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Identifying individual's distractor suppression using functional connectivity between anatomical large-scale brain regions

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ABSTRACT

Distractor suppression (DS) is crucial in goal-oriented behaviors, referring to the ability to suppress irrelevant information. Current evidence points to the prefrontal cortex as an origin region of DS, while subcortical, occipital, and temporal regions are also implicated. The present study aimed to examine the contribution of communications between these brain regions to visual DS. To do it, we recruited two independent cohorts of participants for the study. One cohort participated in a visual search experiment where a salient distractor triggering distractor suppression to measure their DS and the other cohort filled out a Cognitive Failure Questionnaire to assess distractibility in daily life. Both cohorts collected resting-state functional magnetic resonance imaging (rs-fMRI) data to investigate function connectivity (FC) underlying DS. First, we generated predictive models of the DS measured in visual search task using resting-state functional connectivity between large anatomical regions. It turned out that the models could successfully predict individual's DS, indicated by a significant correlation between the actual and predicted DS ($r = 0.32$, $p < 0.01$). Importantly, Prefrontal-Temporal, Insula-Limbic and Parietal-Occipital connections contributed to the prediction model. Furthermore, the model could also predict individual's daily distractibility in the other independent cohort ($r = -0.34$, $p < 0.05$). Our findings showed the efficiency of the predictive models of distractor suppression encompassing connections between large anatomical regions and highlighted the importance of the communications between attention-related and visual information processing regions in distractor suppression. Current findings may potentially provide neurobiological markers of visual distractor suppression.

1. Introduction

The overwhelming surge of external information surpasses our cognitive capacity, emphasizing a crucial role of selective attention to effectively allocate limited resources (Theeuwes, 1993). Selective attention involves selecting task-relevant stimuli while tuning out irrelevant stimuli. The ability of filtering out irrelevant or disruptive information is termed as distractor suppression and it enables better concentration on the chosen goal, crucial on goal-oriented behaviors. Failure of suppressing distractor may lead to difficulty in allocating attention on the relevant information. Along with target facilitation, distractor suppression is a key component of selective attention (Van Moorselaar and Slagter, 2020). Notably, some distracting information (e.g., a unique color item), has intrinsic power to capture attention (Theeuwes, 1992). However, a rapidly growing body of work has shown that physically salient distractors can be actively suppressed to prevent visual distraction (Gaspelin and Luck, 2018a; Sawaki and Luck, 2010). Supporting evidence comes from various studies, including but not limited to behavioral, event-related potential, and eye movements studies (Chang and Egeth, 2019; Gaspelin et al., 2015; Gaspar and McDonald, 2014; Gaspelin and Luck, 2018b; Gaspelin et al., 2019; Hamblin-Frohman et al., 2022). Visual search task is commonly used in these studies. Behaviorally, studies found faster search responses when a salient distractor appeared in the visual search display (Chang and Egeth, 2019; Gaspelin et al., 2015). Such a benefit indicates that the suppressive process was triggered by the salient distractor. In addition to these laboratory measures of distractor suppression, individual's distractibility in daily life can be assessed using a Cognitive Failure

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Questionnaire (CFQ) (Broadbent et al., 1982). Higher distractibility reflects lower distractor suppression in daily environment. Everyday environment is notably complex and dynamic, full of factors that can significantly impact an individual's behavior, cognition, and perception (Peelen and Kastner, 2014). Thus, combination of laboratory measurement and CFQ may provide us a better understanding of distractor suppression.

Distractor suppression renewed interest in recent years (Luck et al., 2021; Schneider et al., 2022), yet the neural mechanism of how the brain suppresses distracting information is still up in the air. In contrast with target facilitation, distractor suppression has been less well understood. Contemporary research highlights that top-down selective attentional control encompasses three primary brain lobes — the frontal, parietal, and temporal lobes. These lobes are interconnected through fiber pathways spanning considerable distances, facilitating the coordination of attention (Sani et al., 2021). The top-down selective attentional control mechanism operates to suppress irrelevant stimuli and prioritizes the processing of task-relevant information, thereby facilitating goal-oriented behaviors. The prefrontal cortex (PFC) is known as a source of top-down control signals, establishing communication not only with the parietal and temporal lobes but also transmitting regulatory signals to various brain regions, encompassing subcortical, occipital areas (Banich, 2009; Ridderinkhof et al., 2004). This not entirely modular organizational pattern aligns with the understanding of coordinated interactions between brain regions required for complex cognitive functions (Katsuki and Christos, 2014). Present evidence indicates that distractor suppression is achieved by modulating sensory processing (Seidl et al., 2012), similar to target facilitation (Reynolds and Leonardo, 2004). Typical attention-related brain regions, such as the occipital, parietal and frontal areas, were devoted to minimizing the impact of distractors and enhancing target processing (Ruff and Driver, 2006). However, it has been demonstrated that the neural mechanisms underlying distractor suppression are distinct from those involved in target facilitation (Gazzaley et al., 2005; Markant et al., 2015; Noonan et al., 2016b; Van Moorselaar and Slagter, 2019; Xie et al., 2020). Within the frontoparietal cortex, distinct and distributed regions were associated with target facilitation and distractor suppression respectively (Xie et al., 2020). This study examined the neural bases of target facilitation and distractor suppression via associating morphologic characteristics and resting-state functional connectivity strength with behavioral performance. Such approach is beneficial for establishing the relationship between the brain and distractor suppression.

Additionally, it has been showed that the resting-state functional connectivity and cognition have a substantial association (Petersen and Sporns, 2015; Smith, 2016). The unique and stable connectivity patterns in individuals offer reliable indicators of their traits and behavioral variations (Bari et al., 2019; Elliott et al., 2019). Shen et al. (2017) introduced a data-driven cross-validation protocol, connectome-based predictive modeling (CPM), based on connectome data. This approach crafts neuroimaging-based biomarkers potentially applicable in real-world scenarios, and can successfully predict individual's traits such as attention (Rosenberg et al., 2016), fluid intelligence (Greene et al., 2018), and anxiety (Yoo et al., 2022). The projection of CPM model features back into brain space facilitates interpretation based on known relationships between brain structure and function. Therefore, CPM based on the resting-state functional connectome offers a convenient and precise perspective to explore intricate relationships between brain function and behavior. However, most CPM studies relied on fine-grained brain region connectivity (e.g., parcellating the brain into 268 regions) and didn't explicitly highlight communication between large anatomical regions, despite its recognized importance in the brain's modular organization (Zamora-López et al., 2011). Previous studies demonstrated the significance of intercommunication among large-scale anatomical brain regions in anxiety using a computational "lesion" method within CPM to simulate disruptions in connectivity between limbic regions and the prefrontal cortex (Wang et al., 2021). While the "lesion" method can demonstrate the contribution of connections between large brain regions to some extent, predictive models using these connections as features may offer greater efficiency in assessing their significance. Although increasing interest has been drawn to how the brain suppresses salient distractors (Luck et al., 2021; Schneider et al., 2022), investigation of the neural bases of distractor suppression remains challenging. Here, our work introduces the application of CPM to investigate the importance of functional connections in distractor suppression.

To do it, we checked the role of the communication between anatomical large-scale brain regions in distractor suppression in the framework of the CPM. Two independent cohort of participants were recruited for the study. In one cohort, individual's DS was measured using a visual search task where a salient distracting singleton recruited distractor suppression in the laboratory (refer to Xie et al., 2022). In the other cohort, individual's distractibility in daily life was assessed using the Chinese version of Cognitive Failures Questionnaire (CFQ) (Zhou et al., 2016). Besides the DS measures, every participant scanned rs-fMRI data. For the predictive model construction, connectivity strength between anatomical large-scale brain regions were computed and served as features. Then, we generated predictive models of DS using a leave-one-out validation procedure. Finally, a predictive model using all participant's data in discovery dataset was generated to predict distractibility in daily life for the external validation. We hypothesize that the communication patterns between anatomical large-scale brain regions reflect the common neural mechanisms of distractor suppression under different circumstances (in-laboratory experiment or daily life). In addition, we expect the significance of prefrontal regions in DS predictive models because the PFC was known as an origin region of DS, transmitting signals through higher-order cognitive control networks, and coordinating the work of various brain regions.

2. Materials and methods

2.1. Participants

Two cohorts from University of Electronic Science and Technology of China were recruited for the study. For discovery sample, 88 normal college students (44 females, mean age = 20.95 years, SD = 1.93 years) were recruited. For validation sample, additional 53 normal college students (26 females, mean age = 23.09 years, SD = 1.95 years) were recruited. All participants had normal or corrected-to-normal vision, no psychiatric and neurological disorders, no history of substance, drug, or alcohol dependence and no contraindications to MRI scans. This study was approved by the University of Electronic Science and Technology of China Institutional Review Board. Written informed consent was given by all participants in accordance with it.

2.2. Experimental paradigms

2.2.1. Assessment of DS using visual search task

For the discovery sample, every participant conducted a visual search task to measure the DS. In the visual search task, each trial started with a white central fixation point (800–1200 ms) which was followed by a search display. The search display comprised of four items, a white target, a white (non-salient) or red (salient) distractor, and two white non-targets ("X" and "K"). Upon the search display onset, the participants needed to identify whether the target was an upright or inverted "T" by pressing the "F" key for an upright "T" and the "J" key for an inverted "T" using their left and right index fingers. For more details of the search task, please refer to Xie et al. (Xie et al., 2022).

In this experimental design, the salient distractor was supposed to benefit the search performance due to the recruitment of distractor suppression (Gaspelin et al., 2015). Hence, we computed the reaction time difference with versus without a salient distractor ($\Delta RT = RT_{non\text{-}salient} - RT_{salient}$) to evaluate individual's DS.

2.2.2. Assessment of DS using CFQ

The Cognitive Failure Questionnaire (CFQ) (Broadbent et al., 1982) was used to evaluate daily distractibility. Every participant filled in Chinese version of CFQ, which has been validated in Chinese college students (Zhou et al., 2016). The CFQ consists of 25 items and captures difficulty with distractibility (10 items), memory (8 items), and psychomotor (7 items). For each item, participants stated how often each of the mentioned events happened to them in the past six months using a five-point Likert scale (ranging from “0=never” to “4=very often”). The score of each item was summed for every subscale and total CFQ score was the summation of three subscale scores. More often an individual experiences daily distractibility, the more susceptible he/she is to distraction. Thus, higher distractibility score represents worse DS.

2.3. Image acquisition, preprocessing, and analysis

2.3.1. Neuroimaging data acquisition and preprocessing

For both cohorts, the structural and functional MRI images were collected using a GE Sigma 3.0-Tesla scanner (General Electric, Milwaukee, WI, USA) at the MRI Brain Imaging Center, at the University of Electronic Science and Technology of China. The T1-weighted structural images (repetition time= 5.96 ms, echo time= 1.96 ms, flip angle=9°, field of view = 256×256 mm^2, matrix size= 256×256, voxel size= $1 \times 1 \times 1$ mm^3, and slices= 176) were acquired. Subsequently, resting-state fMRI were acquired using a echo planar imaging sequence (repetition time= 2000 ms, echo time= 30 ms, flip angle= 90°, field of view = 240×240 mm^2, matrix size= 64×64, voxel size= $3.75 \times 3.75 \times 3.75$ mm^3, and slices= 43). For each participant, a total of 205 functional volumes were acquired. All participants were instructed to simply rest with their eyes closed, and not to think of anything in particular while remaining awake throughout all the scans.

Neuroimaging data were preprocessed using the DPARSF (v6.0, www.restfmri.net) and SPM12 toolkits (www.fil.ion.ucl.ac.uk/spm/software/spm12). Slice-timing correction and realignment were applied to the remaining 200 functional images after excluding the first 5 images. Structural images were then co-registered to the preprocessed functional images, and then segmented into GM, WM, and cerebrospinal fluid (CSF) by using DARTEL. The mean signals from WM, CSF and Global Signal, 24 head motion parameters (six motion parameters, six temporal derivatives, and their respective squares) and linear trend were regressed out from the data. Subsequently, a band-pass filtering (0.01–0.08 Hz) was performed to minimize high-frequency physiological noise sources including the respiration rate. Then spatial normalization to Montreal Neurological Institute space and resampling to $3 \times 3 \times 3$ mm^3. Finally, spatial smoothing with an 8-mm FWHM Gaussian kernel.

2.3.2. Quality control

Participants were excluded from analyzes if their head motion exceeded 3 mm or 3° in any direction or the mean framewise displacement exceeded 0.2 (Power et al., 2014). For the discovery sample, all participants were included for further analysis. For the validation sample, three participants (2 females) were excluded from further analysis. In addition, a participant was excluded from the validation sample because they appeared in the discovery sample. Finally, 88 participants (44 females, mean age = 20.95 years, SD = 1.93 years) were included in the discovery sample; 49 participants (24 females, mean age = 23.02 years, SD = 2.00 years) were included in the validation sample.

2.3.3. Connectome-based predictive modeling (CPM)

2.3.3.1. Functional parcellation and communication definition. Brain nodes were defined by using a functional brain atlas, derived from a graph theory-based parcellation algorithm that maximized the similarity of the voxel wise time series within each node (Shen et al., 2013, 2010). The atlas includes 268 nodes spanning the whole brain including cerebellum and brainstem. After parcellating the brain into 268, functionally coherent nodes, the average time course of each node pair were correlated and correlation coefficients were Fisher transformed, generating 268×268 connectivity matrices per subject. Then removing 268 diagonal elements for further analysis.

To characterize the large-scale brain region communication, the 268 nodes were grouped into 10 macroscale anatomical brain regions (see details in Fig. 1), including the prefrontal lobe (46 nodes), motor lobe (21 nodes), insular lobe (7 nodes), parietal lobe (27 nodes), temporal lobe (39 nodes), occipital lobe (25 nodes), limbic lobe (36 nodes), cerebellum lobe (41 nodes), subcortical lobe (17 nodes) and brainstem lobe (9 nodes) (Feng et al., 2019). And the large-scale brain region communication was computed by summing the set of 268×268 connectivity edge for all the edges spanning tow specific large-scale brain regions, where threshold ($r = 0.2$) was chosen to eliminate weak correlations attributed to signal noise (Liu et al., 2017).

2.3.3.2. Prediction analysis using cross-validation in discovery sample. To investigate whether the communication between anatomical large-scale brain regions could predict DS, we employed a leave-one-out cross-validation (LOOCV) to avoid false positive results from overfitting (Shen et al., 2017). In each LOOCV, N-1 participants were used as the training set and the remaining one was used as the testing set, where N is the number of the participants in the discovery sample. During the training procedure, predictive features were defined as the relevant communications to DS at a significant threshold of $p < 0.05$ in the training set. Next, a simplified general linear model (GLM) was constructed to establish the relationship between communications and DS. During the testing procedure, the left-out participant's predictive features were obtained, and then the trained model was used to predict the testing participant's DS. The training and testing procedures were repeated N times such that each participant was used once as the testing participant (see details in Fig. 1).

Finally, each participant's predicted DS was obtained. Pearson correlation coefficient (r) and mean squared error (MSE) between actual and predicted DS were used to evaluate the power and the accuracy of the predictive model.

2.3.3.3. Permutation test. Although we initially used parametric statistical analysis to obtain p values in the LOOCV procedure, the number of degrees of freedom is overestimated when LOOCV is performed within a single data set (Rosenberg et al., 2016). To confirm that our LOOCV results are still significantly better than chance, the permutation test was applied to compute the sampling distribution for any test statistic under the null hypothesis. Specially, we randomly and repeatedly shuffled DS, and each time re-applied the above LOOCV procedure. If there were no relevant communications selected as predictive features for DS, we consider this situation as a model that has not been constructed and perform a reshuffle. This resulted in a 1000 times sampling distribution of correlation (r) and MSE values. The $p_{permutation}$ value was calculated by dividing shuffled times by the number that was greater than (or with respect to MSE values, less than) or equal to the true value.

Because of nonoverlapping participants in the discovery and validation samples, in validation samples, we evaluated the p value between the observed and predictive DS using parametric statistical analysis only.

2.3.3.4. Identify significant communications. Large-scale brain region communications appeared in the 95 % iterations of the LOOCV were defined as substantial communication connectivity. The strength of these connections was correlated with individual's DS respectively.

2.3.3.5. Predictive model for external validation. To construct a predictive model of DS to apply to a completely independent group, 88

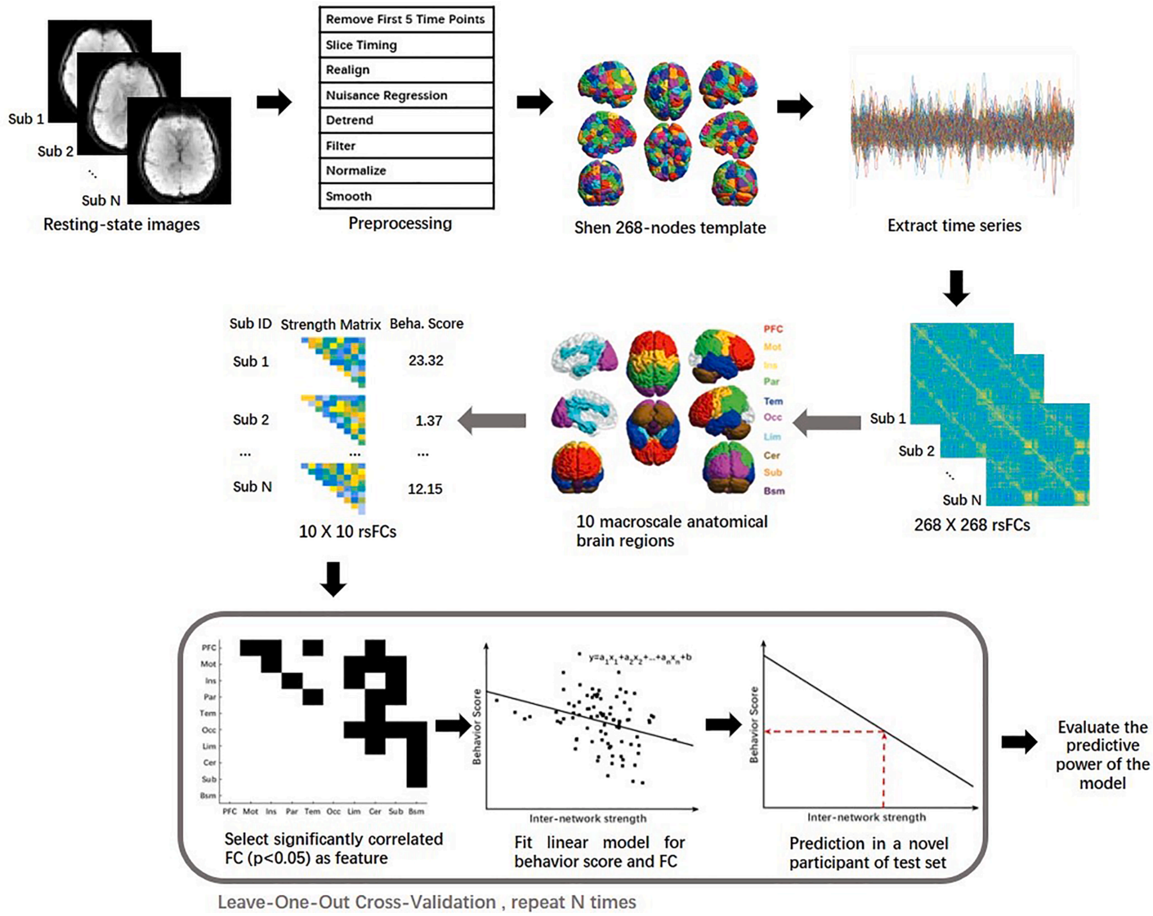

Fig. 1. The schematic flow of connectome-based predictive modeling.
Note: rsFCs, resting-state functional connectivity.

participants in discovery sample were used to establish a general model. We extracted identical communication connections from the validation sample, which had been initially chosen in the general DS predictive model. Following that, these connections were directly fed into the aforementioned general DS predictive model. Finally, we calculated the Spearman correlation between the predicted ΔRT and actual CFQ scores.

2.3.4. *Control analyzes of confounding factors*

Several control analyzes were implemented to further examine the significance of predictions of our models despite potential confounds of age, gender and head motion. To better understand the variables in discovery and validation samples, the relationships between behavior score (actual DS and actual CFQ scores) and confounding factors (age and head motion) were evaluated. The gender-based differences in behavior scores were assessed by *t*-test. We conducted control analyzes for factors with the potential to exert an effect. In these analyzes, new predictive features were generated by utilizing communications that exhibited a partial Pearson correlation with DS at a significant threshold of $p < 0.05$, while controlling for confounding variables (Feng et al., 2019). The remaining procedures were kept constant.

2.4. *Data and code availability*

The software mentioned in Sections 2.3.1 is freely accessible. Data can be obtained from the corresponding author upon reasonable request. Sharing and reusing the data necessitate explicit written consent from the authors, along with approval from the institutional review boards.

3. Results

3.1. *Visual search task performance*

In the discovery dataset, the participants performed a visual search task with and without a task-irrelevant salient distractor (Fig. 2A). As expected, we found faster responses in the trials with the salient distractor (629.18 ms) than without it (635.97 ms) ($t_{(87)} = -3.59$, $p < 0.01$), indicating that the salient distractor triggered the suppressive mechanism. Thus, the difference of mean response time with and without a task-irrelevant salient singleton (ΔRT) of each participant can be used to evaluate their DS.

Furthermore, in order to evaluate the reliability of DS measure, we executed the Monte Carlo splitting combined with stratification (distractor type and target type) 1000 times and used the average split-half Spearman-Brown-adjusted Pearson correlations as an indicator of the reliability of the DS measure in this study (Pronk et al., 2022). We found that the average split-half Spearman-Brown-adjusted Pearson correlation was 0.64, suggesting that the ΔRT can serve as the reliable measure of the DS. Upon the reliability of the ΔRT, we picked the ΔRT in all trials to evaluate individual's DS which varied across individuals (range, −53.84 to 49.34 ms) and followed a normal distribution (Kolmogorov-Smirnov test, $p = 0.20$).

Accuracy was high generally (95.80 %) and was higher in the trials with the salient distractor (salient, 96.09 %; non-salient, 95.52 %; $t_{(87)} = 2.55$, $p < 0.05$), once again indicating superior search performance with the salient distractor. Subsequently, we computed ΔACC ($ACC_{salient} - ACC_{non\text{-}salient}$) for each participant as another measure of DS.

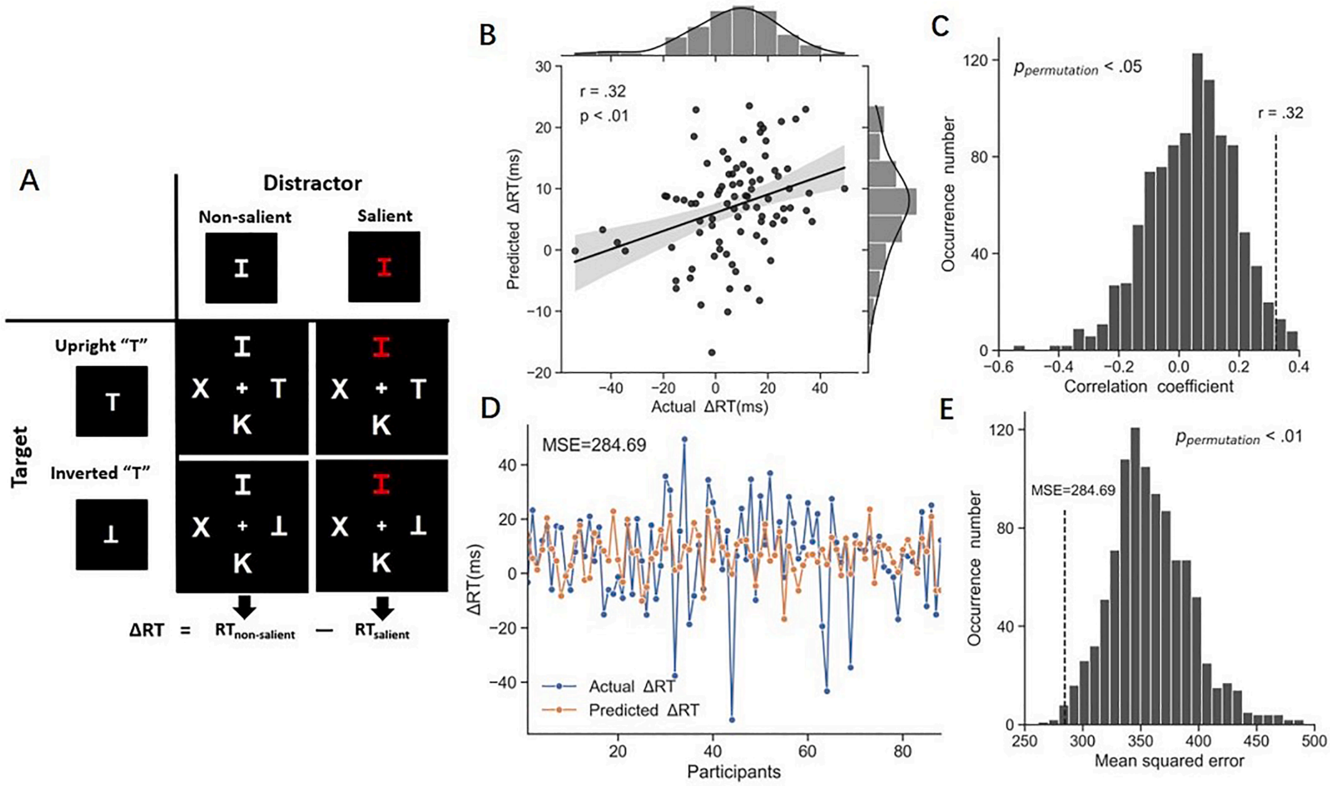

Fig. 2. Large-scale brain region communication patterns can predict individual's DS. (A) Schematic representation of the visual search task. ΔRT served as an index of DS. (B) Correlation between actual and predicted ΔRT scores. (C) Permutation distribution of the correlation coefficient (r) for the prediction analysis. The value obtained using the original scores are indicated by the black dash line. (D) Consistency between actual and predicted ΔRT scores. (E) Permutation distribution of the Mean Squared Error (MSE) for the prediction analysis. The value obtained using the original scores are indicated by the black dash line.

3.2. Predicting distractor suppression based on large-scale brain region communications

We first investigated whether the communication pattern of large-scale brain regions could predict an individual's ΔRT observed in the discovery dataset. Pearson's correlation between the actual and predicted values was used to evaluate the predictive performance of the model. Ultimately, the predictive model based on large-scale brain region communication patterns successfully predicted the ΔRT ($r = 0.32$, $p < 0.01$, Fig. 2B) and survived 1000 permutation test ($p < 0.05$, Fig. 2C), revealing that the model could successfully predict individual's DS. For further evaluation, Mean Squared Error (MSE) was assessed the consistency between actual values and predicted values (Feng et al., 2019), where smaller MSE means better fit of the model to the data and more accurate predictions. Since the value of MSE can be influenced by the data range, it cannot be directly used for comparing different datasets. Thus, we generated a distribution of MSE values during the process of 1000 permutation tests and we found that the estimated p-value of the original MSE was less than 0.01, convincing that large-scale brain region communication patterns capture crucial information related to DS (Fig. 2D and E).

We also tried to establish a predictive model of the ΔACC, but failed to generate models to predict ΔACC. This may be due to too easy search task, leading to a ceiling effect (overall accuracy, 95.80 %). Furthermore, such ceiling effect lacked the dynamic range which is necessary to generate a predictive model using the CPM method (Shen et al., 2017). Besides, we also checked whether the predictive model of the ΔRT could predict the ΔACC and found that the it was unable to predict the ΔACC ($r = 0.10$, $p = 0.37$).

3.3. Significant large-scale brain region communications in predicting DS

Across all folds of LOOCV, 2 to 5 large-scale brain region communication contributed to the predictive model. Notably, 3 of these appeared in the 95 % iterations of the LOOCV, so they were defined as substantial communication connectivity (Jiang et al., 2020; Rosenberg et al., 2016). These significant large-scale brain region communications were Prefrontal -Temporal, Parietal - Occipital, and Insula - Limbic connections (Fig. 3B). The strength of these connections was significantly negatively correlated with individual's ΔRT respectively (Prefrontal -Temporal, $r = -0.28$, $p < 0.01$; Insula – Limbic, $r = -0.32$, $p < 0.01$; Parietal - Occipital, $r = -0.30$, $p < 0.01$;Fig. 3C), revealing that individuals with stronger functional connectivity across these anatomical brain regions demonstrated poorer DS. Upon the significant correlations between the ΔRT and Prefrontal -Temporal, Parietal - Occipital, and Insula - Limbic connections, we tried to generate predictive models of the ΔRT only based on individual network connection. We found that the Insula – Limbic connection ($r = 0.27$, $p < 0.01$, Table 1) and the Parietal - Occipital connection ($r = 0.23$, $p < 0.01$, Table 1) could successfully predict the ΔRT. However, the prefrontal-temporal connection could not predict the ΔRT ($r = 0.19$, $p = 0.08$). These results showed less contribution of the prefrontal-temporal connection to the laboratory-measure of the DS.

3.4. Validating distractor suppression predictive model in an independent sample

In order to validate the predictive model of the DS, we built a predictive model using all participant's data in discovery dataset, resulting in Prefrontal -Temporal, Parietal - Occipital, and Insula – Limbic connections survived for this model. This was consistent with the finding of

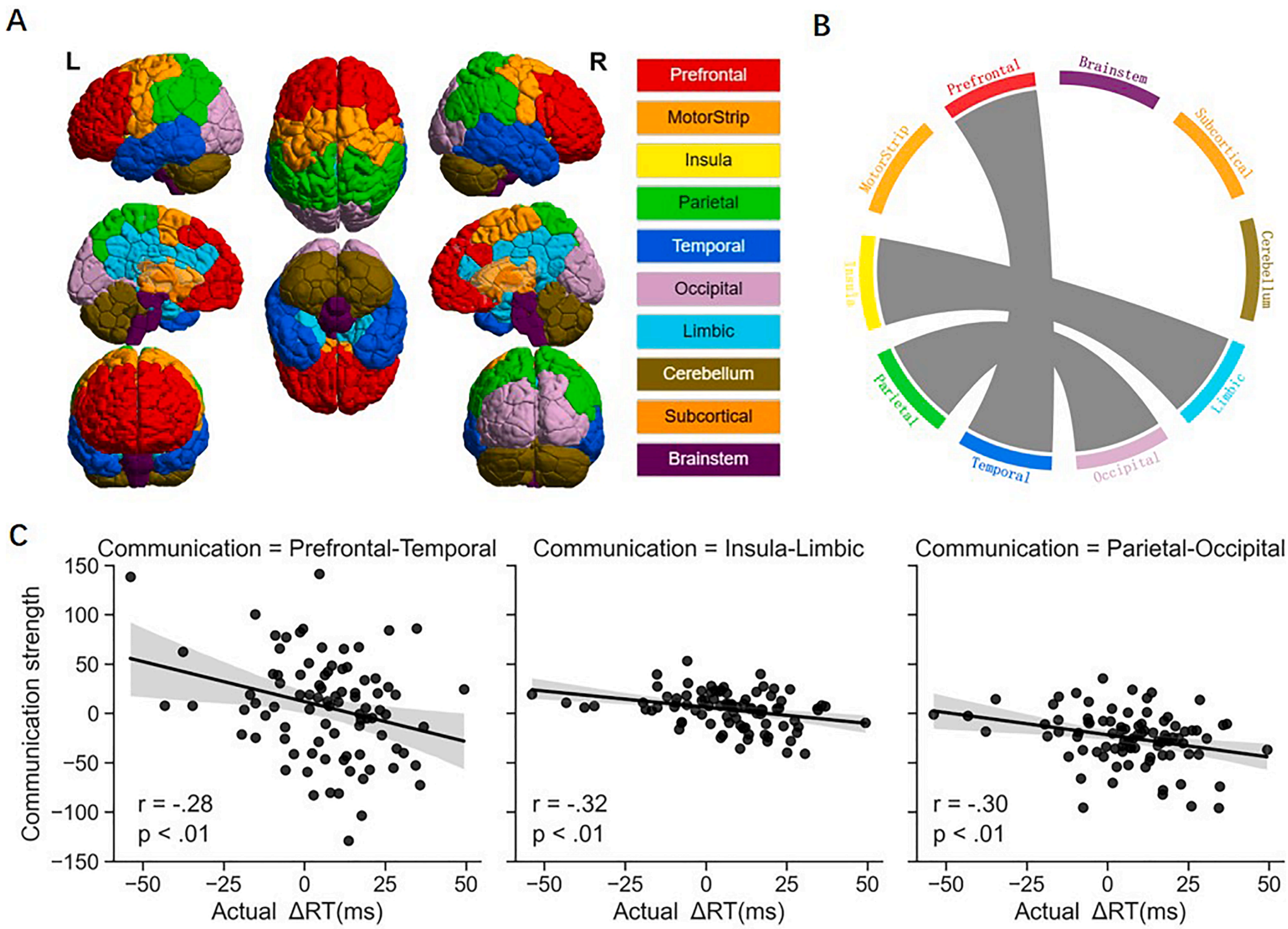

Fig. 3. Contributory large-scale brain region communication to DS prediction. (A) The 268 nodes were grouped into 10 macroscale brain regions. Including the prefrontal lobe (46 nodes), motor lobe (21 nodes), insular lobe (7 nodes), parietal lobe (27 nodes), temporal lobe (39 nodes), occipital lobe (25 nodes), limbic lobe (36 nodes), cerebellum lobe (41 nodes), subcortical lobe (17 nodes) and brainstem lobe (9 nodes). (B) The large-scale brain region communication selected by the prediction model (C) Correlation between communication strength and DS. L, left; R, right.

Table 1
Results of single network connection.

Connections between networks	Internal validation (N = 88)	External validation (N = 49)
Three network connections	$r = 0.41$, $p < 0.01$[a]	$r = -0.34$, $p < 0.05$[b]
Insula – Limbic	$r = 0.27$, $p < 0.01$[a]	$r = -0.06$, $p = 0.67$[b]
Parietal - Occipital	$r = 0.23$, $p < 0.01$[a]	$r = -0.18$, $p = 0.23$[b]
Prefrontal - Temporal	$r = 0.19$, $p = 0.08$[a]	$r = -0.34$, $p < 0.05$[b]

Notes: If the p-value of internal validation is significant, it is obtained through permutation testing.
[a] Pearson's correlation coefficients.
[b] Spearman's correlation coefficients.

significant contribution of the Prefrontal -Temporal, Parietal - Occipital, and Insula - Limbic connection to the laboratory-measured DS prediction. Subsequently, we employed this trained model to make predictions on a completely independent dataset to assess its generalization ability. The validation dataset contained 49 participants whose daily distractibility was assessed using Cognitive Failure Questionnaire (CFQ) (Broadbent et al., 1982; Zhou et al., 2016). In this questionnaire, higher distractibility score represents worse distractor suppression. Distractibility score varied across individuals (range, 5–25) and it didn't follow a normal distribution (Kolmogorov-Smirnov test, $p < 0.05$). Thus, Spearman correlation was used to check the relationship between the actual and predicted scores. Here, the model of ΔRT was able to predict individual's distractibility in an independent sample ($r = -0.34$, $p < 0.05$, Fig. 4), revealing the model's generalization ability across different measure of DS and sample. In addition, the model still could predict the total score of CFQ ($r = -0.29$, $p < 0.05$). Since the total score is simply the summation of each subscale, including distractibility, memory, and psychomotor scores, the distractibility score may have contributed to the total score prediction. Consistently, we found the model could not predict other subscales of the CFQ, such as the memory scores (score range, 0–19; $r = -0.23$, $p = 0.11$), the psychomotor scores (score range, 1–18; $r = -0.13$, $p = 0.38$). These results showed that the model generated for the laboratory-measured DS was able to predict individual's daily distractibility and emphasized the model's specificity in predicting distractor suppression. Moreover, we found the predictive capabilities of the connections between Insula – Limbic connection ($r = -0.06$, $p = 0.67$, Table 1) and the Parietal - Occipital connection ($r = -0.18$, $p = 0.23$, Table 1) declined in external predictions. Interestingly, the Prefrontal - Temporal connection could successfully predict the daily distractibility score of the independent sample ($r = -0.34$, $p < 0.05$, Table 1). Together with the predictability of individual network connection to the ΔRT, these results exhibited the heterogeneity of the contributions of the network connections across different situations. Still, the combination of three network connections has strong predictive capability and generalizability for distractor suppression.

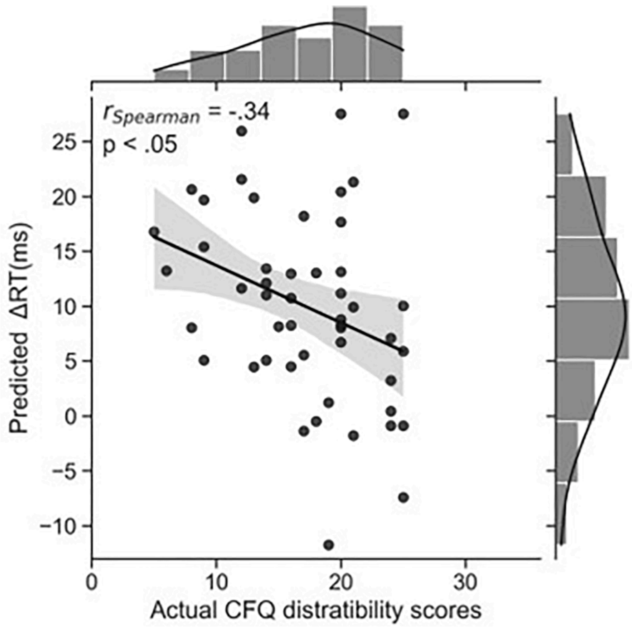

Fig. 4. Performance of the prediction model for external validation. Spearman correlation between actual and predicted CFQ distractibility scores.

3.5. Validations of the effects of confounding factors

In this validation analysis, we aimed to assess the impact of confounding factors on predictive capability. The current data showed no significant correlation between DS measurement and age (see details in Table 2). We found a significant difference in the predicted ΔRT scores between male and female groups in the discovery dataset ($t = 3.07$, $p < 0.05$, Table 2). Besides, the current data did not reveal a significant association between motion (i.e., mean FD) and DS measurement (Table 2). However, minor head motion by participants continues to significantly alter the time series of resting-state functional connectivity magnetic resonance imaging (rs-fcMRI) data, leading to systematic yet spurious functional connections within the brain (Power et al., 2012). Thus, we conducted control analyzes for factors with these three factors potential to exert an effect. In these analyzes, new predictive features were generated by utilizing communications that exhibited a partial Pearson correlation with DS at a significant threshold of $p < 0.05$, while controlling for confounding variables. After controlling for the potential confounders, the predictive models still effectively predicted the DS measurement (Table 3). We deduce that the predictive performance of the DS model remains unaffected by these factors.

Table 3
Results of control analyzes.

Covariates	Internal validation($N = 88$)	External validation($N = 49$)
Age	$r = 0.33$, $p < 0.05$[a]	$r = -0.32$, $p < 0.05$[b]
Sex	$r = 0.32$, $p < 0.05$[a]	$r = -0.32$, $p < 0.05$[b]
Head motion	$r = 0.29$, $p < 0.05$[a]	$r = -0.32$, $p < 0.05$[b]
Age; Sex	$r = 0.34$, $p < 0.05$[a]	$r = -0.32$, $p < 0.05$[b]
Age; Head motion	$r = 0.35$, $p < 0.05$[a]	$r = -0.32$, $p < 0.05$[b]
Sex; Head motion	$r = 0.32$, $p < 0.05$[a]	$r = -0.32$, $p < 0.05$[b]
Age; Sex; Head motion	$r = 0.36$, $p < 0.05$[a]	$r = -0.32$, $p < 0.05$[b]

Notes: If the p-value of internal validation is significant, it is obtained through permutation testing.
[a] Pearson's correlation coefficients.
[b] Spearman's correlation coefficients.

4. Discussion

Here, we generated a robust predictive model of distractor suppression (DS) based on connections between anatomical large-scale brain regions, which was rather independent of measurement method. Our work established a link between the large-scale brain regions communication patterns and DS and revealed the significance of large-scale brain regions' communication underlying DS. These novel findings point to a particularly important role of the connections between attention-related brain regions and visual information processing-related brain regions. This deepens our understanding of the connectome-based neuromarkers of DS, and may have implications for the early identification of individuals suffering from impaired-DS symptomatology in the general population.

4.1. Large-scale brain region's communications predict distractor suppression

The current study successfully constructed a predictive model with vigorous generalization capabilities, using a connectome-based predictive modeling embedded within a machine learning framework, to predict individuals' DS based on intrinsic functional connectivity between anatomical large-scale brain regions. Everyone possesses unique functional brain connectivity patterns that contain information about their cognitive abilities (Finn et al., 2015; Rosenberg et al., 2016). Connectome-based Predictive Modeling (CPM) is one of the approaches to predict individual's cognitive abilities based on their brain connectome. This approach focuses on individual differences and employs data-driven methods within a cross-validation strategy to select

Table 2
Demographic information for samples and correlations between the studied variables.

Samples/Measures	Mean ($_{S.D.}$)	Range	2	3	4	5	t value
Discovery Dataset ($N = 88$)							
1. Sex (male/female)	44/44	–	–	–	–	–	–
2. Age (years)	20.95(1.96)	18 ~ 26	1				−1.20
3. Head motion (mean FD, mm)	0.04(0.02)	0.02 ~ 0.13	0.002[a]	1			−0.13
4. Actual ΔRT scores	6.80(17.75)	−53.84 ~ 49.34	−0.15[a]	0.05[a]	1		1.12
5. Predicted ΔRT scores	7.07(8.16)	−16.73 ~ 23.53	−0.14[a]	−0.003[a]	0.32**[,a]	1	3.07**
Validation Dataset ($N = 49$)							
1. Sex (male/female)	24/25	–	–	–	–	–	–
2. Age (years)	23..02(2.03)	18 ~ 27	1				0.49
3. Head motion (mean FD, mm)	0.05(0.02)	0.02 ~ 0.12	0.08[b]	1			−1.86
4. Actual CFQ distractibility scores	17.14(5.45)	5 ~ 25	−0.26[b]	0.05[b]	1		0.34
5. Predicted ΔRT scores	9.98(8.65)	−11.73 ~ 27.52	−0.09[b]	−0.02[b]	−0.34*[,b]	1	0.55

S.D., standard deviation;FD, framewise displacement.
[a] Pearson's correlation coefficients.
[b] Spearman's correlation coefficients.
[*] $p < 0.05$.
[**] $p < 0.01$.

connections significantly correlated with behavior, thereby establishing a regression prediction model for brain connectivity and behavior (Shen et al., 2017). CPM has been widely applied in various domains, particularly, models like the Sustained Attention Connectome-based Predictive Model (saCPM) developed by Rosenberg (Rosenberg et al., 2016) have demonstrated robust predictions of attentional abilities across various contexts and have been validated in multiple independent datasets. Building upon the aforementioned foundation, we attempted to link the communication between anatomical large-scale brain regions to individual's DS. Since the connectivity strength between large regions was computed by summing all the values of fine-grained connections, it may be more resistant to noise. Accordingly, our model emphasized on the communication patterns among large-scale brain regions, an aspect that has not been strongly emphasized in prior researches.

Existing research indicates that the functional organization of the brain is not entirely modular (Rosenberg et al., 2017). Modules are specific regions of the brain, where each module is tasked with processing particular types of information or performing specific cognitive functions. However, the organization of cognitive functions in the brain extends beyond independent modules to include the transmission and sharing of information between different modules. Most of our complex cognitive abilities, such as attention, working memory, and decision-making, rely on the coordinated activity of a distributed network (Mišić and Olaf, 2016). In the study of sustained attention, researchers have found that predictive connectivity models of attention function comprise numerous connections that span across different brain regions and multiple networks, indicating the importance of the coordinated activity between various modules in the brain (Rosenberg et al., 2017, 2016). We successfully predicted distractor suppression across different datasets using a model based on connections between large-scale brain regions. Based on these reliable results, our study emphasizes the impact of large-scale brain region connectivity patterns on distractor suppression, consistent with the understanding of the crucial role of coordinated activity among different modules in the brain for complex cognitive tasks.

Additionally, the predictive model was generated using intrinsic brain connectivity, which is convenient to collect in clinical settings and task-unconstrained. Certainly, such models can be successfully built based on a fundamental principle, which is that the distractor suppression system is reflected in the functional organization of the resting-state brain (Cole et al., 2021; Xie et al., 2022, 2020). This suggests that the brain maintains characteristics for task execution to some extent even when not engaged in specific tasks. In conclusion, our approach offers a novel perspective for understanding and forecasting cognitive function and holds promise for its significant role in the management of neurological and psychiatric disorders and personalized medical interventions.

4.2. Significant large-scale brain region communications in distractor suppression prediction

By summarizing the connections involved in the model, we found Prefrontal-Temporal, Insula-Limbic and Parietal-Occipital connections contributed to the individual's DS. Checking the predictability of individual network connection to the DS, we found the DS measured using the visual search task (ΔRT scores) could be predicted by Insula-Limbic, Parietal-Occipital connections, while the Prefrontal-Temporal connection could predict distractibility in daily life. These findings suggest heterogeneousness contributions of individual network connection across different situations. Considering the distractibility score using CFQ estimates individual's distractibility in daily life, it seems that the Prefrontal-Temporal connection is more important to the distractor suppression in more cognitively demanding situations. Still, three network connections together have strong predictive capability and generalizability for distractor suppression. These results demonstrated that DS is a network property of brain computation, relying on the communications between networks. Consistently, the parieto-frontal integration theory (P-FIT) model on intelligence emphasizes the importance of network connections (Jung and Haier, 2007). The P-FIT model implicated brain connectivity as having high predictability for fluid intelligence (Jiang et al., 2020).

Specifically, the prefrontal cortex (PFC) and posterior parietal cortex (PPC) have been typically implicated in a variety of tasks requiring attention allocation and maintenance (Chun et al., 2011; Corbetta and Shulman, 2002; Giesbrecht et al., 2003). These regions can contribute to the perceptual selection of salient information, and it can be argued that the PFC and the PPC plays a role in inhibiting the entry of interfering information. In line with these, the present study pointed out the prefrontal and parietal regions as important regions. However, it was not the direct connection between the PFC and PCC that contributed to DS, but the Prefrontal-Temporal and Parietal-Occipital connections that were important to DS. The occipital lobe is the primary visual cortex, encompassing both the primary visual cortex and associated visual regions, which is associated with the perception and processing of visual information and the organization of complex visual perceptual processes (Tran et al., 2019). Similarly, the temporal lobe is involved in higher-level visual processing, handling information related to the color, shape, and other characteristics of visual stimuli. It is a critical brain region within the 'what' pathway of visual processing (Ungerleider, 1994). Thus, we think the Prefrontal-Temporal and Parietal-Occipital communications may reflect the communication between attention regions (PFC and PPC) and visual sensory processing regions (temporal and occipital). This may be related to the importance of the visual information in our measure of DS. In the present study, a visual search task was employed to assess the participants' ability to actively suppress a salient singleton distractor. In daily life, vision occupies more than 80 % of all the received information (Kasteleijn-Nolst Trenité et al., 2004). Consequently, communication between attention-related regions (the PFC and the PPC) and two critical brain regions associated with visual processing (the occipital and the temporal lobes), plays pivotal roles in individual's difference of DS. Besides, the insula, a key node of a salience network, is responsible for salience-processing systems and switching between large-scale brain networks (e.g., the frontoparietal network and the default mode network) to facilitate the allocation of attentional resources (Bressler and Menon, 2010; Goulden et al., 2014; Uddin, 2015). While the limbic system does not have a direct dominant role in attentional control, its significance lies in regulating emotions, emotional memory, and physiological states, all of which can impact the quality and direction of attention (Rolls, 2019). Together, our research findings indicate that the interaction of attention-related brain regions with visual processing-related brain regions contributes to the prediction of an individual's DS. The process of distractor suppression can be viewed as a high-level cognitive function that regulates attention resources from top-down pathways to help us achieve our goals and suppressing distractions. Since impaired distractor suppression has been found in some disorders such as attention deficit hyperactivity disorder (ADHD) (Mishra et al., 2016), schizophrenia (Gur et al., 2007), and autism spectrum disorder (Keehn et al., 2016), understanding of the neural mechanisms of distractor suppression may be helpful to gain a better understanding of these disorders and to elucidate specific symptoms manifested by patients and offering guidance for diagnosing specific diseases.

4.3. Bridging in-laboratory and daily life measured distractor suppression

In the fields of cognitive psychology and neuroscience research, the assessment of specific cognitive functions widely relies on laboratory measurements. These measurements conducted in laboratory settings offer several advantages, such as increased control over external interferences and variables, standardized tools and procedures to guarantee result replicability, and precise, quantitative data (e.g., reaction times, error rates) (Gaspelin et al., 2017, 2015; Sawaki and Luck, 2010). However, laboratory-based measurements may not always fully reflect cognitive performance in daily life. In contrast to the controlled environment of the laboratory, daily life is characterized by greater complexity in environmental situations. For example, distractions in everyday scenarios are well beyond simple geometric shapes. Hence, cognitive challenges related to distractor suppression in daily life may become more diverse. Similarly, as an active individual in daily life, our choices of actions can also influence distractor suppression — a factor often controlled for in laboratory settings to mitigate motion artifacts (Wöstmann et al., 2022). These differences between laboratory settings and real life may lead individuals to employ distinct cognitive demands and strategies in erratic environments (Thomson and Goodhew, 2021). The long-term goal of cognitive neuroscience is to elucidate the cognitive mechanisms in real-world environments, making it crucial to understand how laboratory theories apply in the real world. Non-laboratory measurements, such as self-report methods, can capture information that is not easily obtained through laboratory measurements (Kanai et al., 2011). For example, forgetting the date of a family gathering or being unable to locate a misplaced item can provide insights into cognitive performance in daily tasks. To gain a comprehensive understanding of cognitive functions, researchers often need to integrate laboratory measurements and non-laboratory measurements to ensure the ecological validity of their findings.

We established a predictive model for DS based on laboratory measurements, which can also forecast DS in daily life based on questionnaire reports. This cross-modal predictive model contributes to elucidating the common processes that influence an individual's DS across various contexts. The results mutually validate the reliability of the two measurement approaches. While laboratory measurements provide objective cognitive function data, questionnaire reports capture the subjective experiences and functional abilities of participants in their daily lives.

4.4. Limitation of the study

Regarding the current study, several limitations should be noted. Firstly, our predictions were obtained from a relatively small sample, and the generalizability of the current findings needs further validation using an independent, larger sample, and other cross-validation methods. For example, the narrow age range of the study sample may have limited the impact of age factors. In future research, a wider age range sample may be better to explore the influence of age on the brain-behavior relationship. Secondly, the current study did not thoroughly investigate the directionality of brain region interactions. In fact, interactions between brain regions are a complex process that may involve various forms of directionality (Corbetta and Shulman, 2002; Rolls, 2019). Future research could further elucidate the directionality of brain region interactions that play a pivotal role in DS. Thirdly, laboratory-measured DS used a visual search paradigm, it is worth noting that the findings of the present study may be limited to visual distractor suppression. Future research could extend to explore the mechanisms of distractor suppression across sensory modalities, providing a more comprehensive understanding of the neural basis of distractor suppression.

5. Conclusion

We have demonstrated that the interaction between large-scale brain regions can effectively predict individual's distractor suppression across independent datasets. It is noteworthy that the large-scale brain regions and connections within the predictive network involve the coordination and control of attention-related regions, the prefrontal and parietal lobes, over visual processing regions to achieve top-down distractor suppression. The current data-driven approach offers a novel tool, while the connectivity patterns of large-scale brain regions provide a fresh perspective for characterizing the fundamental neural mechanisms of distractor suppression in various contexts. This establishes a bridge between laboratory and daily life distractor suppression and holds potential applications in clinical practice.

CRediT authorship contribution statement

Lei Zhuo: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zhenlan Jin:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Ke Xie:** Writing – review & editing, Visualization, Methodology, Investigation, Data curation. **Simeng Li:** Writing – review & editing, Visualization, Methodology, Investigation, Data curation. **Feng Lin:** Writing – review & editing, Visualization, Methodology, Investigation, Data curation. **Junjun Zhang:** Writing – review & editing, Investigation, Conceptualization. **Ling Li:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that there were no conflicts of interest.

Data availability

Data will be made available on request.

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