in other contexts (e.g., space and terrestrial exploration, financial markets, aircraft and automobile design; Motter, 2015; Pasqualetti et al., 2014; Zañudo et al., 2017) to explain how systems are controlled through signals that originate at a single point and move through the network. In this project, the self-regulation interventions serve as the means of perturbation and will modulate the activity of specific brain regions, with varying effects on brain and behavior. NCT is a useful framework for identifying which nodes within a structural brain network serve as control points that are optimally positioned to drive network reconfiguration; extensions to data-driven control and to control of functional networks comprise relevant recent advances (Baggio et al., 2021; Menara et al., 2022). NCT can also be conceptualized in multilayer networks such as the networks of brains within social networks (Srivastava et al., 2021). More broadly, applying this theory will allow us to study the causal factors that explain individual responses to the self-regulation interventions, and how they impact the brain, cognition, and downstream changes in behavior such as alcohol consumption.

Additional modeling approaches

We hypothesize that a variety of other approaches for modeling this data will also uncover important relationships between the different factors involved in participants' extra- and intra-personal decision making. Given the especially rich multimodal data collected in this study, we aim to develop novel integrative modeling techniques that combine the various modalities and scales. For example, tools from dynamical systems, especially as they explore and explain emergent phenomena like synchronization (D’Souza et al., 2019; Kroma-Wiley et al., 2021; Zhang et al., 2015) might be compared alternatively at the scale of the behaviors of participants (who drinks together and how often) or the brain activity observed (whose brains show similar patterns that govern drinking behavior). Expanding such models to incorporate greater complexity for mimicking internal decisions within individuals and different interactions between individuals could potentially be done using agent based models (Epstein, 2006), psychometric network analysis (Borsboom et al., 2021; Lydon-Staley et al., 2019), or (possibly coupled) machine learning models (as in, for example, (Rocca & Yarkoni, 2021). Such expanded models could then be used to generate synthetic data for further analysis (e.g., to estimate statistical power in different settings or generate hypotheses about different interventions).

Project aims

The overall goal of this project is to better understand the dynamic connections between mind, brain, and community that increase and decrease the health and well-being of young adults. The SHINE study addresses this goal through the following aims (Figure 1):

1. Use self-regulation strategies (mindful attention and perspective-taking) as instrumental manipulations to document causal links from brain network dynamics to cognition and behavior.
2. Develop a network control model of how different self-regulation strategies can act as interventions that predictably drive new brain states and resultant behaviors.
3. Examine interactions between brain network dynamics and social network variables to predict cognitive and behavioral outcomes.
4. Combine insights from Aims 1-3 to develop integrative mathematical models that link intra-individual (e.g., brain network) and extra-individual (e.g., social network) architectures using a multilayer framework.

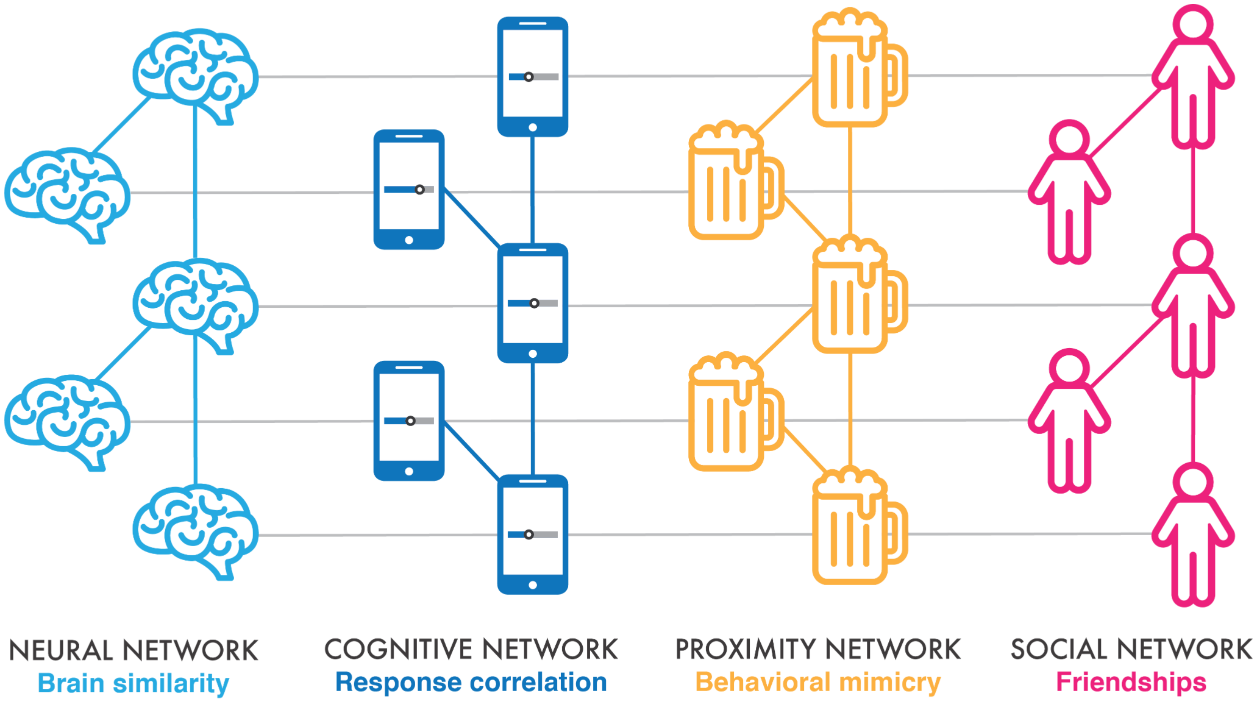

Figure 1. Conceptual overview of the project aims and multilayer network.

Study design and methods

Participants

This study was conducted between January 2019 and April 2021.

Sample size

The target sample size for the MRI component (*n* = 240) was based on the power calculation accompanying the original grant application. Based on this power calculation, within-person effects of trial type were powered to detect *d* = 0.2, 0.5, and 0.8 with 100% power; between-person effects of group were powered to detect *d* = 0.2, 0.5, and 0.8 with 33%, 98%, and 100% power, respectively; and interactions between trial type and group were powered to detect *d* = 0.2, 0.5, and 0.8 with 66%, 100%, and 100% power, respectively. However, recruitment for the MRI component was interrupted due to the COVID-19 pandemic, resulting in a sample of *n* = 111. For *d* = 0.2, 0.5, and 0.8, this translates to: 72%, 100%, and 100% power for within-person effects of trial type; 20%, 80%, and 99% power for between-person effects of group; and 54%, 100%, and 100% power for interactions between trial type and group. No power calculations were conducted for other study components. All invited individuals who wished to enroll in the other components of the study were included.

Recruitment

Participants were undergraduate students recruited from social groups (e.g., Greek organizations, sports clubs, performance groups) at the University of Pennsylvania and Columbia University. Eligible social groups included on-campus organizations containing 20-100 members, with at least 80% of the members interested in participating in the study. The study was advertised through flyers, university websites, in-person information sessions, and email communication. To reach campus groups, the researchers contacted group leaders and then employed a snowball sampling approach, such that participating students could share recruitment information with their peers who were members of on-campus social groups. Of the 1024 individuals in the social groups identified by the study team, 925 individuals stated that they were interested in potentially participating and were invited to enroll in the study. These individuals were from 24 social groups across the two universities (33% performing arts groups, 29% sororities or fraternities, 25% sports clubs, 8% technology clubs, 4% other). Participants who expressed further interest after the initial invite (*n* = 612; 59% of invited participants) consented to participate and completed an hour-long baseline survey, as described below.

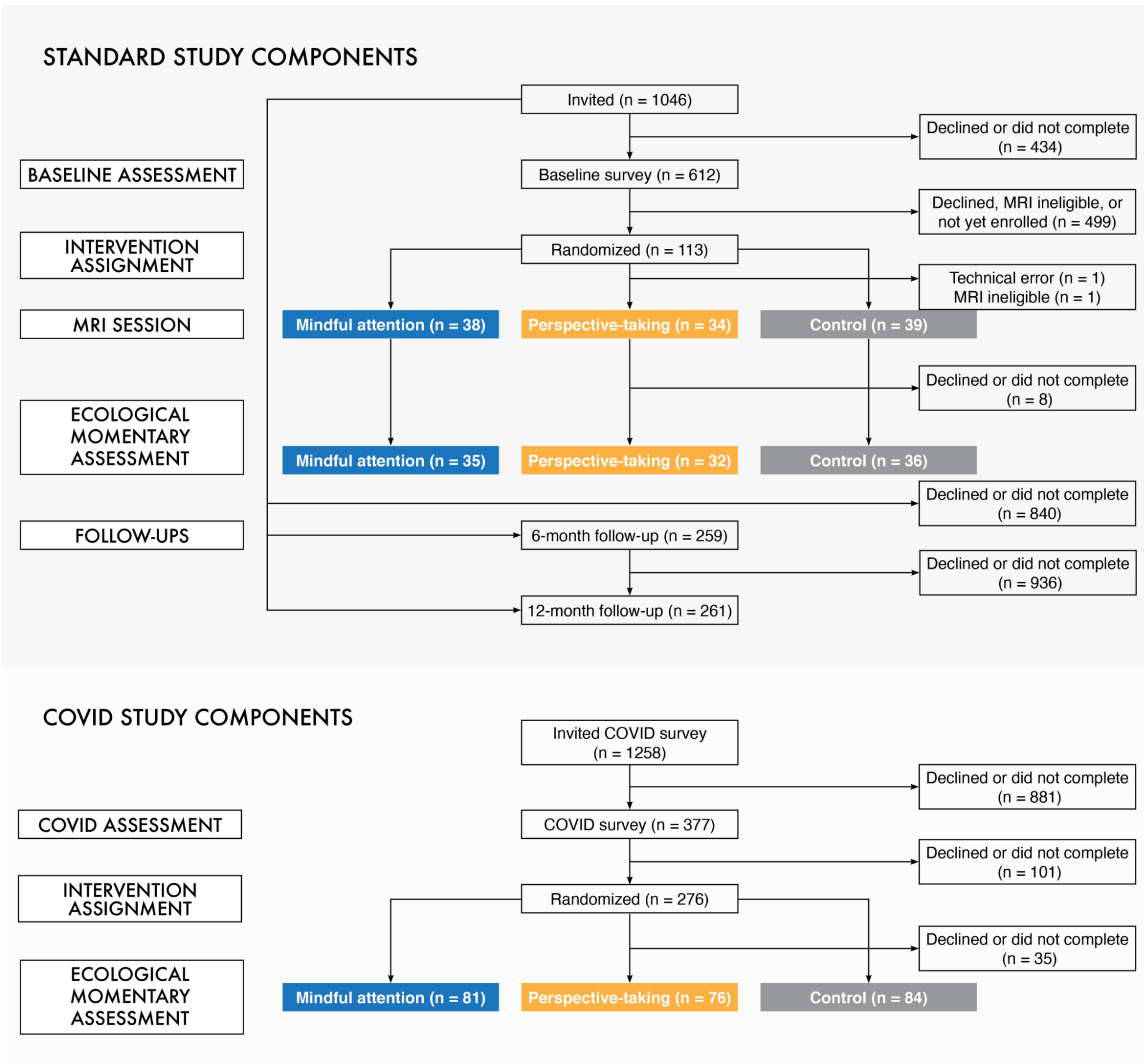

Figure 2. Recruitment and retention flowchart.

Eligibility criteria

Baseline survey. Participants were eligible to enroll in the study if they were a member of one of the social groups invited to participate. Those who were willing to participate were invited to complete the baseline survey.

MRI session. Eligibility for the MRI session was determined by participant responses to questions in the baseline survey and the response completion rate of the social group. Social groups were eligible to have their members invited to the MRI portion of the study if more than 15 people completed the survey or if more than 20% of the group members completed the survey. Based on these criteria, 24 social groups were eligible. Of these groups, individuals were eligible to complete the MRI session if they: were 18 years or older, fluent in English, and free from MRI contraindications; weighed less than 350 lbs; were not studying abroad at the time, claustrophobic, or pregnant; had no history of serious medical issues, psychiatric hospitalization, or substance use disorders; and drank alcohol and listed at least two people in their social group who drank the least in the group apart from themselves. Of the participants who completed the baseline survey and were eligible, 113 participants enrolled in the MRI session. Although we initially planned to enroll a larger sample in this study component, MRI data collection was terminated in March 2020 due to the COVID-19 pandemic.

Demographics

Demographic information for participants who completed at least one component of the study is reported in Table 1.

Table 1
Sample demographics

Age	*M*	*SD*
	20.42	1.7
Gender	Category	%
	Man	29.5
	Non-binary	0.4
	Woman	66.8
	Not reported	3.2
Race and ethnicity	Category	%
	Asian	30.4
	Black or African American	5.6
	Latino/a/x	3.5
	More than once race	11.4
	Other	0.7
	White	45.3
	Not reported	3.1
Income	Category	%
	$0 to $9,999	0.8
	$10,000 to $14,999	0.6
	$15,000 to $19,999	1.5
	$20,000 to $34,999	4.4
	$35,000 to $49,999	5.6
	$50,000 to $74,999	8.2
	$75,000 to $99,999	9.3
	$100,000 to $199,999	29.5

	$200,000 or more	36.1		
	Not reported	3.9		
Education	Category	Self (%)	Mother (%)	Father (%)
	Some high school	2.4	2.5	3.9
	High school or GED	80.0	5.5	6.9
	Associate’s or professional degree	1.0	5.3	2.5
	Some college	—	4.5	5.3
	Bachelor’s degree	12.1	30.8	22.6
	Master’s degree	1.4	29.1	27.6
	Ph.D or equivalent (M.D., J.D., etc.)	—	19.0	27.6
	Not reported	3.1	3.2	3.5

Note. The sample includes participants who completed at least one study component.

Overview of study components

In this section, we provide an overview of the components in the standard and COVID-19 studies. Study components are then described in more detail in the Procedure and measures section (Figure 3).

Standard study components

Baseline assessment. At baseline, participants (*N* = 587 from 24 groups) completed an hour-long online survey that characterized their social networks and assessed MRI eligibility, alcohol use, demographics, as well as individual responses to a number of different questionnaire measures listed in Table 4. An additional 25 participants who enrolled in the study at a later point completed an abbreviated baseline survey in conjunction with the COVID assessment, yielding a total of *N* = 612.

Intervention assignment. Participants who enrolled in the MRI session component (*N* = 113) were randomly assigned to one of three intervention groups: mindful attention, perspective-taking, or control. In the mindful attention and perspective-taking groups, participants were trained to use self-regulation strategies to alter their responses to alcohol cues. The control group was instructed to respond naturally without trying to change their responses.

MRI session. Of the 113 participants who enrolled in this component, 112 completed an MRI session at the University of Pennsylvania or Columbia University. During this session, participants completed a pre-scan survey, a 90-minute MRI scan that included structural, diffusion-weighted, resting-state, and task functional MRI (fMRI) scans, completed a post-scan survey related to the fMRI tasks, and were prepared to complete the ecological momentary assessment component. One participant was deemed ineligible for the MRI scan due to a contraindication discovered at the session, but they completed all behavioral components of the session. Another participant was scanned but the data was lost due to a technical error. This process yielded a total of 111 participants across mindful attention (*n* = 38), perspective-taking (*n* = 34), or control (*n* = 39) groups for MRI analyses.

Ecological momentary assessment. After completing the MRI session, participants (*N* = 109) began a 28-day ecological momentary assessment that measured daily drinking behavior, mood, craving, and emotion regulation, among other measures. For participants in the mindful attention and perspective-taking intervention groups, the ecological momentary assessment procedure also served as an intervention (ecological momentary intervention) by reminding participants of the instructions for how to regulate their responses to alcohol. Of the 109 participants that enrolled in this component, 103 completed at least 70% of the daily surveys.

Follow-ups. Social groups that contained participants who completed the MRI session were also invited to complete 6-month ($N_{complete}$ = 259) and 12-month ($N_{complete}$ = 261) follow-ups in the form of 60-minute online surveys. These surveys were nearly identical to the baseline survey and characterized social networks and alcohol use, among other variables.

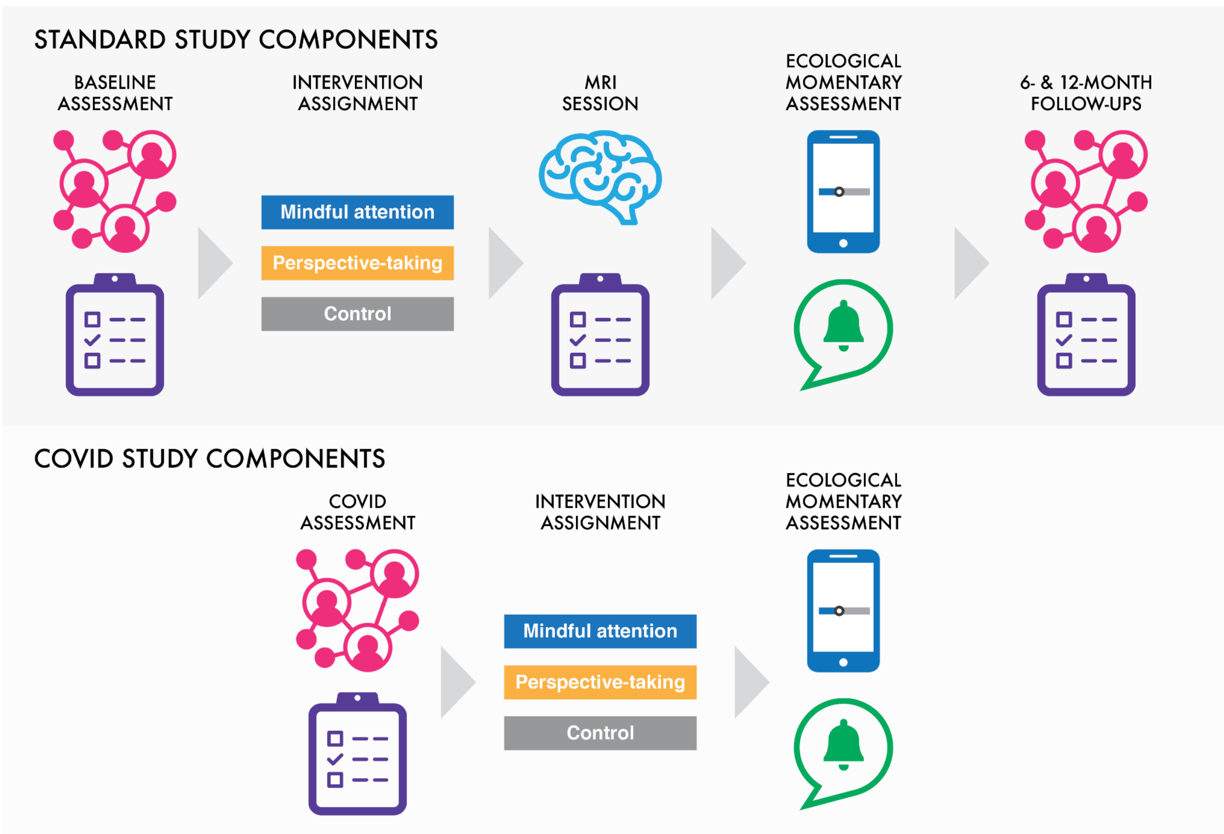

Figure 3. Overview of the standard and COVID study components. In the baseline, COVID, and 6- and 12-month follow up assessments, participants completed the social network characterization and questionnaires. During intervention assignment, a subset of participants were randomly assigned to the mindful attention, perspective-taking, or control group. At the MRI session, a subset of participants underwent structural and functional neuroimaging and completed questionnaires. In the ecological momentary assessment component, a subset of participants completed a 28-day protocol in which they reported their daily experiences and received intervention (or control) prompts reminding them how to respond when they encountered alcohol.

COVID study components

COVID assessment. Due to the unprecedented nature of the COVID-19 pandemic, our team wanted to understand how our participants were being affected and created an additional COVID-specific online survey. Participants who had completed any component of the study, as well as new members from the social groups were invited to participate and 377 completed the survey. In this hour-long survey, we readministered some questionnaires the MRI sample completed in the pre-scan survey, and added new measures specific to COVID-19, including:

perceived risk of contagion, COVID-19 stress, affect, and coping strategies, and additional individual difference measures, such as social connectedness, tolerance for uncertainty, and personality.

COVID ecological momentary assessment. During the COVID-19 pandemic, we expanded the opportunity to complete the 28-day ecological momentary assessment to all participants who completed the COVID survey (i.e., not just those who completed the MRI session). A total of 276 participants enrolled in this component, and 241 participants completed 70 percent or more of the daily surveys. Of these participants, 54 were in the MRI cohort that previously completed this protocol.

Intervention assignment. Participants who completed the COVID assessment and enrolled in the COVID ecological momentary assessment component were randomly assigned to either the mindful attention (n = 92), perspective-taking (n = 93), or control group (n = 94). Participants who had previously been assigned to an intervention group as part of the MRI session remained in the same group they were originally assigned to. Of these participants, 81 in the mindful attention group, 76 in the perspective-taking group, and 84 in the control group completed more than 70 percent of the daily surveys.

Procedure and measures

Self-regulation intervention

Participants who completed the MRI session and those who enrolled in the COVID ecological momentary assessment component were randomized to the mindful attention, perspective-taking, or control group, and were trained to respond to alcohol cues using different self-regulation strategies. Participants who completed the MRI session received training in person, whereas those who completed the COVID ecological momentary assessment component were trained through a scaffolded online training using videos and comprehension checks to mirror the in-person training. The training materials are available online: https://osf.io/3eyh6.

Participants who completed the MRI session were randomized to an intervention group prior to scanning and employed the self-regulation strategies they learned during training in an fMRI alcohol task, as well as in the 28-day ecological momentary assessment component. Participants completing the ecological momentary assessment component for the first time as part of the COVID cohort were randomized to an intervention condition as part of the COVID assessment survey and used the self-regulation strategies only during the ecological momentary assessment procedure (i.e., they did not complete the alcohol fMRI task).

For the mindful attention and perspective-taking groups, the intervention was delivered on alternating weeks during the ecological momentary assessment component. During these “active” weeks, participants received two prompts a day (at 2PM and 9PM) reminding them to use the cognitive strategy when they encountered alcohol. During “inactive” 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 (on/off/on/off or off/on/off/on) was counterbalanced across participants.

Mindful attention. The mindful attention intervention used instructions that were iteratively refined across 14 pilot studies conducted online via Amazon’s Mechanical Turk, described in more detail in the Supplementary Material of Jovanova et al. (2022). These studies found that the most effective instructions for reducing craving emphasized psychological distancing (e.g., versus present moment awareness only). Therefore, participants in the mindful attention group 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.” They were also trained to pay attention to and accept their reactions without getting caught up in them. Participants in the mindful attention group who completed the MRI session used this strategy during the alcohol task (described below). Participants in this group who completed the ecological momentary intervention used this strategy when encountering alcohol in daily life. During intervention (“active”) weeks in the ecological momentary intervention component, participants were reminded to respond mindfully to alcohol cues twice a day (“If you are around alcohol today, REACT MINDFULLY – notice, acknowledge, and accept the thoughts and feelings you have.”).

Perspective-taking. Participants in the perspective-taking intervention group 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.” Although in the alcohol task in the MRI scanner, participants adopted the perspectives of both peers who drank more and who drank less than them, participants were assigned to take the perspective of a specific peer who drank less than themselves and only adopted the perspective of this peer during the ecological momentary intervention components. On intervention (“active”) weeks in the ecological momentary intervention component, participants were reminded twice a day to take the perspective of their peer who drinks less than them when encountering alcohol (“If you are around alcohol today, IMAGINE HOW [PEER NAME] WOULD REACT – try to imagine the thoughts and feelings that [PEER NAME] would have.”).

Control. Participants in the control group were not trained to use any self-regulation strategy to change their responses to alcohol. Instead, they were instructed to approach alcohol cues naturally, without regulating their responses during the alcohol task and in daily life (“If you are around alcohol today, REACT NATURALLY – have whatever thoughts and feelings you would normally have.”) throughout the whole assessment period.

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. For each participant, images were acquired using a 64-channel head coil in the following order: a resting-state scan, two runs of a face perception (“faces”) functional MRI (fMRI) task, a T1-weighted structural scan, four runs of an alcohol cue-reactivity and regulation (“alcohol”) fMRI task, a fieldmap for the BOLD scans, a diffusion-weighted (DWI) scan, a fieldmap for the diffusion-weighted (DWI) scan, and a T2-weighted structural scan. The scan sequence parameters are listed in Table 2. 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).

Table 2
Scan sequence parameters

Scan sequence	Voxel size (isometric mm)	N slices	FOV (mm)	TR (ms)	TE (ms)	N volumes	MBAF	Flip angle (°)
T1-weighted MPRAGE	0.9 x 0.9 x 1.0	160	240	1850	3.91	1		8
T2-weighted anatomical	1.0	176	250	3200	408	1		120
Diffusion-weighted	1.7	81	240	4200	89	103	3	90
Resting-state BOLD EPI	3.0	42	210	1000	30	300	3	62
Alcohol task BOLD EPI	3.0	42	210	1000	30	460	3	62
Faces task BOLD EPI	3.0	42	210	1000	30	414	3	62
Field map 1 (DWI)	1.7	81	240	12400	89	2 x 1		90
Field map 2 (BOLD)	3.0	42	210	8000	66	2 x 3		90

Note. These parameters were used with the majority of participants; a subset of participants (n = 16) were scanned with a TE = 405ms for the T2-weighted anatomical scan and a TR = 4200ms for the diffusion-weighted fieldmap, or a voxel size of 1.7 x 1.7 x 3.0mm (n = 1) for the diffusion-weighted and associated fieldmap scans. MBAF = multiband acceleration factor.

Structural, DWI, and resting-state scans. During the structural and DWI scans, participants reviewed the instructions for the alcohol task or viewed relaxing pictures of nature. During the resting-state scan, participants were instructed to keep their eyes open and focus on a fixation cross. Heart rate was monitored during all scans using a pulse oximeter attached to the middle finger of the participant's non-dominant hand.

Alcohol fMRI 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. Before the task, participants were randomized to one of three groups (mindful attention, perspective-taking, or control) and were trained on how to do the task according to their group. During the task, participants saw images of alcohol (e.g., bottle of beer) and control images of non-alcoholic beverages (e.g., water bottle) selected from the Galician Beverage Picture Set (López-Caneda & Carbia, 2018). This normed stimulus set contains images that are compositionally similar and without beverage brands, and balances social contexts (alone versus in a social setting). While viewing the images, participants were either instructed to react naturally ("React" trials) or regulate their responses to the images ("Regulate" trials). After each image, they rated their craving on a 5-point scale (1 = not at all, 5 = very much). On half of the React trials, participants saw images of alcoholic beverages; on the other half, they saw control, non-alcoholic beverages. Participants in the control group completed the React trials only, whereas participants in the mindful attention and perspective-taking groups completed both React and Regulate trials.

On Regulate trials, participants in the mindful attention group were instructed to attend mindfully to their experience, accepting their thoughts and feelings in a non-judgemental way. Participants in the perspective-taking group took the perspective of peers from their group and regulated their responses to alcohol in two ways. On half of the Regulate trials, they took the perspective of two peers who they nominated in the baseline survey as drinking less than them and responded to the images of alcohol from their peer's perspective ("Down-regulate"); on the other half, they took the perspective of two peers who they nominated as drinking more than them ("Up-regulate"). On these trials, participants in the perspective-taking group were cued on how to respond by the name of their peers who drank less or more than them, and rated how much they thought their peer would crave the drinks in the images (versus rating their own craving). Detailed instructions for the task are provided on OSF (https://osf.io/3eyh6).

Participants completed 96 trials across 4 task runs. 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 4 trials and each task run consisted of 6 blocks. Each block (Figure 4) began with a condition cue (3s) followed by 4 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 within each group; that is, participants were assigned one of 9 randomized orders. The number of trials per condition for each group is listed in Table 3. 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 cognitive strategies they used during the task and their level of confidence using the strategies in the post-scan survey.

Table 3

Number of trials per condition and group in the alcohol fMRI task

Group	React: non-alcoholic	React: alcoholic	Regulate: alcoholic	
			Down-regulate	Up-regulate
Control	48	48	–	–
Mindful attention	32	32	32	–
Perspective-taking	24	24	24	24

Faces fMRI task. This task was adapted from a method used by Zerubavel et al. (2015), variants of which have been used in other studies as well (Morelli et al., 2018; Zerubavel et al., 2018). In this task, participants viewed photographs of the members of their social group while in the scanner. In brain systems that code the affective significance of social targets and support mental state inferences about them, neural responses to these faces have been shown to track with the social status of pictured individuals and their social network distance to the participant viewing them (Zerubavel et al., 2015). For the SHINE study, the task was carefully adapted to maximize synergy with other elements of the project: based on data collected in the baseline survey, we selected group member faces to be presented during the task that systematically varied in terms of their social network distance to, and whether they drink more and less than, the participant. In addition, the selection of faces paralleled the selection of group members in the perspective-taking task to enable integration across study components. During the baseline survey, members from each group uploaded a picture of themselves. Faces of the first 22 group members to complete the survey and upload pictures were included in the task. In addition, the faces of the four group members whose perspective was taken during the alcohol task and the participant's own face were also included. Therefore, participants saw a total of 27 faces (including themselves) during the task. However, because not all groups had at least 27 people, participants in smaller groups saw fewer faces (minimum = 18) and therefore had fewer trials. Included images were then converted to grayscale and adjusted to have equivalent luminance.

The task consisted of two runs, during which participants viewed their own face, the faces of their peers, and control images with a red dot in the center, appearing one at a time.

Though the number of trials differed as a function of group size, the majority of participants viewed 162 face trials and used an event-related design with the following timing: face or dot presentation (1s); jittered fixation cross (*M* = 5.5s, *SD* = 2.8). Each face was presented 6 times (3 times per run) and the order was randomized across participants in each group. To ensure participants were engaged during the task, control trials (*n* = 12-14) were included and participants were instructed to press a button each time they saw a red dot. Stimuli were presented using PsychoPy (Version v3.0.0b11; Peirce, 2007) and participants responded using a five-button box. In a post-scan survey, participants rated the group members from this task on the following dimensions: leadership, influence, closeness, attractiveness, liking, extroversion, intelligence, honesty, competence, self-esteem, anxiety, and how frequently they drink together using a 9-point scale (1 = low, 9 = high).

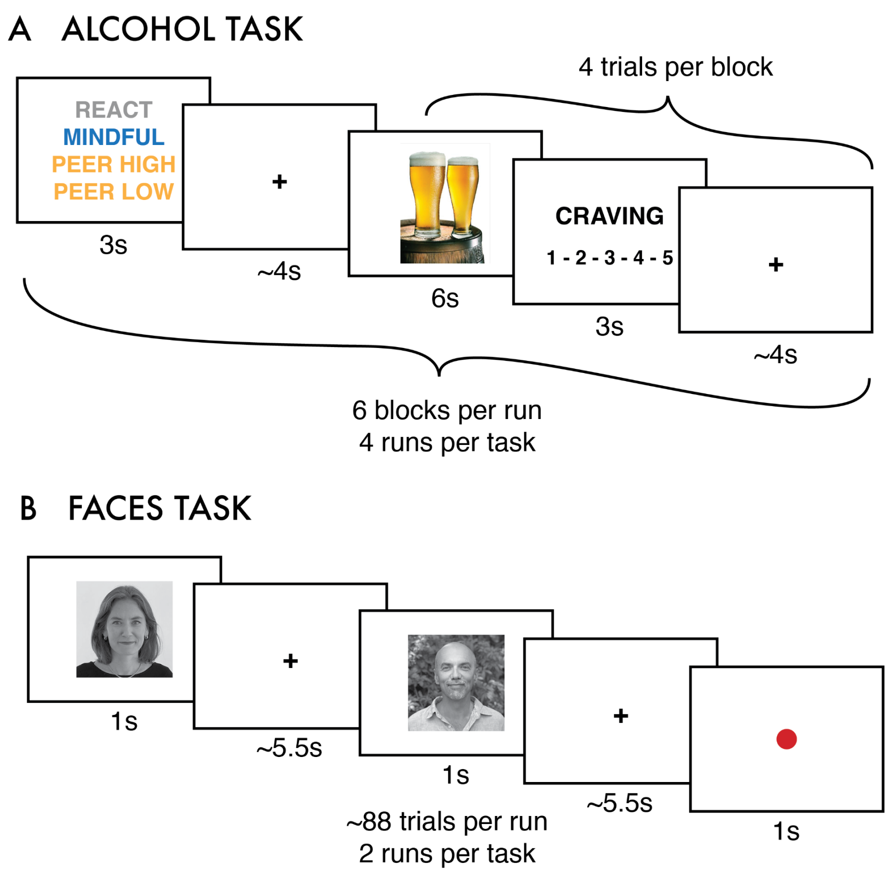

Figure 4. Design of the (A) alcohol and (B) faces fMRI tasks. During the alcohol task (A), participants completed trials based on the group they were randomized into (mindful attention, perspective taking, or control; see Table 3). At the beginning of each block, participants saw an instruction cue and followed the instruction throughout the 4 trials in the block. After each beverage image, participants rated their craving or the perceived craving of their peer, depending on the instruction. Each task run contained 6 blocks, and participants completed 4 task runs. During the faces task (B), participants viewed faces of their peers, themselves, or a control image (red dot), and pressed a button each time they saw the dot.

Ecological Momentary Assessment

We used ecological momentary assessment to assess dynamic, intra-individual fluctuations in mood, craving, and alcohol consumption, among other variables. For participants randomized to the mindful attention and perspective-taking intervention groups, this protocol was also a means for delivering the interventions in the form of an ecological momentary intervention. 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 the following variables: positive and negative mood; alcohol consumption; conversations about alcohol and being drunk; alcohol craving; and use of emotion regulation strategies. The evening survey also contained a manipulation check, assessing whether participants reacted mindfully to alcohol, imagined how someone else would react to alcohol, and/or reacted naturally to alcohol. The other two daily surveys (2PM and 9PM) assessed alcohol craving. On alternating weeks, this second set of surveys also reinforced the intervention with a statement dependent on the participant's intervention group (see the section titled "Self-regulation intervention" for details). A list of the items and response options is available in the codebook for this study (https://osf.io/3eyh6). In all analyses, implausibly high values for the number of alcoholic drinks consumed since the previous survey will be trimmed (i.e., winsorized) to the next highest plausible value.

fMRI cohort. Following the MRI session (and the respective intervention training associated with each group), participants began the ecological momentary assessment protocol. Participants in this cohort completed the ecological momentary assessment between February 2, 2019 and April 7, 2020.

COVID cohort. During the COVID-19 pandemic, we expanded the opportunity to complete the ecological momentary assessment to all participants who had completed any component of the study. As described above, participants completing this component for the first time (i.e., participants who did not complete this component after their MRI session) were randomly assigned to one of the three intervention groups—control, mindful attention, or perspective-taking—and were trained virtually. Participants who had previously completed this component after their MRI session remained in their initial intervention group and completed a second round of the intervention and ecological momentary assessment during the pandemic. The same procedure used for the MRI cohort was followed here, with the addition of survey items related to: daily purpose, discrete emotions, emotion regulation context, physical activity, eating behavior, sleep, social media use, COVID-19 news consumption, social interactions, and positive events. Participants in this cohort completed the ecological momentary assessment between May 30 and October 27, 2020.

Social network

Participants' social networks were characterized in two ways in each of the following surveys: baseline survey, 6-month follow-up, 12-month follow-up, and COVID survey. For the full network survey, the members listed in the social group were updated to add new group members who had enrolled after the baseline survey.

Full network survey. Participants characterized the members of their social group who were recruited into the study according to the following dimensions: popularity, closeness, recent interaction, social support, leadership, influence, and alcohol consumption. For each prompt, participants were presented with a list of all their group members and were allowed to select as many names as they wanted. If participants were interested in completing the ecological momentary assessment component, they were required to nominate at least 3 people for the alcohol consumption prompts. For group members nominated in the alcohol consumption prompts, participants also rated how much and how frequently they believed the group members consumed alcohol.

In the COVID survey, participants also nominated group members on the following dimensions: distance, face-to-face and virtual interaction, off-campus social connection, and COVID attitudes. For group members nominated in the interaction prompts, participants also rated how recently they interacted with the group member in person, virtually, and via text message. Participants also rated the perceived probability of contracting COVID and perceived emotional adjustment to COVID for each group member that they nominated as being either close to or not close to.

Participants' nominations can be aggregated to form multiple distinct social network layers (different types of nominations) for each group. There are 10 network layers in the baseline and follow-up surveys, and 16 network layers in the COVID survey. Within each layer, a link from individual A to individual B exists if A nominates B on the corresponding prompt. For example, if Amy nominates James on the question "Which group members are you closest to?", a link is created from Amy to James in the closeness social network layer of their group. The social network data were processed in the igraph package in R (Version 1.3.0; Csardi & Nepusz, 2006) and network characteristics of each layer (e.g., in-degree, out-degree, eigenvector centrality, page rank, hub, authority, transitivity, community, closeness centrality, betweenness, and coreness) were extracted.

Ego-network survey. We characterized each participant's ego-network beyond the social group recruited into the study using the Friendly Universe task (Pei et al., 2022) or an earlier version of this task called Friendly Ocean, which are name-generation based methods to capture the ego-network of the participants. Using this tool, we collected information about node attributes as well as which nodes are connected to each other, to allow for construction of an egocentric network with structural ties. This task includes five steps: 1) name generation, 2) duplicate removal, 3) closeness rating, 4) node description, and 5) node connection. First, participants were asked to input up to 10 names of people they know personally and interact with on a regular basis for each of the following categories: family, best friends, people they talk with on the phone, people they text, people they talked with face-to-face in the past week, people they interacted with on Facebook in the past week (i.e., up to 60 names if they listed 10 names in each category, with no overlap). Next, the participant identified nodes that were listed in more than one category and these duplicate nodes were removed. For each unique node, participants then rated their closeness. Participants were presented with a sun representing themselves, and all the nominated nodes as planets. They were asked to drag the planets into orbits representing how emotionally close they are to each of the nodes. Next, participants rated each node on various dimensions listed in the study codebook (https://osf.io/3eyh6). To minimize participant burden, only the 15 nodes who are rated as closest to the participant were included in this section. Finally, participants specified the connections between the nodes. To do so, participants were presented with each node and were asked to identify which of the remaining nodes know the presented node. This step enabled us to capture how the nodes within the ego network are connected. The ego network data were processed in the igraph package in R (Version 1.3.0; Csardi & Nepusz, 2006) and key network characteristics for each participant were extracted. These network characteristics include density, degree centrality, eigenvector centrality, modularity, community, and closeness centrality.

Questionnaires

Participants completed an array of questionnaire measures in the following surveys: baseline survey, pre-scan survey, post-scan survey, 6-month follow-up, 12-month follow-up, and COVID survey. All surveys were administered online via Qualtrics. The questionnaires and which surveys they were included in are listed in Table 4. Detailed information about the items in each questionnaire can be found in the study codebook (https://osf.io/3eyh6).

Table 4
Questionnaires by survey session

Category	Questionnaire	Baseline	Scan	Follow-up	COVID
COVID-specific	[a]COVID-19 affect change				■
	[ab]COVID-19 stressors				■
	[a]Housing survey				■
	[ab]Perceived COVID-19 risk				■
	[ab]Perceived risk and coping				■
	Physical distancing survey				■
	Social interaction survey				■
Emotion regulation	[b]COPE Inventory				■
	Difficulties with Emotion Regulation Short Form		■		
	Emotion Regulation Questionnaire	■	■		
	Implicit Theories of Emotion Scale		■		
	Interpersonal Regulation Questionnaire		■		■
	[b]Positive Emotion Regulation				■
Health	BMI				■
	[b]Dieting efficacy and norms				■
	International Physical Activity Questionnaire				■
	Self-Report Habit Index				■
	[a]Sleep and wake times		■		
Mental health	Center for Epidemiologic Studies Depression Scale (CESD-R-10)		■	■	■
	Interaction Anxiousness Scale (IAS-3)		■		
	Positive and Negative Affect Schedule				■
	State Trait Anxiety Scale (STAI-6)		■		■
	UCLA Loneliness Scale (ULS-4)		■		■
Other	[a]Demographics	■		■	
	[b]Impression formation		■	■	
	MacArthur Scale of Subjective Social Status	■		■	
	[a]MRI eligibility	■			
	[a]Political orientation				■
	[a]Post-scan survey		■		
	[a]Social group identify, attitudes, norms, information	■		■	■
	[a]Social media use	■			■
	System Justification Scale		■		

Personality	Attentional Control Scale		■		
	Barratt Impulsivity Scale (BIS-11)		■		
	Future Time Perspective Scale				■
	Holt-Laury Risk Task		■		
	Interpersonal Reactivity Index		■		
	Intolerance of Uncertainty Scale (IUS)		■		■
	Resistance to Peer Influence		■		
	Ten-Item Personality Inventory				■
Substance use	[ab]Alcohol attitudes	■		■	
	[a]Alcohol consumption perceptions	■		■	
	[b]Alcohol intentions and consequences	■		■	
	[b]Alcohol norms	■		■	
	Alcohol Readiness to Change Ruler	■	■		
	Alcohol Use Questionnaire	■	■		
	Cigarette and e-cigarette use	■		■	■
	Drinking Expectancy Questionnaire—Revised Adolescent Version		■		
	Drinking Motive Questionnaire—Revised		■		
	[a]Psychotropic drug use		■		
Well-being	Connor-Davidson Resilience Scale				■
	Five-Dimensional Curiosity Scale Revised				■
	Flourishing Scale	■	■		■
	Index of Autonomous Functioning				■
	Mindful Attention Awareness Scale		■		
	[b]Purpose in Life Scale		■	■	■
	Revised Life Orientation Test				■
	Single Item Self-Esteem scale				■
	Social Connectedness Scale				■

Note. Scan includes questionnaires administered in both the pre- and post-scan surveys; Follow-up includes both the 6- and 12-month surveys. More detailed information, including citations, can be found in the codebook (https://cnlab.github.io/SHINE-codebook/codebook). [a]Questionnaire items or scales developed in the context of this study that have not been psychometrically validated, [b]adapted measures.

Neuroimaging data processing and analysis

In this section, we describe the neuroimaging standard operating procedures for this study. The exact procedures reported in subsequent manuscripts may differ depending on the nature of the specific research questions being asked. The structural, resting-state, and task-based fMRI scans were preprocessed using fMRIPrep (Version 20.0.6; Esteban et al., 2019), which is based on Nipype (Version 1.4.2; Gorgolewski et al., 2011). The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al., 2010), distributed with ANTs (Version 2.2.0; Avants et al., 2008), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a Nipype implementation of the ANTs brain extraction workflow, using OASIS30ANTs as the target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM), and gray-matter (GM) was performed on the brain-extracted T1w using *fast* (FSL Version 5.0.9; Zhang et al., 2001). Brain surfaces were reconstructed using *recon-all* (FreeSurfer Version 6.0.1; Dale et al., 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (Klein et al., 2017). Volume-based spatial normalization to one standard space (MNI152NLin2009cAsym; Fonov et al., 2009) was performed through nonlinear registration with antsRegistration (ANTs 2.2.0), using brain-extracted versions of both the T1w reference and the T1w template.

For each of the resting-state and task BOLD scans, the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. A B0-nonuniformity map (or fieldmap) was estimated based on two echo-planar imaging (EPI) references with opposing phase-encoding directions, with *3dQwarp* (Cox & Hyde, 1997) with AFNI 20160207. Based on the estimated susceptibility distortion, a corrected EPI reference was calculated for a more accurate co-registration with the anatomical reference. The BOLD reference was then co-registered to the T1w reference using *bbregister* from FreeSurfer, which implements boundary-based registration (Greve & Fischl, 2009). Co-registration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) were estimated before any spatiotemporal filtering using *mcflirt* (FSL Version 5.0.9; Jenkinson et al., 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox & Hyde, 1997). The BOLD time-series were resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. The BOLD time-series were resampled into standard space, generating a preprocessed BOLD run in MNI152NLin2009cAsym space. All resamplings were performed with a single interpolation step by composing all of the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using *antsApplyTransforms* (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) resamplings were performed using *mri_vol2surf* (FreeSurfer). Various confounds (e.g., framewise displacement, DVARS, global signal) were also calculated for each TR and logged in a confounds file (for additional details, see https://fmriprep.org/en/20.0.6/outputs.html#confounds). The outputs from fMRIPrep were then manually checked for quality to ensure adequate preprocessing.

DWI. The DWI data were preprocessed and reconstructed through QSIprep (Version 0.8.0; Cieslak et al., 2021). Briefly, the data was first denoised and bias corrected, and then underwent susceptibility distortion correction, motion and eddy current correction via FSL 6.0, and coregistered to T1 space. We also warped both the Schaefer atlas (Schaefer et al., 2018) and the Harvard Oxford subcortical atlas (Smith et al., 2004) into individual T1 space to subdivide the brain into 200 cortical and 14 subcortical regions. Then, the preprocessed DWI data was reconstructed using generalized Q-sampling Imaging (Yeh et al., 2010) in DSI-Studio (http://dsi-studio.labsolver.org). Deterministic tractography (Yeh et al., 2013) was performed until 5×10^6 streamlines were reconstructed, yielding individual structural networks where nodes represented brain regions and where edges were weighted by the number of streamlines connecting two regions. Preprocessing was performed using QSIPrep, which is based on Nipype (Version 1.4.2; Gorgolewski et al., 2011).

MP-PCA denoising as implemented in MRtrix3's *dwidenoise* (Veraart et al., 2016) was applied with a 5-voxel window. After MP-PCA, Gibbs unringing was performed using MRtrix3's *mrdegibbs* (Kellner et al., 2016). Following unringing, B1 field inhomogeneity was corrected using *dwibiascorrect* from MRtrix3 with the N4 algorithm (Tustison et al., 2010). After B1 bias correction, the mean intensity of the DWI series was adjusted so that the mean intensity of the b=0 images matched across each separate DWI scanning sequence. FSL (Version 6.0.3:b862cdd5) *eddy* was used for head motion correction and Eddy current correction (Andersson & Sotiropoulos, 2016). Eddy was configured with a q-space smoothing factor of 10, a total of 5 iterations, and 1000 voxels used to estimate hyperparameters. A linear first level model and a linear second level model were used to characterize Eddy current-related spatial distortion. Q-space coordinates were forcefully assigned to shells. Field offset was attempted to be separated from subject movement. Shells were aligned post-eddy. Eddy's outlier replacement was run (Andersson & Sotiropoulos, 2016). Data were grouped by slice, only including values from slices that contained at least 250 intracerebral voxels. Groups deviating by more than 4 standard deviations from the prediction had their data replaced with imputed values. Fieldmaps were collected with reversed phase-encode blips, resulting in pairs of images with distortions going in opposite directions. Here, a b=0 fieldmap image with reversed phase encoding direction was used along with b=0 images extracted from the DWI scans. From these pairs, the susceptibility-induced off-resonance field was estimated using a method similar to that described in Andersson et al. (2003). The fieldmaps were ultimately incorporated into the Eddy current and head motion correction interpolation. Final interpolation was performed using the *jac* method.

Several confounding time-series were calculated based on the preprocessed DWI: framewise displacement (FD) using the implementation in Nipype (following the definitions by Power et al., 2014). The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. Slicewise cross correlation was also calculated. The DWI time-series were resampled to ACPC, generating a preprocessed DWI run in ACPC space with 1.7 mm isotropic voxels. Many internal operations of QSIPrep use Nilearn (Version 0.7.0; Abraham et al., 2014) and Dipy (Garyfallidis et al., 2014).

Resting-state. Following preprocessing with fMRIPrep, these data were denoised using the XCP Engine pipeline (Version 1.0; Ciric et al., 2017). Specifically, XCP Engine was used to remove motion-related confounds from BOLD sequences using the most stringent of current standards. These steps were as follows: (1) demeaning and removal of linear and quadratic trends from time series, (2) de-spiking using AFNI's 3DDESPIKE utility, (3) temporal bandpass filtering using a first-order Butterworth filter to retain signal in the range 0.01-0.08Hz, (4) 36-parameter confound regression including 6 realignment parameters, mean signal in white matter, CSF and mean global signal, as well as the first power and quadratic expansions of their temporal derivatives. These denoised time series were then used to calculate connectivity matrices.

Task fMRI. Prior to first-level modeling, we generated motion regressors using an automated motion assessment tool (Cosme et al., 2018). This tool applies a predictive model that utilizes the confound files generated by fMRIPrep and classifies whether or not fMRI volumes contain motion artifacts. The classifier is applied to each participant's task run and returns a binary classification indicating the presence or absence of motion artifacts for each volume. In addition, this tool transforms the realignment parameters into Euclidean distance for translation and rotation separately, and calculates the displacement derivative of each. This procedure yields a total of 5 motion regressors for first-level modeling. Task runs that contain >10% of volumes classified as containing a motion artifact will be excluded from further analyses (*n* regulation = 1, *n* faces = 0). For group-level analyses, multiple comparisons are corrected using cluster-extent thresholding as implemented in AFNI (Cox, 1996). In accordance with recent guidelines (Cox et al., 2017), the spatial autocorrelation function is first estimated for each subject and task run separately using AFNI *3dFWHMx* on the residuals, and then averaged across subjects. To determine probability estimates of false-positive clusters given a random field of noise, Monte-Carlo simulations are conducted with AFNI *3dClustSim* using the average autocorrelation across subjects.

Discussion

The SHINE study takes a multilevel, multimodal approach to understanding individual and group-level factors that promote health and well-being—integrating mind, brain, and community. This project adopts an interdisciplinary model, bringing together insights from social psychology, health communication, network neuroscience, and the mathematics of dynamical systems and data science. It focuses on alcohol use in college students as a test case, but also aims to identify generalizable principles governing the relation between these factors. This project will extend our current understanding of how self-regulation strategies, including mindful attention and perspective-taking, can reduce craving during explicit instruction in the lab and the degree to which implementing these strategies in daily life alters alcohol-related behavior. Applying network control theory will allow us to develop a mechanistic model of how perturbation in a single node of a network, for example through the self-regulation interventions, can result in system-wide changes at the level of individual brains as well as social groups. Examining individuals in the context of their social groups will allow us to better understand bi-directional links between individual and group dynamics. We do this by integrating distinct types of data—neural, cognitive, physiological, behavioral, and social—that have been previously isolated in mathematical models of individual trajectories in order to model how behavior unfolds in the context of social networks using multilayer network modeling methods.

This project has several strengths that increase its potential impact.

- Including multiple cohorts from two universities promotes generalizability.
- Intervening in the laboratory as well as via ecological momentary assessment enables us to test the efficacy of the self-regulation strategies under ideal conditions, as well as their effectiveness in daily life.
- Comparing multiple self-regulation strategies can help us to determine which are the most effective in changing drinking behavior, for whom, and in which contexts.
- Incorporating various timescales—from seconds in the scanner, hours and days during ecological momentary assessment, to months and years in the follow-up surveys—provides a rich dataset to examine temporal relationships.
- Collecting data that spans multiple levels of analysis within and between individuals in social groups enables comprehensive integration and examination of how behavior change unfolds, from individuals to groups.

Overall, the SHINE study will further our understanding of how interactions between the mind, brain, and community give rise to alcohol use, how alcohol-related behavior can be modified via self-regulation interventions, and how thoughts, feelings, and behaviors unfold in the context of social networks. Furthermore, it provides the opportunity to derive generalizable principles about relationships between the multilevel, multimodal data through application of mathematical approaches, such as network control theory and multilayer networks. Ultimately, these principles can then be applied in new contexts to examine other behaviors that support health and well-being.

Ethics and dissemination

The University of Pennsylvania served as the Institutional Review Board of record, following reliance agreements and local context review approvals at Columbia University. This study was approved by the University of Pennsylvania Institutional Review Board and the Army Research Office's Human Research Protection Office. All participants provided informed consent and were paid for their participation.

Findings from this study may be disseminated in the following ways: preprint articles, peer-reviewed journal articles, conference presentations, seminars and colloquia, and public talks and interviews.

Author contributions

Conceptualization: BPD, DML, DSB, EBF, KNO, NC, PJM, YK, ZMB
Methodology: BPD, DML, EBF, KNO, NC, OS, PJM, YK, ZMB
Software: BPD, CH, NC, OS, PJM, RP, ZMB
Validation: EBF, YK, ZMB
Formal analysis for this paper: AR, DC, JC, YK
Investigation: BPD, AMP, CH, JC, MJ, NC, OS, RP, SL, TZ, YK, YZ
Resources: BPD, AMP, CH, FC, JC, OS, SL, TZ, YK, YZ
Data Curation: AR, ASM, DC, DML, EBF, FC, JA, JC, MJ, OS, SL, TZ, XH, YK, YZ, ZMB
Writing - Original Draft: DC, JC, YK, ZMB
Writing - Review & Editing: all authors
Visualization: DC
Supervision: CH, DC, DML, EBF, KNO, NC, OS, PJM, YK, ZMB
Project administration: AMP, BPD, CH, DC, DML, EBF, FC, JC, KNO, NC, OS, PJM, SL, TZ, YK, YZ, ZMB
Funding acquisition: DSB, EBF, KNO, PJM

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, 2 authors self-identified as non-binary, 12 authors identified as women, and 8 authors identified as men. With respect to race and ethnicity, 4 authors self-identified as Asian, 2 authors identified as East Asian, 1 author identified as Southeast Asian, 1 author identified as White Latinx, and 14 authors identified as

White. With respect to engagement with college students, when this study was conducted, 7 were recent undergraduates and/or research coordinators who train and manage students, 4 were doctoral students who teach and/or mentor other students, 8 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 the first and last author of each reference (excluding software package 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 (and excluding self-citations to the first and last authors of our current paper), our non-software references contain 22.89% woman(first)/woman(last), 20.48% man/woman, 19.28% woman/man, and 37.35% man/man, and software references contain 0.0% woman(first)/woman(last), 3.12% man/woman, 0.0% woman/man, and 96.88% man/man. This method is limited in that a) names, pronouns, and social media profiles used to construct the databases may not, in every case, be indicative of gender identity and b) it cannot account for intersex, non-binary, or transgender people.

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