Connectome predictive modeling of trait mindfulness

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Abstract:

Trait mindfulness refers to one's disposition or tendency to pay attention to experiences in a mindful way. Trait mindfulness has been robustly associated with positive mental health outcomes, but its neural underpinnings are poorly understood. To explore the neural networks associated with trait mindfulness and their relationship to different facets, we conducted a pre-registered connectome predictive modeling analysis in 367 adults across three sites. This is the largest study to date examining trait mindfulness using resting-state fMRI. We identified significant neural models for two mindfulness subscales, *Acting with Awareness* (AA) and *Non-judging* (NJ). These models involved notable connections within the fronto-parietal network (FPN), default mode network (DMN), and somatomotor network (SMN). We determined that the AA model generalized to one dataset, while the NJ model generalized to another dataset. Thus, our results suggest that whole-brain functional connections can be used as markers of trait mindfulness.

Keywords: Trait mindfulness; resting-state fMRI; connectome; attention; predictive models; multi-site

Introduction

Trait mindfulness refers to one's tendency to attend to experiences in a mindful way, and is often measured using self-report scales, such as the Five Facet Mindfulness Questionnaire (FFMQ) (Baer, Smith, & Allen, 2004). Greater trait mindfulness has been associated with positive mental health outcomes (Allen, Romate, & Rajkumar, 2021; Amundsen et al., 2020; Chu & Mak, 2020; Kong, Wang, & Zhao, 2014; Schutte & Malouff, 2011), and negatively associated with outcomes such as anxiety, stress, and negative affect (Carpenter et al., 2019; Coffey & Hartman, 2008; de Bruin, Zijlstra, & Bögels, 2014; Greco, Baer, & Smith, 2011; Tomlinson et al., 2018; Treves et al., 2023). Moreover, neuroimaging of trait mindfulness can provide some insight into understanding mental health disorders (Zhuang et al., 2017).

Prior correlational research between resting-state static functional connectivity (SFC) and trait mindfulness has revealed inconsistencies in the relationships between trait mindfulness and brain networks (Bilevicius, Smith, & Kornelsen, 2018; Doll et al., 2015; Harrison et al., 2019; Hunt et al., 2022; Kong et al., 2016; Li et al., 2022; Parkinson, Kornelsen, & Smith, 2019; Shaurya Prakash et al., 2013; Wang et al., 2014), potentially due to fMRI methodological limitations and the multidimensional nature of mindfulness. Motivated by these discrepancies, this study aimed to investigate the functional neuroimaging basis of trait mindfulness.

Method

Training and Test Datasets

Training Dataset: Wisconsin. Data from the University of Wisconsin-Madison Meditation Study (NCT02157766) comprised of 206 meditation-naïve participants who completed a 12 minute resting-state MRI scan (age M = 30.9, SD = 13.1 years, 85 male). **Test Dataset: Stanford Science of Behavior Change Project.** Data consisted of 82 meditation-naïve participants who completed an 8 minute resting-state MRI scan (age M = 23.6, SD = 4.9 years, 27 male) (https://scienceofbehaviorchange.org/projects/poldrack-marsch/). **Test Dataset: Leipzig Mind-Brain-Body.** Data (open-source) consisted of 79 meditation-naïve participants (mode age range 20-25, 45 male) who completed four resting-state scans (Mendes et al., 2019).

Measures and Procedures

Five Facet Mindfulness Questionnaire (FFMQ). The FFMQ consists of five facets: *Acting with Awareness, Non-judging, Non-reactivity, Describing,* and *Observing* (Baer et al., 2006; 2008). We used the scores of subscales, total FFMQ, and the total FFMQ scale without *Observing*, as it may show limited validity (Gu et al., 2016). We used Pearson's correlations to assess relationships between subscales in the training dataset, and we conducted unpaired, heteroskedastic t-tests to compare total FFMQ scores between the datasets.

Preprocessing and denoising run in the CONN Toolbox (Whitfield-Gabrieli & Nieto-Castanon, 2012). We extracted preprocessed BOLD time series and computed a matrix of FC values between all region pairs (i.e., connections, edges) based on the Fisher z-transformed Pearson correlation coefficient of time series.

Predictive modeling analysis. The Wisconsin sample was chosen for training as it is the largest (Poldrack, Huckins, & Varoquaux, 2020). Using leave-one-participant-out cross-validation (LOOCV), we generated model-based predictions of the FFMQ and subscales for all participants, correlating FC edges with FFMQ scores at $P < 0.01$. Futher, we computed a single network strength (S) value and fitted a linear model ($FFMQ = \beta^{*}S + c$) to evaluate predicted versus observed FFMQ scores. To assess significance, we compared true correlations with null values obtained through 1000 random permutations. We also controlled for head motion (framewise displacement, FD) and conducted 10-fold CV. As we trained seven models for each of the measures, we controlled for multiple comparisons using FDR-correction (Benjamini & Hochberg, 1995). Finally, we conducted additional predictive modeling (e.g. Elastic Net), which showed no improvements in generalization compared to CPM.

Validation in test datasets. We applied the trained models to the Leipzig and Stanford datasets, averaging across runs and excluding data with FD > 0.15 mm.

Results

Neural features from the training dataset. The models predicting Acting with Awareness (AA-CPM) and Non-judging (NJ-CPM) scores showed positive correlations between overall network strength (positive - negative) and the respective subscale (AA: *r*(186) = .22; NJ: *r*(186) = .21), and had non-parametric ps of .017 and .025, respectively, which, when corrected for multiple comparisons, were both pFDR = .087.

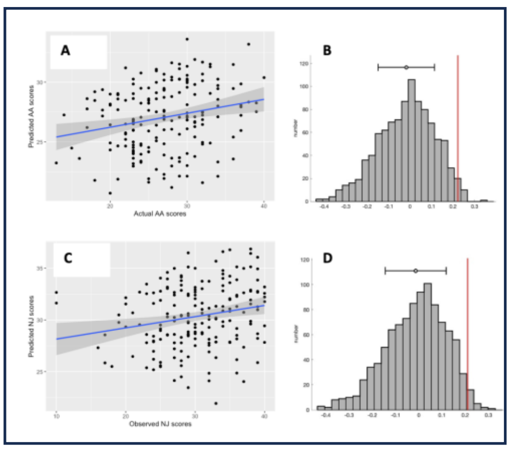

Figure 1: Prediction performance in the training datset. Predicted vs. observed values from LOOCV for AA (**A**) and NJ (**C**) subscales. Correlation coefficient compared to the distribution of null correlation coefficients for AA (**B**) and NJ (**D**).

AA-CPM features. Masked edges from the AA model were analyzed. In the positive network (sets of pairwise connections that positively predicted mindfulness with increasing connectivity), notable connections involved the FPN with sensory networks and between the FPN-DMN. The negative network (edges that negatively correlated with AA scores) involved connections within the SMN and between the SMN-VIS, involving auditory and DMN networks. **NJ-CPM features.** Masked edges from the NJ model were analyzed. In the positive network, DMN connections to the SMN and CO edges were most prevalent. The negative network was widely distributed, with many edges in the SMN network and between VIS-DMN.

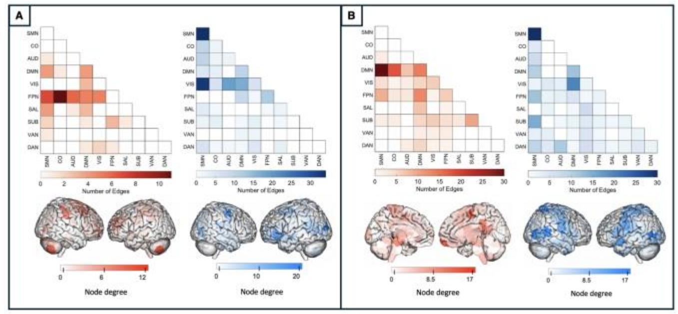

Figure 2: Edges included in AA model (**A**) and NJ model (**B**) of FFMQ according to the Shen atlas (Shen et al., 2013). Edges that positively predict subscale scores are in red; edges that negatively predict subscale scores are in blue. Node degree refers to the number of connections including that node (brain area). SMN: somatomotor network, CO: cingular-opercular network, AUD: auditory network, DMN: default-mode network, VIS: visual network, FPN: frontoparietal network, SAL: salience network, SUB: subcortical network, VAN: ventral attention network, DAN: dorsal attention network.

Testing performance of AA-CPM and NJ-CPM. When the AA-CPM model was applied to the Leipzig dataset, we found a significant positive association between predicted and observed scores (*r*(73) = .24, *p* = .037). However, there was no significant relationship between AA-CPM predictions and observed AA scores in the Stanford dataset (*r*(80) = .03, *p* = .80). When the NJ-CPM model was applied to the Leipzig dataset, we found no association between predicted and observed scores (*r*(73) = .17, *p* = .14). However, we found a positive relationship between NJ-CPM predictions and observed NJ scores in the Stanford dataset (*r*(80) = .28, *p* = .012).

Conclusion

While we did not find a generalizable model of total FFMQ scores that predicted overall trait mindfulness, we found that models of *Acting with Awareness* and *Non-judging* subscales generalized to the Leipzig dataset and Stanford dataset, respectively. The AA model found positive connectivity (relating to attention regulation (Mooneyham et al., 2016)), and SMN negative connectivity (implicated in mind-wandering (Mckeown et al., 2020; Vatansever et al., 2019)), whereas the NJ model implicated the DMN (related to rumination and self-referential processing (Raichle et al., 2001)). These findings provide neural support for a two-dimensional model of mindfulness, delineating awareness-cognitive and non-judgment-affective facets.

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