Electrophysiological neural mechanisms for domain-general intelligence

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Abstract:

Understanding the mechanisms supporting domain-general intelligence is crucial for both cognitive neuroscience and artificial intelligence. While human fMRI studies have identified a frontoparietal multiple-demand network that contribute to multiple tasks, it is largely unknown whether the human brain supports multiple tasks with common electrophysiological responses. Here, we recorded magnetoencephalography and electroencephalography (MEG/EEG) signals while participants completed three different cognitive tasks with different content (alphanumeric vs. colour stimuli) and cognitive demand (easy vs. hard). After separating the oscillatory and the aperiodic components of the electrophysiological signals, we used multivariate pattern analysis (MVPA) to decode task demand for each subtask. We found that both oscillatory and aperiodic components could decode task demand for all six subtasks. Aperiodic broadband power showed the strongest generalisability on coding task demand across different subtasks. Source estimation results showed distinct spatial patterns for domain-general oscillatory and aperiodic components, with the aperiodic broadband power overlapping with the frontoparietal multiple-demand network. Our findings suggested the existence of oscillatory and aperiodic electrophysiological mechanisms in support of human domain-general cognition, which provides a novel way to understand how domain-general intelligence arises and might inspire relevant research in the fields of neuroscience and artificial intelligence.

Keywords: General intelligence; Generalisability; Neural oscillations; Aperiodic activity; MEG/EEG

Introduction

Building network models that are able to achieve good performance across a wide range of tasks is one of the key aspirations of artificial intelligence research. To implement this goal, a promising way is to establish brain-inspired network architectures based on theoretical and empirical results from cognitive neuroscience research on domain-general intelligence (e.g., Achterberg et al., 2023). For decades, many fMRI studies have shown a similar set of frontoparietal regions are commonly involved in supporting domain-general cognition (Cole & Schneider, 2007; Duncan & Owen, 2000). We refer to this widely distributed domain-general system as the multiple-demand (MD) network (Assem, Glasser, Van Essen, & Duncan, 2020; Duncan, 2010). Despite these findings in the fMRI, however, it is largely unknown about how the human brain supports domain-general cognition with electrophysiological signals such as oscillatory and/or aperiodic activity. To address this question, this study recorded neural signals using combined MEG/EEG when participants were doing three different cognitive tasks with different contents and demands and examined whether any oscillatory and/or aperiodic signals show domain-generality across all these subtasks.

Methods

Participants We analysed data from 43 participants recruited from the local community and the online participant database at the University of Cambridge.

Task design We used three cognitive tasks (working memory task, WM; switching task, SWIT; and multi-source interference task, MSIT) with different demands (hard/easy) and different stimuli contents (alphanumeric/colour). Behavioural results confirmed that participants performed faster and more accurate in easy conditions for all the subtasks (Figure 1).

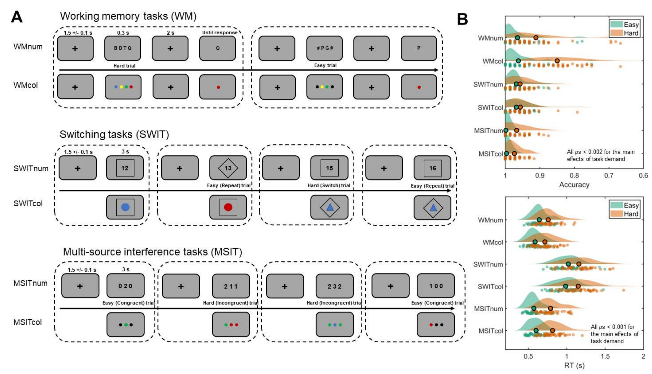

Figure 1: Task design and behavioural results.

Data acquisition and preprocessing MEG data were acquired using a Neuromag system with 204 planar gradiometers and 102 magnetometers. EEG data were acquired concurrently using a 70-channel EEG cap. Structural MRI data were acquired using a Siemens 3T Prisma scanner. We used MNE-Python (Gramfort et al., 2013) for all the MEG/EEG processing steps, including a signal-space separation to reduce environmental artefacts, an independent component analysis to remove eye movement and heart-beat artefacts, and a band-pass filter between 1-40 Hz.

Source reconstruction Based on participants' structural MRI scan, we used FreeSurfer to obtain the reconstructed surface. We computed a boundary element forward model for each participant and computed inverse models for each subtask using the dynamic statistical parametric mapping (dSPM). Human Connectome Project multimodal parcellation (Glasser et al., 2016) and corresponding network definition (Assem et al., 2020; Ji et al., 2017) were used for analyses involving regions of interest (ROIs).

Irregular-resampling auto-spectral analysis (IRASA) and multivariate pattern analysis (MVPA) All MEG and EEG sensors were used for sensor space MVPA.

After removing evoked potentials from each trial for each condition, we used IRASA (Wen & Liu, 2016) to separate the oscillatory and aperiodic components from the mixed power spectrum using the time window of 0.3-1.5 s for each subtask (Figure 2A). For decoding based on oscillatory components, we used averaged oscillatory power for each frequency band (theta: 3-7 Hz; alpha: 8-12 Hz; beta: 15-30 Hz). For decoding based on aperiodic components, three aperiodic parameters (broadband power, slopes, and intercepts) were used. We used a 5-fold cross-validation procedure with a linear support vector machine for classification. For the cross-task generalisation, we trained classifiers on task demand based on one subtask and then tested them in all other subtasks. For source space MVPA, we used activity from 360 ROIs for decoding analysis and then used the weight projection method (Haufe et al., 2014) to obtain source patterns.

Results

Both oscillatory and aperiodic components support domain-general intelligence

After separating the oscillatory and the aperiodic components, as shown in Figure 2A and 2B, we found that oscillatory power in theta, alpha, and beta bands, as well as aperiodic components (broadband power, slopes, and intercepts) could decode task demand (hard vs. easy) for all six subtasks with above-chance decoding accuracy (all *t*s > 3.22; FDR-corrected *p*s < 0.002). These results highlighted the significant roles of both oscillatory and aperiodic activity in coding various task demands that support domain-general cognition.

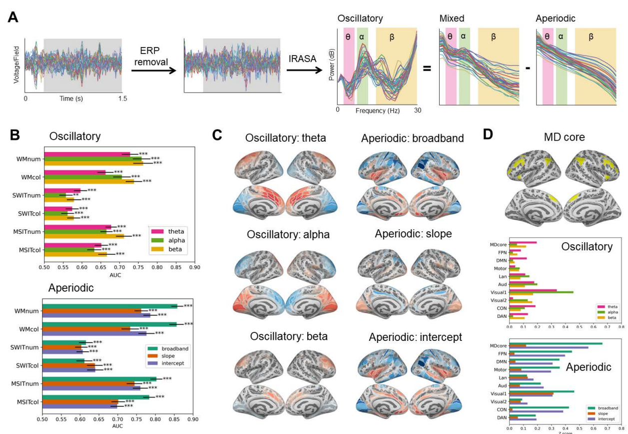

Figure 2: (A) Illustration of ERP subtraction and IRASA. (B) Decoding results on task demand using oscillatory or aperiodic components. (C) Source patterns contributing to demand decoding (averaged across all the subtasks). (D) The core regions of the MD network and the absolute mean z-scores of patterns within in each network that contributed to classifying task demand.

Distinct cortical sources for oscillatory and aperiodic components in domain-general intelligence

We then estimated the cortical sources of these domain-general oscillatory and aperiodic signals. As shown in Figure 2C, compared to easy conditions, oscillatory components showed increases in mid-frontal theta, occipital alpha, and lateral-frontal beta activity under hard conditions. In contrast, the demand-related aperiodic components (especially the broadband power and intercepts) showed distributed patterns across the brain, partially overlapping with the domain-general MD network (Figure 2D). These results revealed distinct spatial sources for oscillatory and aperiodic components in domain-general cognition.

Cross-task generalisability

We then tested whether the way that demand modulated these signals generalised across different subtasks. As shown in Figure 3, we found that although both oscillatory and aperiodic components showed some generalisability across subtasks, the aperiodic broadband power showed the strongest generalisability.

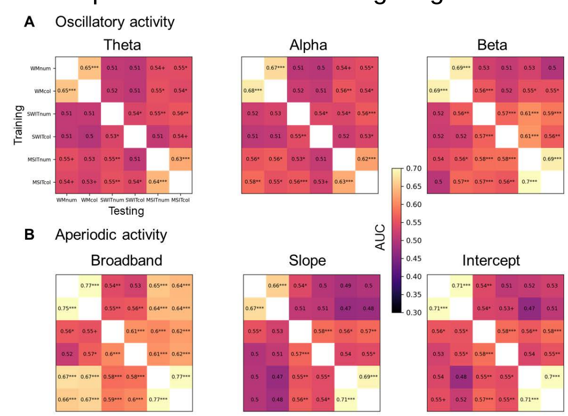

Figure 3: Cross-task generalisation on task demand for (A) oscillatory and (B) aperiodic components.

Conclusion

This study investigated the neural mechanisms for domain-general intelligence reflected in oscillatory and aperiodic electrophysiological responses in humans. We found that both oscillatory (in theta, alpha, and beta bands) and aperiodic activity (broadband power, slopes, and intercepts) are modulated by task demand across all the subtasks but with distinct sources. Cross-task generalisation results suggested that the aperiodic broadband power was the most domain-general property, in consistent with its MD-like source pattern. These findings provide a novel way to understand how domain-general intelligence arises and have the potential to inspire relevant research in both fields of neuroscience and artificial intelligence.

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