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Brain functional connectivity in Raven's progressive matrices: a fNIRS study

Vadim Grubov[1,2,a], Vladimir Antipov[2], and Artem Badarin[2]

[1] Immanuel Kant Baltic Federal University, A. Nevskogo Str., 14, Kaliningrad 236041, Russia
[2] Research Institute of Applied Artificial Intelligence and Digital Solutions, Plekhanov Russian University of Economics, Stremyannyy Ln., 36, Moscow 115054, Russia

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Abstract In this study, we used fNIRS to examine functional connectivity during the Raven's progressive matrices performance. The goal was to determine whether increased reasoning demands are associated with condition-dependent changes in large-scale cortical interactions. Based on the P-FIT framework and previous fMRI-based studies, we hypothesized that an increase in the task difficulty would be associated with network reorganization, particularly in the frontal and parietal regions. The results showed increased connectivity within and between the frontal, parietal, and occipital regions increased parieto-temporal connectivity, decreased fronto-temporal connectivity, and unchanged within-temporal connectivity. These results aligned with previous fMRI studies, but also offered new insight.

1 Introduction

The neurophysiological correlates of intelligence have long been a topic of interest. Jung and Haier [1] proposed the parieto-frontal integration theory (P-FIT), which suggests that human intelligence is closely linked to the structural and functional properties of several brain regions, primarily located in the parietal and frontal cortices. According to P-FIT, solving abstract reasoning tasks involves multiple processing stages and requires the harmonious interaction of these brain regions. From this perspective, functional connectivity (FC) between these cortical regions is a particularly relevant target for studying the neural basis of intelligence. Notably, the P-FIT model suggests that intelligent thinking originates from the successful recognition and elaboration of information from the sensory cortices. However, most empirical studies investigating the relationship between reasoning task performance and FC use a similar paradigm with functional magnetic resonance imaging (fMRI). Some studies assess resting-state FC, which is then correlated with reasoning task performance [2]. Directly measuring FC during the task most likely provides greater insight into intelligence-related brain activity; however, fMRI technology limits such studies.

Functional near-infrared spectroscopy (fNIRS) is an emerging low-cost noninvasive neuroimaging technique that measures cortical blood flow. fNIRS has gained interest as a more mobile alternative to fMRI since it can be implemented as a wearable multi-channel imaging system [3]. Recent methodological advances have significantly expanded the analytical toolkit for studying fMRI-based functional networks, moving from classical pairwise connectivity to higher-order interactions and multiscale network organization [4, 5]. These approaches have proven sensitive to disruptions in brain network segregation and integration in clinical populations, such as major depressive disorder and disorders of consciousness [5–7]. While such advanced frameworks have been primarily developed for fMRI, they underscore the importance of capturing reconfiguration of FC beyond simple pairwise correlations—a consideration that also applies to fNIRS-based studies of cognitive tasks. Duan et al. [8] demonstrated that fNIRS is capable of providing resting-state FC measures comparable to fMRI. Fishburn et al. [9] tested the ability of fNIRS to detect linear changes in activation and FC in response to cognitive load, and FC changes when transitioning from a task-free resting state to a task. They showed that FC differed between resting-state and n-back task scans, with greater fronto-parietal connectivity during the n-back task. Recent fNIRS and eye-tracking evidence has also shown that prolonged cognitive task performance is accompanied by compensatory changes in

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[a] e-mail: vvgrubov@gmail.com (corresponding author)

functional network organization, highlighting the sensitivity of fNIRS to task-dependent cortical network adaptation [10]. Nevertheless, it remains unclear whether fNIRS can provide additional insight into cortical network reconfiguration during abstract reasoning tasks.

The next step is to identify a reasoning task that robustly engages the cognitive processes relevant to intelligence. One of the most well-known reasoning tasks is Raven's progressive matrices (RPM). The RPM is a nonverbal test designed to assess fluid intelligence, i.e., the ability to reason and solve problems independently of acquired knowledge [11]. The RPM is often considered a suitable test for assessing the general intelligence, or g [12]. g is believed to represent a single underlying cognitive ability that influences performance across diverse mental tasks, although its generalizability is sometimes questioned [13]. Some researchers debate whether the RPM is a pure g test or if it accounts for other aspects in its assessment [14]. Studies suggest that RPM items have loadings on three factors: gestalt continuation, verbal-analytic reasoning, and visuospatial ability [15]. Some RPM items may be more suitable for assessing perceptual processes, while others may be more suitable for assessing analytic processes. Carpenter et al. [16] showed that the processing characteristic common to all subjects during the RPM is an incremental, reiterative strategy for encoding and inducing the regularities in each problem. The processes that distinguish individuals primarily involve the ability to induce abstract relations and the ability to dynamically manage a large set of problem-solving goals in working memory. Thus, the RPM is a suitable experimental paradigm for investigating task-related changes in FC within the framework suggested by P-FIT because it combines low-level visual perception with high-level abstract and structural reasoning.

In this study, we used fNIRS to examine FC during the RPM performance. Our goal was to determine whether increased reasoning demands are associated with condition-dependent changes in large-scale cortical interactions. Based on the P-FIT framework and previous fMRI studies, we hypothesized that an increase in the RPM task difficulty would be associated with a reorganization of FC, particularly in networks involving the frontal and parietal regions. Our results showed increased connectivity within and between the frontal, parietal, and occipital regions, increased parieto-temporal connectivity, decreased fronto-temporal connectivity, and unchanged within-temporal connectivity. These results aligned with previous fMRI studies, but also offered new insight.

2 Materials and methods

2.1 Experiment and dataset

The dataset analyzed in this study consisted of 33 subjects—all unpaid student volunteers from Immanuel Kant Baltic Federal University, aged 20 ± 2. Prior to the study, the subjects were instructed to limit their alcohol and caffeine consumption, avoid excessive physical activity, and get an 8-h night rest. The study was conducted in a well-lit room with the subject sitting comfortably in a chair.

The task was RPM, consisting of 60 items divided into five sets (A–E) of progressively increasing difficulty. Each item was an image with a certain spatial pattern and a missing patch. The items were separated by pauses and there was no strict time limit. An example of RPM item is shown on Fig. 1A. Subjects were asked to identify the missing element that completes a pattern from the suggested variants. In this study, the RPM was used in a digital form. The RPM items were presented to the subjects on a monitor in front of them, and they used a computer

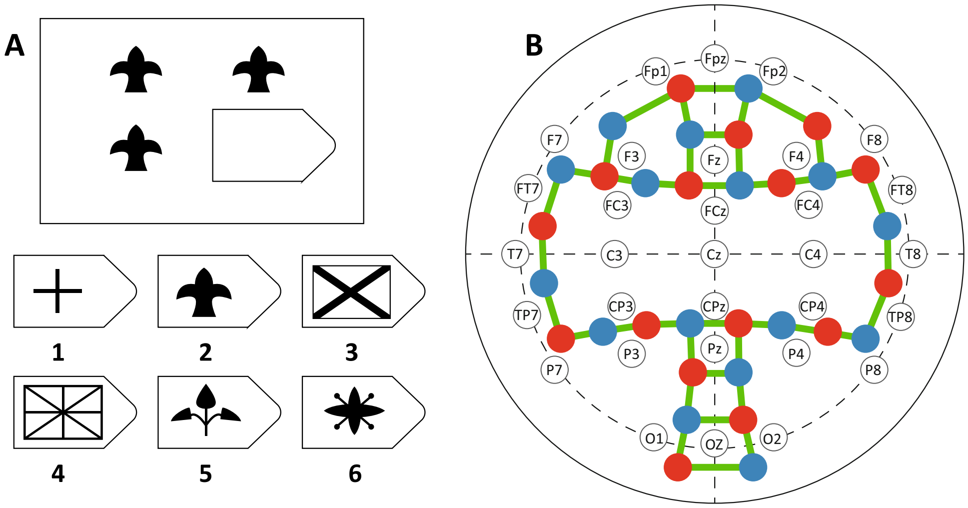

Fig. 1 **A** Example of RPM item. **B** Optode placement scheme (sources—red, detectors—blue) and legitimate fNIRS channels (green). EEG channels are shown for the reference

mouse to select the answers. This approach allowed us to collect behavioral data and synchronize it with fNIRS data. This facilitated the study of behavioral characteristics, such as reaction time.

For fNIRS data recording, we used a wearable device NIRSport by NIRx. The device has 16 sources and 16 detectors, with each source–detector pair forming a fNIRS channel. However, the optimal distance between the source and detector is ∼3 cm due to the specific traveling path of near-infrared light in cortex's tissue: the light diffuses in the tissue and is reflected toward the detector, forming a so-called banana-shaped path. Thus, we only considered the pairs that satisfied this condition. Due to the limited number of optodes, they were primarily placed in the frontal and occipital regions, which were the regions of interest in terms of P-FIT. The optode placement scheme and legitimate fNIRS channels are shown on Fig. 1B.

fNIRS data preprocessing suggested using modified Beer–Lambert law [17] to calculate the characteristic measure HbO, which reflects the speed of relative changes in oxygenated hemoglobin level. HbO is considered the most informative fNIRS-based measure, demonstrating a high correlation with fMRI's blood-oxygenation-level-dependent (BOLD) signals [8]. fNIRS signals are often exposed to internal and external noises, whose characteristic frequencies lie within the fNIRS frequency band. These include physiological artifacts such as Mayer waves (∼0.1 Hz), respiration (∼0.25 Hz), and heartbeat (∼1 Hz). According to common practice [18], the band-pass filtering is often sufficient for removing low-frequency physiological noise in fNIRS data. We applied a band-pass filter (0.01–0.1 Hz) to the experimental fNIRS data before performing any calculations based on the modified Beer–Lambert law. We acquired and preprocessed the fNIRS data using the NIRx software.

2.2 Behavioral data analysis

We analyzed the behavioral data by considering two characteristics: the correctness of answers (CoA) and the response time (RT). CoA is the percentage of correct answers out of all the items in a set. RT is the average time interval between when an item starts and when a subject answers, calculated for all the items in a set. We calculated both CoA and RT for each of the five RPM sets. The results of this analysis were then used to introduce experimental conditions c_i—subsets of the RPM session unified by a similar level of behavioral performance.

Our next goal was to identify differences between the experimental conditions c_i. To do so, we implemented a repeated-measures analysis of variance (RM ANOVA) to test for the main effect. Subsequently, we performed a post hoc analysis that included paired comparisons between sets with Holm correction for multiple comparisons.

2.3 Functional connectivity analysis

To assess FC between brain regions, we computed Spearman correlation coefficients S between HbO time series for all pairs of fNIRS channels within a trial. A trial was defined as the time interval from stimulus onset to the subject's response. This procedure resulted in subject-level correlation matrices, which were averaged within each experimental condition c_i to obtain condition-specific FC matrices.

To identify condition-related differences in FC, we applied the network-based statistics (NBS) method proposed by Zalesky et al. [19]. To test for the main effect of condition c_i, we used an F-statistic for each channel pair. A primary component-forming threshold corresponding to $p < 0.001$ was applied to identify edges exceeding this threshold. The connected components formed by these edges were then extracted, and their significance was assessed using a permutation test ($k = 1000$ iterations, repeated-measures design). Components with permutation-based corrected $p < 0.05$ were considered statistically significant. The resulting significant edges were then used to define the network mask.

To further characterize the network's functional organization, channel-level connections were aggregated across major anatomical regions: frontal (F), parietal (P), occipital (O), and temporal (T). Such aggregating provides a more interpretable description of a large-scale network organization. This representation is also conceptually relevant to P-FIT, which focuses on coordinated interactions between distributed cortical systems rather than on individual measurement channels. This regional representation improves interpretability, reduces the influence of interindividual anatomical variability, and aligns with the large-scale organization of the brain commonly considered in neuroscience.

To evaluate within- and between-region connectivity, we defined an integral connectivity index for each pair of regions:

$$\mathrm{FC}^{(c_i)} = \frac{n_{\mathrm{mask}}}{n_{\mathrm{all}}} \cdot \langle |\rho^{(c_i)}| \rangle_{\mathrm{mask}}, \tag{1}$$

where n_{mask} is the number of channel pairs between the two regions included in the network mask, n_{all} is the total number of channel pairs between these regions, and $\langle |\rho^{(c_i)}| \rangle_{\mathrm{mask}}$ is the mean absolute Spearman correlation across masked channel pairs for condition c_i. This index captures both the proportion of altered connections and their average strength, yielding condition-specific matrices of regional connectivity.

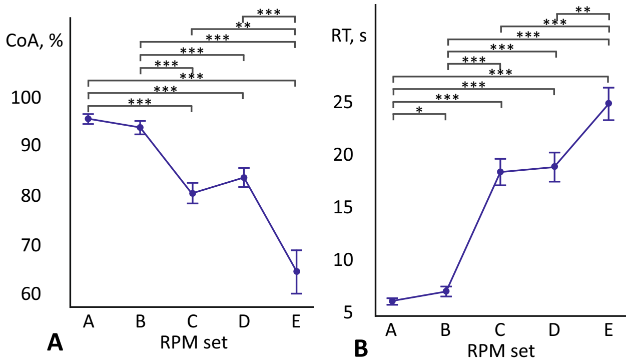

Fig. 2 Behavioral characteristics (mean ± standard error) in different RPM sets: CoA **A** and RT **B**. Bridges show statistical differences between RPM sets at following significance levels: $p < 0.05$ (*), $p < 0.01$ (**), and $p < 0.001$ (***)

To quantify condition-related changes in inter-regional connectivity, we computed the relative change in the connectivity index between pairs of experimental conditions:

$$\Delta\mathrm{FC}^{(c_1,\,c_2)} = \frac{\mathrm{FC}^{(c_2)} - \mathrm{FC}^{(c_1)}}{\mathrm{FC}^{(c_1)}}, \tag{2}$$

where $\mathrm{FC}^{(c_i)}$ denotes the connectivity index for condition c_i. Thus, $\Delta\mathrm{FC}^{(c_1,\,c_2)}$ represents the relative change in connectivity from condition c_1 to condition c_2. Diagonal elements reflect within-region changes, whereas off-diagonal elements reflect between-region changes.

3 Results

3.1 Results of behavioral data analysis

RM ANOVA was used to compare behavioral characteristics between RPM sets and revealed a significant main effect for both CoA (F(4, 128) = 34.995, $p < 0.001$) and RT (F(4, 128) = 86.664, $p < 0.001$). These results suggest the existence of statistically significant differences between RPM sets.

Thus, we performed a post hoc analysis. The results are shown on Fig. 2. One can see, that CoA (see Fig. 2A) gradually decreases and RT (see Fig. 2B) gradually increases as RPM task progresses. At the same time, there were no significant differences between sets A and B or sets C and D. These results enabled us to categorize the RPM sets into three experimental conditions based on task difficulty: c_1—“low difficulty” (LD, sets A and B), c_2—“medium difficulty” (MD, sets C and D), and c_3—“high difficulty” (HD, set E). This categorization was subsequently used in the FC analysis.

These results align well with those of Morin et al. [20], who described matching and reasoning conditions in the RPM task, as well as with those of Lynn et al. [15], who claimed that certain RPM items are more suitable for assessing perceptual processes, while others are more suitable for assessing analytic processes. We tied LD RPM items to the matching condition and perceptual processes, and HD RPM items to the reasoning condition and analytic processes.

3.2 Results of functional connectivity analysis

Condition-specific FC matrices reconstructed from HbO signals for the LD, MD, and HD conditions are shown in Fig. 3A. Visual inspection indicates that the overall organization of FC was preserved across conditions, while the strength and spatial distribution of channel-wise connections varied with task difficulty. To identify statistically reliable network-level effects, we applied NBS, which revealed significant condition-related changes in the functional network structure (Fig. 3B). The identified connected component indicates that task difficulty modulated FC at the level of a distributed functional network rather than through isolated changes in individual channel pairs. In conceptual terms, this suggests that increasing reasoning demands were associated with large-scale reorganization of coordinated cortical interactions.

The NBS analysis was performed to test the main effect of task condition across all three difficulty levels: LD, MD, and HD. The resulting significant network therefore reflects condition-dependent connectivity changes rather than a single pairwise contrast. For regional-level characterization, we focused on the LD-to-HD transition, as it

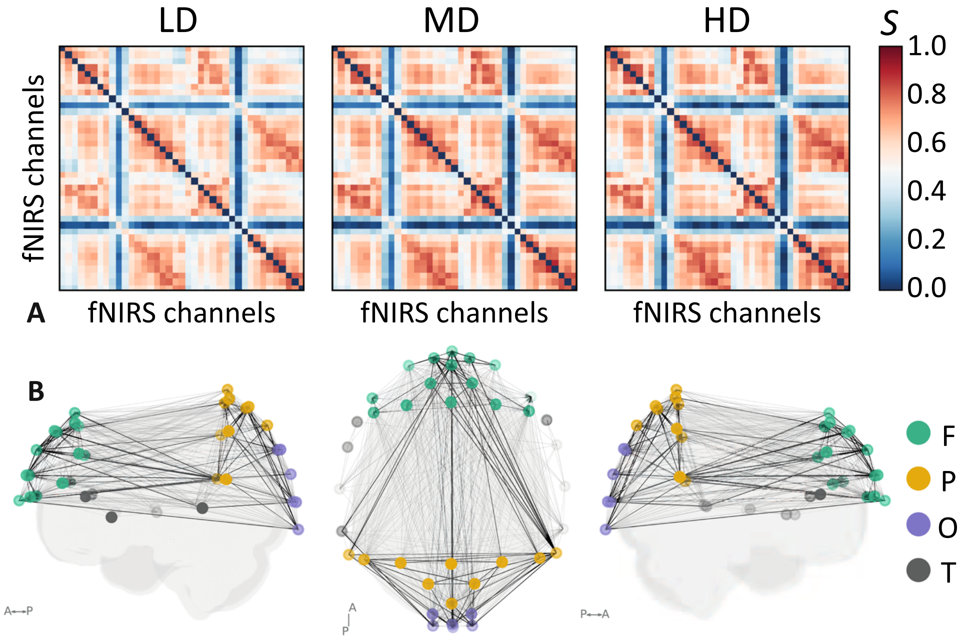

Fig. 3 **A** FC matrices reconstructed from HbO for three experimental conditions: LD, MD, and HD. **B** Statistically significant changes in FC between fNIRS channels found comparing different experimental conditions in four major anatomical regions: frontal (F), parietal (P), occipital (O), and temporal (T). FC cluster has significance level of $p < 0.05$. MNI152 template is used for visualization

represents the strongest contrast in reasoning demand and provides the clearest description of the direction and magnitude of difficulty-related connectivity changes within the identified network.

To facilitate anatomical interpretation, channel-level FC was aggregated across the major cortical regions: frontal (F), parietal (P), occipital (O), and temporal (T). Relative changes in inter- and intra-regional FC are summarized in Fig. 4. The largest changes were observed for fronto-parietal and temporo-parietal interactions, indicating that connectivity involving the parietal cortex was most strongly modulated by task difficulty. In contrast, changes in fronto-temporal and parieto-occipital connectivity were less pronounced. In particular, the transition from LD to HD was associated with reduced FC between the frontal and temporal regions, whereas FC increased for the remaining region pairs. Within-region changes were also heterogeneous, further supporting a redistribution of functional interactions with increasing task difficulty.

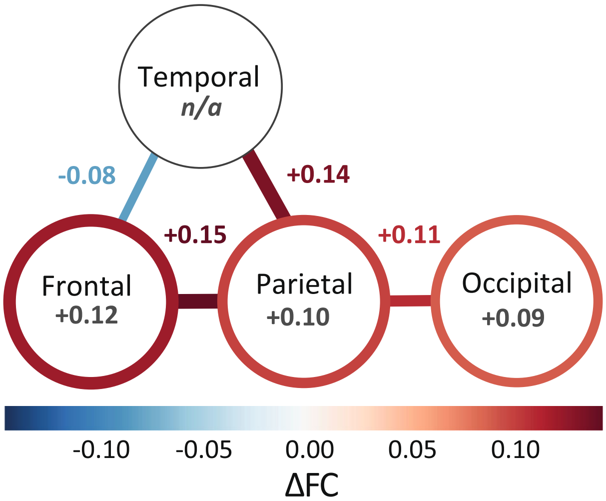

Fig. 4 Relative changes in inter-regional FC during the transition from LD to HD condition. Edge width is proportional to the magnitude of relative change $|\Delta\mathrm{FC}^{(LD,HD)}|$; edge color encodes the direction of change (red: increase, blue: decrease). Node border width and color reflect within-region changes; numerical values inside nodes show the corresponding $\Delta\mathrm{FC}^{(LD,HD)}$ (*n/a* indicates that no statistically significant changes were detected). Numerical labels on edges indicate $\Delta\mathrm{FC}^{(LD,HD)}$ between the respective regions

4 Discussion

In this study, we examined functional connectivity during the performance of RPM, a nonverbal task commonly used to assess abstract and relational reasoning. We evaluated whether increasing task difficulty was associated with changes in behavioral performance and cortical functional connectivity. During task execution, fNIRS signals were recorded, and response accuracy and reaction time were analyzed as behavioral measures. Based on these behavioral measures, RPM items were classified into three difficulty conditions: low, medium, and high. Functional connectivity between fNIRS channels was subsequently estimated for each condition to identify task-difficulty-related changes in network organization.

The obtained results indicate a difficulty-dependent reconfiguration of functional connectivity during RPM performance. Specifically, the transition from the LD to the HD condition was characterized by increased connectivity within and between frontal, parietal, and occipital regions, increased parieto-temporal connectivity, decreased fronto-temporal connectivity, and unchanged within-temporal connectivity. This pattern suggests that higher reasoning demands are associated with a selective redistribution of cortical interactions, primarily involving visual, parietal, and frontal systems. This interpretation is consistent with previous neuroimaging evidence on task-related network reconfiguration during abstract reasoning.

First, we demonstrated increased connectivity within and between frontal, parietal, and occipital regions. This pattern is consistent with the P-FIT framework [1], which emphasizes coordinated interactions between posterior sensory regions, parietal integrative areas, and frontal control regions during abstract reasoning. In the context of RPM, increased occipital–parietal–frontal connectivity may reflect stronger integration of visual pattern analysis, relational processing, and rule induction under higher task difficulty.

This interpretation is supported by previous neuroimaging studies of reasoning-related network reconfiguration. Hearne et al. [21] found that fronto-parietal and visual cortical regions exhibited increased reconfiguration during a Latin Squares reasoning task, forming a more integrated community structure. Similarly, Morin et al. [20] showed that fronto-parietal and visual regions, which were relatively fragmented at rest, became integrated into a strongly connected community during a simplified RPM task. They also reported stronger fronto-parietal activation during reasoning than during matching conditions, paralleling the shift in cognitive demands captured by the LD-to-HD transition in the present study. Importantly, disruptions in similar fronto-parietal and visual networks have been observed in clinical conditions such as major depressive disorder, where resting-state FC alterations correlate with cognitive deficits [6, 22]. This suggests that the same large-scale cortical systems that reconfigure during demanding reasoning in healthy individuals may be compromised in psychiatric disorders, offering a potential link between task-evoked FC dynamics and clinical applications. Similar involvement of fronto-parietal regions has also been reported across other abstract reasoning paradigms, including analogical reasoning [23], rule learning [24], and matrix reasoning [25].

Second, we observed a differentiated pattern of temporal-region connectivity: parieto-temporal connectivity increased, whereas fronto-temporal connectivity decreased. This pattern suggests that increasing RPM difficulty was associated with a selective redistribution of temporal-region interactions rather than a uniform increase or decrease in temporal connectivity.

The decrease in fronto-temporal connectivity can be interpreted in the context of controlled semantic cognition. Fronto-temporal interactions linking prefrontal and temporal regions are central to controlled access to conceptual representations and language-related semantic processing [26, 27]. At the same time, fluid reasoning is primarily supported by fronto-parietal multiple-demand regions rather than by language-selective temporal cortices [28, 29]. Therefore, the reduction of fronto-temporal coupling at higher RPM difficulty is consistent with a lower relative contribution of semantic-control mechanisms as task demands increasingly rely on domain-general reasoning processes.

In contrast, the increase in parieto-temporal connectivity may reflect stronger interaction between temporal regions and parietal systems involved in attentional orienting, visuospatial integration, and the integration of task-relevant visual information. This interpretation is consistent with the role of temporo-parietal regions in stimulus-driven attention and contextual updating [30, 31], as well as with the account of Carpenter et al. [16], who emphasized iterative encoding, goal management, and abstract relation induction as key mechanisms of RPM solving.

Together with the strengthened frontal–parietal–occipital connectivity described above, this pattern supports the interpretation that high-difficulty RPM performance is associated with a redistribution of functional interactions toward cortical networks supporting visuospatial-relational processing and domain-general reasoning. This account is consistent with the broader framework of task-dependent network reconfiguration, according to which cortical regions can participate in different functional coalitions depending on task demands [32].

Taken together, these findings provide fNIRS-based evidence consistent with the P-FIT framework [1]. Increased fronto-parieto-occipital connectivity at high task difficulty supports the role of coordinated sensory, integrative, and control-related cortical interactions in abstract reasoning. In parallel, the temporal-region pattern indicates a connection-specific redistribution of long-range coupling, with reduced fronto-temporal connectivity and enhanced parieto-temporal connectivity, consistent with a shift from semantic-control mechanisms toward attentional and visuospatial-relational processing.

From a methodological perspective, recent work has demonstrated that fNIRS can effectively capture task-related cortical activation patterns, including classification of motor-related brain activity at the sensor level [33]. Moreover, machine learning approaches combined with functional network measures have shown promise in distinguishing clinical populations from healthy controls [34], and similar frameworks could be applied to fNIRS-based reasoning data to predict individual fluid intelligence scores or detect early signs of cognitive decline. The integration of fNIRS with interpretable machine learning models [34] thus represents a promising avenue for future research, particularly given the portability and low cost of fNIRS compared to fMRI. For a broader overview of brain–computer interface rehabilitation methods that could potentially incorporate fNIRS-based reasoning paradigms, we refer the reader to a recent review [35, 36].

4.1 Limitations

These findings should be interpreted in light of several limitations. The sample size was modest ($n = 33$), limiting generalization to broader populations and individual-differences analysis. In addition, fNIRS coverage was restricted by the optode montage and did not provide whole-head recordings; therefore, effects involving parietal and temporal regions or the dorsal pathway should be interpreted with caution. Future studies should investigate other optode schemes or a greater number of optodes, along with a larger sample size. Notably, fNIRS is also limited to cortical surface signals and cannot capture contributions from deeper structures potentially involved in reasoning.

The anatomical regions were represented by different numbers of fNIRS channels, which may affect estimates of within- and between-region connectivity. Although the regional connectivity index was normalized by the total number of possible channel pairs, the results should still be interpreted as montage-dependent estimates.

Although the repeated-measures design reduces the influence of stable interindividual differences in RPM performance, variability in task strategy, accuracy, and response time among individuals may still contribute to estimates of functional connectivity. This should be considered when interpreting the results.

5 Conclusion

In this study, we used fNIRS to examine functional connectivity during RPM performance. The results showed that increasing RPM difficulty was associated with a reconfiguration of cortical connectivity, including stronger frontal—parietal—occipital coupling and a differentiated pattern of temporal-region interactions. These findings are consistent with the P-FIT framework and suggest that fNIRS may complement fMRI as a mobile tool for studying cortical network dynamics during abstract reasoning. Future work could extend this paradigm by applying higher-order network analysis techniques, such as those recently developed for fMRI [4, 7], to fNIRS data, potentially revealing reconfiguration patterns beyond pairwise connectivity that are missed by conventional FC measures. Overall, the fNIRS-based RPM paradigm provides a promising approach for investigating cortical mechanisms underlying high-level reasoning.

Data Availability The data that support the findings of this study are not publicly available due to privacy or ethical restrictions. The data are available on a reasonable request from a corresponding author.

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