Monitoring Attention in Self and Others

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Abstract

■ The ability of the brain to monitor its own attention is important for controlling attention. The ability to reconstruct and monitor the attention of others is important for behavioral prediction and therefore interaction with others. Do the same cortical networks participate in constructing a metacognitive representation of attention, whether one's own or someone else's attention? We studied the brain activity of human participants in an fMRI scanner. The participants performed two attention-monitoring tasks. One involved focusing attention on their own breathing and pressing a button when they realized their attention had wandered. In the other, participants watched a video of an actor performing the same focused-attention task, and participants pressed the button if the actor's attention appeared to have wandered. In both cases, we analyzed brain activity just before the button presses, when participants were engaged in metacognition with respect to attention. In the Self condition, activity was obtained in a distinctive set of areas including the TPJ, precuneus, dorsomedial pFC, anterior cingulate, and anterior insula. The activity partly overlapped the default mode network, social cognition network, and salience network. In the Other condition, activity was found in a similar set of areas including the TPJ, precuneus, dorsomedial pFC, anterior cingulate, and anterior insula. These results suggest that there may be a common set of cortical areas that provide an overarching mechanism for metacognition concerning attention, although Self and Other processing are also clearly not identical. ■

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INTRODUCTION

Selective attention involves enhancing the processing of some stimuli at the expense of others. The ability of the brain to monitor attention, or to construct a metacognitive representation of attention, may be of great importance in helping to control attention. People are also able to reconstruct and monitor the attentional state of others, helping with behavioral prediction and interaction with others. The possibility arises that similar underlying brain mechanisms are recruited for building representations of one's own attention and of the attention of others.

The metacognition of attention has been studied in four main ways. The four approaches have been treated largely as separate fields of study, but we suggest that they are deeply connected, representing different approaches to the same underlying phenomenon. In one approach, it has been suggested that the brain constructs a descriptive and predictive model of attention, the attention schema, to help control attention, much as it constructs a model of the body, the body schema, to help control movement of the body (Graziano, 2013, 2022; Wilterson & Graziano, 2021; Webb & Graziano, 2015; Graziano & Kastner, 2011). In that perspective, knowing the current state of your attention and predicting where it is likely to go next and how specific distractors are likely to deflect attention from desired targets—all aspects of the metacognitive understanding of attention—are important for a good control of attention. In a second approach related to the monitoring of attention, it has been observed that a specific network within cortex, sometimes called the ventral attention network (VAN), becomes active when attentional state deviates from expectation, especially when exogenous or bottom–up attention is engaged in an unexpected way (Wilterson, Nastase, Bio, Guterstam, & Graziano, 2021; Kim, 2014; Geng & Vossel, 2013; Serences et al., 2005; Shulman et al., 2009, 2010; Corbetta, Patel, & Shulman, 2008; Stevens, Skudlarski, Gatenby, & Gore, 2000). The behavior of the VAN implies that the brain constructs a predictive model of how attention is expected to behave and then detects mismatches between the model and reality. A third body of research on the metacognition of attention has studied mind wandering, in particular investigating the moment when people realize that their attention has deviated from a desired state (Fox, Spreng, Ellamil, Andrews-Hanna, & Christoff, 2015; Smallwood & Schooler, 2015; Tang, Hölzel, & Posner, 2015; Hasenkamp, Wilson-Mendenhall, Duncan, & Barsalou, 2012; Baird, Smallwood, & Schooler, 2011; Stawarczyk, Majerus, Maj, Van der Linden, & D'Argembeau, 2011; Lutz, Slagter, Dunne, & Davidson, 2008; Mason et al., 2007). Fourth, a growing body of research has investigated how people reconstruct the attention state of other people in a social context. Although there is a great deal of insightful research on how one person attends to aspects of another person in social interaction (e.g., Fiske, 1980; Hamilton &

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Gifford, 1976), here, we focus on one aspect of social attention: how the brain of one person builds a model of the attention state of another person (Ziman, Kimmel, Farrell, & Graziano, 2023; Guterstam, Bio, Wilterson, & Graziano, 2021; Guterstam, Wilterson, Watchell, & Graziano, 2020; Guterstam & Graziano, 2020; Guterstam, Kean, Webb, Kean, & Graziano, 2019; Pesquita, Chapman, & Enns, 2016; Webb, Igelström, Schurger, & Graziano, 2016; Kelly, Webb, Meier, Arcaro, & Graziano, 2014; Bayliss, Bartlett, Naughtin, & Kritikos, 2011; Frischen, Bayliss, & Tipper, 2007; Langton, Watt, & Bruce, 2000; Baron-Cohen, 1991).

These four broad areas of research on the metacognition of attention often point to similar or partially overlapping cortical networks, including the default mode network (DMN), which extensively overlaps the social cognition network, and the salience network, which overlaps the VAN. For example, studies on building models of one's own attention point to the TPJ, the precuneus, and dorsomedial prefrontal cortex (DMPFC) often considered core parts of the social cognition network (Wilterson et al., 2021; Webb et al., 2016). Studies using mind wandering to examine metacognition of attention point to the DMN and the salience network (Fox et al., 2015; Hasenkamp et al., 2012). Studies on how people monitor the attention states of others point to the social cognition network (Guterstam et al., 2020, 2021; Kelly et al., 2014). It can be difficult to evaluate how much the activation patterns from these different kinds of studies overlap. In particular, monitoring one's own attention and inferring the attention states of others are seemingly very different tasks, typically tested in different experiments, yet by hypothesis might involve overlapping mechanisms.

The broader hypothesis that monitoring one's own internal processes and monitoring similar processes in others may involve overlapping networks in the brain has considerable support. For example, the DMN, active during self-focused metalizing, has extensive overlap with the social cognition network, active during mentalizing about others (e.g., Schilbach et al., 2012). In behavioral experiments, attending to the self-regulatory behavior of another person causes depletion in the perceiver's own self-regulatory resources (Ackerman et al., 2009). When people vicariously experience the rewards of others, the same brain systems are engaged as when a direct reward is experienced (Putnam, Chu, Fagan, Dal Monte, & Chang, 2023). These and many other examples suggest that the ability to build models of and monitor the internal states of others may depend on the same, or at least extensively overlapping networks, as those used for modeling and monitoring one's own internal states. Does the same pattern pertain to the metacognition of attention? Do people monitor, model, and make decisions about the state of other people's attention using similar brain mechanisms as those used for monitoring, modeling, and making decisions about their own attention?

In the present study, we used a mind-wandering paradigm on participants in an fMRI scanner. The design of the study (Figure 1) allowed for a comparison between a self-monitoring condition and a social, or other-monitoring condition, to test the hypothesis that the brain networks involved in these two seemingly different tasks might overlap. In one condition, participants focused their attention on their own breathing and pressed a button when they realized that their attention had wandered and needed to be directed back on task. In another

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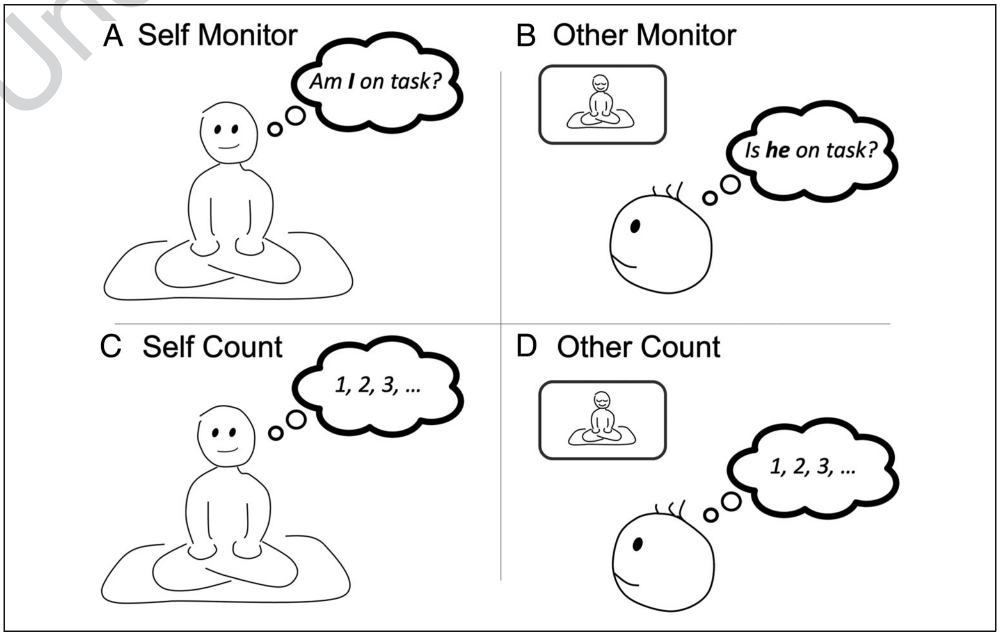

Figure 1. Four behavioral conditions. (A) In the Self Monitor condition, participants focused attention on their own breathing and monitored their attentional state. When they noticed that their attention had lapsed, they pressed a button and refocused attention on breathing. (B) In the Other Monitor condition, participants monitored the perceived attentional focus of a meditating actor in a video. When they believed the actor's attention had lapsed, they pressed a button. (C) In the Self Count condition, participants counted their own breaths and pressed a button at every fifth breath. (D) In the Other Count condition, participants counted the breaths of a meditating actor in a video and pressed a button at every fifth breath.

condition, participants watched a video of a meditating actor and pressed a button when they judged that the actor's attention may have wandered from his breathing. The distinction lies in monitoring one's own attentional state versus constructing inferences about the attentional state of another. The goal of the study was to determine the cortical networks involved and, in particular, to test the hypothesis that similar clusters of activity are evoked in the self-monitoring condition as in the other-monitoring condition.

It is important to point out that the self-report, mind-wandering task does not fully control the mind state of the participants throughout the experiment. Some participants may be better than others at monitoring or controlling their attention, and some may have different judgment thresholds for deciding whether they have mind-wandered. However, we take the button press to be an indicator that the participant has made a decision about their own attention (it is not where they want it to be). Regardless of differences among participants and of mental processes between button presses, if participants are following the instructions, then they are pressing the button when they notice that their attention is off task. Therefore, the time window just before the button press captures a similar process across all participants. It is a process of judging the state of one's own attention. This self-report task is one of many standard mind-wandering paradigms widely used in the literature (Fox et al., 2015; Smallwood & Schooler, 2015; Tang et al., 2015; Hasenkamp et al., 2012; Baird et al., 2011; Stawarczyk et al., 2011; Lutz et al., 2008; Mason et al., 2007).

METHODS

Participants

Twenty-eight healthy human volunteers (aged 18–50 years, normal or corrected-to-normal vision, 27 right-handed, 16 female) were recruited from the community and from a participant pool sponsored by Princeton University. On the basis of prior literature with fMRI experiments using social cognition tasks, we estimated that 25 participants would be sufficient for statistical power. We recruited 28 in case of attrition, but no participants were eliminated from the study. All participants were novice meditators—none were expert. All participants provided consent and received either $40 or course credit for participation. All procedures were approved by the Princeton Institutional Review Board.

Experimental Setup

Participants lay supine on the MRI bed. Visual stimuli were projected onto a screen 80 cm from the eyes through an angled mirror mounted on top of the head coil using a digital light processing projector (Hyperion MRI Digital Projection System, Psychology Software Tools) with a resolution of 1920 × 1080 pixels at 60 Hz. Stimuli were presented using PsychoPy2 (Peirce et al., 2019). All responses were recorded using a button box held in the participant's right hand and operated with the index finger.

Task Design

The task design, shown in Figure 1, involved four conditions: Self Monitor, Self Count, Other Monitor, and Other Count. In the Self Monitor condition, participants were instructed to pay attention to the rhythmic sensation of their breathing for 5 min. If at any point during this period they noticed that their mind had wandered from their breath, they were to indicate the moment by pressing the button. Following the button press, they were to reorient attention back to their breath and continue the task. The task thus required participants both to focus attention on a target (breathing) and to use metacognition, monitoring the state of attention to ensure that it was on target. To help remain on task, participants were instructed to silently recite, "breathe in, breath out," in synchrony with their breath. A fixation cross was presented at the center of the screen throughout the task, and participants were additionally instructed to keep their eyes open and on the cross, to reduce the chance of falling asleep while also reducing variability in visual input.

We defined a period of interest from 3 to 0 sec before each button press. It has been suggested, based on prior work (Hasenkamp et al., 2012), that this time period is the most likely window during which participants realized that they had mind-wandered. The moment of realization presumably took less than 3 sec, but the time window in which that realization was most likely to occur has been estimated to be between about 3 and 0 sec before the button press. This time window is therefore the most likely to contain brain activity associated with the most intense metacognitive monitoring of attention, with the realization that an error has occurred (a discrepancy between desired and actual attention), and with the decision to press the button.

The Self Count condition was designed to serve as a control for the Self Monitor condition. For the Self Count condition, participants were again instructed to pay attention to the rhythmic sensation of their breathing for 5 min while silently reciting, "breathe in, breath out," keeping their eyes open, and maintaining fixation on a central cross. However, instead of pressing the button when they noticed their attention had drifted from the task, participants were instructed to count their breaths. Each breath was defined as a complete sequence of inhalation and exhalation. When participants reached a count of five breaths, they were to press the button and restart the count. This control task included many of the elements of the Self Monitor task (attention to breathing and pressing a button to indicate a specific event) but lacked the metacognitive element

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of monitoring one's own attention and noting when that attention deviated from the desired state. Counting up to five breaths was chosen based on pilot experiments, in which the average rate of button press was approximately the same for the five-breath Self Count condition as for the Self Monitor condition.

In the Other Monitor condition, participants watched a 5-min video of an actor engaged in the Self Monitor meditation task. The participants were instructed to press the button when they judged that the actor's attention had wandered from the meditation task. Thus, rather than monitoring their own attention on their own breath and pressing the button when they realized an attentional lapse had occurred, the participants monitored the inferred attention of someone else, and they pressed the button when they thought the other person had experienced an attentional lapse.

In the Other Count condition, participants again watched a 5-min video of an actor engaged in the Self Monitor meditation task. The participants were instructed to watch the video, to carefully monitor and count the actor's breath, and to press the button at every fifth breath that the actor took. Thus, rather than counting their own breath and pressing at every fifth one, the participants monitored the breath of someone else and pressed at every fifth one.

To make the stimulus videos for the Other Monitor and Other Count conditions, two volunteer male actors were recorded (Actor A and B), for two separate 5-min films. The actors sat cross legged on a cushion and rested the right index finger on the spacebar of a computer used to record button presses. The actors were told to focus their attention on their own breathing, to repeat silently "breath in, breath out," and to press the button at the moment they realized their mind had wandered from the task. The camera was positioned to exclude view of the hands and computer (and thus of the button presses) and to capture an image of the actor above the waist.

Each participant performed 10 scanning runs of 5 min each. First, the participant performed four runs corresponding to the four behavioral conditions in a randomized order. The same video, showing Actor A, was presented for both the Other Monitor and Other Count conditions. The participant then performed a second iteration of the four runs, corresponding to the four behavioral conditions, but in a different randomized order. For this second iteration, the video of Actor B was presented for the Other Monitor and Other Count conditions. In addition to the eight runs in which the behavioral task was performed, participants performed two, 5-min runs of rest, one at the start of testing and one at the end. During the rest condition, participants were instructed to keep their eyes open and on a crosshair in the middle of the screen but to let their mind wander freely. Between runs, participants were offered a 30-sec rest that they could skip by pressing a "continue" button. Total scan time was approximately 1 hr.

fMRI Data Acquisition

Functional imaging data were collected using a 3 T MAGNETOM Skyra scanner (Siemens Healthineers AG), equipped with a 64-channel head/neck coil. Gradient-echo T2*-weighted echo-planar images with BOLD contrast were used as an index of brain activity (Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001). Functional image volumes were composed of 40 near-axial slices with no interslice gap and an in-plane acceleration factor of 2 using Generalized Autocalibrating Partially Parallel Acquisition, with slice thickness = 3.0 mm, field of view = 200 mm, 80 × 80 matrix, 2.5 mm × 2.5 mm in-plane resolution, echo time = 30 msec, flip angle = 70°, and bandwidth of 1690 Hz/Px. The TR length was 1.5 sec. Whole-brain coverage excluding the cerebellum was obtained for all participants. Ten runs consisting of 209 functional volumes were collected, totaling 2090 functional volumes per participant. The first five volumes of each run were discarded to account for non-steady-state magnetization.

Before functional runs, matching spin-echo EPI pairs with reversed phase-encode blips produced pairs of images with distortions going in opposite directions for blip-up/blip-down susceptibility distortion correction. An additional high-resolution structural image was collected for each participant, with 3-D magnetization prepared rapid acquisition gradient echo sequence, voxel size = 1 mm isotropic, field of view = 256 mm, matrix size = 256 × 256, 176 slices, repetition time = 2300 msec, echo time = 2.96 msec, inversion time = 1000 msec, flip angle = 9°, iPAT Generalized Autocalibrating Partially Parallel Acquisition = 2, bandwidth = 240 Hz/Px, anterior–posterior phase encoding, and ascending acquisition.

fMRI Preprocessing

Data were preprocessed using FMRIPREP Version 1.2.3 (Esteban et al., 2019). T1-weighted volumes were corrected for intensity nonuniformity using N4BiasFieldCorrection v2.1.0 (Tustison et al., 2010) and skull-stripped using the OASIS template in antsBrainExtraction.sh v2.1.0. Spatial normalization through nonlinear registration to the ICBM 152 Nonlinear Asymmetrical template Version 2009c (https://nist.mni.mcgill.ca/icbm-152-nonlinear-atlases-2009/) was completed using the antsRegistration tool of ANTs v2.1.0 (Avants, Epstein, Grossman, & Gee, 2008). Brain tissue segmentation of cerebrospinal fluid (CSF), white matter (WM), and gray matter using FAST (Zhang, Brady, & Smith, 2001) was performed on extracted T1w images.

Functional data were slice time corrected using 3dTshift from AFNI v16.2.07 (Cox, 1996) and motion corrected using MCFLIRT (FMRIB Software Library v5.0.9; Jenkinson, Bannister, Brady, & Smith, 2002). FLIRT (FMRIB Software Library) performed boundary-based registration with 6 degrees of freedom to coregister the

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corresponding T1w images to functional data (Greve & Fischl, 2009). Motion correcting transformations, BOLD-to-T1w transformation, and T1w-to-template warp were concatenated and applied in a single step using antsApplyTransforms (ANTs v2.1.0) with Lanczos interpolation. All functional images were high-passed (0.001) and low-passed (0.25) using Nilearn's signal cleaning function (https://nilearn.github.io/stable/modules/generated/nilearn.signal.clean.html). Further description of fMRIPrep's preprocessing pipeline is available (https://fmriprep.readthedocs.io/en/latest/workflows.html).

In additional preprocessing procedures, confound regression was performed to minimize the effects of physiological noise, head motion, and scanner drift. Physiological noise regressors were determined through aCompCor using the CSF and WM masks projected from subject-specific space to the T1w space. The first five principle components for CSF and WM were selected for each functional run, totaling 10 aCompCor components. Head motion parameters included three translation and three rotation time series as well as censor time series for volumes with a framewise displacement (FD) exceeding 0.3 mm. For each volume with FD exceeding 0.3 mm (a stringent standard), a vector of zeros was constructed with a value of one assigned to the time point corresponding to the offending volume. If more than 30% of volumes in a run had an average FD of 0.3 mm or larger, those runs were omitted from the analysis (9.6% of runs met this stringent criterion). For each run, censor time series as well as 10 aCompcor components, six head motion parameters, and three cosine drift parameters were inserted as regressors of no interest into the general linear model.

fMRI Analysis

For each of four behavioral conditions (Self Monitor, Self Count, Other Monitor, and Other Count), the time of each button press was recorded. We defined a period of interest from 3 to 0 sec before the button press. BOLD activity was analyzed during this time window. The predicted BOLD activity for each of these 3-sec pre-button-press periods was treated as a regressor of interest in a single design matrix along with the defined nuisance regressors. First-level regression was performed using the Nilearn's FirstLevelModel function (https://nilearn.github.io/dev/glm/first_level_model.html). BOLD time series were spatially smoothed using a 4-mm FWHM Gaussian kernel and standardized to mean zero and unit variance. Regressors of interest were convolved with a canonical hemodynamic response function (Glover, 1999). First-level design matrices were estimated across functional runs available for each condition, producing regression coefficients (beta weights) across all voxels. These beta weights capture how well each voxel's BOLD time series was predicted by the 3 sec regressor for each condition.

The first-level general linear model resulted in four beta maps, one for each condition, for each participant. We then performed two subtractions: Self Monitor minus Self Count, and Other Monitor minus Other Count. This produced two final whole-brain contrasts.

These subject-level contrast maps were submitted to a group-level one-sample t test using AFNI's 3dttest++ (Cox, Chen, Glen, Reynolds, & Taylor, 2017). Cluster-level statistical thresholds were determined using a nonparametric permutation-based approach implemented in 3dttest++ (randomly flipping the sign of the subject-level maps; Eklund, Nichols, & Knutsson, 2016). A whole-brain, cluster-level statistical threshold of $p < .05$ was obtained based on a single-voxel, cluster-forming threshold of $p < .005$. This yielded cluster thresholds between 60 and 100 voxels using the NN1 2-sided option (Cox et al., 2017).

RESULTS

Behavioral Results

All data are available online at https://github.com/isaacrc/Attn_to_Attn_fMRI. We first assessed whether the four conditions were comparable in the frequency of button presses. On average, participants pressed the button every 24.50 sec. Across participants, the mean number of button presses during each run of each of the four conditions was: Self Monitor, mean = 10.86, *SEM* = 0.81; Self Count, mean = 12.05, *SEM* = 0.53; Other Monitor, mean = 11.16, *SEM* = 1.00; and Other Count, mean = 11.75, *SEM* = 0.39. These button press counts did not significantly differ between monitoring and count conditions or between self and other conditions (2 × 2 within-subject ANOVA: for monitoring vs. count conditions, $F = 0.78$, $p = .38$; for self vs. other conditions, $F = 0.08$, $p = .78$; for interaction, $F = 0.14$, $p = .71$). With respect to the frequency of button presses, the conditions therefore appeared to be relatively well balanced.

MRI Results

To analyze brain activity, we first contrasted the Self Monitor condition with the Self Count condition, to determine if any brain areas were more active during monitoring of one's own attention than during the control condition. Figure 2A shows the result. Significantly greater activity in the Self Monitor versus the Self Count condition was found in the right and left TPJ, the DMPFC, ACC, posterior cingulate cortex (PCC), the left superior temporal sulcus, the right and left inferior frontal gyrus (IFG) extending into the anterior insula, the right and left dorsolateral prefrontal cortex (DLPFC), and a large cluster in visual cortex that extended into the precuneus (see Tables 1 and 2 for all activation clusters).

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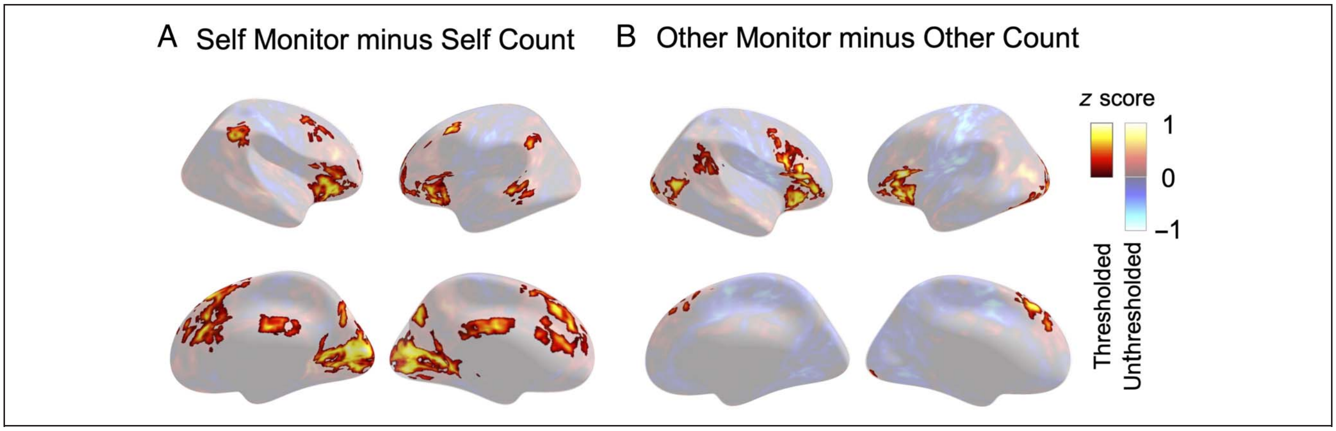

Figure 2. fMRI results. (A) Results from the Self Monitor condition minus the Self Count condition. Activations are shown for the 3-sec period before the button press event, when participants determined they were off task (for the Self Monitor condition) or that they had reached the fifth breath (for the Self Count condition). Lateral and medial views of both hemispheres are shown on inflated cortical surfaces. Color shows z-statistic output from group-level analysis. Light colors show subthreshold z values across entire cortex, and bright colors show the clusters that were above statistical threshold (cluster threshold $p < .05$, voxelwise threshold $p < .005$). Only positive significant clusters are shown. (B) Results from the Other Monitor condition minus the Other Count condition.

We then contrasted the Other Monitor condition with the Other Count condition, using the same univariate analysis method. Figure 2B shows the result. Significantly greater activity in the Other Monitor versus the Other Count condition was found in a ventral part of the right TPJ, the DMPFC, the IFG bilaterally extending into the anterior insula, right DLPFC, and in several locations in occipital visual cortex.

Although the total area of significant activation in the Other contrast was less than in the Self contrast, the

Table 1. Positive Significant Clusters

Contrast	*Region*	*Cluster Size*	*x*	*y*	*z*	*t (Max)*
OM - OC	R Insula / IFG	716	−53.5	−21.5	0	5.169
OM - OC	L Insula / IFG	462	31.5	−22.5	−6.5	5.2848
OM - OC	L Visual	376	34	82.5	−15.5	4.7363
OM - OC	ACC / DMPFC	225	6.5	−30	44.5	4.7099
OM - OC	R Visual	161	−28.5	90	2.5	4.4961
OM - OC	R TJP	105	−51	45	26.5	4.6441
SM-SC	Bilateral Visual	1867	−8.5	67.5	17.5	5.1731
SM-SC	Bilateral ACC / DMPFC	1104	1.5	−20	56.5	5.3808
SM-SC	L DLPFC / IFG / Insula	792	31.5	−22.5	−12.5	5.1726
SM-SC	R IFG / Insula	511	−48.5	−22.5	−9.5	5.8284
SM-SC	R TPJ	246	−56	47.5	32.5	4.8253
SM-SC	R DLPFC	198	−18.5	−62.5	20.5	4.3087
SM-SC	L Ant PFC	170	46.5	−15	41.5	5.1556
SM-SC	R Ant PFC	143	−48.5	−22.5	41.5	4.1099
SM-SC	Bilateral PCC	113	−3.5	17.5	29.5	4.7068
SM-SC	L Superior Temporal	93	64	35	−0.5	4.1503
SM-SC	L TPJ	85	64	50	32.5	5.1048

Data from Self Monitor minus Self Count (SM – SC) subtraction, and Other Monitor minus Other Count (OM – OC) subtraction. For each cluster, the table lists the task contrast; the brain region; the cluster size in voxels; the peak *x, y,* and *z* coordinates in MNI space; and the peak *t* statistic.

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Table 2. Negative Significant Clusters

Contrast	*Region*	*Cluster Size*	*x*	*y*	*z*	*t (Max)*
OM - OC	L Supplementary Motor	662	54	17.5	50.5	−4.8824
OM - OC	L Somatosensory	417	39	12.5	17.5	−5.6749
OM - OC	L Supplementary Motor	191	9	10	44.5	−4.7127
OM - OC	L IFG	178	−43.5	−2.5	11.5	−4.6965
OM - OC	Precuneus	148	4	75	29.5	−4.4293
OM - OC	R Somatosensory	123	−63.5	10	41.5	−4.8035
OM - OC	R Fusiform	121	−13.5	57.5	−9.5	−5.1045
OM - OC	L Superior Parietal	105	6.5	57.5	50.5	−4.4327
OM - OC	R Motor	83	−23.5	42.5	74.5	−4.5445
OM - OC	L Fusiform	76	11.5	65	−0.5	−4.5768

Data from Self Monitor minus Self Count (SM – SC) subtraction (no significant clusters), and Other Monitor minus Other Count (OM – OC) subtraction. For each cluster, the table lists the contrast; the brain region; the cluster size in voxels; the peak *x*, *y*, and *z* coordinates in MNI space; and the peak *t* statistic.

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patterns overlapped (compare Figure 2A with 2B). To show this overlap more clearly, Figure 3 shows the areas that were significant in the Self conditions (Self Monitor – Self Count) and also significant in the Other conditions (Other Monitor – Other Count). This conjunction map shows activity in, among other areas, the right TPJ, DMPFC, the IFG extending into the right anterior insula, and part of lateral pFC.

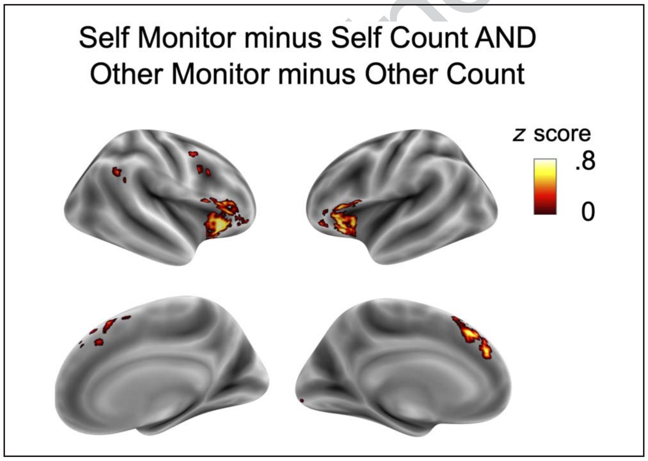

Figure 3. Conjunction of contrasts. Colored areas show only voxels that were significant for the Self Monitor minus Self Count contrast and also significant for the Other Monitor minus Other Count contrast. For each of these voxels, the activity value (in *z* score) from the Self contrast and from the Other contrast were averaged together. The average value for each voxel was then used to generate the surface map shown here. Only positive significant voxels are shown.

DISCUSSION

The present experiment used a paradigm in which participants self-reported when they noticed that their attention had wandered, or reported when they judged that an actor's attention had wandered. The use of self-reported mind-wandering events may not be a true indication of the amount of mind wandering that occurred during the experiment, and differs from other methods such as the "probe caught" method that more precisely captures mind-wandering (Murray, Krasich, Schooler, & Seli, 2020; Weinstein, 2018). However, the goal of the present study was not to accurately capture instances of mind wandering. Instead, we were more interested in brain activity during instances of heightened attention monitoring, when participants made judgments about the state of their own attention, and for this reason, the self-caught method made sense.

In previous mind-wandering literature, it has been suggested that mind wandering itself is associated with activity in the DMN, whereas awareness that mind wandering has occurred (the metacognitive realization that one's attention is not in a desired state) is associated with activity in the salience network (Fox et al., 2015; Hasenkamp et al., 2012; Brewer et al., 2011). There are some methodological differences between the present study and these previous studies. In particular, we contrasted the activity during the self-caught mind-wandering task with activity during a control, counting task. Despite these methodological differences, the results show some similarities. Activity in the present experiment, during the Self conditions, was obtained in the DMN (especially in the TPJ, DMPFC, ACC, PCC, and precuneus). Activity was also observed in the salience network (especially in the anterior insula bilaterally and ACC). It is worth noting that in prior research, differences have been seen between novice and expert meditators, with less activity in the DMN in experts (Brewer et al., 2011). Here, we used novice meditators, consistent with the pronounced activity throughout the DMN.

Another difference between the present and previous studies is the inclusion of Other conditions, in which participants judged the attention states of actors, in addition to the Self conditions, in which participants judged their own attention states. A large body of work dating back at least to the 1970s relates attention to social cognition (e.g., Fiske, 1980; Hamilton & Gifford, 1976). One specific topic within that larger area of research on social attention focuses on how people reconstruct the attentional state of others, as a foundational piece of theory of mind. Much of that work on how an agent reconstructs and monitors the attention of others has emphasized how the brain monitors the gaze direction of others (Frischen et al., 2007; Hoffman & Haxby, 2000; Calder et al., 2002; Baron-Cohen, 1991). Eye position is clearly important in this process, but more recent studies suggest that the brain constructs a deeper model of other people's attentional states, sometimes called the attention schema. This model depends on a combination of many cues in addition to eye position, it predicts attentional dynamics, and it predicts the effects of attention on behavior (Ziman et al., 2023; Guterstam et al., 2019, 2020, 2021; Guterstam & Graziano, 2020; Pesquita et al., 2016; Kelly et al., 2014). Imaging studies on the networks that might construct that deeper model of attention have pointed to the TPJ with an emphasis on the right, DMPFC, ACC, and the precuneus (Guterstam et al., 2021; Guterstam & Graziano, 2020; Kelly et al., 2014), all of which are part of the social cognition network (van Veluw & Chance, 2014; Saxe & Powell, 2006; Saxe & Kanwisher, 2003). Activity in DLPFC has also been reported in some tasks where participants judged the attentional state of others (Kelly et al., 2014). In the present study, we found overall less activity in the Other conditions than in the Self conditions, but the activity was obtained in many of the same areas including the DMN (especially the DMPFC and parts of the right TPJ) and the salience network (especially the anterior cingulate). One possible interpretation of the present results is that the activity in the DMN, especially in areas related to social cognition, might reflect the monitoring of attention, or the building of metacognitive models of attention, whether one's own attention or the attention of others, and the activity in the salience network might reflect the realization that expected attentional state and actual attentional state are discrepant, again whether related to one's own or someone else's attention. The results suggest that, as hypothesized, there is extensive overlap in the cortical systems that monitor one's own attention and that monitor other people's attention.

Activity patterns obtained in the Self and Other conditions were clearly not identical, however, and one difference lies in the right TPJ. Although both conditions evoked activity in the right TPJ, and although the two areas of activity overlapped, they were not fully coextensive. Instead, the Other conditions evoked a peak cluster of activity in a more ventral TPJ location, whereas the Self conditions evoked a peak of activity in a more dorsal location. This difference could of course be the result of the noisy nature of fMRI data, in which case the two TPJ activations may be effectively the same. However, it is also possible that the trend reflects a meaningful difference in functional anatomy. It could be that while the right TPJ broadly has a role in modeling attention, self-models and other-models might emphasize different subregions of the TPJ (Nicolle et al., 2012).

Why Metacognition of Attention Is Important

A large and growing body of literature focuses on the brain basis of consciousness. One proposal in particular involves metacognition with respect to attention (Wilterson & Graziano, 2021; Graziano, 2013, 2022; Webb & Graziano, 2015; Graziano & Kastner, 2011). In that proposal, called the attention schema theory, you become conscious of a particular item X in the following way. First, you have some attention enhancing the processing of item X. Second, the brain constructs a metacognitive model of attention, the attention schema. Third, when information in that model reaches higher cognitive systems and speech systems, you are able to report not only that item X is present but also that you have a state of mental focus on item X. The key to the proposal is that, not only does information about X reach higher cognition, but so does metacognitive information about the state of attention on X. Because the metacognitive model of attention is schematic, and not literally accurate in its portrayal of attention, the picture it paints and therefore the claim that people ultimately make depicts an ethereal, physically substanceless essence of mental experience—consciousness. The proposal potentially explains the source of the information in the brain from which derives the claim, "I have a conscious experience, or a subjective feeling, associated with X." In that framework, mind wandering and attention are both closely related to consciousness. In effect, during mind wandering, the participant is no longer conscious of breathing or conscious that they are supposed to be attending to their breathing. The conscious mind has wandered to something else. At the moment that the participant notices they have let their attention wander, they become conscious again of the task at hand.

In this approach, called the attention schema theory, the brain not only models one's own attention but also construct models of the attention of others, in effect attributing conscious experience to them. That ability is proposed to be fundamental to theory of mind—to reconstructing the mind states and motivations of others such that we can predict their behavior and interact more effectively. In the attention schema theory, the mechanism of

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consciousness is crucial partly for monitoring and controlling one's own attention, but also for social interaction and cooperation. By using the same mechanism, or at least an extensively overlapping mechanism, the brain has a built-in bias for empathy. Broadly, when building predictive models of the self that are used to help guide behavior, those models are tuned to benefit the self. If the same machinery, the same underlying learning, applies to building models of others and guiding behavior toward others, then the system has an intrinsic bias toward seeking the same beneficial outcomes for others as for oneself. This bias may be especially strong when those models of others are particularly elaborated, as for people we know well. The overlap between self-focused processing and other-focused processing therefore may have profound consequences for empathy, cooperation, close relationships, and even the general ability of people (and perhaps many other species) to form complex, prosocial societies.

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Data Availability Statement

All data for this experiment are available online at https://github.com/isaacrc/Attn_to_Attn_fMRI.

Author Contributions

Isaac R. Christian: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Writing—Original draft; Writing—Review & editing. Samuel A. Nastase: Data curation; Methodology; Validation; Writing—Review & editing. Mindy Yu: Data curation; Investigation; Writing—Review & editing. Kirsten Ziman: Formal analysis; Visualization. Michael S. A. Graziano: Conceptualization; Funding acquisition; Investigation; Methodology; Project administration; Supervision; Validation; Visualization; Writing—Original draft; Writing—Review & editing.

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Diversity in Citation Practices

Retrospective analysis of the citations in every article published in this journal from 2010 to 2021 reveals a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience* (*JoCN*) during this period were M(an)/M = .407, W(oman)/M = .32, M/W = .115, and W/W = .159, the comparable proportions for the articles that these authorship teams cited were M/M = .549, W/M = .257, M/W = .109, and W/W = .085 (Postle and Fulvio, *JoCN*, 34:1, pp. 1–3). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance.

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