

Reviewed Preprint
v1 • March 10, 2026
Not revised

Neural Mechanisms of Willed Attention Control

✉ For correspondence:

mding@bme.ufl.edu

Competing interests: No competing interests declared

Funding: See [page 18](#)

Reviewing editor: Ming Meng, University of Alabama at Birmingham, United States

© 2026, Xiong et al. This article is distributed under the terms of the [Creative Commons Attribution License](#), which permits unrestricted use and redistribution provided that the original author and source are credited.

Changhao Xiong¹, Qiang Yang¹, Sungkean Kim², Sreenivasan Meyyappan³, Jesse J Bengson³, George R Mangun^{3,4}, Mingzhou Ding¹ ✉

¹J. Crayton Pruitt Family Department of Biomedical Engineering, University of Florida, Gainesville, United States •

²Department of Human-Computer Interaction, Hanyang University, Seoul, Republic of Korea • ³Center for Mind and Brain, University of California, Davis, Davis, United States • ⁴Departments of Psychology and Neurology, University of California, Davis, Davis, United States

eLife Assessment

This **useful** study supplements previous publications of willed attention by addressing a frontoparietal network that supports internal goal generation. The evidence is **solid** in analyzing two datasets collected at different independent sites, using the same willed-attention paradigm and combining fMRI and EEG. This work will interest cognitive psychologists and neuroscience researchers.

<https://doi.org/10.7554/eLife.110199.1.sa3>

Abstract

Cueing paradigms are commonly used to study the neural mechanisms of visual spatial attention control. In these paradigms, each trial starts with an external cue, which instructs the subject to pay covert attention to a spatial location in anticipation of an impending stimulus (instructed attention). Recent work has introduced a new type of cue which prompts the subject to spontaneously decide which spatial location to attend (willed attention). We studied the neural mechanisms of willed attention control by analyzing fMRI and EEG data recorded at two institutions (UF and UC Davis) using the same willed attention paradigm. The findings include: (1) both instructional cues and the choice cue activated the DAN, (2) the choice cue additionally activated a frontoparietal decision network consisting of dorsal anterior cingulate cortex (dACC), anterior insula (AI), anterior prefrontal cortex (APFC), dorsal lateral prefrontal cortex (DLPFC), and inferior parietal lobule (IPL), (3) the decision about where to attend can be decoded in frontoparietal decision network in choice trials but not in instructional trials, and (4) EEG alpha oscillation patterns immediately preceding the choice cue, but not the instructional cues, predicted the postcue direction of attention and the frontoparietal decision network activity. Based on these findings we proposed a model of willed attention control revealing how the direction of visual spatial attention was decided upon in the absence of external instructions.

Introduction

Visual spatial attention can be voluntarily directed in advance of stimulus processing to align with behavioral goals. The control of voluntary attention is often studied using cueing paradigms where each task trial begins with a cue that informs the participant where in visual space a task-relevant target stimulus may appear. This information enables participants to selectively prioritize stimuli at the cued location (Posner et al., 1980 [DOI](#)). The neural underpinnings of voluntary attention control have been extensively studied using cuing paradigms in humans using a multitude of techniques including patient lesion analyses (Posner et al., 1984 [DOI](#)), neuroimaging methods (Arrington et al., 2000 [DOI](#); Corbetta et al., 2000 [DOI](#); Hopfinger et al., 2000a [DOI](#); Woldorff et al., 2004 [DOI](#)) and electrophysiological and magnetoencephalographic recordings (Hopf & Mangun, 2000 [DOI](#); Yang et al., 2024 [DOI](#)). Converging evidence shows that the cue activates the dorsal attention network

(DAN), comprising the frontal eye fields (FEF) and the intraparietal sulcus (IPS), which then issues top-down control signals to bias sensory cortex to enhance relevant information and suppress irrelevant information (Corbetta & Shulman, 2002 [↗](#); Hopfinger et al., 2000b [↗](#); Meyyappan et al., 2025 [↗](#)), and the sensory biasing signals manifest as distinct patterns of alpha oscillations (Worden et al., 2000 [↗](#)).

In order to study voluntary attention control in more realistic circumstances, another method has been introduced. In this method, instead of presenting cues that tell the subject where a relevant item is likely to appear or instructs them where to focus attention, subjects are permitted to freely choose where to attend (Taylor et al., 2008 [↗](#)). These so-called “choice cues” prompt the subject to spontaneously decide where to attend among a set of alternatives (e.g., left visual field vs. right visual field locations). This form of voluntary attention has been termed “willed attention” (Bengson et al., 2015 [↗](#)). Studies of willed attention control have shown that in addition to DAN, the choice cue elicits activation in an additional set of frontoparietal areas, including DLPFC, IPL, dACC and anterior insula (Bengson et al., 2015 [↗](#); Hopfinger et al., 2010 [↗](#); Rajan et al., 2019 [↗](#); Taylor et al., 2008 [↗](#)). The functional role of these frontoparietal areas, however, has yet to be clarified. Given that prior work has shown that these areas are involved in decision-making, it is thus reasonable to expect that in willed attention, these areas play a role in making the decision about where to attend. The first goal of this study is to test this idea.

The control of willed attention begins with the decision about where to direct spatial attention when prompted by the choice cue, which appears unpredictably both in time and among the three cue types (attend-left, attend-right, choose). Previous work on the neuroscience of decision-making has shown that the ongoing brain state before the stimulus can exert a significant influence on the outcome of the decision-making process. A key variable indexing the ongoing brain state is the alpha oscillation (8-12 Hz) (Jensen & Mazaheri, 2010 [↗](#); Klimesch et al., 2007 [↗](#)). In stimulus-based decision-making, prestimulus alpha power is shown to mainly affect the response criterion. When prestimulus alpha power is low, individuals exhibit a more liberal detection criterion, manifesting as an increased tendency to report stimulus presence even when the evidence is ambiguous (Limbach & Corballis, 2016 [↗](#)). Conversely, higher pre-stimulus alpha power promotes a more conservative response strategy, characterized by increased “no” responses and higher decision thresholds (Iemi et al., 2017 [↗](#)).

In typical willed attention studies, however, the decision is between two equal alternatives, attend-left versus attend-right visual field locations, and the choice cue offers no sensory information that favors either one. The previous study (Bengson et al., 2014 [↗](#)) reported that the amplitude of left parieto-occipital EEG alpha power in the 1 sec period immediately before the unpredictable appearance of the choice cue predicted the decision about where to attend. How far does this alpha-based predictability extend before the choice cue? Bengson and colleagues (2014) [↗](#) investigated sequential 1 sec period prior to the choice cue, and reported no significant predictive value of the parieto-occipital alpha power earlier in time. But this analysis had rather low temporal resolution, relying on alpha power across rather large and arbitrary time windows. Knowing more about the timecourse of pre-choice cue alpha power would help determine whether the decision about where to attend is made spontaneously based on momentary patterns of brain activity, or is instead based on longer biases in brain activity patterns. In addition, understanding how the pattern of the precue alpha power affects the subsequent choice cue-evoked neural activity in the frontoparietal decision network would offer deeper insight into the role of the ongoing brain state in shaping decision-making during willed attention. The second goal of this study, therefore, is to address these questions.

Healthy volunteers performed a cued visual spatial willed attention paradigm, in which each trial started with one of three types of cues: two instructing the participant to covertly attend the left or the right visual field and the third prompting the participant to spontaneously choose between the left and the right visual field to covertly attend. Following a random time delay, a stimulus was presented, and the participant discriminated features of the stimulus if it appeared in the attended visual field and ignored it completely if it appeared in the unattended visual field. EEG and fMRI

data were recorded at two different sites, University of Florida (UF) and University of California at Davis (UCD), using the same paradigm. The data from the two sites were combined to enhance reproducibility and statistical rigor.

Materials and Methods

Overview

Two independent datasets were recorded at two different sites, University of Florida (UF) and University of California Davis (UCD), using the same experimental paradigm. These datasets have been analyzed and published on before to address different questions (Bengson et al., 2015 [↗](#); Liu et al., 2017 [↗](#); Meyyappan et al., 2025 [↗](#)). None of the previously published studies examined the questions considered here.

UF Dataset: The experimental protocol was approved by the Institutional Review Board of the University of Florida. A total of 18 right-handed college students whose age between 18-22 gave written informed consent and participated in the study. They had normal or corrected to normal vision and no history of neurological or psychological disorders. Data from five participants were excluded from the analysis based on the following reasons: (1) the behavioral performance was below criterion (< 70% accuracy, one participant); (2) unable to follow the task instructions (one participant); and (3) excessive body or eye movements in the scanner (three participants). The remaining thirteen participants analyzed here included 5 females and 8 males.

UCD Dataset: The experimental protocol was approved by the Institutional Review Board of the University of California, Davis. Overall, 19 right-handed college students whose age between 18-22 gave written informed consent and participated in the study. All participants had normal or corrected to normal vision and had no history of neurological or psychological disorders. One participant was excluded due to unstable performance and failure to follow instructions during the experiment. The remaining eighteen participants were analyzed which included 2 females and 16 males.

Paradigm and procedure

See Figure 1 [↗](#). Each trial began with one of three symbolic cues (circle, square, or triangle) displayed slightly above the central fixation for a duration of 200 ms. Two of the cues, called instructional cues, required the participant to covertly direct their attention to the left or right visual field while maintaining central fixation (instructed attention). The third cue, called the choice cue, prompted the participant to freely choose one of the two visual fields to attend while maintaining central fixation (willed attention). The three cue conditions occurred with equal probability and the symbols used as cues were counterbalanced as to their meanings across participants. Further, the willed and the instructed attention trials were randomly interleaved in order to discourage stereotypic responses. Following a cue-target interval randomized between 2000 and 8000 ms, a black and white grating of two possible spatial frequencies (low vs. high) appeared in one of the two visual fields with equal probability for 100 ms (50% target validity). Participants discriminated the spatial frequency of the target grating appearing in the attended visual field as fast and accurately as possible through a button-press and ignored the grating appearing in the unattended visual field. The gratings were difficult to discriminate so that focused spatial attention was required for successful execution of the task. Compared to the probabilistic cueing used in the Posner style paradigms (Posner, 1980), in which participants responded to the stimulus appearing in either visual field, the current design further encouraged the full deployment of focused covert spatial attention prior to the appearance of the stimulus.

Following an inter-stimulus interval (ISI) randomized between 2000 and 8000 ms after the stimulus onset, participants were prompted by the visual cue “?SIDE?” to report the visual field they were attending on that trial through a button-press (self-report). This reporting was used to determine the direction of attention for willed attention trials but was included in instructed attention trials as well to maintain trial structure consistency. Reporting of the attended side was highly accurate across the participants with the accuracy of 98.4% averaged across conditions. For

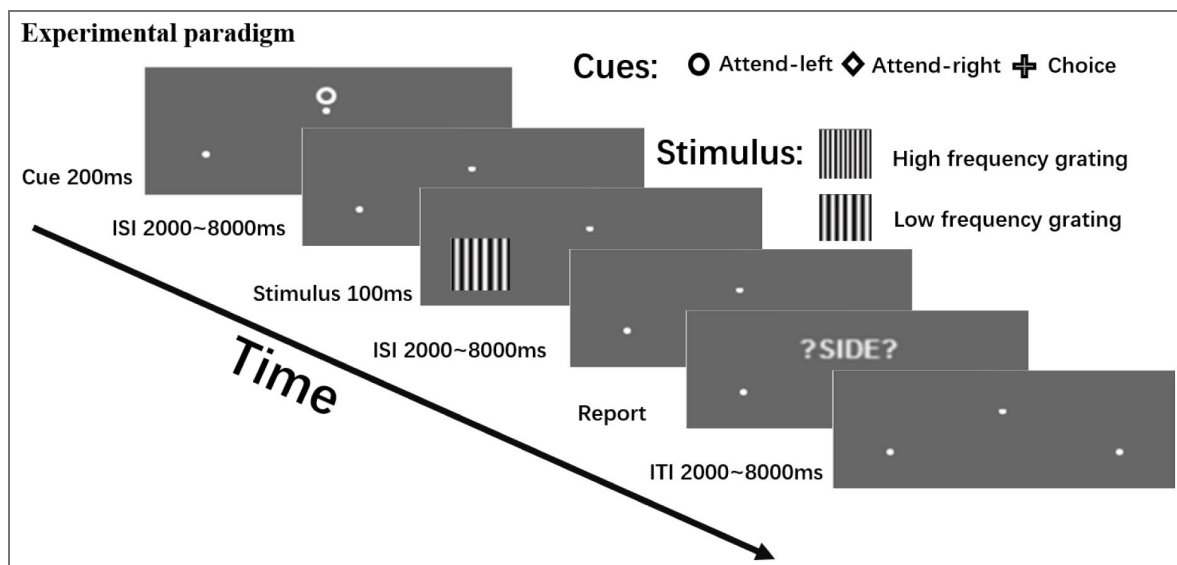


Figure 1. Experimental paradigm.

Each trial began with the presentation of one of three visual cues for 200 ms. Two of the cues—the instructional cues—instructed the participant to covertly attend to either the left or right visual field, the third cue—the choice cue—prompted participants to choose whether to attend to the left or right field. Shown in the figure is an example of the cue symbol-to-attention mappings which were randomized across participants. After a variable cue-to-target interval (2,000–8,000 ms), a target stimulus (a grating with high or low spatial frequency) appeared briefly (100 ms) with equal probability in either visual field. Participants were asked to discriminate the spatial frequency of the grating presented at the cued or chosen location (attended location), while ignoring stimuli on the uncued or unchosen side (unattended location). Following a variable inter-stimulus interval (ISI; 2,000–8,000 ms), a “?SIDE?” prompt appeared, asking participants to report the visual field they attended to on that trial. Finally, a variable inter-trial interval (ITI; 2,000–8,000 ms) elapsed before the onset of the next trial.

instructed attention trials, side reporting accuracy could be determined by comparing the self-report with the cue instruction, while for willed attention trials, the accuracy was determined by examining the consistency between the participant's response (or lack of response) and the self-report. An inter-trial interval (ITI) randomized between 2000 and 8000 ms was inserted after the self-report. This ITI is critical for generating uncertainty about when the next cue would occur, thus making it impossible for the subject to choose where to attend in advance of the choice cue within a narrow time window.

Prior to recording, all participants went through a training session to familiarize with the task and to ensure stable performance (above 70% accuracy). During recording, the experiment was divided into blocks of trials with the length of each block kept around six minutes. All participants completed at least eight blocks of trials. For willed attention, participants were explicitly told to avoid relying on any stereotypical strategies of generating decisions, such as always attending the same/opposite side they attended during the previous trial, as well as to avoid randomizing or equalizing their decisions to choose left or right across trials; prior studies found that decisions to explicitly randomize decisions might invoke additional working memory related processes (Spence & Frith, 1999 [\[4\]](#)).

Data collection

UF fMRI: fMRI data were acquired using a 3T Philips Achieva scanner (Philips Medical Systems, Netherlands) with a 32-channel head coil. Functional images were obtained using a single-shot echo planar imaging (EPI) sequence with the following parameters: repetition time (TR) = 1980 ms, echo time (TE) = 30 ms, flip angle = 80°, field of view = 224 mm. Thirty-six transverse slices (slice thickness: 3.5 mm) oriented parallel to the plane connecting the anterior and posterior commissures were obtained in an ascending order with a voxel resolution of 3.5×3.5×3.5 mm³.

UF EEG: Continuous EEG data was recorded inside the MRI scanner simultaneously with fMRI using a 32-channel MR-compatible EEG recording system (Brain Products, Germany). Thirty-one Ag/AgCl electrodes were located on the scalp according to the 10–20 system via an elastic cap. One additional electrode was located on the participant's upper back to record the electrocardiogram (ECG), which was used to remove the ballistocardiogram (BCG) artifacts (Ertl et al. 2010). The FCz channel was used as a reference during recording. The impedance of all scalp channels was kept under 5 kΩ throughout the experiment. The sampling frequency was 5000 Hz.

UCD fMRI: fMRI data were acquired using a 3T Siemens Skyra scanner (Siemens, Germany) with a 32-channel head coil. Functional images were obtained using a single-shot EPI sequence with the following parameters: TR = 2100 ms, TE = 30 ms, flip angle = 90°, field of view = 218 mm, slice thickness = 3.4 mm. Thirty-four transverse slices were obtained in an interleaved acquisition order. The voxel resolution was 3.5×3.5×3.5 mm³.

UCD EEG: Continuous EEG data was recorded in a separate session from 64 electrodes mounted in an elastic cap (Electro-cap International Inc., OH) using a SynAmps II amplifier (Compumedics Neuroscan, USA). The reference electrode was placed at the right mastoid during recording. The impedance of all scalp channels was kept below 5 kΩ. The sampling frequency was 1000 Hz.

fMRI data preprocessing

The preprocessing of fMRI data was performed with SPM8 and included the following steps: slice time correction, motion realignment, spatial normalization and smoothing. Slice timing correction was carried out using sinc interpolation. Motion realignment was performed by co-registering all images with the first scan of each session. Six motion parameters (3 translational and 3 rotational) were calculated and entered into the final design matrix to be regressed out in the general linear model (GLM) analysis. All images were spatially normalized to the standard MNI space and resampled to a voxel resolution of 3×3×3 mm. Finally, the spatially normalized images were smoothed using a Gaussian kernel of 8 mm full width at half maximum. A high pass filter with a cut off frequency of 1/128 Hz was used to remove any low frequency noise. Global effects were adjusted by the proportional scaling approach (Fox et al., 2009 [\[4\]](#)).

EEG data preprocessing

For the UF dataset, since EEG data were recorded simultaneously with fMRI inside the scanner, extra preprocessing steps were required to remove the MRI artifacts. Both gradient and ballistocardiogram (BCG) artifacts were corrected via a template based average artifact subtraction method (Allen et al. 1998, 2000) implemented in Brain Vision Analyzer 2.0 (Brain Products, Germany). The gradient artifacts were corrected by constructing an average artifact template over 41 consecutive volumes in a sliding-window fashion and then subtracting this template from the raw EEG data for each volume. For the BCG artifacts, ECG R-waves were first detected, and 21 consecutive ECG segments defined around the R-waves were averaged to produce a BCG artifact template. This template was then subtracted from the EEG data to correct for BCG contamination.

After removing the MRI artifacts, the preprocessing and data analysis procedures for UF and UCD EEG datasets were the same, both using EEGLAB. EEG data were down sampled to 250 Hz and bandpass filtered between 0.1 and 50 Hz. Two types of epoching were carried out. In the first type, the bandpass filtered continuous EEG data were epoched from 500 ms before cue onset to 1500 ms after the cue onset, namely, -500 ms to 1500 ms. In the second type, the bandpass filtered continuous EEG data were epoched from -2500 ms before the cue onset to the cue onset, namely, -2500 ms to 0 ms. The data epoched from -500 ms to 1500 ms were used to examine neural activity immediately preceding the cue onset, the cue-evoked responses, and how the two might related to one another, whereas the data epoched from -2500 ms to 0 ms were used to examine whether neural activity farther ahead of the cue onset could impact the decisions and cue-evoked responses. It is worth noting that since the intertrial intervals (ITIs) varied between 2000 ms to 8000 ms, trials whose cue onset occurred within 3000 ms of the end of the previous trial were not considered for the second type of epoching, resulting in fewer trials. The epoched data were visually inspected and trials with large artifacts were rejected. Independent component analysis was then applied to remove EEG components related to eye blinks, eye movements and other artifacts.

fMRI activation analysis

Univariate BOLD activation analysis was carried out using the general linear model (GLM) method. Seven regressors were used to model the relevant events during the experiment: two for instructional cues (cue-left and cue-right), two for choice-left and choice-right, one for incorrect trials, and two for the stimulus appearing in the left and the right visual field. The cue-evoked activation was obtained for each voxel within each subject by applying t-test to the appropriate regressors. The group-level activation map was obtained by performing a one-sample t-test on each subject's contrast maps with a threshold of $p < 0.05$ correcting for multiple comparisons with false discovery rate (FDR).

fMRI multivariate pattern analysis

Multivariate pattern analysis (MVPA) was performed using the linear support vector machine (SVM) method implemented in the LibSVM package (<https://www.csie.ntu.edu.tw/~cjlin/libsvm/>) (Chang & Lin, 2011) with $c = 1$. The trial-by-trial BOLD estimate following cue onset was first obtained using the beta series regression method (Rissman et al., 2004). This method involved modeling each trial with a separate regressor in the GLM and the beta coefficients represented the estimated single-trial BOLD responses to the cue. The beta coefficient of each voxel in a participant was z-normalized across time to remove any intrinsic trend. For decoding, cue-related data were normalized within each ROI by subtracting the voxel-wise mean and dividing by the voxel-wise standard deviation, which removed the mean activation level and allowed the focus on pattern information. A 10-fold cross-validation procedure was then employed: a SVM classifier was trained on nine folds of the data and tested on the remaining fold. This process was repeated 10 times, each time using a different subset of trials for testing, and the decoding accuracies were then averaged across folds. To improve the robustness of the decoding estimates, the entire 10-fold cross-validation procedure was repeated 100 times with different random groupings of the data. The decoding accuracy for each ROI was computed by averaging across all repetitions. This

decoding accuracy was then averaged across participants to obtain the group level decoding accuracy. Above-chance decoding accuracy was interpreted as evidence for the presence of task-relevant information in the ROI.

EEG multivariate pattern analysis

One of the main foci of this study was on whether multi-electrode patterns of alpha power in the time period prior to cue onset predicted the postcue decision about where to attend, and what the time course of those predictive patterns might be. For the EEG data epoched from -500 ms to 1500 ms, with 0 ms denoting cue onset, trial-by-trial alpha power (8-12 Hz) were calculated over -500 ms to 0 ms interval using the Fast Fourier transformation (FFT). The power of other frequencies between 5 Hz and 25 Hz was also calculated over -500 ms to 0 ms interval. For the EEG data epoched from -2500 ms to 0 ms, we computed the alpha power as a time series from -2500 ms to 0 ms using a moving window approach, where the window duration was 500 ms and the step size was 20 ms. The time of the window was labeled by the time of the rightmost point (e.g., the time of the window -2500 ms to 2000 ms was labeled as 2000 ms). The MVPA on the EEG data was also performed using linear support vector machine (SVM) method implemented in the LibSVM package (<https://www.csie.ntu.edu.tw/~cjlin/libsvm/>) (Chang & Lin, 2011) with $c = 1$. The pattern of alpha power across electrodes was used as the input feature to predict the attended spatial location (left vs. right) after the cue. The classification accuracy for each participant was calculated using a 10-fold cross validation technique. In this technique, 90% of the labeled data (i.e., attend-left and attend-right; choose-left and choose-right) was randomly chosen and used for training a classifier to generate a predictive model. The remaining 10% of the data was used to test the model by comparing the actual labels against the predicted labels. This process was repeated 100 times and the prediction accuracy from each 10-fold partition was averaged to yield the final decoding accuracy. For the EEG data epoched from -500 ms to 1500 ms, this analysis produced a single decoding accuracy, which informed whether precue alpha power pattern in (-500 ms to 0 ms) can predict the postcue direction of attention. For the EEG data epoched from -2500 ms to 0 ms, this analysis produced a time series of decoding accuracy, which determined at which time point prior to cue onset, the pattern of alpha activity began to predict the postcue direction of attention.

Relating precue EEG activity with postcue fMRI activity

To examine the relation between precue alpha power patterns and cue-evoked fMRI activity, we divided the participants into two groups via a median split in terms of precue alpha decoding accuracy: *low* precue alpha decoding accuracy group and *high* precue alpha decoding group. We then compared cue-evoked BOLD activation and BOLD decoding accuracy in the frontoparietal decision network between the two groups, including ROIs in the dACC, aPFC, DLPFC, IPL, and AI. Furthermore, we utilized a metric called *neural efficiency* combining BOLD activation and decoding accuracy to quantify postcue fMRI activity, which is defined as:

$$\text{neural efficiency} = \frac{\text{choice cue decoding accuracy} - \text{instructional cue decoding accuracy}}{\text{choice cue BOLD activation} - \text{instructional cue BOLD activation}}.$$

In this definition, univariate BOLD activation in the denominator is used to reflect the overall metabolic activity underlying the decision about where to attend, whereas the decoding accuracy in the numerator is used to indicate the strength of the decision about where to attend. Larger numerator coupled with smaller denominators yield higher neural efficiency. For statistical analysis, we conducted bootstrap resampling on both the BOLD signal differences and the decoding accuracy differences using 10,000 iterations, drawing, with replacement, samples equal in size to the original dataset and computing the mean for each resample. This yielded a bootstrap distribution consisting of 10,000 sample means. It is expected that for the choice trials, when compared to the instructional trials, the participants who are more efficient decision-makers will exhibit clearer frontoparietal brain patterns corresponding to the decision, while consuming less energy in doing so, and the precue EEG alpha activity pattern should predict postcue neural efficiency. It is worth noting that whereas the notion of neural efficiency is not new (Dunst et al., 2014; Haier et al., 1988), the definition above, however, has not been attempted in the past.

Combining the two datasets via meta-analysis

The UF dataset and the UCD dataset were separately analyzed, and the results were examined for consistency and reproducibility. In cases where discrepancies arose in the comparisons, a meta-analysis combining the two datasets was carried out via the Liptak-Stouffer Z-score meta-analysis method (Lipták, 1958). This method has been used to combine results from multiple datasets to enhance statistical power and rigor (Cheng et al., 2015; Huang & Ding, 2016; Liu et al., 2017). In this method, the following procedure was used to obtain the meta-analysis p values for the statistical tests. First, the p value of each dataset was transformed into Z-score according to the formula: $Z = \Phi^{-1}(1-p)$, where Φ denotes the standard normal cumulative distribution function. Second, the Liptak-Stouffer Z-score of the meta-analysis level was calculated according to the formula (Lipták, 1958):

$$Z = \frac{\sum_{i=1}^k (w_i Z_i)}{\sqrt{\sum_{i=1}^k (w_i)^2}}$$

where Z is the meta-analysis Z-score of the two different datasets (here, $k=2$), i refers to the i th dataset, $w_i = \sqrt{N_i}$ is the weight of the i -th dataset, and N_i is the number of participants in i th dataset. Finally, the p values of the meta-analysis were obtained from the Liptak-Stouffer Z-scores.

Results

Behavioral analysis

UF dataset: See Table 1. For cue-left and cue-right trials, the reaction times (RTs) to valid targets were 918.56 ± 24.49 ms and 911.81 ± 23.28 ms and the target discrimination accuracies were $85.72 \pm 2.14\%$ and $85.80 \pm 1.24\%$, respectively. There were no statistically significant differences between cue-left and cue-right conditions in either RT ($p = 0.67$) or accuracy ($p = 0.97$). For choose-left and choose-right trials, RTs to valid targets were 942.27 ± 47.75 ms and 938.25 ± 29.04 ms, and accuracies were $88.41 \pm 1.88\%$ and $90.78 \pm 1.28\%$, respectively. Statistical comparisons revealed no significant differences were found between conditions in either RT ($p = 0.93$) or accuracy ($p = 0.25$).

UCD dataset: See Table 1. For cue-left and cue-right trials, RTs to valid targets were 1027.02 ± 55.60 ms and 1041.87 ± 54.95 ms and accuracies were $82.45 \pm 2.30\%$ and $81.97 \pm 2.10\%$, respectively. No significant differences were observed between the two attention conditions for either RT ($p = 0.50$) or accuracy ($p = 0.67$). For choose-left and choose-right trials, RTs were 1034.42 ± 48.06 ms and 1043.43 ± 45.84 ms and accuracies were $84.07 \pm 1.98\%$ and $82.60 \pm 2.14\%$, respectively. Statistical comparisons revealed no significant differences in RT ($p = 0.72$) or accuracy ($p = 0.34$).

Univariate analysis of cue-evoked BOLD activation

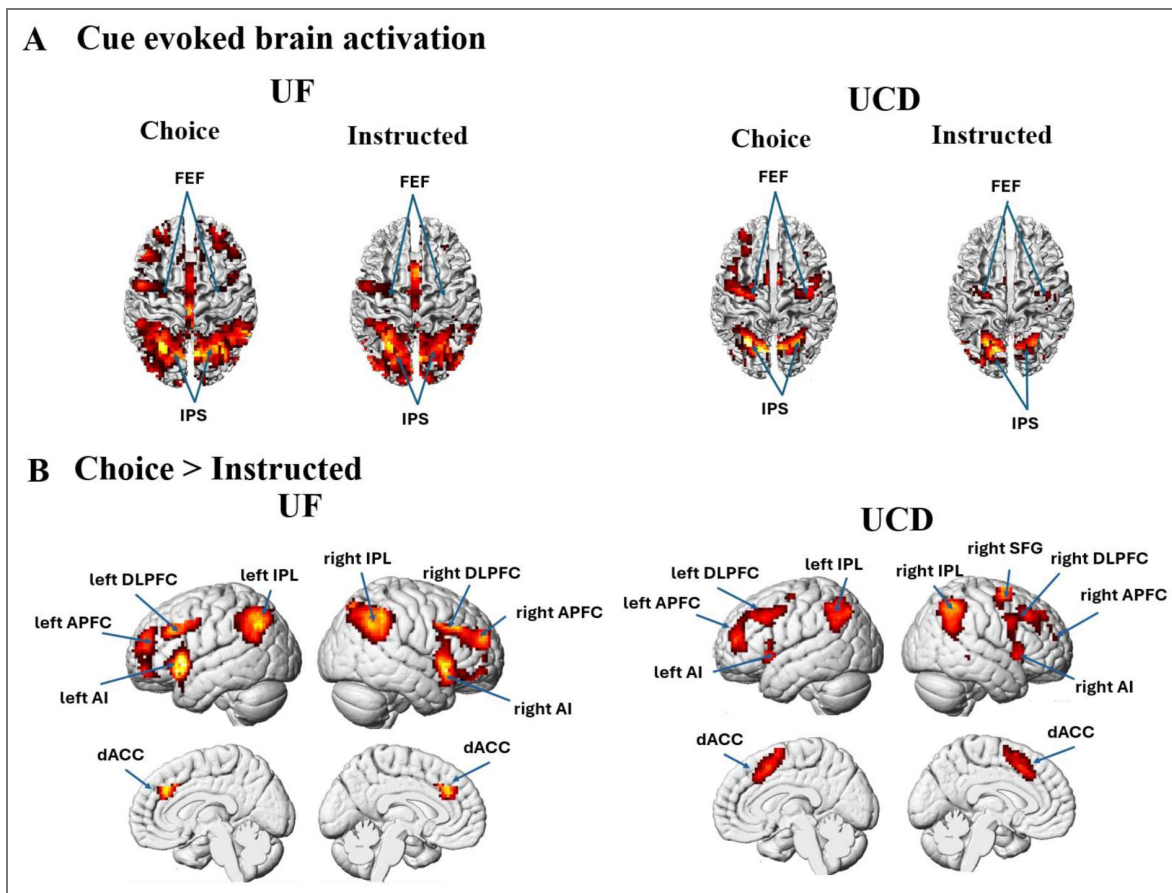
Both the instructional cues and the choice cues evoked a distributed network of regions in the frontoparietal cortex (Figure 2A). In particular, the dorsal attention network (DAN), comprising the intraparietal cortex/superior parietal lobule (IPS/SPL) and the frontal eye field (FEF), was activated by both types of cues. To identify the brain networks selectively engaged during willed attention control, we contrasted the choice cue-evoked BOLD activations with the instructional cue-evoked BOLD activations. This is shown in Figure 2B, where willed attention control involves a network comprising the bilateral anterior insula (AI), bilateral anterior prefrontal cortex (APFC), bilateral dorsal lateral prefrontal cortex (DLPFC), dorsal anterior cingulate cortex (dACC), and bilateral inferior parietal lobule (IPL); the results were consistent across the two datasets. These brain regions, summarized in Table 2, will be used as ROIs for further analysis below. In addition, we note that the dorsal attention network does not appear in the choice>instructed contrast maps, indicating that it is similarly active irrespective of whether the attention is deployed according to external (cued) instructions or internal (willed) decisions. See (Rajan et al., 2019) and (Bengson et al., 2015) for similar analysis on these datasets.

Table 1. Behavioral results for UF and UCD datasets.

Dataset	Condition	Reaction time (ms)	Accuracy (%)	p (RT)	p (Accuracy)
UF	Cue-Left	918.56 ± 24.49	85.72 ± 2.14%	0.67	0.97
	Cue-Right	911.81 ± 23.28	85.80 ± 1.24%		
	Choose-Left	942.27 ± 47.75	88.41 ± 1.88	0.93	0.25
	Choose-Right	938.25 ± 29.04	90.78 ± 1.28		
UCD	Cue-Left	1027.02 ± 55.60	82.45 ± 2.30	0.50	0.67
	Cue-Right	1041.87 ± 54.95	81.97 ± 2.10		
	Choose-Left	1034.42 ± 48.06	84.07 ± 1.98	0.72	0.34
	Choose-Right	1043.43 ± 45.84	82.60 ± 2.14		

Figure 2. Univariate BOLD activation analysis.

(A) The DAN was activated by both the instructional cues and the choice cue in both datasets. (B) Choice cue, however, additionally activated a frontoparietal network consisting of AI, APFC, DLPFC, dACC, and IPL in both datasets. (AI: anterior insula; APFC: anterior prefrontal cortex; DLPFC: dorsal lateral prefrontal cortex; dACC: dorsal anterior cingulate cortex; IPL: inferior parietal lobule; SFG: superior frontal gyrus).



UF					UCD				
ROI	MNI			PEAK-T	ROI	MNI			PEAK-T
	X	Y	Z			X	Y	Z	
dACC	-6	25	36	16.39	dACC	-6	12	45	8.75
IAI	-54	18	3	18.47	IAI	-42	12	-3	10.41
IAPFC	-33	54	18	18.59	IAPFC	-33	51	15	15.17
IDLPCF	-42	27	39	18.88	IDLPCF	-42	15	42	10.39
IIPL	-54	-63	42	15.88	IIPL	-42	-54	42	10.11
rAI	45	18	-6	18.43	rAI	39	18	3	7.89
rAPFC	30	57	24	20.55	rAPFC	33	57	18	6.88
rDLPFC	39	24	33	13.52	rDLPFC	39	24	42	11.13
rIPL	45	-42	42	9.77	rIPL	45	-48	45	11.4

Table 2. The MNI coordinates of the frontoparietal regions preferentially activated consistently by the choice cue across both datasets.

These regions are chosen as regions of interest (ROIs) in the sequel.

Multivariate analysis of cue-evoked BOLD activation

To test whether neural activity patterns in the ROIs differentiated the two attention conditions, MVPA was applied to each ROI to decode attend-left versus attend-right for instructional trials and choice trials separately; see [Figures 3A](#) and [3B](#). For both datasets, decoding accuracy for the instructed trials was not significantly different from chance level (50%) for all the ROIs. For the choice trials, decoding accuracy was significantly above chance level only for a small number of ROIs in the individual datasets (1 for UF dataset) and 3 for UCD dataset). To increase statistical power, we combined the data from the UF dataset and the UCD dataset via meta-analysis, and the result is shown in [Figure 3C](#). For the choice (willed) trials, decoding accuracy between attend-left and attend-right conditions was significantly above chance in all the ROIs, but for the instructed trials, it remained at chance level in all the ROIs. These results demonstrate that the network of frontal and parietal brain regions preferentially activated during willed attention is involved in deciding (choosing) the direction of attention (left vs. right). In contrast, during instructed attention, the same ROIs were not significantly engaged in attentional control. We henceforth refer to the frontoparietal regions preferentially activated by the choice cue as the frontoparietal decision network.

Precue alpha power predicts the decision about where to attend

For both the UF and UCD datasets, precue alpha power in the interval from -500 ms to 0 ms was extracted from each electrode and subjected to MVPA analysis to examine whether it predicted the postcue direction of attention ([Figure 4A](#)). In the UF dataset, decoding accuracy based on precue alpha power was 55.74% for the choice condition ($p = 0.04$), significantly above chance level. In contrast, decoding accuracy for the instructed condition was 49.57%, which did not exceed chance ($p = 0.67$). Similarly, in the UCD dataset, decoding accuracy was 57.29% for the choice condition ($p < 0.0001$), again significantly above chance, and 49.22% for the instructed condition ($p = 0.46$), which was not above chance. Together, these highly consistent results across two independent datasets demonstrate that multichannel patterns of EEG alpha power in the -500 to 0 ms interval prior to the onset of the choice cue predicted the direction of attention during willed attention, whereas, as expected, alpha patterns preceding instructional cues did not. These findings from MVPA analysis support and further substantiate the findings of [Bengson et al. \(2014\)](#).

To investigate whether the -500 ms to 0 ms alpha power pattern that predicted decisions about where to attend following the choice cue might have begun yet earlier in time, we performed a moving-window decoding analysis over the time period of -2500 ms to 0 ms where the duration of the moving window was 500 ms and the step size was 20 ms; the time of the window was labeled by the time of the rightmost point (e.g., the time label for the window -2500 to 2000 ms was “2000 ms”). [Figure 4B](#) shows the results. Similar patterns were seen for both the UF and UCD datasets. Combining the two datasets, we found that from -2000 ms to -1200 ms, the decoding accuracy hovered around 50%. Starting at around -1200 ms, the decoding accuracy began to rise and became above chance level around -650 ms prior to the onset of the cue, supporting the idea that the decision about where to attend was made spontaneously upon reception of the unpredictable choice cue, influenced only by the pattern of alpha power in the few hundred milliseconds immediately before the decision was required.

Relation between precue alpha and postcue frontoparietal activity

To investigate the relation between precue alpha power pattern and postcue frontoparietal brain activity during willed attention, we divided the subjects into two groups (median split)—a high precue alpha decoding accuracy group and a low precue alpha decoding accuracy group. We then computed the univariate BOLD activations and multivariate decoding accuracies for each alpha power decoding accuracy group. For conciseness, in this analysis, we combined all the ROIs in [Table 2](#) into a single frontoparietal decision ROI. [Figure 5A](#) shows the difference in BOLD activation between the two alpha power decoding-defined groups. For both the UF and UCD datasets, the subjects with high precue alpha decoding accuracy showed lower BOLD activation in the frontoparietal decision network. The difference was statistically significant in the combined

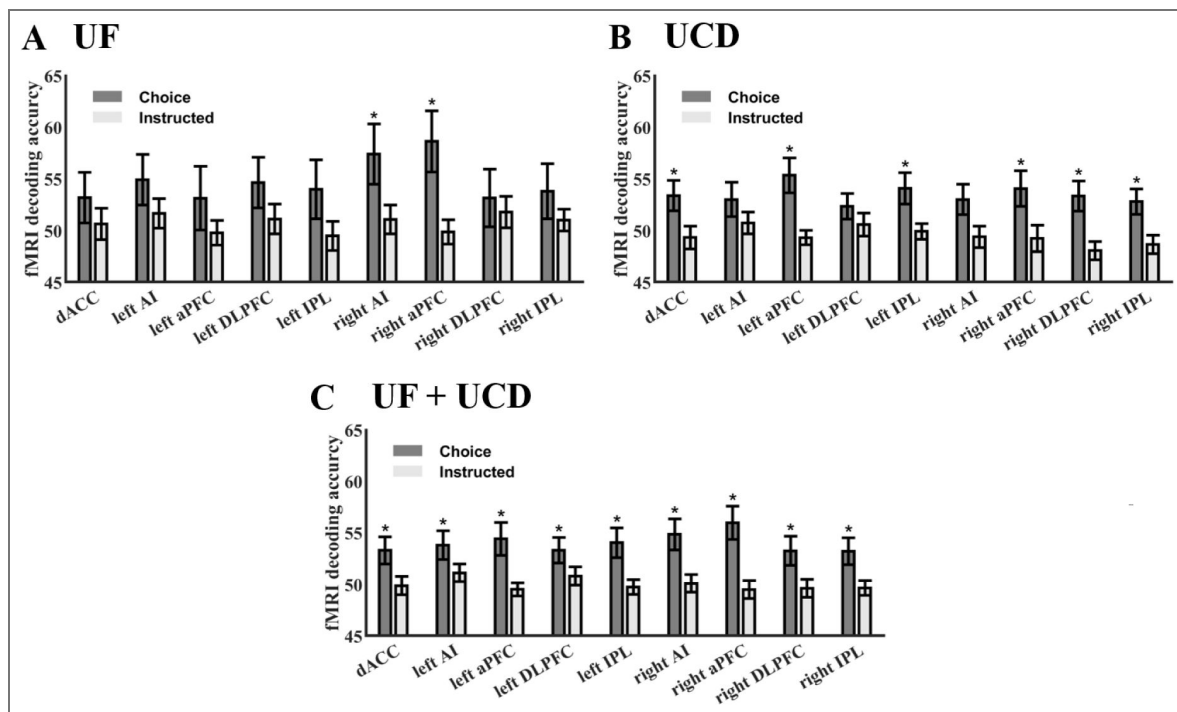


Figure 3. Decoding accuracy between attend-left and attend-right for instructed (cued) and choice (willed) trials in frontoparietal ROIs during the cue-to-target period.

(A) UF dataset. (B) UCD dataset. (C) Combining UF and UCD via meta-analysis, it was observed that in all 7 ROIs, decisions about where to attend could be decoded only in choice trials but not in instructed trials. *: $p \leq 0.05$.

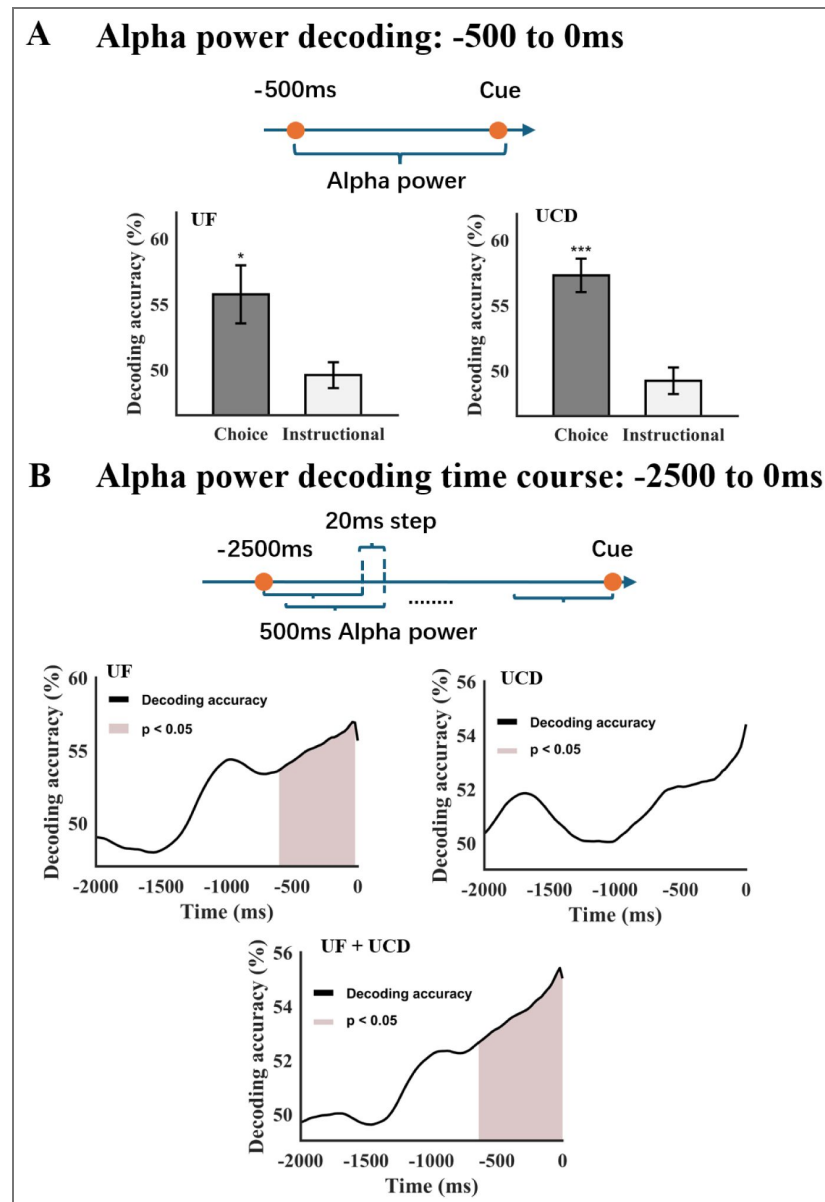


Figure 4. Precue alpha power patterns and postcue direction of attention.

(A) Alpha power decoding accuracy (-500 to 0 ms) for UF and UCD datasets. For both datasets, the postcue direction of postcue attention can be decoded for choice trials, but not for instructional trials. (B) Precue decoding accuracy time course suggests that only alpha activity immediately preceding the cue onset predicted the post cue direction of attention. *: $p < 0.05$, ***: $p < 0.001$.

UF/UCD dataset using meta-analysis. Figure 5B shows the difference in decoding accuracy between the two groups. In contrast to the pattern from the univariate BOLD activation results, the decoding accuracy in the frontoparietal decision network evoked by the choice cue was higher for participants with higher precue alpha decoding accuracy.

Based on the results in Figures 5A and 5B, we computed the neural efficiency of decision-making in the frontoparietal decision network (Figure 5C), defined as the difference between the decoding accuracy for the choice trials and that for the instructed trials divided by the difference between the univariate BOLD activation for the choice trials and that for the instructed trials (see Methods). This definition is motivated by considering the decoding accuracy as index of the strength of the decision about where to attend and the univariate BOLD activation as index of the energetic cost of the decision; stronger decisions being reached at smaller energetic costs is considered more neurally efficient. We applied bootstrap resampling to each of the two groups of subjects (high vs low precue alpha decoding accuracy) to obtain a distribution of 10000 neural efficiencies. For the UF dataset, the mean neural efficiency=12.18 for the high precue decoding accuracy group and the mean neural efficiency=3.89 for the low precue decoding accuracy group; for the UCD dataset, the mean neural efficiency=4.51 vs -2.02 for the high vs low precue decoding accuracy groups. The high vs low means were significantly different, as the two distributions differed significantly according to the Kolmogorov–Smirnov test ($p < 0.0001$), and the result was consistent across both datasets. This precue-postcue relationship analysis suggests that subjects whose precue alpha power pattern better predicts the decision about where to attend are more efficient decision-makers.

Discussion

In this study, we analyzed fMRI and EEG data from two independent willed attention datasets, acquired using the same paradigm, to address the following questions. What is the neural network underlying willed attention control? What is the functional role of this willed attention control network? How does the neural activity prior to willed decisions about where to attend influence brain activations related to willed attention control? We found that (1) relative to instructed attention, during willed attention control, there were higher BOLD activations in regions of the frontal and parietal cortex, including in the dorsal anterior cingulate (dACC), bilateral anterior insular (AI), bilateral anterior prefrontal cortex (APFC), bilateral dorsolateral prefrontal cortex (DLPFC), and bilateral inferior parietal lobule (IPL), (2) choices to attend left versus attend right could be decoded from the neural activity patterns in these frontoparietal regions, but this was not true for instructions to attend left versus attend right, (3) multichannel patterns of EEG alpha power immediately prior to the onset of the choice cue predicted subsequent decisions about where to attend, but this was not true for instructed attention, and (4) subjects with higher precue alpha decoding accuracy are more efficient in making decisions about where to attend.

Role of the frontoparietal decision network

Willed attention is volitional behavior. As such, some parallels can be drawn with volitional movements (actions), particularly in the context of freely choosing among multiple motor alternatives. Studies of volitional movements have consistently revealed that the anterior cingulate cortex (ACC) serves as a critical component of the volitional control network, playing essential roles in voluntary response selection, conflict monitoring, and evaluation of outcomes of self-generated decisions (Rushworth et al., 2011; Walton et al., 2004). Similarly, the dorsolateral prefrontal cortex (DLPFC) has been identified as crucial for choosing between alternative predefined movements, particularly in tasks requiring selection among multiple alternatives (Frith et al., 1991; Jahanshahi et al., 1995). Remarkably, in willed attention, a cognitive act, a similar frontoparietal network is activated by the choice cue processing (Bengson et al., 2014; Liu et al., 2017; Rajan et al., 2019). Although earlier work employing univariate analysis has reported similar findings (Greenberg et al., 2010; Hopfinger et al., 2010; Taylor et al., 2008), our contribution employing multivariate pattern analysis (MVPA) extends the prior work by directly demonstrating that the frontoparietal regions activated by the choice cue encode

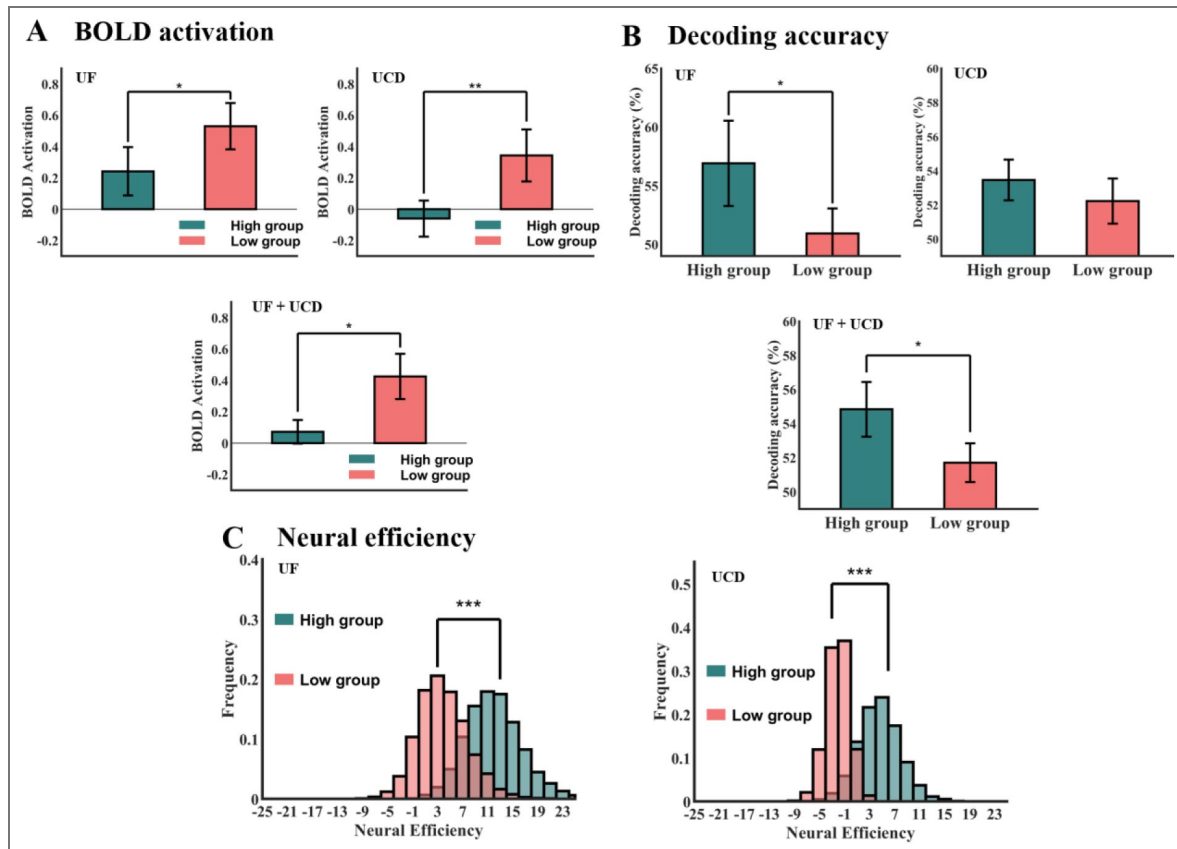


Figure 5. EEG informed fMRI analysis.

Subjects were divided into two groups (median split) based on their precue alpha decoding accuracy being high or low. (A) The BOLD activation in the frontoparietal decision network for the two datasets (top) and meta-analysis combining the two datasets (bottom). (B) The decoding accuracy in the frontoparietal decision network for the two datasets (top) and meta-analysis combining the two datasets (bottom). (C) The bootstrap distributions of the neural efficiency for the two groups for the two datasets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

decision-relevant information, even in the absence of overt motor output. This led us to refer to these frontoparietal regions collectively as the frontoparietal decision network. One might be tempted to link the findings to the premotor theory of attention and view the differential activation patterns as reflecting potential movement plans. This, however, is unlikely, as the motor response requirement is the same for both instructed and willed attention and we observed no differential patterns between attend left and attend right in the instructed (cued) trials.

Network neuroscience has suggested that the frontoparietal decision network can be further divided into two complementary networks: the central executive network (CEN) and the salience network (SN). The CEN, anchored in the dorsolateral prefrontal cortex (DLPFC) and inferior parietal lobule (IPL), is central to deliberative processes such as weighing multiple alternatives, integrating task-relevant information, and executing context-appropriate choices (Niendam et al., 2012 [↗](#); Walsh et al., 2011 [↗](#)). When faced with multiple movement options, the CEN employs competitive accumulation mechanisms where each potential choice has a corresponding neural accumulator that simultaneously accumulates evidence until one reaches the decision threshold (Cisek & Kalaska, 2010 [↗](#)). The SN, comprising the anterior insula (AI) and dorsal anterior cingulate cortex (dACC), supports the identification of behaviorally salient cues and initiates cognitive shifts needed to implement decisions (Menon & Uddin, 2010 [↗](#); Seeley et al., 2007 [↗](#)). In multi-choice volitional movements, the SN coordinates competitive inhibition between alternative motor programs, with increased lateral inhibition mechanisms required to manage competition among multiple options rather than simple binary choices (Cisek, 2007 [↗](#)). Our results contribute to the growing literature by demonstrating that in willed attention, where no motor planning is involved, these two networks form an integrated decision-making architecture that mirrors multi-choice motor control. The anterior prefrontal cortex (apFC), while it is not typically associated with the two networks, being situated at the apex of the prefrontal hierarchy, it is thought to maintain higher-order abstract goals to top-down bias decision-making processes (Badre & D'Esposito, 2009 [↗](#)).

Influence of precue brain state on postcue decision-making

Decision-making is under the influence of both external and internal factors. In willed attention, because the same choice cue prompts the two possible decisions (attend-left or attend-right), the external environment does not bias the choice being made. The internal environment defined by the momentary state of the brain, however, fluctuates from trial to trial. It is reasonable to hypothesize that such fluctuations prior to the onset of the choice cue might contribute to bias the decisions prompted by the choice cue. In a perceptual guessing task, in which the participants guessed the object category of the noisy input (Bode et al., 2012 [↗](#)), it was shown that EEG activity immediately preceding the onset of pure noise patterns predicted the participant's guessed object category, demonstrating the biasing influence of the brain state on perceptual decision-making when the stimulus input contains no discriminating information.

It is known that alpha oscillations is an important index of ongoing brain state (Jensen & Mazaheri, 2010 [↗](#); Klimesch et al., 2007 [↗](#)). In the context of decision-making, alpha power in specific brain regions has been related to decision outcomes in paradigms in which the stimulus contains information favoring one decision over another (Jensen & Mazaheri, 2010 [↗](#); Klimesch et al., 2007 [↗](#); Sadaghiani & Kleinschmidt, 2016 [↗](#)). Our approach differs from previous work in several aspects. First, our multivariate approach captures distributed spatial patterns across multiple electrodes simultaneously (Grootswagers et al., 2017 [↗](#); King & Dehaene, 2014 [↗](#)), potentially revealing decision-relevant information that could be missed by examining single channels in isolation. Second, our paradigm represents a significant departure from conventional decision-making research (Britten et al., 1992 [↗](#); Gold & Shadlen, 2007 [↗](#); Newsome & Pare, 1988 [↗](#); Ratcliff & McKoon, 2008 [↗](#)) by having the same choice cue elicit two different decisions (choices), eliminating the influence of stimulus-driven evidence accumulation and placing more emphasis on the role of internal brain state fluctuations. Our findings demonstrate that multivariate alpha patterns can bias upcoming choices even in the complete absence of external evidence. Moreover, the temporal dynamics of alpha-based predictability helps to confirm the spontaneity of the

decision-making prompted by the choice cue, and thus rules out the possibility that decisions about where to attend were formed well in advance of the appearance of the choice cue. Whether the choices made were the result of selection history—a carryover from prior decisions (Anderson & Britton, 2019) —was ruled out in prior analysis by Bengson et al. (2014) showing that no first or second order sequence effects explained the choices made during willed attention.

Linking precue activity to postcue response

In the foregoing, we discussed postcue frontoparietal encoding of decision-related variables and precue brain state biasing of postcue decision-making. How might the two relate to one another? We addressed this question by showing that individuals whose precue brain states more effectively predicted their postcue decisions demonstrated enhanced encoding of decision variables within the choice-activated frontoparietal decision network (i.e., higher decoding accuracy). To understand the possible neural bases of this effect, let us consider the role of the dACC, which is known to play an important role in monitoring the cognitive environment, detecting conflicts, and directing the central executive network to exert top-down modulation of sensorimotor processing (M. M. Botvinick et al., 2001; Carter et al., 1998; Shackman et al., 2011). Whereas early work emphasized the dACC's role in the monitoring of the external environment (Bush et al., 2000; Devinsky et al., 1995), later studies have begun to investigate the dACC's role in monitoring the internal environment as well (Alexander & Brown, 2011; Heilbronner & Hayden, 2016; Shenhav et al., 2013). In particular, evidence suggests that dACC, as part of the broader frontoparietal decision network, monitors ongoing neural oscillatory patterns, including alpha activity (Jensen & Mazaheri, 2010; Klimesch, 2012; Sauseng et al., 2011). In addition, deciding between two equal alternatives represents a conflict situation, and the role of the dACC in conflict resolution is well-established (M. Botvinick et al., 1999; Kerns et al., 2004; Sheth et al., 2012). These considerations make it plausible that during choice trials, dACC monitors the internal brain state, indexed by the pattern of alpha oscillations, and resolves the conflict of choosing where to attend among equal alternatives under the influence of such monitoring. Importantly, our findings further extend the role traditionally assigned to dACC to the entire frontoparietal decision network (Cole & Schneider, 2007; Dosenbach et al., 2007; Vincent et al., 2008), consistent with the reports showing that frontoparietal areas, including dLPFC and posterior parietal cortex, contribute to monitoring uncertainty and implementing control adjustments based on assessment of internal state (Brass et al., 2005; Corbetta & Shulman, 2002; Hampshire et al., 2010). In addition to enhanced representation of the decision variables, participants whose precue alpha better predicted the postcue decision had lower BOLD activity to the choice cue in the frontoparietal decision network, suggesting better postcue decision at lower energy costs (Attwell & Iadecola, 2002; Neubauer & Fink, 2009). Introducing a new variable called neural efficiency to quantify this, we found that participants who can better incorporate the precue brain state into postcue decision-making are more neurally efficient decision-makers.

A model of willed attention control

Both instructional and choice cues activated the dorsal attention network. When choice cue-evoked BOLD signals were contrasted with those evoked by instructional cues, the dorsal attention network did not appear in the resulting brain map, suggesting that it plays a similar role in both willed and instructed attention, and thus gets cancelled out. In addition, in a recent study (Meyyappan et al., 2025), we showed that the direction of attention during the cue-target interval could be decoded in the dorsal attention network (DAN) as well as in the entire retinotopic visual cortical hierarchy, irrespective of whether the covert attentional state was generated by external instructions or internal decisions. These results, along with the findings of the present work, suggest that willed attention control is achieved through the collaborative effort of the frontoparietal decision network and the dorsal attention network. A possible model is shown in Figure 6: (1) following the choice cue, the decision about where to attend is formed in the frontoparietal decision network, which is under the biasing influence of the ongoing brain state,

(2) this decision is transmitted to the DAN to initiate attention control, (3) DAN issues top-down biasing signals to the retinotopic visual cortex in anticipation of the visual stimulus, and (4) the neural mechanism of (3) is shared between willed and instructed attention.

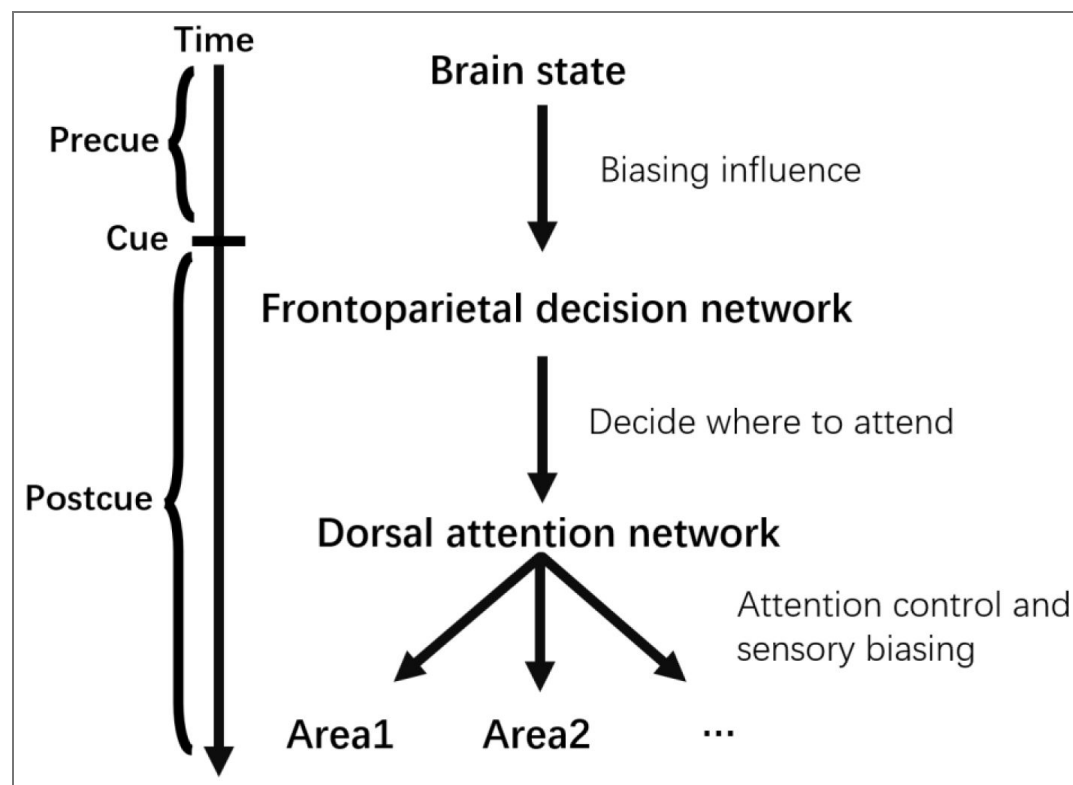


Figure 6. The model of willed attention control. The frontoparietal decision network, under the biasing influence of the ongoing precue brain state, makes the decision about where to attend upon reception of the choice cue and sends the decision to the dorsal attention network. The dorsal attention network executes attention control and issues top-down signals to bias visual areas in anticipation of the upcoming visual processing. Attention selection of sensory input occurs as the result of top-down biasing. Sensory biasing and stimulus selection mechanisms are shared between willed and instructed attention.

Data availability

The data availability statement will be uploaded after the first submission.

Acknowledgements

This work was supported by NIH grant MH117991 and NSF grant BCS2318984.

Additional information

Funding

Funder	Grant reference number	Author
HHS National Institutes of Health (NIH)	MH117991	Changhao Xiong
National Science Foundation (NSF)	BCS2318984	Sungkean Kim

Author ORCID iDs

Mingzhou Ding: <https://orcid.org/0000-0002-1024-3503>

References

1. **Alexander W. H.**, Brown J. W (2011) Medial prefrontal cortex as an action-outcome predictor. *Nature Neuroscience* **14**:1338-1344 <https://doi.org/10.1038/nn.2921>
2. **Anderson B. A.**, Britton M. K (2019) Selection history in context: Evidence for the role of reinforcement learning in biasing attention. *Attention, Perception, & Psychophysics* **81**:2666-2672 <https://doi.org/10.3758/s13414-019-01817-1>
3. **Arrington C. M.**, Carr T. H., Mayer A. R., Rao S. M (2000) Neural Mechanisms of Visual Attention: Object-Based Selection of a Region in Space. *Journal of Cognitive Neuroscience* **12**:106-117 <https://doi.org/10.1162/089892900563975>
4. **Attwell D.**, Iadecola C (2002) The neural basis of functional brain imaging signals. *Trends in Neurosciences* **25**:621-625 [https://doi.org/10.1016/S0166-2236\(02\)02264-6](https://doi.org/10.1016/S0166-2236(02)02264-6)
5. **Badre D.**, D'Esposito M (2009) Is the rostro-caudal axis of the frontal lobe hierarchical?. *Nature Reviews Neuroscience* **10**:659-669 <https://doi.org/10.1038/nrn2667>
6. **Bengson J. J.**, Kelley A., Mangun G. R. (2015) The neural correlates of volitional attention: A combined fMRI and ERP study. *Human Brain Mapping* **36**:2443-2454 <https://doi.org/10.1002/hbm.22783>
7. **Bengson J. J.**, Kelley T. A., Zhang X., Wang J.-L., Mangun G. R (2014) Spontaneous Neural Fluctuations Predict Decisions to Attend. *Journal of Cognitive Neuroscience* **26**:2578-2584 https://doi.org/10.1162/jocn_a_00650
8. **Bode S.**, Sewell D. K., Lilburn S., Forte J. D., Smith P. L., Stahl J (2012) Predicting Perceptual Decision Biases from Early Brain Activity. *The Journal of Neuroscience* **32**:12488-12498 <https://doi.org/10.1523/JNEUROSCI.1708-12.2012>
9. **Botvinick M. M.**, Braver T. S., Barch D. M., Carter C. S., Cohen J. D (2001) Conflict monitoring and cognitive control. *Psychological Review* **108**:624-652 <https://doi.org/10.1037/0033-295X.108.3.624>
10. **Botvinick M.**, Nystrom L. E., Fissell K., Carter C. S., Cohen J. D (1999) Conflict monitoring versus selection-for-action in anterior cingulate cortex. *Nature* **402**:179-181 <https://doi.org/10.1038/46035>
11. **Brass M.**, Derrfuss J., Von Cramon D. Y. (2005) The inhibition of imitative and overlearned responses: A functional double dissociation. *Neuropsychologia* **43**:89-98 <https://doi.org/10.1016/j.neuropsychologia.2004.06.018>
12. **Britten K.**, Shadlen M., Newsome W., Movshon J (1992) The analysis of visual motion: A comparison of neuronal and psychophysical performance. *The Journal of Neuroscience* **12**:4745-4765 <https://doi.org/10.1523/JNEUROSCI.12-12-04745.1992>
13. **Bush G.**, Luu P., Posner M. I (2000) Cognitive and emotional influences in anterior cingulate cortex. *Trends in Cognitive Sciences* **4**:215-222 [https://doi.org/10.1016/S1364-6613\(00\)01483-2](https://doi.org/10.1016/S1364-6613(00)01483-2)
14. **Carter C. S.**, Braver T. S., Barch D. M., Botvinick M. M., Noll D., Cohen J. D (1998) Anterior Cingulate Cortex, Error Detection, and the Online Monitoring of Performance. *Science* **280**:747-749 <https://doi.org/10.1126/science.280.5364.747>
15. **Chang C.-C.**, Lin C.-J (2011) LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology* **2**:1-27 <https://doi.org/10.1145/1961189.1961199>
16. **Cheng W.**, Palaniyappan L., Li M., Kendrick K. M., Zhang J., Luo Q., Liu Z., Yu R., Deng W., Wang Q., et al. (2015) Voxel-based, brain-wide association study of aberrant functional connectivity in schizophrenia implicates thalamocortical circuitry. *Npj Schizophrenia* **1**:15016 <https://doi.org/10.1038/npjischz.2015.16>
17. **Cisek P** (2007) Cortical mechanisms of action selection: The affordance competition hypothesis. *Philosophical Transactions of the Royal Society B: Biological Sciences* **362**:1585-1599 <https://doi.org/10.1098/rstb.2007.2054>
18. **Cisek P.**, Kalaska J. F (2010) Neural Mechanisms for Interacting with a World Full of Action Choices. *Annual Review of Neuroscience* **33**:269-298 <https://doi.org/10.1146/annurev.neuro.051508.135409>

19. Cole M. W., Schneider W (2007) The cognitive control network: Integrated cortical regions with dissociable functions. *NeuroImage* **37**:343-360 <https://doi.org/10.1016/j.neuroimage.2007.03.071>
20. Corbetta M., Kincade J. M., Ollinger J. M., McAvoy M. P., Shulman G. L (2000) Voluntary orienting is dissociated from target detection in human posterior parietal cortex. *Nature Neuroscience* **3**:292-297 <https://doi.org/10.1038/73009>
21. Corbetta M., Shulman G. L (2002) Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience* **3**:201-215 <https://doi.org/10.1038/nrn755>
22. Devinsky O., Morrell M. J., Vogt B. A (1995) Contributions of anterior cingulate cortex to behaviour. *Brain* **118**:279-306 <https://doi.org/10.1093/brain/118.1.279>
23. Dosenbach N. U. F., Fair D. A., Miezin F. M., Cohen A. L., Wenger K. K., Dosenbach R. A. T., Fox M. D., Snyder A. Z., Vincent J. L., Raichle M. E., et al. (2007) Distinct brain networks for adaptive and stable task control in humans. *Proceedings of the National Academy of Sciences* **104**:11073-11078 <https://doi.org/10.1073/pnas.0704320104>
24. Dunst B., Benedek M., Jauk E., Bergner S., Koschutnig K., Sommer M., Ischebeck A., Spinath B., Arendasy M., Böhner M., et al. (2014) Neural efficiency as a function of task demands. *Intelligence* **42**:22-30 <https://doi.org/10.1016/j.intell.2013.09.005>
25. Fox M. D., Zhang D., Snyder A. Z., Raichle M. E (2009) The Global Signal and Observed Anticorrelated Resting State Brain Networks. *Journal of Neurophysiology* **101**:3270-3283 <https://doi.org/10.1152/jn.90777.2008>
26. Frith C. D., Friston K., Liddle P. F., Frackowiak R. S. J (1991) Willed action and the prefrontal cortex in man: A study with PET. *Proceedings of the Royal Society of London Series B: Biological Sciences* **244**:241-246 <https://doi.org/10.1098/rspb.1991.0077>
27. Gold J. I., Shadlen M. N (2007) The Neural Basis of Decision Making. *Annual Review of Neuroscience* **30**:535-574 <https://doi.org/10.1146/annurev.neuro.29.051605.113038>
28. Greenberg A. S., Esterman M., Wilson D., Serences J. T., Yantis S (2010) Control of Spatial and Feature-Based Attention in Frontoparietal Cortex. *The Journal of Neuroscience* **30**:14330-14339 <https://doi.org/10.1523/JNEUROSCI.4248-09.2010>
29. Grootswagers T., Wardle S. G., Carlson T. A (2017) Decoding Dynamic Brain Patterns from Evoked Responses: A Tutorial on Multivariate Pattern Analysis Applied to Time Series Neuroimaging Data. *Journal of Cognitive Neuroscience* **29**:677-697 https://doi.org/10.1162/jocn_a_01068
30. Haier R. J., Siegel B. V., Nuechterlein K. H., Hazlett E., Wu J. C., Paek J., Browning H. L., Buchsbaum M. S (1988) Cortical glucose metabolic rate correlates of abstract reasoning and attention studied with positron emission tomography. *Intelligence* **12**:199-217 [https://doi.org/10.1016/0160-2896\(88\)90016-5](https://doi.org/10.1016/0160-2896(88)90016-5)
31. Hampshire A., Chamberlain S. R., Monti M. M., Duncan J., Owen A. M (2010) The role of the right inferior frontal gyrus: Inhibition and attentional control. *NeuroImage* **50**:1313-1319 <https://doi.org/10.1016/j.neuroimage.2009.12.109>
32. Heilbronner S. R., Hayden B. Y (2016) Dorsal Anterior Cingulate Cortex: A Bottom-Up View. *Annual Review of Neuroscience* **39**:149-170 <https://doi.org/10.1146/annurev-neuro-070815-013952>
33. Hopf J.-M., Mangun G. R (2000) Shifting visual attention in space: An electrophysiological analysis using high spatial resolution mapping. *Clinical Neurophysiology* **111**:1241-1257 [https://doi.org/10.1016/S1388-2457\(00\)00313-8](https://doi.org/10.1016/S1388-2457(00)00313-8)
34. Hopfinger J. B., Buonocore M. H., Mangun G. R (2000a) The neural mechanisms of top-down attentional control. *Nature Neuroscience* **3**:284-291 <https://doi.org/10.1038/72999>
35. Hopfinger J. B., Buonocore M. H., Mangun G. R (2000b) The neural mechanisms of top-down attentional control. *Nature Neuroscience* **3**:284-291 <https://doi.org/10.1038/72999>
36. Hopfinger J. B., Camblin C. C., Parks E. L (2010) Isolating the internal in endogenous attention. *Psychophysiology* <https://doi.org/10.1111/j.1469-8986.2010.00981.x>

37. Huang H., Ding M (2016) Linking Functional Connectivity and Structural Connectivity Quantitatively: A Comparison of Methods. *Brain Connectivity* **6**:99-108 <https://doi.org/10.1089/brain.2015.0382>
38. Iemi L., Chaumon M., Crouzet S. M., Busch N. A (2017) Spontaneous Neural Oscillations Bias Perception by Modulating Baseline Excitability. *The Journal of Neuroscience* **37**:807-819 <https://doi.org/10.1523/JNEUROSCI.1432-16.2016>
39. Jahanshahi M., Jenkins I. H., Brown R. G., Marsden C. D., Passingham R. E., Brooks D. J (1995) Self-initiated versus externally triggered movements: I. An investigation using measurement of regional cerebral blood flow with PET and movement-related potentials in normal and Parkinson's disease subjects. *Brain* **118**:913-933 <https://doi.org/10.1093/brain/118.4.913>
40. Jensen O., Mazaheri A (2010) Shaping Functional Architecture by Oscillatory Alpha Activity: Gating by Inhibition. *Frontiers in Human Neuroscience* **4** <https://doi.org/10.3389/fnhum.2010.00186>
41. Kerns J. G., Cohen J. D., MacDonald A. W., Cho R. Y., Stenger V. A., Carter C. S (2004) Anterior Cingulate Conflict Monitoring and Adjustments in Control. *Science* **303**:1023-1026 <https://doi.org/10.1126/science.1089910>
42. King J.-R., Dehaene S (2014) Characterizing the dynamics of mental representations: The temporal generalization method. *Trends in Cognitive Sciences* **18**:203-210 <https://doi.org/10.1016/j.tics.2014.01.002>
43. Klimesch W (2012) Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences* **16**:606-617 <https://doi.org/10.1016/j.tics.2012.10.007>
44. Klimesch W., Sauseng P., Hanslmayr S (2007) EEG alpha oscillations: The inhibition-timing hypothesis. *Brain Research Reviews* **53**:63-88 <https://doi.org/10.1016/j.brainresrev.2006.06.003>
45. Limbach K., Corballis P. M (2016) Prestimulus alpha power influences response criterion in a detection task. *Psychophysiology* **53**:1154-1164 <https://doi.org/10.1111/psyp.12666>
46. Lipták T (1958) On the combination of independent tests. *Magyar Tudományos Akadémiai Matematikai Kutató Intézetének Közleményei* **3**:171-197
47. Liu Y., Hong X., Bengson J. J., Kelley T. A., Ding M., Mangun G. R (2017) Deciding where to attend: Large-scale network mechanisms underlying attention and intention revealed by graph-theoretic analysis. *NeuroImage* **157**:45-60 <https://doi.org/10.1016/j.neuroimage.2017.05.048>
48. Menon V., Uddin L. Q (2010) Saliency, switching, attention and control: A network model of insula function. *Brain Structure and Function* **214**:655-667 <https://doi.org/10.1007/s00429-010-0262-0>
49. Meyyappan S., Rajan A., Yang Q., Mangun G. R., Ding M (2025) Decoding Visual Spatial Attention Control. *Eneuro* **12**:ENEURO.0512-24.2025 <https://doi.org/10.1523/ENEURO.0512-24.2025>
50. Neubauer A. C., Fink A (2009) Intelligence and neural efficiency. *Neuroscience & Biobehavioral Reviews* **33**:1004-1023 <https://doi.org/10.1016/j.neubiorev.2009.04.001>
51. Newsome W., Pare E (1988) A selective impairment of motion perception following lesions of the middle temporal visual area (MT). *The Journal of Neuroscience* **8**:2201-2211 <https://doi.org/10.1523/JNEUROSCI.08-06-02201.1988>
52. Niendam T. A., Laird A. R., Ray K. L., Dean Y. M., Glahn D. C., Carter C. S (2012) Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cognitive, Affective, & Behavioral Neuroscience* **12**:241-268 <https://doi.org/10.3758/s13415-011-0083-5>
53. Posner M. I., Snyder C. R., Davidson B. J (1980) Attention and the detection of signals. *Journal of Experimental Psychology: General* **109**:160-174 <https://doi.org/10.1037/0096-3445.109.2.160>
54. Posner Walker, Friedrich F., Rafal R. (1984) Effects of parietal injury on covert orienting of attention. *The Journal of Neuroscience* **4**:1863-1874 <https://doi.org/10.1523/JNEUROSCI.04-07-01863.1984>
55. Rajan A., Siegel S. N., Liu Y., Bengson J., Mangun G. R., Ding M (2019) Theta Oscillations Index Frontal Decision-Making and Mediate Reciprocal Frontal-Parietal Interactions in Willed Attention. *Cerebral Cortex* **29**:2832-2843 <https://doi.org/10.1093/cercor/bhy149>

56. Ratcliff R., McKoon G (2008) The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks. *Neural Computation* **20**:873-922 <https://doi.org/10.1162/neco.2008.12-06-420>
57. Rissman J., Gazzaley A., D'Esposito M (2004) Measuring functional connectivity during distinct stages of a cognitive task. *NeuroImage* **23**:752-763 <https://doi.org/10.1016/j.neuroimage.2004.06.035>
58. Rushworth M. F. S., Noonan M. P., Boorman E. D., Walton M. E., Behrens T. E (2011) Frontal Cortex and Reward-Guided Learning and Decision-Making. *Neuron* **70**:1054-1069 <https://doi.org/10.1016/j.neuron.2011.05.014>
59. Sadaghiani S., Kleinschmidt A (2016) Brain Networks and α -Oscillations: Structural and Functional Foundations of Cognitive Control. *Trends in Cognitive Sciences* **20**:805-817 <https://doi.org/10.1016/j.tics.2016.09.004>
60. Sauseng P., Feldheim J. F., Freunberger R., Hummel F. C (2011) Right Prefrontal TMS Disrupts Interregional Anticipatory EEG Alpha Activity during Shifting of Visuospatial Attention. *Frontiers in Psychology* **2** <https://doi.org/10.3389/fpsyg.2011.00241>
61. Seeley W. W., Menon V., Schatzberg A. F., Keller J., Glover G. H., Kenna H., Reiss A. L., Greicius M. D (2007) Dissociable Intrinsic Connectivity Networks for Salience Processing and Executive Control. *The Journal of Neuroscience* **27**:2349-2356 <https://doi.org/10.1523/JNEUROSCI.5587-06.2007>
62. Shackman A. J., Salomons T. V., Slagter H. A., Fox A. S., Winter J. J., Davidson R. J (2011) The integration of negative affect, pain and cognitive control in the cingulate cortex. *Nature Reviews Neuroscience* **12**:154-167 <https://doi.org/10.1038/nrn2994>
63. Shenhav A., Botvinick M. M., Cohen J. D (2013) The Expected Value of Control: An Integrative Theory of Anterior Cingulate Cortex Function. *Neuron* **79**:217-240 <https://doi.org/10.1016/j.neuron.2013.07.007>
64. Sheth S. A., Mian M. K., Patel S. R., Asaad W. F., Williams Z. M., Dougherty D. D., Bush G., Eskandar E. N (2012) Human dorsal anterior cingulate cortex neurons mediate ongoing behavioural adaptation. *Nature* **488**:218-221 <https://doi.org/10.1038/nature11239>
65. Spence S. A., Frith C. D (1999) Towards a functional anatomy of volition. *Journal of Consciousness Studies* **6**:11-29
66. Taylor P. C. J., Rushworth M. F. S., Nobre A. C (2008) Choosing Where to Attend and the Medial Frontal Cortex: An fMRI Study. *Journal of Neurophysiology* **100**:1397-1406 <https://doi.org/10.1152/jn.90241.2008>
67. Vincent J. L., Kahn I., Snyder A. Z., Raichle M. E., Buckner R. L (2008) Evidence for a Frontoparietal Control System Revealed by Intrinsic Functional Connectivity. *Journal of Neurophysiology* **100**:3328-3342 <https://doi.org/10.1152/jn.90355.2008>
68. Walsh B. J., Buonocore M. H., Carter C. S., Mangun G. R (2011) Integrating Conflict Detection and Attentional Control Mechanisms. *Journal of Cognitive Neuroscience* **23**:2211-2221 <https://doi.org/10.1162/jocn.2010.21595>
69. Walton M. E., Devlin J. T., Rushworth M. F. S (2004) Interactions between decision making and performance monitoring within prefrontal cortex. *Nature Neuroscience* **7**:1259-1265 <https://doi.org/10.1038/nn1339>
70. Woldorff M. G., Hazlett C. J., Fichtenholtz H. M., Weissman D. H., Dale A. M., Song A. W (2004) Functional Parcellation of Attentional Control Regions of the Brain. *Journal of Cognitive Neuroscience* **16**:149-165 <https://doi.org/10.1162/089892904322755638>
71. Worden M. S., Foxe J. J., Wang N., Simpson G. V (2000) Anticipatory Biasing of Visuospatial Attention Indexed by Retinotopically Specific α -Band Electroencephalography Increases over Occipital Cortex. *The Journal of Neuroscience* **20**:RC63-RC63 <https://doi.org/10.1523/JNEUROSCI.20-06-j0002.2000>
72. Yang X., Fiebelkorn I. C., Jensen O., Knight R. T., Kastner S (2024) Differential neural mechanisms underlie cortical gating of visual spatial attention mediated by alpha-band oscillations. *Proceedings of the National Academy of Sciences* **121**:e2313304121 <https://doi.org/10.1073/pnas.2313304121>

Peer reviews

Reviewer #1 (Public review):

Summary:

This study addresses a fundamental question in cognitive neuroscience regarding how the brain transitions from a reactive state of following external instructions to a proactive state of self-directed agency. The authors utilize an ambitious multimodal design by combining the spatial precision of fMRI with the temporal resolution of EEG across two independent datasets from the University of Florida and UC Davis. By applying multivariate pattern analysis, the work demonstrates that while both instructed and willed attention engage the Dorsal Attention Network, willed choices uniquely recruit a frontoparietal decision network including the dACC and anterior insula. Furthermore, the study shows that pre cue alpha oscillations can predict subsequent spontaneous choices. This provides a neural link between pre-existing brain states and intentional action, representing a significant technical effort to characterize the neural scaffolding of internal goal generation.

Strengths:

The primary strengths of this work include the integration of fMRI and EEG which allows the authors to bridge the gap between slow metabolic signals and fast oscillatory brain states. The use of two independent cohorts is a commendable effort to ensure the reproducibility of the willed attention effect, which is often a concern in small sample neuroimaging studies. Additionally, the move beyond univariate activation toward information based mapping demonstrates that the identified networks actually contain specific information about the direction of attention.

Weaknesses:

However, several critical weaknesses must be addressed to support the fundamental claims made in the manuscript. There are significant behavioral differences in performance between the two sites, specifically regarding the UC Davis cohort exhibiting slower reaction times and lower accuracy compared to the UF group. These discrepancies suggest potential differences in subject populations or experimental environments that are not currently accounted for in the neural models. The fMRI analysis lacks temporal precision because the use of beta series regression collapses the complex BOLD response into a single estimate per trial. This loss of temporal information obscures the evolution of the decision process and makes it difficult to distinguish whether the identified patterns represent a truly spontaneous choice or a slow building pre planned strategy.

Furthermore, the EEG decoding approach utilized the entire topography of electrodes rather than a biologically motivated posterior region of interest. Given that alpha mediated spatial attention is traditionally localized to parieto occipital sensors, using the full electrode set risks the inclusion of non neural artifacts such as micro saccades or muscle activity which can contaminate multivariate classifiers. The introduction of the neural efficiency metric also requires further validation as the current ratio is mathematically sensitive to small denominators in the BOLD contrast.

Crucially, the manuscript does not address the physiological implications of recruiting additional frontoparietal networks when behavioral performance remains identical across conditions. The activation of the anterior insula and dACC is frequently associated with increased autonomic arousal and effort. If the willed condition requires more extensive neural scaffolding to reach the same behavioral output as the instructed condition, it raises the question of whether this internal decision process is accompanied by changes in arousal

levels. The authors should consider whether the lack of a behavioral tax is due to a compensatory increase in arousal, which could be reflected in the EEG data or pupil diameter if recorded, and potentially also in the amplitude of BOLD activity, which is being masked by the neural efficiency metric. Without an account of how the brain balances this increased computational demand without impacting behavioral performance, the functional significance of the willed attention network remains partially obscured.

<https://doi.org/10.7554/eLife.110199.1.sa2>

Reviewer #2 (Public review):

Summary:

This manuscript combines fMRI and EEG investigations performed at two research sites to examine 'willed' or volitional visuospatial attention, as contrasted with more standard cued (or 'instructed') visuospatial attention. The primary findings are: 1) willed attention (vs. instructed attention) drives additional cortical circuitry across a broad fronto-parietal network; 2) the direction of willed attention, but not instructed attention can be decoded from the pre-cue EEG data and from MVPA analysis of the trial-level fMRI data; and 3) the subjects with high EEG decoding also exhibited high neural efficiency (i.e., high decoding with low BOLD signal change) in the fMRI data. The methods and data analysis are generally sound, and these results appear solid. On the negative side, it is not made clear how the present findings extend our understanding beyond prior published work from one of the senior authors. There are also three significant concerns regarding interpretation of the findings. One has to do with the causal interpretation of the pre-cue alpha EEG signal determining the direction of willed attention. The second concern is the degree to which the present research paradigm adequately examines 'willed attention.' The third is that the MVPA analysis is not sufficiently described, and Permutation testing needs to be done to validate these findings. Otherwise, this manuscript appears methodologically sound, but questions about interpretation may mute the potential impact.

Strengths:

The focus on willed attention attempts to move beyond some of the many limitations of standard laboratory investigations of attention.

The shared paradigm across two modalities and two research sites demonstrates solid reproducibility, even though a few minor differences are observed across sites.

Weaknesses:

(1) There are concerns about this experimental paradigm carrying the banner of Willed Attention, because the application of 'Will' appears quite modest. Yes, extra brain activity is exhibited for this condition vs. its control, but do the cognitive processes isolated adequately stand in for 'Willed Attention?' Willed attention, as operationally defined here, appears to involve a simple decision process prior to the shifting of spatial attention. The cue is internally generated, but after that the rest of the attentional processes appear identical to standard externally cued visuospatial attention experiments. This self-generated cue process likely involves some sort of memory/history of the recently selected cues and then some random-ish selection between A and B. This appears very similar to asking the subject to guess whether a fair coin flip will be heads or tails on each trial. A mental 'coin flip' feels like a very weak version of 'will.' As a potential remedy, it would be helpful to discuss what other phenomena might fall within 'willed attention' and what some future studies might choose to focus on, along with some potential pitfalls (e.g., the reasons why the current study avoided more robust exemplars of will).

(2) The manuscript is lacking a description of the decision processes used during the willed attention paradigm and is lacking evidence as to WHEN subjects made their willed decision. Both of these points are of major concern:

(a) The authors state: "For willed attention, participants were explicitly told to avoid relying on any stereotypical strategies of generating decisions, such as always attending the same/opposite side they attended during the previous trial, as well as to avoid randomizing or equalizing their decisions to choose left or right across trials; prior studies found that decisions to explicitly randomize decisions might invoke additional working memory related processes (Spence & Frith, 1999)." Subjects were instructed NOT to apply a simple heuristic and NOT to randomize or try to equalize their decisions, but exactly HOW the subjects made their decisions is not at all clear. What options does that leave? How does this strategy avoid the working memory-related processes mentioned in the Spence & Frith, 1999 citation? The brain regions that comprise the network of interest (aka Frontoparietal Decision Network) are activated by a very broad range of visual cognitive tasks, including many working memory paradigms. The Anterior Insula and dACC nodes Saliency Network often simply reflect task difficulty. Obviously, making a choice is more cognitively demanding than not making a choice. The present experiments do not distinguish functional roles between different regions of the Frontoparietal Decision Network. On the whole, the study does very little to isolate the cognitive processes or neural bases of willed attention beyond calling out the set of 'Usual Suspects' for visual cognition.

(b) The finding that pre-cue EEG signals predicted the postcue decision is intriguing. It could mean that the seemingly irrelevant and transient state of the brain causally and unconsciously biased the subject to one direction or the other. Alternatively, it could mean that the subjects utilized the pre-cue period to make their decision and hold it in case it was needed (i.e., that it was a choice trial). While 2-8 seconds ITI variability makes sense for fMRI decoding, it is a long time for a subject to idly wait, so they might fill that time preparing for the next trial. There appears to have been a substantial amount of individual difference in the pre-cue alpha decoding, which could reflect individual differences in cognitive strategy, specifically in the use of the pre-cue period to make their decision. More efficient decision makers might have pre-decided, which might account for the neural efficiency. The experiments lack any measurement of WHEN participants made their decision. For that reason, I would ask that the authors temper their claims about the significance of the alpha decoding and its possible causality.

(3) Did individual subjects exhibit a choice bias of location for the willed trials? If not, doesn't that raise concerns that subjects were trying to equalize their trials? If they do exhibit location biases, how does that impact the decoding? A simple decoder could learn to always just guess the biased direction for a subject and would perform > 50%. Consider the example in which an individual subject chooses 'Left' 55% of the time. A classifier that simply learns to choose 'Left' on every trial will be correct on 55% of trials. The training data would likely be sufficient to learn the direction of choice bias in each individual subject. So the classifiers could perform significantly above 50% without learning anything beyond the tendency of each subject. That is to say, 50% is not truly chance in this data set. It doesn't appear that Permutation testing has been performed to empirically determine chance for an individual's data. Permutation methods, scrambling the labels 1000 or 10000 times to establish a true baseline would be preferred over simply comparing to 50% and would address concerns about individual subject biases.

(4) The novel contributions of this work beyond the two prior Bengson et al papers from Dr. Mangun's lab appear quite modest. The discussion would be enhanced by specifically stating how the present work advances understanding beyond the prior Bengson studies.

<https://doi.org/10.7554/eLife.110199.1.sa1>

Reviewer #3 (Public review):

Summary:

This manuscript analyzes two independent datasets collected at different sites. Using the same willed-attention paradigm (instructional vs. choice cues) and combining fMRI and EEG analyses, the authors investigate how attentional direction is selected when no external instruction is provided. Their main claims are that the dorsal attention network is engaged by both cue types, whereas the choice cue additionally involves a frontoparietal decision network. Moreover, left-versus-right attentional decisions can be decoded in this decision network only on choice trials, and multichannel pre-stimulus alpha patterns predict the subsequent attentional choice. Finally, individuals with more predictive alpha patterns show greater neural efficiency in the decision network, i.e., higher decoding with lower BOLD activation.

The question is worthwhile and the two-site design is a genuine strength. At the same time, several central inferences rely on decoding analyses for which the statistical testing and cross-validation structure are not described in enough detail to assess robustness. In addition, using a ratio-based neural-efficiency measure make the interpretation more fragile than it needs to be. With a focused revision that tightens inference around MVPA and clarifies a few methodological points, I think the paper could become substantially more convincing.

Strengths:

The work extends previous willed attention studies by attempting to link pre-stimulus alpha pattern predictability to post-cue frontoparietal representations, and by testing reproducibility across two datasets. The conceptual advance beyond previous studies, e.g., Bengson et al. (2015), however, depends on how solid the decoding-based evidence is and whether alternative explanations are convincingly excluded. At present, the strength of support is limited mainly by incomplete reporting and/or controls for MVPA significance testing, as well as potential inflation of decoding estimates if folds are not independent of run structure. Concerns about statistical assessment of decoding accuracy are well documented in the literature (Combrisson & Jerbi, 2015).

Weaknesses:

(1) The manuscript describes the decoding pipeline for both fMRI and EEG MVPA. However, it does not clearly specify how "significantly above chance" is determined for the fMRI ROI decoding, nor how multiple comparisons across ROIs are handled, even though p-values are reported. The same issue applies to the time-resolved EEG analysis across many time points. For each decoding analysis, please specify the inferential test (e.g., permutation test within participant, group-level test on subject accuracies, binomial test, etc.) and report effect sizes with confidence intervals (e.g., Combrisson & Jerbi, 2015). Further, for EEG decoding over time, it would be preferable to control family-wise error, e.g., cluster-based permutation, rather than thresholding pointwise p-values. A standard approach here is the nonparametric cluster framework (e.g., Maris & Oostenveld, 2007).

(2) The cross-validation approach used here is appreciated and appropriate in principle. However, random 10-fold splits across trials can inflate accuracy if training and test folds share run-specific noise, scanner drift, or autocorrelated structure. The manuscript should indicate whether folds were blocked by run or randomized across the entire session. In addition, please report the number of trials per condition after artifact rejection and after removing short ITIs for the long prestimulus epochs (–2500 ms to 0 ms) for each dataset in the section of EEG preprocessing. Similarly, please report how often participants chose left vs. right on choice trials, and whether balanced folds (or an equivalent balancing procedure) were used if needed.

(3) Moreover, ROI definition is not sufficiently specified and independence should be clarified. The ROIs are defined based on peaks from the choice-instructed univariate contrast (Table 2) and then used for MVPA. First, are these ROIs defined as spheres around peaks or using anatomical masks? What radius or voxel count was used? This needs to be explicit. Second, I am concerned about circularity risk. Although choice-vs-instructed selection is not identical to left-vs-right decoding, ROI selection from the same dataset can still bias descriptive estimates and encourages overinterpretation if not carefully justified (Kriegeskorte et al., 2009). At minimum, the authors should explain why their selection criterion is independent of the decoded contrast under the null, and ideally provide a robustness check using either anatomical ROIs or independently defined ROIs, e.g., from prior literature or an atlas.

(4) Using an index of neural efficiency is conceptually interesting. However, if the denominator, computed as the activation difference between choice and instructional conditions, is near zero or noisy, the ratio can become unstable. I would rather see a multivariate model that treats activation and decoding as separate dependent measures, or a latent-variable approach, than a single ratio.

<https://doi.org/10.7554/eLife.110199.1.sa0>