Connectome-based Models Predict Separable Components of Attention in Novel Individuals

Monica D. Rosenberg¹, Wei-Ting Hsu¹, Dustin Scheinost², R. Todd Constable¹,², and Marvin M. Chun¹,²

Abstract

Although we typically talk about attention as a single process, it comprises multiple independent components. But what are these components, and how are they represented in the functional organization of the brain? To investigate whether long-studied components of attention are reflected in the brain’s intrinsic functional organization, here we apply connectome-based predictive modeling (CPM) to predict the components of Posner and Petersen’s influential model of attention: alerting (preparing and maintaining alertness and vigilance), orienting (directing attention to a stimulus), and executive control (detecting and resolving cognitive conflict) [Posner, M. I., & Petersen, S. E. The attention system of the human brain. Annual Review of Neuroscience, 13, 25–42, 1990]. Participants performed the Attention Network Task (ANT), which measures these three factors, and rested during fMRI scanning. CPMs tested with leave-one-subject-out cross-validation successfully predicted novel individual’s overall ANT accuracy, RT variability, and executive control scores from functional connectivity observed during ANT performance. CPMs also generalized to predict participants’ alerting scores from their resting-state functional connectivity alone, demonstrating that connectivity patterns observed in the absence of an explicit task contain a signature of the ability to prepare for an upcoming stimulus. Suggesting that significant variance in ANT performance is also explained by an overall sustained attention factor, the sustained attention CPM, a model defined in prior work to predict sustained attentional abilities, predicted accuracy, RT variability, and executive control from task-based data and predicted RT variability from resting-state data. Our results suggest that, whereas executive control may be closely related to sustained attention, the infrastructure that supports alerting is distinct and can be measured at rest. In the future, CPM may be applied to elucidate additional independent components of attention and relationships between the functional brain networks that predict them.

INTRODUCTION

The ability to pay attention differs substantially across people. Although these individual differences are most pronounced in clinical populations such as attention-deficit/hyperactivity disorder, variation exists even among healthy individuals. Variability exists, too, in the type of attention with which people succeed or struggle. One person, for example, might be unable to resist distraction for long periods of time but easily switch between tasks, whereas another might have no trouble maintaining uninterrupted focus but suffer productivity costs when shifting from one task to the next. Dissociations of this type have been observed in action video game players, who, compared with nongamers, show better visual-selective attention (Green & Bavelier, 2003) but not more efficient allocation of attention in response to external cues (Green & Bavelier, 2012).

Although phenomenology suggests that focusing on a lecture, braking quickly to avoid an obstacle in the road, and scanning a crowd for a friend tax different forms of attention, do these behaviors in fact rely on distinct mechanisms? As suggested previously, psychology research has long demonstrated that attention is not a single monolithic ability but rather can be divided into several subtypes (Chun, Golomb, & Turk-Browne, 2011). One recent study, for example, tested more than 200 participants on at least nine common attention tasks and used cross-correlations to identify a “general attention factor” related to intelligence, inhibition, and task switching, as well as several highly specific factors related to spatial orienting, attentional capture, and inhibition of return (Huang, Mo, & Li, 2012).

An earlier, influential model divided attention into three major components: alerting, or preparing and maintaining alertness and vigilance; orienting, or directing overt or covert attention to a stimulus; and executive control, or detecting and resolving cognitive conflict (Petersen & Posner, 2012; Posner & Petersen, 1990). Behavioral studies show that alerting, orienting, and executive control are largely uncorrelated within participant (Fan, McCandliss, Fossella, Flombaum, & Posner, 2005; Fan, McCandliss, Sommer, Raz, & Posner, 2002; but see MacLeod et al., 2010). Supporting these distinctions, neuroimaging studies have found that these components are related to activity in different brain regions (Petersen & Posner, 2012;
Fan et al., 2005; Posner & Petersen, 1990) and integrity in different white matter tracts (Yin et al., 2012; Nioji, Mukherjee, Ghajar, & McCandliss, 2010), as well as to cortical thickness (Westlye, Grydeland, Walhovd, & Fjell, 2011), white matter asymmetry (Yin et al., 2013), and functional connectivity in the dorsal attention and default mode networks (Madhyastha, Askren, Boord, & Grabowski, 2015; Visintin et al., 2015). Despite these models, however, the comprehensive set of attentional components and their underlying neural mechanisms are still debated.

A new approach in cognitive neuroscience, connectome-based predictive modeling (CPM; Shen et al., 2017), may help elucidate the independent factors of attention (Rosenberg, Finn, Scheinost, Constable, & Chun, 2017). This approach uses models based on functional brain connectivity, or coordinated activity in spatially distinct regions of the brain, to predict behavior in previously unseen individuals. One benefit of making predictions from functional connectivity is that connectivity can be measured in resting-state fMRI data—that is, data collected as participants simply lie still in the MRI scanner. Furthermore, from a broad perspective, models that make individualized predictions from brain data can offer both theoretical insights and translational applications (Woo, Chang, Lindquist, & Wager, 2017; Gabrieli, Ghosh, & Whitfield-Gabrieli, 2015).

Using CPM, our group developed a model that predicts how well novel individuals sustain attention based on their unique functional connectivity patterns (Rosenberg, Finn, et al., 2016). This model, the sustained attention connectome-based predictive model, comprises two functional networks whose strength is related to performance on a challenging sustained attention task, the gradCPT (Esterman, Noonan, Rosenberg, & Degutis, 2013; Rosenberg, Noonan, DeGutis, & Esterman, 2015). Even during rest, high-attention network strength predicts better gradCPT performance, and low-attention network strength predicts worse gradCPT performance. The sustained attention CPM has generalized to predict attention-deficit/hyperactivity disorder symptom severity in children (Rosenberg, Finn, et al., 2016) and stop signal task performance in adults (Rosenberg, Zhang, et al., 2016), and is sensitive to changes in attention function resulting from pharmacological intervention (Rosenberg, Zhang, et al., 2016). This model’s success demonstrates that sustained attention can be measured while a person is not actively paying attention, providing novel evidence that sustained attentional abilities are reflected in the intrinsic functional organization of the brain.

Although the sustained attention CPM shows promise for quantifying the ability to maintain focus over time, again, more than a century of behavioral research demonstrates that sustained attention is just one aspect of human attention (Chun et al., 2011). To investigate whether other proposed facets of attention are (1) related to the sustained attention factor described previously and (2) reflected in the brain’s intrinsic functional organization, here we apply CPM to predict individual differences in alerting, orienting, and executive control from task-based and resting-state functional connectivity. Practically, this effort represents a first step toward developing a suite of models that predict a person’s overall attentional abilities. Theoretically, it may shed light on the relationships (or lack thereof) between proposed components of attention and the functional networks that support them.

METHODS
Participants
Fifty-six participants from Yale University and the surrounding community were scanned during Attention Network Task (ANT) performance and rest. Eight individuals were excluded for excessive head motion, defined a priori as >2 mm translation, >3° rotation, or >0.15 mm mean-frame-to-frame displacement (Rosenberg, Zhang, et al., 2016) in three or more of the six task runs, and four were excluded for missing data from three or more task runs because of insufficient scan time or technical issues such as a failure to record button presses. The remaining 44 participants, all of whom were right-handed and had normal or corrected-to-normal vision, were included in the subsequent analyses (29 women, ages 18–37 years, mean age = 23.9 years). All participants gave written informed consent in accordance with the Yale University human subjects committee and were paid for their participation.

Task Paradigm
ANT trials began with a 200-msec cue period. On central-cue trials, an asterisk appeared in the center of the screen. On spatial-cue trials, an asterisk appeared above or below a central fixation cross. (This cross was present on the screen for the entire experiment.) On no-cue trials, no cue appeared at all. After a variable SOA of 0.3–11.8 sec (mean = 2.8 sec), five arrows appeared above or below the central fixation cross. Participants were instructed to press a button with their right index finger if the center arrow (the third in the row of five) pointed to the right of the screen and to press a button with their left index finger if the center arrow pointed to the left. On congruent trials, the central or target arrow pointed in the same direction as the surrounding distractor arrows. On incongruent trials, the target pointed in the opposite direction as the four arrows that flanked it. After a button press or 2 sec, the arrows disappeared, and a variable intertrial interval (ITI; 5–17 sec, mean = 8 sec) began.

Participants performed the ANT during six runs of fMRI data collection. Each run consisted of two buffer trials followed by 36 task trials. Task trials were divided equally between the cue and target conditions, and each run included six examples of each of the six trial types (3 cue types: central-cue vs. spatial-cue vs. no-cue × 2 target
types: congruent vs. incongruent). Trial order was counter-balanced within and across runs. Timing parameters, trial order, and counterbalancing procedures exactly replicate Fan et al. (2005), except that, in that article, the ITIs ranged from 3 to 15 sec (mean = 6 sec). Here, we used the same distribution of ITIs but increased the length of each by 2 sec to facilitate functional connectivity analyses, which benefit from longer time windows over which to calculate correlations.

Behavioral Analysis
The ANT purports to measure three types of attention—alerting, orienting, and executive control—by comparing RTs on different trial types (Fan et al., 2002, 2005). For each participant, alerting is measured as the difference in mean correct-trial RT to no-cue and central-cue trials. Because central cues provided information about when a target will appear, we expect positive alerting scores—that is, faster RTs to central-cue than no-cue trials. Orienting is measured as the difference in mean correct-trial RT to central-cue and spatial-cue trials. Unlike central cues, which provide information about the timing but not spatial location of targets, spatial cues always indicated whether the upcoming target would appear above or below the central fixation cross. Thus, we expect positive orienting scores or faster RTs to spatial-cue than central-cue trials. Finally, executive control is measured as the difference in mean correct-trial RT to incongruent and congruent trials. We expect faster RTs to trials in which the distractor arrows point in the same direction as the target arrow than to those in which they point in the opposite direction, and so positive executive control scores.

In addition to measuring alerting, orienting, and executive control, we assessed ANT accuracy as the percentage of correct responses. Because accuracy was near ceiling, however, we used RT coefficient of variation (the standard deviation divided by the mean of correct-trial RTs) as a more sensitive measure of overall task performance (Wojtowicz, Omisade, & Fisk, 2013; Lundervold et al., 2011; Adolfsdóttir, Sørensøren, & Lundervold, 2008; Kelly, Uddin, Biswal, Castellanos, & Milham, 2008). On cognitive and attentional tasks, higher intraindividual response variability indicates less successful sustained attention or attentional control (Rosenberg et al., 2013; Sonuga-Barke & Castellanos, 2007; MacDonald, Nyberg, & Bäckman, 2006; Castellanos et al., 2005; Stuss, Murphy, Binns, & Alexander, 2003). On the ANT in particular, greater RT standard deviation has been associated with attention impairments in attention-deficit/hyperactivity disorder (Adolfsdóttir et al., 2008) and multiple sclerosis (Wojtowicz et al., 2013).

Imaging Parameters and Preprocessing
Experimental sessions began with a high-resolution anatomical scan, followed by two 6-min resting-state scans and six 7.05-min ANT runs. Participants were instructed to fixate on a cross presented in the center of the screen during rest runs and to respond to arrow stimuli as quickly and accurately as possible during task runs.

fMRI data were collected at the Yale Magnetic Resonance Research Center on a 3T Trio TIM system (Siemens, Erlangen, Germany). Resting-state runs included 360 whole-brain volumes, and task runs included 425 volumes. Both were acquired using a multiband EPI sequence with the following parameters: repetition time = 1000 msec, echo time = 30 msec, flip angle = 62°, acquisition matrix = 84 × 84, in-plane resolution = 2.5 mm², 51 axial-oblique slices parallel to the AC-PC line, slice thickness = 2.5 mm, multiband 3, acceleration factor = 2. MPGRAGE parameters were repetition time = 2530 msec, echo time = 2.77, flip angle = 7°, acquisition matrix = 256 × 256, in-plane resolution = 1.0 mm², slice thickness = 1.0 mm, 176 sagittal slices. A 2-D TI-weighted image with the same slice prescription as the EPI images was also collected for registration purposes.

Data were analyzed using BioImage Suite (Joshi et al., 2011) and custom scripts in MATLAB (The MathWorks, Natick, MA). Motion correction was performed using SPM8. Nuisance regressors including linear and quadratic drift, mean signal from cerebrospinal fluid, global signal, and a 24-parameter motion model (six motion parameters, six temporal derivatives, and their squares) were removed from the data. Data were temporally smoothed with a zero mean unit variance Gaussian filter (cutoff frequency = 0.12 Hz).

Global signal regression was included as a preprocessing step because of its well-established role in reducing the confounding effects of motion in functional connectivity data (Ciric et al., 2017; Power, Plitt, Laumann, & Martin, 2017; Power, Schlaggar, & Petersen, 2015; Power et al., 2014; see Motion Controls section for detail). One concern about global signal regression, that it may induce false negative functional connections (edges), is not relevant here because we do not interpret edge sign. Instead, in taking an individual differences approach, we only consider the relative strength of edges across participants.

Data Exclusion
In the final set of 44 participants, runs with excessive head motion, defined a priori as >2 mm translation, >3° rotation, or 0.15 mm mean frame-to-frame displacement (Rosenberg, Finn, et al., 2016; Rosenberg, Zhang, et al., 2016), were excluded from analysis. One task run was excluded from three participants, and two task runs were excluded from one participant for excessive motion. Because of technical issues or insufficient scan time, two additional participants were missing 205 and 81 volumes, respectively, from one task run; five participants were missing one task run; one participant was missing two task runs; and one participant was missing three task runs. All participants had two rest runs with acceptable
levels of motion. All exclusion was performed before functional connectivity data were analyzed.

**Network Construction**

Whole-brain functional connectivity networks were defined as described previously (Rosenberg, Finn, et al., 2016; Rosenberg, Zhang, et al., 2016; Finn et al., 2015). Briefly, network nodes were defined with the Shen 268-node functional brain atlas (Shen, Tokoglu, Papademetris, & Constable, 2013; https://www.nitrc.org/frs/?group_id=51). The atlas was warped from MNI space into individual-subject space with a concatenation of linear and nonlinear registrations between the functional images, 2-D and 3-D anatomical scans, and the MNI brain.

Transformations, which were estimated using intensity-based registration algorithms in BioImage Suite (New Haven, CT), were calculated independently, combined into a single transform, and inverted.

For each participant, a task matrix was calculated using data concatenated across task runs, and a rest matrix was calculated using data concatenated across resting-state runs. The first eight frames (8 sec) of each run were excluded from analysis. A mean time course for each node was then calculated by averaging the time courses of all voxels in the node. The time courses of every pair of nodes were correlated, and the resulting Pearson correlation coefficients were Fisher z-transformed to yield symmetric 268 × 268 functional connectivity matrices. Cells in these matrices represent functional connections or edges.

We generated one task matrix rather than six condition-specific matrices (i.e., no-cue, center-cue, spatial-cue, congruent-target, and incongruent-target matrices) for each individual for several reasons. This approach maximizes the amount of data used to calculate correlations and thus the reliability of functional connectivity estimates (Noble et al., 2017; Shah, Cramer, Ferguson, Birn, & Anderson, 2016; Birn et al., 2013). It also facilitates testing models on resting-state data, from which condition-specific connectivity patterns cannot be calculated. Furthermore, tasks like the ANT may serve as attentional "stress tests" that put participants in a task-engaged state, perturb attention-related brain circuitry, and enhance individual differences in behaviorally relevant patterns of functional connectivity (Finn et al., 2017). Here, we investigated whether functional connectivity observed during task-engaged and task-free states predicts individual differences in attention. Future work could explore whether, for example, functional connectivity patterns observed during single trials or trial types of a cognitive or attentional task predict behavior.

**Connectome-based Predictive Modeling**

We used a recently developed technique, CPM (Shen et al., 2017; Rosenberg, Finn, et al., 2016; Finn et al., 2015), to predict individual differences in alerting, orienting, executive control, percent accuracy, and RT variability on the ANT. CPM includes three steps: feature selection, model building, and model validation.

First, we selected one of the five behavioral variables of interest: accuracy, RT variability, alerting, orienting, and executive control. We then set aside data from one participant. Using task matrices from the remaining 43 participants, we identified functional connections related to the selected performance measure by correlating every edge in the matrices with behavior across participants. We used Spearman’s rank correlation at this step because two of the five behavioral scores (accuracy and executive control) were not normally distributed (Jarque-Bera test p values < .041). Correlation coefficients were thresholded at p < .05 and separated into a positive tail (edges greater in individuals with higher behavioral scores) and a negative tail (edges greater in individuals with lower behavioral scores). We applied an edge threshold of p < .05 rather than p < .01, which was applied previously (Rosenberg, Finn, et al., 2016), because approximately 27.3% of all possible connections in the brain were excluded from analysis due to correlations with motion parameters (see Motion Controls section). The choice of this feature selection threshold does not affect the validity of predictions, because cross-validation is a built-in guard against false-positive results. Positive and negative network strengths, summary measures that represent overall functional connectivity strength, were calculated for each training subject by summing edges in the tails (i.e., taking a dot product between the positive and negative tail masks and each training subject’s task matrix).

Next, we defined a linear model relating positive and negative network strength to behavior in the training set. Because Spearman’s correlations and rank were used, this model included coefficients for positive and negative network strength but not an intercept (Shen et al., 2017). The left-out subject’s positive and negative network strengths, measured during task or rest, were input into the model to generate a predicted behavioral score.

We repeated this procedure so that each participant was left out of the training set once and measured models’ predictive power by correlating the predicted values and observed behavioral scores, controlling for motion (see Motion Controls section below). Spearman’s rho (r_s) was used to evaluate model performance because it is less sensitive to the effect of outliers than Pearson’s r and because CPM predictions are best considered relative rather than absolute (Rosenberg, Finn, et al., 2016). Permutation (i.e., randomization) testing was used to assess significance because standard r-to-p conversions assume that the number of degrees of freedom is equal to the number of participants – 2, and this assumption is violated in leave-one-out cross-validation because folds are not independent (e.g., Rosenberg, Finn, et al., 2016). To
perform permutation testing, we randomly shuffled participants’ behavioral scores 1000 times and ran these shuffled values through our prediction pipeline to generate 10 null distributions (a task-based distribution and a resting-state distribution for each of our five behavioral variables). p Values associated with each model were based on the corresponding null distribution with the formula $p = \left( 1 + \frac{\text{number of permutation } r_s \text{ values greater than or equal to the observed } r_s \text{ value}}{1001} \right)$.

Finally, the entire pipeline was repeated to define one CPM for each of the five behavioral measures.

### Motion Controls

Because head motion can confound functional connectivity analyses, we investigated whether measures of head motion were correlated with behavior across participants (Table 1).

Given the nonzero correlations between some head motion parameters and behavior, we excluded any edge in the task and rest matrices that was correlated with motion across participants. That is, we correlated the strength of every edge in the task matrices with maximum displacement, maximum rotation, and mean frame-to-frame displacement during task across participants using Spearman’s correlation. We also correlated the strength of every edge in the rest matrices with motion measured during rest. Edges related to motion at $p < .05$ were removed, or masked, in every participant’s task and rest matrices. This step resulted in the removal of 9772 edges from the matrices. (When global signal regression is not included as a preprocessing step but the rest of the pipeline is identical, 17,688 edges [or 49.44%] of all possible functional connections are excluded based on the same criteria. Thus, global signal regression effectively reduces the relationship between head motion and functional connectivity in this data set.) 26,006 edges or 72.7% of the original 35,778 edges remained. Given the large number of multiple comparisons, this step almost certainly resulted in the removal of edges related to motion parameters by chance. However, given the substantial confounding effects of head motion on functional connectivity estimates (van Dijk, Sabuncu, & Buckner, 2012), this conservative edge exclusion step is justified.

Finally, after eliminating fMRI runs with excessive head motion, correcting for head motion during preprocessing, and excluding edges related to motion parameters across participants, we controlled for head motion at the model evaluation step. Specifically, we evaluated model predictions with Spearman’s partial correlations between observed and predicted behavioral scores, controlling for motion parameters. Partial correlations between observed scores and task-based predictions included maximum displacement, rotation, and mean frame-to-frame displacement during task runs. Correlations between observed scores and rest-based predictions included these three measures from both task and resting-state runs, because models were trained using task data and tested using rest.

### Predictive Network Anatomy

To investigate network anatomy, we first defined common networks for each behavioral measure that was successfully predicted from functional connectivity. That is, because network models were defined using leave-one-subject-out cross-validation, there were as many different models as there were rounds of cross-validation. Because our data set included 44 participants, there were 44 unique models per behavioral measure. For each measure of behavior, we retained edges that appeared in every round of cross-validation—those edges that appeared in all 44 positive tails and all 44 negative tails—for further analysis (Rosenberg, Finn, et al., 2016). This

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<th>Table 1. Correlation between Motion Parameters and Behavior</th>
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Cells contain Spearman’s correlation coefficients. Maximum displacement is the average maximum displacement in millimeters across runs; maximum rotation is the average maximum rotation in degrees across runs. Mean frame-to-frame displacement is the average displacement in millimeters from one frame to the next.

*p < .05 uncorrected.
resulted in a common positive network (edges that consistently predicted higher behavioral scores) and a common negative network (edges that consistently predicted lower behavioral scores) for each measure. Although we could have visualized edges that appeared in any round of leave-one-out cross-validation, we elected to apply this conservative edge retention step to identify edges most consistently related to behavior and facilitate concise visualization.

We visualized common positive and negative network anatomy by grouping nodes into macroscale brain regions, which included prefrontal, motor, parietal, temporal, occipital, and limbic cortex, as well as the insula, cerebellum, subcortex, and brainstem (Finn et al., 2015).

**Sustained Attention CPM**

Previous work using CPM demonstrated that two large-scale functional connectivity networks, the high-attention network and the low-attention network, predict sustained attention performance in several data sets (Rosenberg, Finn, et al., 2016; Rosenberg, Zhang, et al., 2016). To test whether this model, the sustained attention CPM, predicts ANT performance in the current data set, we applied it to each of 41 participant’s task and rest matrices. (Data from three participants who had previously participated in the study used to define the sustained attention CPM were excluded from this analysis.) In other words, we calculated the dot product between the high- and low-attention network masks and each task or rest matrix to measure high- and low-attention network strength for each participant. Edges removed from ANT matrices for relationships with motion were excluded from analysis, leaving 478 of the original 757 high-attention network edges and 412 of the original 630 low-attention network edges. We input these network strength values into the sustained attention CPM, a linear model with coefficients for high- and low-attention network strength, to generate a predicted behavioral score. This predicted score corresponds to how well that participant would hypothetically perform on a challenging continuous performance task—in essence, a measure of their overall ability to sustain attention (Rosenberg, Finn, et al., 2016).

We assessed predictive power with Spearman’s partial correlations between sustained attention CPM predictions, observed ANT performance, and head motion parameters. Partial correlations between behavior and sustained attention CPM predictions from task data included maximum displacement, rotation, and mean frame-to-frame displacement during task runs; partial correlations between behavior and sustained attention CPM predictions from resting-state data included these measures during rest runs. P values were calculated with two-tailed permutation tests. To generate null distributions, ANT scores and motion measures were shuffled together across participants and correlated with observed high- and low-attention network strength values 100,000 times.

**Relationships between Predictive Networks**

To investigate the relationship between networks predicting overall ANT performance (accuracy and RT variability) and the sustained attention networks defined previously (Rosenberg, Finn, et al., 2016), we counted the number of edges common to each ANT and sustained attention network pair. We assessed the statistical significance of edge overlap with the hypergeometric cumulative density function (Rosenberg, Zhang, et al., 2016). This was implemented in MATLAB with \( p = 1 - \text{hygecdf}(x, M, K, N) \), where \( x \) = number of overlapping edges, \( M = 26,006 \), the total number of edges, \( K \) = number of edges in the first network of interest, \( N \) = number of edges in the second network of interest, and \( p \) = the probability of observing up to \( x \) of \( K \) possible edges in \( N \) drawings without replacement from a full set of \( M \) edges (The MathWorks Inc., 2016). For this analysis, high-attention network size was 478 (the number of edges that could have possibly overlapped with ANT networks due to motion-related edge removal), and low-attention network size was 412.

Significance of the overlap between three networks was assessed with 100,000 permutation tests. For each permutation, we randomly generated six networks from 26,006 possible edges whose size matched the high- and low-attention, high- and low-accuracy, and low- and high-RT variability networks. We counted the number of edges that appeared in the high-attention, high-accuracy, and low-RT variability networks as well as the number of edges that appeared in the low-attention, low-accuracy, and high-RT variability networks. Significance of observed overlap was computed as \( p = (1 + \text{the number of permutations on which three-network overlap was greater than or equal to the observed overlap})/100,001. \)

To account for the fact that accuracy and RT variability networks were not independent because they were defined using inversely correlated behavioral variables, we confirmed that results did not change if we performed this analysis with the constraint that the smaller of the high-accuracy/lOW-RT variability and low-accuracy/high-RT variability network pairs be a subset of the larger (i.e., the most extreme possible scenario).

We expected significant overlap between networks that predicted more successful attention (the high-attention network defined previously and networks predicting higher accuracy and lower RT variability) and the networks that predicted worse attention (the low-attention network defined previously and networks predicting lower accuracy and higher RT variability).

**RESULTS**

**Task Performance**

Mean accuracy was 95.69% (SD = 5.88%), mean RT was 754 msec (SD = 108 msec), and RT variability (coefficient of variation) was 21.66% (SD = 5.03%). As predicted,
alerting scores were positive, meaning that participants were faster to respond to center-cue than to no-cue trials \((M = 39.99\text{ msec}, SD = 34.38\text{ msec})\). Average orienting score was also positive, indicating that participants were faster to respond on spatial-cue than center-cue trials \((M = 57.38\text{ msec}, SD = 34.85\text{ msec})\). Positive executive control scores \((M = 120.10\text{ msec}, SD = 57.04\text{ msec})\) indicated that, as expected, participants were faster to respond to congruent than incongruent trials (Figure 1).

Previous work arguing that alerting, orienting, and executive control measure independent components of attention has demonstrated that the scores are largely uncorrelated within participants (Fan et al., 2002, 2005). We replicated this result and observed a relationship between higher alerting and executive control scores and worse overall ANT performance. In addition, we saw a strong negative correlation between accuracy and RT variability, providing further evidence that the coefficient of variation is a sensitive measure of overall attentional performance (Table 2).

**Behavioral Predictions**

We used CPM to predict individual differences in accuracy, RT variability, alerting, orienting, and executive control. Models trained and tested on task-based functional connectivity matrices significantly predicted novel individuals’ accuracy, RT variability, and executive control scores, but not alerting or orienting scores (Table 3, Column 1).

To test whether models generalized to predict behavior from resting-state functional connectivity patterns, we applied models trained on task-based data to left-out participants’ rest matrices. The alerting model successfully predicted scores from resting-state data alone (Table 3, Column 2). Interestingly, the alerting model was not significant in the task-based data (although results

![Figure 1. Histogram of ANT performance.](image)

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<th>Table 2. Correlations between Behavioral Measures</th>
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Cells show Spearman’s correlation coefficients.

*p < .05 uncorrected.

**p < .05 Bonferroni-corrected for 10 comparisons.
were the most common edge in the high-accuracy, low-variability, and low-executive control score networks, making up over 9.8% of the edges in each. Subcortical–cerebellar edges were most common in the low-accuracy network (11.6% of all edges), intracerebellar edges were most common in the high-accuracy network (8.6%), and subcortical–prefrontal edges were most common in the high-executive control score network (6.9%). The importance of the cerebellum in networks that predict ANT performance underscores a growing appreciation for its role in attention and high-level cognition (Buckner, 2013; Castellanos & Proal, 2012; Stoodley, 2012), and the out-sized role of intracerebellar connections, in particular, replicates a trend previously observed in the sustained attention CPM’s low-attention network (Rosenberg, Finn, et al., 2016).

The alerting network shared several anatomical trends with the accuracy, variability, and executive control networks. In particular, intratemporal connections predicted higher scores, whereas temporal–cerebellar connections predicted lower scores. Temporal–motor and occipital–parietal connections also predicted higher alerting scores. Previous work has found that fMRI activity in parietal regions of the dorsal visual stream is related to alerting (Petersen & Posner, 2012; Fan et al., 2005; Posner & Petersen, 1990); here, connections between the occipital and parietal cortices may also reflect coordinated dorsal stream activity. Interestingly, these connections predict individual differences in alerting during rest, suggesting that resting-state functional connectivity between dorsal stream regions may support attentional abilities related to arousal and vigilance. Finally, the most common connections in the low-alerting score network were between the cerebellum and temporal lobes, and the most common connections in the high-alerting score network were between temporal and motor cortex, potentially reflecting the coordination of responses during task performance.

### External Validity: Sustained Attention CPM Predictions

As a demonstration of external validity, the sustained attention CPM, predefined in Rosenberg, Finn, et al. (2016), generalized to predict several measures of ANT performance from task-based and resting-state functional connectivity. Predictions from task matrices were positively correlated with accuracy and negatively correlated with RT variability and executive control scores, and predictions from rest matrices were negatively correlated with variability (Table 4). Inverse correlations between sustained attention CPM predictions and variability and executive control scores were expected given that higher predictions correspond to better attention (that is, better predicted performance on a sustained attention task), whereas higher variability and executive control scores correspond to worse attention. The relationship between sustained attention CPM predictions and ANT performance,
especially RT variability, suggests that significant variance in performance on this task is explained by an overall sustained attention factor.

**Relationship between Predictive Networks**

As predicted, we observed significant overlap between the high-attention, high-accuracy, and low-RT variability networks. We also observed significant overlap between the low-attention, low-accuracy, and high-RT variability networks (Figure 3). Given that accuracy and variability were inversely correlated in this data set, the overlap between networks predicting these measures was expected. The high- and low-attention networks, however, were defined to predict a different attention task in a completely independent data set. Along with results showing that these networks generalize to predict ANT performance, their similarity to networks explicitly defined to predict ANT behavior suggests that a common sustained attention factor supports the ability to successfully complete the ANT and the gradCPT, the task used to define the sustained attention CPM.
Table 4. Correlations between Sustained Attention CPM Predictions and ANT Behavior

<table>
<thead>
<tr>
<th></th>
<th>Predictions from Task-based Functional Connectivity</th>
<th>Predictions from Resting-state Functional Connectivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>( r_s = .49, p = .0024^* )</td>
<td>( r_s = .09, p = .5844 )</td>
</tr>
<tr>
<td>RT variability</td>
<td>( r_s = -.68, p = 9.99 \times 10^{-6} )</td>
<td>( r_s = -.56, p = .0288^* )</td>
</tr>
<tr>
<td>Alerting</td>
<td>( r_s = -.28, p = .0099 )</td>
<td>( r_s = -.98, p = .6346 )</td>
</tr>
<tr>
<td>Orienting</td>
<td>( r_s = -.12, p = .4741 )</td>
<td>( r_s = -.05, p = .7782 )</td>
</tr>
<tr>
<td>Executive control</td>
<td>( r_s = -.34, p = .3885^* )</td>
<td>( r_s = -.16, p = .3244 )</td>
</tr>
</tbody>
</table>

Cells show Spearman’s partial correlations between predicted and observed behavioral scores, controlling for head motion. Forty-one novel participants (out of 44) who had not previously participated in Rosenberg, Finn, et al. (2016) were included in this analysis. Negative correlations between RT variability and ANT component scores were expected, given that higher sustained attention CPM predictions correspond to better attention, whereas higher variability and alerting, orienting, and executive control scores correspond to worse attention.

*Significant at \( p < .05 \).

There was no significant overlap in the unexpected directions. That is, the following network pairs only had one edge in common: high-attention and low-accuracy, high-attention and high-RT variability, low-attention and high-accuracy, high-attention and low-RT variability. This degree of overlap was not significant in any case (\( p > .99 \)). The edges appearing in the low-attention and high-accuracy networks and the low-attention and low-RT variability networks were the only two overlapping edges not pictured in Figure 3 due to visualization constraints.

Edges that appear in all three “successful attention” networks (high-attention, high-accuracy, and low-RT variability) and all three “unsuccessful attention” networks (low-attention, low-accuracy, and high-RT variability) may represent core functional systems supporting the ability to sustain attention to task. With the exception of temporal–motor connections, connections between occipital, temporal, motor, and cerebellar regions were more common in the successful than the unsuccessful core attention network. Given that predictive networks were defined as participants performed visuomotor attention tasks, these edges may represent response coordination. Intratemporal and intracerebellar connections, on the other hand, were more common in the unsuccessful core attention network (Figure 4).

DISCUSSION

In their influential model of attention, Posner and Petersen propose that attending and responding to the environment is accomplished with three distinct processes: remaining alert to upcoming stimuli, orienting toward salient or behaviorally relevant stimuli, and identifying and resolving cognitive conflicts (Petersen & Posner, 2012; Posner & Petersen, 1990). Although previous work has identified fMRI activity correlates of alerting, orienting, and executive control and has related individual differences in these abilities to functional and structural features of the brain, these relationships have not been leveraged to predict abilities in novel individuals. To investigate whether models based on functional brain connectivity predict individual differences in alerting, orienting, and executive control, we applied CPM to performance on the ANT.

Models trained on 43 participants’ task-based connectivity and applied to the left-out participant’s task data successfully predicted overall ANT performance, measured by accuracy and RT variability, and executive control scores. In addition, models generalized to predict left-out participants’ alerting scores from resting-state connectivity alone. Thus, signatures of the ability to prepare for upcoming behaviorally relevant stimuli (measured by alerting scores) and detect and resolve cognitive conflicts (measured by executive control scores) are reflected in patterns of coordinated activity across the cortex, subcortex, and cerebellum during task performance or rest. Furthermore, predictions from resting-state data suggest that the intrinsic functional architecture supporting alerting is distinct from that supporting the other components of attention.

Orienting scores were not significantly predicted for novel individuals. It is perhaps unsurprising that orienting results did not follow the same pattern as other...
measures of attention, as evidence suggests that orienting abilities are dissociated from a general attention factor that underlies performance on many attention tasks (Huang et al., 2012). One possible reason that orienting models failed to generalize is that orienting scores themselves are unreliable. Recently, Wang and colleagues found that orienting score reliability was the lowest of the three ANT components (Wang et al., 2015), and a meta-analysis of 15 ANT studies estimated the reliability or orienting scores at $r = .32$, considered low (alerting score reliability, however, was also considered low; MacLeod et al., 2010). Another possibility is that the neural mechanisms of orienting are simply not reflected in functional connectivity patterns consistently across individuals. Functional connectivity analyses, rather, may be best suited for ongoing processes such as sustaining attention and maintaining alertness rather than attention reorienting, a more transient process.

It is worth pointing out that the predictive power of all models introduced here, not just the orienting model, is limited by a variety of factors. Theoretical ceilings on predictive power are set by the reliability of behavioral and imaging measures as well as the hypothetical “ground truth” relationship between individual differences in attention and pairwise BOLD signal time-series correlations. Practical limits are also imposed by study features such as sample size, participant population, data quality, scan duration, and modeling method. Future work can explore ways to optimize models for individualized attention predictions, perhaps by leveraging large, open-access data sets with appropriate behavioral measures, applying alternative prediction algorithms, and/or considering multiple imaging and behavioral measures simultaneously.

To investigate the relationship between ANT performance and a general sustained attention factor, the sustained attention CPM, a model defined in a completely
independent data set, was applied to the current ANT data. Predictions from task-based data were positively correlated with ANT accuracy and inversely correlated with RT variability and executive control scores. Predictions from resting-state data were inversely correlated with RT variability and were, surprisingly, even more accurate than predictions of the leave-one-subject-out model explicitly defined to predict erratic responding. (One potential explanation for this result is that the sustained attention CPM was defined using data collected as participants in a previous study performed a taxing go/no-go task, which could have amplified individual differences in behavior and underlying network connectivity more effectively than did the ANT, resulting in a model with stronger predictive power.) In other words, when the sustained attention CPM predicted that a participant had strong sustained attentional abilities, that person would go on to perform well on the ANT. He or she would also show low executive control scores, or relatively small differences in RT between trials with distracting flanker stimuli that were congruent or incongruent with a central target. Anatomically, there was significant overlap between the sustained attention CPM’s high-attention network and the networks predicting better overall ANT performance and significant overlap between the low-attention network and the networks predicting worse ANT performance. Together, these results underscore the fact that overall ANT performance, and potentially performance on a diverse range of psychological tasks, can be largely explained by a person’s ability to sustain attention. Furthermore, the relationship between sustained attention network strength and executive control, but not alerting, further reinforces the independence of the alerting component from other factors of attention. Given that alerting scores are thought to measure the preparation and maintenance of focus whereas executive control scores are thought to measure conflict detection and resolution, this perhaps counterintuitive result should be investigated in future studies.

The overlap between the sustained attention and ANT networks—the core “successful” and “unsuccessful” attention networks visualized in Figure 4—may constitute a neuromarker of sustained attention function with improved generalizability. In other words, by constraining model features to edges that predict the ability to focus on multiple attention tasks, we may be homing in on networks with the most robust and reliable relationships to behavior. Thus, new “core” or “overlap” models may generalize to novel data sets more successfully than models defined using a single data set. To our knowledge, the current study represents the first attempt to consider the features in common between distinct but related predictive network models and may be an important approach in building and improving new models of attention and cognition. Moreover, together with existing models of the ability to sustain attention (Kessler, Angstadt, & Sripada, 2016; Rosenberg, Finn, et al., 2016) and suppress distractors (Poole et al., 2016), the alerting and executive control models represent preliminary steps toward developing a set of models that predict different components of attention function from a single connectivity matrix (Rosenberg et al., 2017). Future studies should test the predictive power of current network models of attention using novel data sets to validate and refine them.

In summary, we demonstrated for the first time that components of a highly influential model of attention can be predicted from brain data for novel individuals. Specifically, patterns of functional connectivity observed during attention task performance predict individual participants’ overall performance and executive control abilities, and patterns of connectivity observed during the resting state predict alerting. In concert with the observed relationship between sustained attention CPM predictions and individual differences in executive control, our results provide evidence that, whereas executive control may be closely related to sustained attention, the functional infrastructure of alerting is distinct and can be measured at rest. In the future, the CPM approach may be applied to investigate other factors of attention and cognition and shed light on the relationships between them.

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