Individual differences in functional brain connectivity predict social attention abilities and

attention switching autistic traits

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### Abstract

The ability to attend to relevant social information in the environment, referred to as social attention, is necessary for successful social functioning. Individuals with autism typically exhibit disordered social attention processes and also experience difficulties during social interactions. Within a neurotypical population, the degree to which social stimuli automatically capture attention is highly variable, as is the degree of subclinical autistic traits that individuals possess. Here, we investigated the neural systems underlying the wide range of individual variability in social attention abilities in a neurotypical sample. Participants underwent fMRI while performing a one-back matching social attention task involving either selective attention to faces or selective attention to houses in composite images. We found that whole-brain functional connectivity models reliably predicted social attention task performance when participants selectively attended to faces, but not when participants selectively attended to houses and ignored salient face stimuli. We also demonstrated that connectivity strength while selectively attending to faces predicted the subclinical autistic trait of poor attention switching abilities. While network connectivity included numerous regions distributed throughout the brain, the cerebellum and the prefrontal cortex emerged as particularly predictive regions involved in the automaticity of social cognitive processes and attentional control, respectively. These results have implications for our basic understanding of the neural systems underlying individual differences in social attention abilities in a neurotypical population, which are related to varying levels of autistic attention switching traits. This research provides a framework for the reliable predictive modeling of individual differences in social cognitive behavior.

### Introduction

Social attention, which includes the basic attention processes occurring in the context of social streams of information (Salley & Colombo, 2016), is critical to successful social functioning. One aspect of social attention is the capacity to visually attend to conspecific faces. For humans, social cues are particularly relevant and informative, leading to classification as highly salient stimuli (Wang & Adolphs, 2017). Even within the first week of life, typical newborns give preferential attention to the eyes of others, demonstrating an innate understanding of how the faces of others convey significant information (Farroni et al., 2002). However, the degree to which social stimuli automatically capture attention is highly variable in the general population, leading to a range of social attention abilities. While little is known about the neural systems underlying individual differences in social attention abilities in a healthy population, previous research has provided insight into the neural systems underlying disordered social attention processes in individuals with developmental and psychiatric disorders.

For example, individuals with autism spectrum disorder (ASD) often show reduced attention to social stimuli and experience difficulties during social interactions (Chita-Tegmark, 2016). Herrington and colleagues utilized a one-back selective social attention task to examine the neural mechanisms of social attention in individuals with ASD (Herrington et al., 2015). While undergoing functional magnetic resonance imaging (fMRI), participants viewed composite images of faces overlaid upon houses and made same or different judgments about the previous image. In this task, the key manipulation was that participants were instructed to either selectively attend to the faces or to the houses in the composite images while making the decision judgments. The authors found that individuals with ASD showed increased neural responses in multiple prefrontal regions, particularly in right dorsolateral prefrontal cortex (DLPFC), when selectively attending to faces. The right DLPFC is a key node in the attentional control network (Hopfinger et al., 2000), leading to the conclusion that in a clinical ASD population, additional attentional control mechanisms are required to attend to the social stimulus in a complex scene. This suggests an important role for prefrontal attentional control structures as a potential compensatory mechanism that allows individuals to overcome disordered social attentional processes.

Another study employed the same social attention paradigm that distinguished between neurotypical and ASD populations (Herrington et al., 2015) to investigate the relationship between neural responses and social attention abilities in a healthy, neurotypical population (Puglia et al., 2018). In particular, connectivity between the right DLPFC and brain regions in the salience network that are involved in perceiving and responding to demands, such as the dorsal anterior cingulate and orbital frontoinsular cortices (Seeley et al., 2007), was examined. The authors found that individuals with low connectivity showed better task performance with increased activation of the DLPFC, whereas individuals with high connectivity showed poorer task performance with increased activation of the DLPFC. This result provides evidence that this social attention task is capable of generating significant variability in performance, which is ideal for studying individual differences in social attention abilities in the general population. This result also demonstrates that the relationship between neural responses and social attention abilities cannot be easily explained by quantifying activity in one candidate brain region. Instead, the interaction between multiple brain regions and neural networks is required to successfully explain individual differences in social attention abilities, highlighting a limitation of many fMRI approaches that only consider single candidate regions, or a small network of regions, associated with specific behaviors.

For example, one commonly used task-fMRI analysis contrasts regional blood oxygenation level dependent (BOLD) signal during a condition of interest with the BOLD signal during a control condition. This approach is useful for measuring within-person differences in order to map brain activity to specific cognitive functions, such as in determining the involvement of the fusiform area in detecting faces (Kanwisher et al., 1997). However, this approach is less useful for studying between-person or individual differences because traditional task-fMRI analysis has poor test-retest reliability for individuals across scan sessions (Elliott et al., 2020). As a result, it is difficult to identify neuromarkers that can reliably predict behavior, health outcomes, and disease states with many current fMRI methods. Connectome-Based Predictive Modeling (CPM) is a data-driven approach that addresses the limitations of traditional fMRI analyses by assessing variability in whole-brain functional connectivity to predict behavior, which may be more sensitive to detecting stable individual differences (Shen et al., 2017). In addition to predicting behavioral performance on fMRI tasks, CPM models can also predict stable cognitive traits. For example, CPM models trained to predict sustained attention abilities have shown great utility in predicting the symptoms of attention deficit hyperactivity disorder (ADHD; Rosenberg et al., 2016).

In the present study, we test the hypothesis that task-based functional connectivity will reliably predict behavioral performance on a social attention task. While we expect connectivity with brain regions previously implicated in social attention, such as the prefrontal cortex, to emerge as important, we also anticipate that successful social attentional mechanisms will require coordinated activity beyond traditionally involved brain regions and networks. To test this hypothesis, neurotypical individuals performed an fMRI social attention task (Puglia et al., 2018), and CPM was implemented to identify biological neural networks predictive of behavioral performance during both task conditions. In an exploratory analysis, we also considered whether functional connectivity during social attention predicts subclinical autistic traits related to attention switching ability.

#### Methods

# Participants.

Fifty-two individuals (17 males) aged 18-31 (M = 21.00, SD = 2.78) performed a social attention task during fMRI data acquisition. All participants were Caucasians of European descent. A homogenous sample was specifically recruited to avoid potential epigenotyping artifacts related to population stratification when examining DNA methylation of the oxytocin receptor gene, another variable of interest not discussed here (Zhang et al., 2011). All participants provided written informed consent for a protocol approved by the University of Virginia Institutional Review Board for Health Sciences Research and were paid \$50. *Social attention paradigm*.

Participants completed a one-back selective social attention task while undergoing fMRI (Puglia et al., 2018). In this one-back matching task, participants either selectively attend to faces or selectively attend to houses in composite images of faces and houses while making a same or different judgment about the previous image (Fig. 1). Stimuli consisted of Caucasian faces obtained from the Chicago (Ma et al., 2015) and Stirling/ESRC (http://pics.stir.ac.uk/) face databases and houses photographed in neighborhoods surrounding Yale University (provided by investigators at the Center for Autism Research, Children's Hospital of Philadelphia) and the University of Virginia. All images were converted to grayscale, matched on luminance and

spatial frequency using the MATLAB SHINE toolbox (Willenbockel et al., 2010), and presented on a black background.

At the beginning of each block, participants saw a prompt instructing them to either selectively attend to faces (Attend Faces condition) or selectively attend to houses (Attend Houses condition) in the composite images. Participants completed six blocks each of the Attend Faces and Attend Houses conditions. Each block consisted of 10 images with either four or five same hits and lasted 40 seconds. The order and pairing of face and house images were randomized for each participant. Block order was pseudorandomized for each participant such that blocks always alternated between Attend Faces and Attend Houses conditions. Stimulus presentation sequence and timing were determined using optseq2

(https://surfer.nmr.mgh.harvard.edu/optseq/). Stimuli were presented for 1800 milliseconds with an inter-stimulus interval ranging from 200-2400 milliseconds during which a white crosshair was displayed on a black background. Participants responded same or different via button press while the image was still on the screen. Before completing this task, participants completed a practice n-back task to ensure they understood the instructions.

# Behavioral analysis.

Performance on the social attention task was assessed with sensitivity (d') using the formula: d' = z(hit rate) - z(false alarm rate). A hit occurred when participants responded same and the correct response was same. For example, a hit occurred for the Attend Faces condition when the face in the current trial was the same as the face in the previous trial and the participant correctly identified it as the same face. Meanwhile, a false alarm occurred when participants responded same but the correct response was different. For example, a false alarm occurred for the Attend Faces in the current trial was the face in the current trial was different from the face in the participants responded same but the correct response was different. For example, a false alarm occurred for the Attend Faces condition when the face in the current trial was different from the face in the

previous trial and the participant incorrectly identified it as the same face. Due to extreme hit and false alarm proportions, correction prior to d' calculation was necessary. The log linear approach was applied to prevent z-scores from taking on infinite values by adding 0.5 to both the number of hits and the number of false alarms and adding 1 to both the number of signal trials and the number of noise trials (Hautus, 1995). D' was calculated separately for the Attend Faces condition and the Attend Houses condition. In both instances, higher d' values indicate better performance on the social attention task.

## Autistic traits analysis.

To quantify the occurrence of autistic traits, participants (N = 50, 16 males) completed the Autism-Spectrum Quotient Questionnaire (AQ), a fifty-item self-report measure that assesses traits and behaviors associated with autism (Baron-Cohen et al., 2001). Each question is rated on a four-point scale and scores one point if the respondent records the autistic-like behavior either mildly or strongly. The questionnaire consists of five subscales with 10 questions each that measure a distinct aspect of the autistic phenotype. We focused analyses on the AQ attention switching subscale because the ability to maintain attention during each condition and switch attention between conditions is key to performance on the social attention task. Higher AQ scores indicate more autistic-like traits and behaviors. On the AQ attention switching subscale, higher scores are associated with poor attention switching abilities and a strong focus of attention, while lower scores are associated with better attention switching abilities. *Imaging parameters and preprocessing*.

MRI scanning was performed at the University of Virginia Fontaine Research Park on a Siemens 3 Tesla MAGNETOM Prisma Fit high-speed imaging device equipped with a 32channel head-coil. First, high-resolution T1-weighted anatomical images were acquired using Siemens' magnetization-prepared rapid-acquired gradient echo (MPRAGE) pulse sequence with the following specifications: echo time (TE) = 2.98 ms; repetition time (TR) = 2300 ms; flip angle (FA) = 9°; image matrix = 240 mm × 256 mm; slice thickness = 1 mm; 208 slices. Then, whole-brain functional images were acquired using a T2\*-weighted echo planar imaging (EPI) sequence sensitive to BOLD contrast with the following specifications: TE = 30 ms; TR = 800 ms; FA = 52°; image matrix = 90 mm x 90 mm; slice thickness = 2.4 mm; slice gap = 2.4 mm; 660 slices. Stimuli were presented with the Psychophysics Toolbox (Brainard, 1997) for MATLAB using an LCD AVOTEC projector onto a screen located behind the participant's head and viewed through an integrated head-coil mirror.

Data preprocessing was carried out using the Configurable Pipeline for the Analysis of Connectomes (C-PAC version 1.5.0, <u>https://fcp-indi.github.io/</u>), an open-source, configurable pipeline for the automated preprocessing and analysis of fMRI data (Craddock et al., 2013). C-PAC is a software implemented in Python that integrates tools from AFNI (Cox, 1996), FSL (Smith et al., 2004), and ANTs (Avants et al., 2008) with custom tools and uses the Nipype (Gorgolewski et al., 2011) pipelining library to achieve high-throughput processing on high performance computing systems. Head motion was assessed with an algorithm that quantifies the root mean square of the relative framewise displacement (FDRMS) between each volume of functional data (Smith et al., 2004). No participants were excluded for excessive head motion, which was defined *a priori* as mean FDRMS greater than 0.15 mm.

First, anatomical images were skull stripped using AFNI (Cox, 1996). Skull-stripped images were resampled to RPI orientation and then a non-linear transform between images and a 2 mm MNI brain-only template (FSL; Smith et al., 2004) was calculated using ANTs (Avants et al., 2008). The skull-stripped images were additionally segmented into white matter (WM), gray

matter (GM), and cerebrospinal fluid (CSF) using FSL's FAST tool (Zhang et al., 2001). A WM mask was calculated by applying a 0.96 threshold to the resulting WM probability map and multiplying the result by a WM prior map (avg152T1\_white\_bin.nii.gz - distributed with FSL) that was transformed into individual space using the inverse of the linear transforms previously calculated during the ANTs procedure. A CSF mask was calculated by applying a 0.95 threshold to the resulting CSF probability map and multiplying the result by a ventricle map derived from the Harvard-Oxford atlas distributed with FSL (Makris et al., 2006). The thresholds were chosen and the priors were used to avoid overlap with gray matter.

Functional preprocessing began with resampling the data to RPI orientation and slice timing correction. Next, motion correction was performed using a two-stage approach in which the images were first coregistered to the mean fMRI and then a new mean was calculated and used as the target for a second coregistration (AFNI 3dvolreg; Cox & Jesmanowicz, 1999). Nuisance variable regression was performed on motion-corrected data using a second order polynomial, a 24-regressor model of motion (Friston et al., 1996), nuisance signals obtained from white matter (CompCor; Behzadi et al., 2007), and mean CSF signal. WM and CSF signals were extracted using the previously described masks after transforming the fMRI data to match them in 2 mm space using the inverse of the linear fMRI-sMRI transform. Nuisance variable regression residuals were written into MNI space at 3 mm resolution and subsequently smoothed using a 6 mm FWHM kernel.

# Connectome-based predictive modeling.

For each participant, parcellation of the social attention functional scan was performed by taking the framewise average of the voxelwise signals in each of 268 nodes from the Shen atlas (Shen et al., 2013). For the Attend Faces and the Attend Houses conditions separately, we

correlated activity timecourses between all possible pairs of nodes to construct 268 x 268 symmetric matrices. Only the upper triangle of each matrix was extracted and vectorized, and the resulting matrices represented the set of connections or edges in each participant's task-based connectivity profile that served as inputs to CPM.

We used a 10-fold cross-validation procedure that was repeated 100 iterations to assess sensitivity of model accuracy to different fold splits (Shen et al., 2017; Finn & Bandettini, 2021). The data was divided into 10 folds where models were trained using 9 of the 10 folds, and the resulting models were tested on data from the held-out fold. First, mass univariate correlation between the strength of each edge in the functional connectivity matrices and the target behavioral scores was performed in the training set. A threshold of |r| = 0.2, which corresponds to a two-tailed p-value of approximately 0.01, was applied so only the most significantly correlated edges were selected for further analysis. Then, the selected edges were divided into a positive and a negative tail based on the sign of their correlation with behavior. For each participant, the strength across all edges was summed into a single value, separately for the connections positively and negatively correlated with behavior. Next, linear models were fit with network strength as the independent variable and the behavioral measure as the dependent variable. Lastly, positive and negative network strength for each participant in the test set were calculated by applying the masks defined by the training set to their functional connectivity data. Network strength then served as input to the linear model to generate predicted behavioral scores for all participants in the test set. Since head motion produces well-known artifacts in functional connectivity (Van Dijk et al., 2012), we included FDRMS as a covariate during CPM to mitigate the effect of head motion. For further details, see Finn and Bandettini (2021).

Prediction accuracy of the models was considered the correlation between observed behavior and behavior predicted by CPM. To assess the statistical significance of prediction accuracies, we generated a null distribution of expected accuracies due to chance by shuffling behavioral scores with respect to connectivity matrices and reperforming the entire analysis pipeline for a total of 1,000 randomizations. Then, we assessed model performance using the non-parametric p-value formula in Finn and Bandettini (2021), which compares the median accuracy of the 100 true models to the accuracy of each of the 1,000 random models.

First, CPM was performed using functional connectivity during the Attend Faces condition of the social attention task to predict d' during the Attend Faces condition. Next, CPM was performed using functional connectivity during the Attend Houses condition of the social attention task to predict d' during the Attend Houses condition. Lastly, CPM was performed using functional connectivity during the Attend Faces condition of the social attention task to predict AQ attention switching scores.

For significant CPM models, we performed additional steps to analyze the anatomy of predictive networks. First, we measured the importance of individual nodes by ranking them according to the sum of their connections in the positive and negative networks. Then, we grouped the 268 nodes into macroscale brain regions that were anatomically defined, such as cortical lobes. We examined anatomical trends that distinguished between positive and negative networks by comparing relative numbers of connections between each pair of regions in each network.

# Results

*Functional connectivity models predict social attention performance during the Attend Faces condition.* 

We demonstrated that functional connectivity during the Attend Faces condition of the social attention task is predictive of d' during the Attend Faces condition. For both the positive network and the negative network, observed and predicted d' values were significantly correlated (positive network: median r = 0.32, p = 0.031; negative network: median r = 0.31, p = 0.037; Table 1, Fig. 2a). A general linear model (GLM) constructed using strength in both positive and negative networks also generated significant d' predictions (median r = 0.30, p = 0.042; Table 1, Fig. 2a). This effect cannot be explained by head motion, as FDRMS during the social attention task was not significantly correlated with d' (r = -0.24, p = 0.082) and FDRMS was included as a covariate during CPM.

The positive network consisted of 912 edges, and the negative network consisted of 820 edges. The positive network is also referred to as the high-attention network because its edges predict higher d' during the Attend Faces condition, suggesting more attention to faces (Fig. 3a). Conversely, the negative network is also referred to as the low-attention network because its edges predict lower d' during the Attend Faces condition, suggesting less attention to faces (Fig. 3a). The most important nodes in the high- and low-attention networks are presented in Table 2. All of the top 10 most highly connected nodes were located in the cerebellum, prefrontal cortex, occipital cortex, motor strip, parietal cortex or temporal cortex, emphasizing the involvement of numerous regions in social attentional function. Specifically, a node in the left cerebellum had the highest total edges. Additionally, we found that connections between the cerebellum and occipital cortex were primarily predictors of better social attention since there were 99 of those connections in the high-attention network and only 6 of those connections in the low-attention

network (Fig. 4a). Meanwhile, connections between prefrontal cortex and occipital cortex, temporal cortex, and the cerebellum predicted worse social attention (Fig. 4a). Specifically, there were 74 prefrontal cortex and occipital cortex connections in the low-attention network and only 5 of those connections in the high-attention network, there were 74 prefrontal cortex and temporal cortex connections in the low-attention network and only 28 of those connections in the high-attention network and only 28 of those connections in the high-attention network and cerebellum connections in the low-attention network and cerebellum connections in the low-attention network. *Functional connectivity models fail to predict social attention performance during the Attend Houses condition*.

Despite the fact that functional connectivity is predictive of d' during the Attend Faces condition of the social attention task, we failed to demonstrate that functional connectivity during the Attend Houses condition is predictive of d' during the Attend Houses condition. For the positive network and the general linear model, observed and predicted d' values were not significantly correlated (positive network: median r = 0.18, p = 0.155; GLM: median r = 0.21, p = 0.118; Table 1, Fig. 2b). However, for the negative network, observed and predicted d' values were significantly correlated (median r = 0.27, p = 0.049; Table 1, Fig. 2b). These results cannot be explained by head motion, as FDRMS during the social attention task was not correlated with d' (r = -0.15, p = 0.287) and FDRMS was included as a covariate during CPM. As mentioned in the Methods section, network analyses relied on a comparison between connectivity in the positive and negative networks. Therefore, since neither the positive model nor the general linear model, which included connectivity strength in the positive model, were significant, functional connectivity patterns were not examined.

*Functional connectivity models predict the autistic trait of attention switching during the Attend Faces condition.* 

In our sample, AQ attention switching scores ranged from 1-8 (M = 4.70, SD = 1.80). For males, AQ switching scores ranged from 2-7 (M = 5.00, SD = 1.46), while for females, AQ switching scores ranged from 1-8 (M = 4.56, SD = 1.94). There was not a significant difference in AQ switching scores between males and females (t = 0.89, p = 0.378). Additionally, there was not a significant correlation between social attention abilities, specifically d' during the Attend Faces condition, and AQ switching scores (r = -0.23, p = 0.109). We used CPM to demonstrate that functional connectivity during the Attend Faces condition of the social attention task is predictive of AQ switching scores. For both the positive network and the general linear model, observed and predicted d' values were significantly correlated (positive network: median r = 0.31, p = 0.039; GLM: median r = 0.33, p = 0.032; Table 1, Fig. 2c). However, the negative network failed to generate significant d' predictions (median r = 0.25, p = 0.078; Table 1, Fig. 2c). This effect cannot be explained by head motion, as FDRMS during the social attention task a covariate during CPM.

Although the negative model was not significant, functional connectivity patterns were examined due to the significance of the general linear model, which included connectivity strength in the negative model. The positive network consisted of 852 edges, and the negative network consisted of 842 edges. The positive network is referred to as the high-AQ switching network because its edges predict higher AQ switching scores, suggesting poorer attention switching abilities (Fig. 3b). Conversely, the negative network is referred to as the low-AQ switching network because its edges predict lower AQ switching scores, suggesting better attention switching abilities (Fig. 3b). The most important nodes in the high- and low-AQ switching networks are presented in Table 3. All of the top 10 most highly connected nodes were located in the prefrontal cortex, motor strip, temporal cortex or parietal cortex, and a node in the right prefrontal cortex (Brodmann's area 45) had the highest total edges. Additionally, we found that connections between prefrontal cortex and the cerebellum were primarily predictors of worse attention switching abilities since there were 65 prefrontal cortex and cerebellum connections in the high-AQ switching network and only 25 of those connections in the low-AQ switching network (Fig. 4b). Meanwhile, connections within the prefrontal cortex predicted better attention switching abilities since there were 108 of those connections in the low-AQ switching network and only 23 of those connections in the high-AQ switching network (Fig. 4b).

### Discussion

Here, we identified functional neural networks predictive of individual differences in social attention abilities in a neurotypical population. Whole-brain functional connectivity models reliably predicted social attention task performance when participants selectively attended to faces, but not when participants selectively attended to houses and ignored salient face stimuli. Additionally, connectivity strength while selectively attending to faces predicted the autistic trait of poor attention switching abilities. These results have implications for our basic understanding of the neural systems underlying individual differences in social attention abilities in the general population and how varying levels of subclinical autistic traits related to attention switching selective attention to faces. These results also demonstrate that CPM is a viable method for future fMRI research aimed at the predictive modeling of social cognitive behavior.

While a multitude of brain regions emerged in the high- and low-attention networks, a node in the left cerebellum had the highest total edges. In humans, the cerebellum plays a major role in the process by which an action becomes automatic with practice, including the automatic execution of overlearned cognitive behaviors (Jenkins et al., 1994). Additionally, although the cerebellum was originally thought to be only marginally involved in social cognitive processes, recent evidence suggests that the cerebellum is critical to numerous social cognitive processes (Van Overwalle et al., 2014). Connectivity between the cerebellum and the occipital cortex, which is involved in the processing of visual information during attention (Posner & Petersen, 1990), was most predictive of better social attention abilities. This suggests that for individuals with better social attention abilities, selective attention to faces in the context of other distracting stimuli has become a more automatic process than for individuals with poor social attention abilities. Meanwhile, the prefrontal cortex is involved in effortful processing and attentional control (Hopfinger et al., 2000). Connectivity between the prefrontal cortex and occipital cortex, temporal cortex, and the cerebellum was most predictive of worse social attention abilities. This suggests that individuals with poor social attention abilities fail to ascribe salience to social information and require additional prefrontal attentional control mechanisms to complete the task. While the current study supports previous findings that individuals with ASD typically have poor social attention abilities and show increased neural responses in multiple prefrontal regions during selective attention to faces (Herrington et al., 2015), it also extends these results in two important ways. First, the current study demonstrates that connectivity of the prefrontal cortex with other brain regions, not just activity of the prefrontal cortex, is predictive of poor social attention abilities. Second, this finding accounts for individual differences in social attention abilities within a neurotypical population where individuals possess varying degrees of

subclinical autistic traits, emphasizing the necessity of studying social cognitive behaviors on a continuum instead of only comparing neurotypical and clinical ASD populations.

Similarly, connectivity in the high- and low-AQ switching networks involved numerous regions distributed throughout the brain. In individuals with high AQ switching scores and worse attention switching abilities, connectivity between the prefrontal cortex and the cerebellum was particularly important, which is the same pattern of connectivity that was predictive of worse social attention abilities. Even though the inverse correlation between AQ switching scores and social attention abilities was not significant, individuals with more autistic attention-related traits and individuals with poorer social attention abilities exhibited similar functional connectivity patterns, suggesting that similar neural processing was occurring while these individuals selectively attended to faces. Meanwhile, connectivity within the prefrontal cortex predicted low AQ switching scores and better attention switching abilities. Previous research has found that increased functional connectivity within neural networks is related to better cognitive functioning (Geerligs et al., 2014). Therefore, increased connectivity within the prefrontal cortex suggests the ability to successfully switch the focus of attention to and from socially salient face stimuli when prompted is one facet of healthy cognitive functioning.

One limitation of the current study is the relatively small sample size. With the current sample size of 52 participants, power = 0.34 when predicting a two-tailed bivariate correlation (r = 0.30) between observed and predicted behavior during CPM with  $\alpha = 0.01$  (Faul et al., 2009). Meanwhile, a post-hoc power analysis predicting a two-tailed bivariate correlation (r = 0.30) between observed and predicted behavior during CPM with power = 0.80 and  $\alpha = 0.01$  (suggested a target sample size of 125 participants. Future work should increase sample size to further improve the predictive power of the social attention connectome, particularly so CPM can

successfully predict social attention abilities while individuals selectively attend to houses in this social attention task. Previous research also supports the recruitment of a larger sample because having more data typically boosts the accuracy of behavioral predictions when using CPM (Finn et al., 2015). Also, individuals across a wider range of age, racial, and ethnic groups should be included in the sample to better understand the generalizability of these results.

Additionally, the present study excluded individuals with ASD, therefore limiting our ability to discuss the full autistic trait continuum. Although ideal to include both neurotypical and clinical populations in our sample, recruiting individuals with ASD poses certain challenges, such as potential difficulty completing the social attention task. However, CPM predictions can also be made from resting-state fMRI data (Finn et al., 2015). Therefore, future work can apply the social attention connectome established in a neurotypical population to resting-state data from a novel group of individuals with ASD to make predictions about social deficits in autism. Specifically, individuals with more connectivity in the previously-constructed high-attention network, which consists of edges predictive of better social attention abilities, would be hypothesized to show less severe symptoms of ASD.

Despite our preliminary network analyses, the predictive networks that best characterize individuals' social attentional abilities should not be oversimplified to a handful of regions. Future work is necessary to reduce the size of the networks and identify functional connections and subnetworks critical to the composition of the high- and low-attention networks, as well as to the high- and low-AQ switching networks. One possibility is to calculate a variety of network statistics and use the network statistic jackknife, a novel computational lesioning framework (Henry et al., 2020), to identify how individual connections and predefined subnetworks contribute to the global positive and negative networks. The network statistic jackknife method detects relevant local differences in network structure and has revealed differences in functional brain network organization between children with ADHD and typically developing children (Henry et al., 2020). Additional analyses should investigate differences between social attention and sustained attention by repeating the same procedure with previously-constructed sustained attention networks (Rosenberg et al., 2016).

In summary, this research demonstrates that complex brain network models can predict social attention abilities and autistic attention switching traits during selective attention to faces. Social attention is a critical process in the development of strong social relationships, and research on this topic benefits all people that need social connections to live fulfilling, healthy lives. By beginning to reliably predict social attention abilities and autistic attention switching traits from individual differences in functional connectivity, this research has the potential to identify neuromarkers of typical and atypical social behavior that will ultimately be predictive of social experience and health outcomes. Additionally, this research helps move the field of neuroimaging towards a more reliable and predictive framework of studying individual differences in neural networks that the scientific community can use to study any number of cognitive processes.

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**Figure 1.** One-back selective social attention task. Here, participants are prompted to selectively attend to faces (Attend Faces condition) in composite images of faces and houses while making a same or different judgment about the previous image.



**Figure 2.** Prediction accuracy of connectome-based predictive models trained to predict a) d' during the Attend Faces condition, b) d' during the Attend Houses condition and c) AQ attention switching scores from social attention task data. Accuracy was measured as the Pearson correlation between observed and predicted scores (*y* axis). Blue dots show results from 100 true iterations of 10-fold cross-validation, and red dots show results from 1,000 permutations in which behavioral scores and connectivity matrices were randomized across participants. Blue horizontal lines denote median accuracy for the true models. Results for the general linear model

(GLM), positive model and negative model are shown (x axis). Statistical significance was calculated by comparing the median of the true models to the null distribution. ns: p > 0.05; \*p < 0.05.



**Figure 3.** Functional connections predicting performance on a social attention task and AQ switching scores. a) The 912 edges in the high-attention network (predicting higher d' values on the Attend Faces condition of the social attention task) are visualized in red. The 820 edges in the low-attention network (predicting lower d' values on the Attend Faces condition of the social attention task) are visualized in blue. b) The 852 edges in the high-AQ switching network (predicting higher AQ switching scores and worse attention switching abilities) are visualized in red. The 842 edges in the low-AQ switching network (predicting lower AQ switching scores and better attention switching abilities) are visualized in blue. For both (a) and (b), macroscale regions include prefrontal cortex, motor cortex, insula, parietal, temporal, occipital, limbic (including the cingulate cortex, amygdala and hippocampus), cerebellum, subcortical (thalamus and striatum) and brainstem.

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**Figure 4.** Anatomy of predictive networks. a) Lobewise visualization of edges in the high- and low-attention networks. b) Lobewise visualization of edges in the high- and low-AQ switching networks. For both (a) and (b), size corresponds to the sum of edges in the positive and negative networks and color corresponds to the difference between edges in the positive and negative networks, such that red corresponds to mostly positive edges and blue corresponds to mostly negative edges. Positive refers to edges positively correlated with behavior (high- networks), while negative refers to edges inversely correlated with behavior (low- networks). PFC,

prefrontal cortex; Mt, motor strip; Ins, insula; Par, parietal; Tp, temporal; Oc, occipital; Lb, limbic; SC, subcortical; BS, brainstem.

Train:	Attend Faces data		Attend Houses data		Attend Faces data	
Test:	Attend Faces data		Attend Houses data		AQ switching data	
	median	p-value	median	p-value	median	p-value
	r-value		r-value		r-value	
GLM	0.30	0.042	0.21	0.118	0.33	0.032
positive network	0.32	0.031	0.18	0.155	0.31	0.039
negative network	0.31	0.037	0.27	0.049	0.25	0.078

**Table 1.** Prediction accuracy of connectome-based predictive models trained on social attention task data and tested on social attention behavioral performance and AQ attention switching score data. Accuracy was assessed with Pearson correlations between observed and predicted values. Since model predictions were generated with 100 iterations of 10-fold cross-validation, only median *r-values* and the corresponding *p-values* are reported.

Node location	High-attention network	Low-attention network	Sum (high + low)	Difference (high – low)
L Cerebellum	24	15	39	9
L Prefrontal	16	21	37	-5
R Prefrontal	19	17	36	2
R Cerebellum	17	18	35	-1
L Occipital	12	22	34	-10
R Motor Strip	23	11	34	12
L Parietal	21	11	32	10
R Occipital	20	11	31	9
R Temporal	17	14	31	3
R Temporal	13	17	30	_4

**Table 2.** Ten nodes with the most connections in the high- and low-attention networks based onthe sum of connections between the high- and low-attention networks at a specific node.Difference is the number of connections at a specific node in the low-attention networksubtracted from the number of connections at the same node in the high-attention network.

Node location	High-AQ switching network	Low-AQ switching network	Sum (high + low)	Difference (high – low)
R Prefrontal	40	32	72	8
R Motor Strip	19	20	39	-1
R Motor Strip	11	28	39	-17
R Temporal	17	19	36	-2
L Temporal	14	21	35	-7
R Parietal	7	25	32	-18
L Prefrontal	17	14	31	3
R Motor Strip	13	18	31	-5
L Prefrontal	17	13	30	4
R Prefrontal	9	20	29	-11

**Table 3.** Ten nodes with the most connections in the high- and low-AQ switching networks based on the sum of connections between the high- and low-AQ switching networks at a specific node. Difference is the number of connections at a specific node in the low-AQ switching network subtracted from the number of connections at the same node in the high-AQ switching network.