

Research letter

Spatiotemporal Dynamics of Functional Connectivity Networks in EEG-based Motor Imagery

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Received 31 October 2025, Revised 2 December 2025, Accepted 5 December 2025

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Abstract: Understanding how motor imagery (MI) is represented in large-scale neural networks of the brain is important for improving electroencephalography (EEG)-based brain-computer interfaces (BCIs) and MI-based neurorehabilitation. This study examined frequency-specific functional connectivity during MI using EEG. MI demonstrated distinct network patterns: beta-band connectivity was higher during nondominant hand imagery, whereas alpha-band connectivity increased during dominant hand imagery. Subjective imagery ratings showed a statistically significant but weak correlation with global beta-band connectivity ($r=0.07$). These results imply that MI recruits distributed alpha- and beta-band networks and suggest that subjective experience reflects solely a limited portion of the underlying neural dynamics.

Keywords: motor imagery, functional connectivity, EEG, brain-computer interface, graph theory, alpha and beta rhythms, network-based statistic.

Cite as Badarin AA, Antipov VM, Drapkina OM, Kiselev AR. Spatiotemporal dynamics of functional connectivity networks in EEG-based motor imagery. *Russian Open Medical Journal* 2025; 14: e0423.

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Introduction

Motor imagery (MI) is the mental representation of a movement without actually performing it. MI is considered a complex cognitive process, partly based on neural mechanisms shared with real movement, thereby making it a convenient model for studying sensorimotor control and plasticity [1, 2]. From an applied perspective, MI is a key paradigm in non-invasive electroencephalography (EEG)-based brain-computer interfaces (BCIs) and is widely used in rehabilitation, particularly in motor function recovery protocols after stroke [3, 4, 5, 6].

However, despite the practical effectiveness of MI protocols, the network mechanisms that support the stable maintenance of MI and its lateralization remain poorly understood. Traditionally, neurophysiological assessment of MI relied on local markers of sensorimotor cortical activity, primarily event-related desynchronization/synchronization (ERD/ERS) in the mu and beta bands [1, 7, 8]. Although these indices reliably reflect rhythm modulation in sensorimotor areas, they provide just a limited understanding of the interactions between spatially distant brain regions. Modern neuroscience increasingly views motor cognition as the result of the dynamic integration of large-scale networks rather than isolated local modules [9]. Therefore, a more complete understanding of MI requires a shift from local power analysis to an assessment of functional connectivity, i.e., coordinated activity between spatially distant areas.

A network approach also allows for the investigation of the frequency-specific organization of MI. In current models, alpha activity (8-13 Hz) is associated with selective gating and top-down

suppression of task-irrelevant sensory information, while beta oscillations (13-30 Hz) are associated with the maintenance of the current sensorimotor state and long-range integration within sensorimotor circuits [10, 11; 12, 13]. It is important to note that interpreting EEG connectivity requires careful selection of metrics due to volumetric conductivity and spurious zero-lag synchrony, as highlighted in methodological reviews of functional connectivity [14].

Both intrinsic and extrinsic factors can modulate the stability and topology of MI networks. First, hand laterality and dominance can lead to differences in patterns of sensorimotor coordination, as representing the nondominant hand often requires a different strategy to maintain MI [15]. Second, the type of visual stimulus matters: the level of abstraction and realism of the visual guidance can alter the involvement of attentional and sensorimotor integration networks and influence subjective task load [16, 17, 18, 19]. Finally, the BCI for MI is characterized by significant interindividual variability and the phenomenon of BCI inefficiency (also known as BCI illiteracy), in which a significant proportion of users fail to produce sufficiently distinct EEG patterns even after training. A growing body of research attributes this to network organization and human factors [20, 21, 22].

This study employed a graph theoretic approach to analyze the reorganization of functional brain networks during MI. Based on EEG data, we estimated functional connectivity using the imaginary part of coherency (ImCoh) (which reduces the contribution of zero-phase lag interactions) and identified statistically significant subnetworks. We then investigated how imagery laterality and visual stimulus type modulate the topology

of alpha and beta networks and evaluated the relationship between objective network metrics and subjective assessments of MI quality.

Material and Methods

Experimental procedure

The experimental study was designed to examine neurophysiological patterns of MI under various visual stimulation experimental settings. [Figure 1A](#) shows the general structure of the experimental procedure, which included several stages. Initially, eye movement calibration was conducted, during which participants performed controlled oculomotor actions (saccades, gaze fixations, blinks) on command. These data were subsequently used to identify oculomotor activity via independent component analysis (ICA), which facilitated the detection and removal of oculomotor artifacts, thereby improving the quality of the EEG signal in the main task. Next, background activity was recorded: one minute of resting-state EEG without stimulus presentation. This segment served as the baseline for subsequent analysis.

The main experimental block included 60 MI trials evenly distributed across four different experimental settings. Participants were presented with two types of visual stimuli: a realistic image of a hand (left or right) and an abstract dot located to the left or right of the center of the screen. In the experimental settings including the hand image, subjects were asked to imagine a movement of the corresponding hand. In the experimental settings with the dot, participants were also required to imagine a movement with the left hand when the dot appeared on the left, and with the right hand when it appeared on the right. Thus, the stimuli differed both in form (realistic/abstract) and in the direction of the imaginary movement (left/right).

Each experimental trial had a clear structure and consisted of four sequential phases ([Figure 1B](#)). The first phase (*rest*): a neutral background was displayed on the screen for four seconds, followed by a cross (the second phase: *gaze fixation*). The cross's duration was randomly selected from a range of 1-1.5 seconds.

Following this, a visual stimulus was presented for 4 s (the third phase) triggering MI (*MI task*). The experiment concluded with a subjective self-assessment phase: the participant was asked to indicate how well they had visualized the movement using a visual analog scale (VAS) ranging from 'poor' to 'good'. The time allotted for this assessment was unlimited and averaged 3-5 s. After the main block, a final background recording (1 min) was conducted, which was identical to the initial phase.

Data collection and preprocessing

EEG signals were recorded using a NeoRec cap 21 system. Eighteen electrodes were selected for subsequent analysis according to the international 10-20 system: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T7, T8, P7, P8, Cz, and Pz. The reference electrodes and ground electrodes were placed at Fz and Fpz, respectively. EEG signals were recorded at a sampling rate of 500 Hz.

The raw EEG data were bandpass filtered in the range of 1-40 Hz to remove low-frequency drift and high-frequency noise. ICA was used to identify and remove artifacts associated with oculomotor activity and muscle noise. This method allows for the separation of statistically independent source signals (including neural activity and various artifacts) from the recorded EEG mixture. After artifact removal, continuous data were segmented into epochs ranging from -1 to 4 s relative to stimulus onset. Epochs containing artifacts with peak-to-peak amplitudes exceeding 150 μ V were automatically discarded. On average, 5% of epochs were discarded due to artifacts with no significant difference observed between experimental settings. Baseline correction was applied using a pre-stimulus interval from -1 to 0 seconds. The analysis included epochs corresponding to the following experimental settings: perception of abstract (Dot) and realistic (Image) stimuli for the left and right hands, as well as the combined experimental settings, DLeft (Dot + Image Left) and DRight (Dot + Image Right).

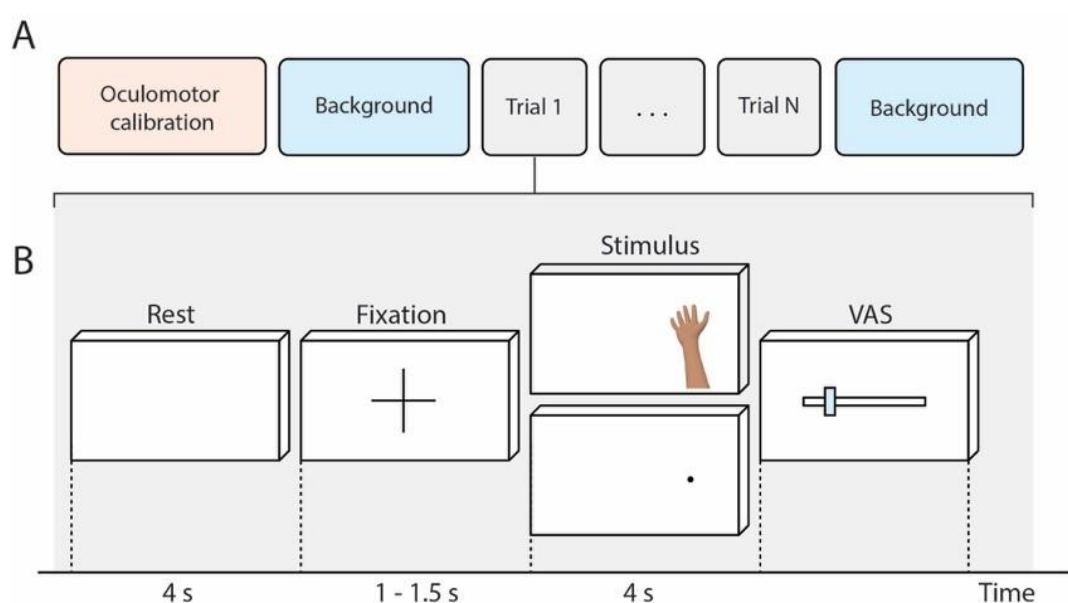


Figure 1. Experimental design. (A) Experimental session structure, including calibration, resting states, and the main experimental block. (B) Timeline of one trial: rest (4 s), gaze fixation (1-1.5 s), motor imagery (MI) task (4 s), and subjective assessment on the visual analogue scale (VAS).

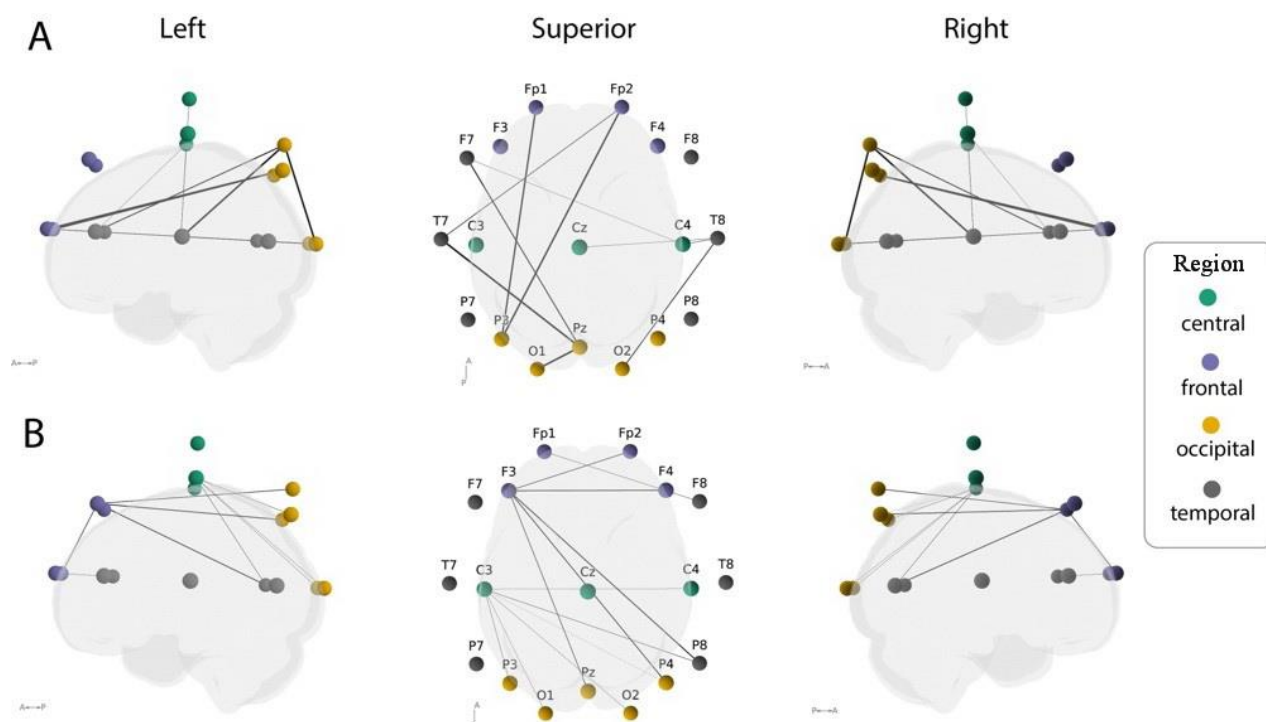


Figure 2. Functional connectivity networks showing statistically significant differences between the left and right motor imagery experimental settings (NBS, $p < 0.05$). (A) Significant cluster in the alpha band (8-13 Hz) for both the left and right hemispheres, revealing long-range fronto-occipital interactions characteristic of attentional control. (B) Significant cluster in the beta band (13-30 Hz) for both the left and right hemispheres, revealing a topology centered on sensorimotor integration areas. Node color indicates brain region: frontal, central, temporal, and occipital.

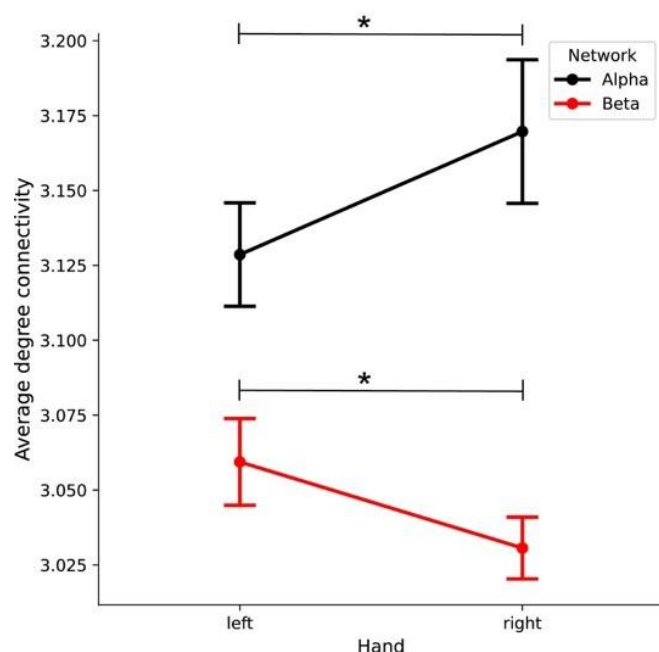


Figure 3. Average degree connectivity within significant alpha and beta networks for left and right hands.

Functional connectivity between brain regions was assessed using the ImCoh metric, which is robust to volume conduction effects [23]. Connectivity matrices were calculated using the multitaper analysis for the active task interval (0 to 4 seconds) in three frequency bands: theta (4-8 Hz), alpha (8-13 Hz), and beta (13-30 Hz).

To identify significant differences in functional connectivity patterns between experimental settings (specifically, DLeft vs. DRight), we employed the network-based statistic (NBS) approach [24]. This nonparametric method controls for type I error when conducting mass univariate testing of graph edges. The t-statistic threshold for initial connectivity-level comparisons was determined based on a two-tailed significance level of $\alpha = 0.05$, $t = 2.06$. The significance of the identified connected components (clusters) was assessed using permutation testing with 1,000 iterations.

Graph theoretical metrics were calculated for the identified significant subnetworks (clusters), as well as for the global network, using the NetworkX library. These metrics included average degree connectivity, mean clustering coefficient, and betweenness centrality. To assess the specific contribution of the identified clusters, metrics were calculated on weighted graphs constructed by masking the original connectivity matrices with binary cluster masks obtained from the NBS analysis.

Statistical analysis of the resulting network metrics included paired t-tests to compare experimental settings (e.g., left vs. right hand). To examine the relationship between objective neurophysiological markers and subjective perception of task performance, a repeated measures correlation analysis (RMCrr) was conducted. Before the correlation analysis, both graph metrics and subjective VAS scores were normalized using a z-transform for each participant to account for interindividual variability.

Participants

Twenty-four healthy volunteers (aged 20 to 32 years; mean age 25.3 ± 3.4 years) participated in the study. All participants reported no history of neurological or psychiatric disorders and

had normal or corrected-to-normal vision. Handedness was determined by self-report: 22 participants were right-handed, while 2 were left-handed. Before the experiment, each participant received a full explanation of the study protocol and provided written informed consent.

The study protocol was approved by the local ethics committee and was conducted in accordance with the Declaration of Helsinki. Participants were recruited voluntarily and participated in a single experimental session lasting approximately 30 minutes. Data from all 24 participants were included in the group-level analysis after artifact removal and preprocessing.

Results

To characterize the neurophysiological mechanisms underlying MI under different stimulation conditions, we performed a quantitative analysis of functional connectivity using ImCoh. This metric was chosen to minimize spurious zero-lag synchrony due to volume conduction and common reference effects, thereby enhancing the validity of sensory-level connectivity analyses using EEG signals [23, 25]. The analysis focused on the theta, alpha, and beta frequency bands, which play a key role in sensorimotor control, attention mechanisms, and the maintenance of motor representations [11].

NBS revealed statistically significant differences in the functional organization of neural networks depending on imagery laterality. Specifically, two functional connectivity clusters ($p < 0.05$) were identified that differentiated left- and right-sided MI. The alpha-band cluster ($p = 0.004$) included 19 edges connecting 13 nodes; The beta-band cluster ($p = 0.019$) comprised 17 edges connecting 15 nodes.

In the alpha band (8-13 Hz), a significant subnetwork was detected between left- and right-sided MI when comparing combined stimulation conditions (Dot + Image) (Figure 2A). The topology of this network was spatially distributed and included long-range connections linking frontal, central, and occipital regions. The involvement of fronto-occipital pathways suggests that alpha-band modulation during MI extends beyond the sensorimotor cortex, engaging large-scale networks responsible for coordinating visual processing and internal motor representations. This pattern is consistent with the hypothesis that posterior alpha activity facilitates top-down control by suppressing task-irrelevant sensory input and enabling selective allocation of attentional resources [10, 11]. The predominance of this network during combined stimulation may indicate increased cognitive demands on the mechanisms that integrate different types of visual cues (abstract and realistic) during the formation of stable MI.

In the beta band (13-30 Hz), analysis revealed a separate significant cluster for the same comparison (left hand vs. right hand, combined data for the 'Dot' and 'Image' experimental settings; Figure 2B). Topologically, the beta network showed a denser concentration of connections in the central and parietal regions, which constitute the main components of the sensorimotor system. Taken together, these data indicate that beta oscillations are associated with the maintenance of the current motor or cognitive state, the integration of proprioceptive and predictive cues, and the support of long-range communication within sensorimotor circuits [13; 26]. In this context, the observed lateralized beta connectivity suggests that imaginary actions of the left and right hands are based on partially different patterns of

organization of the sensorimotor network. The specific involvement of this network under combined signal conditions suggests a role for robust beta synchronization in stabilizing motor representations during MI in a more complex visual context.

To quantify the structural reorganization of the identified subnetworks, we calculated the average degree within each significant cluster. This measure reflects the mean number of functional connections associated with nodes in a given subnetwork and serves as an index of connectivity density and integration within the identified subgraph [27, 28]. A comparative analysis of the average degree for left- and right-hand images within the corresponding clusters is shown in Figure 3.

Paired t-tests revealed statistically significant differences in network density for both frequency bands. In the alpha-band cluster, connectivity was significantly higher for right-hand images vs. left-hand images ($t = -2.160$, $p = 0.0425$, Cohen's $d = -0.461$). In contrast, in the beta-band cluster, connectivity was statistically significantly higher for left-hand MI ($t = 2.329$, $p = 0.0299$, Cohen's $d = 0.496$).

The dissociation between connectivity patterns in the alpha and beta bands (Figure 3) provides a frequency-specific perspective on the mechanisms underlying MI lateralization. Specifically, the alpha subnetwork exhibits higher connectivity during right-hand imagery, whereas the beta subnetwork exhibits increased connectivity during left-hand imagery. This crossover effect suggests that alpha – beta connectivity reflects complementary processes: alpha-band connectivity is more strongly associated with control mechanisms, whereas beta-band connectivity is more closely associated with the stabilization of sensorimotor representations [11, 10, 13].

In the beta band, the higher average degree during left-hand MI indicates enhanced coordination within the centroparietal sensorimotor circuits. In a predominantly right-handed sample, this finding is consistent with the notion that imagery of the non-dominant hand requires stronger maintenance of a stable internal motor state, which may be accompanied by increased beta connectivity supporting robust MI [15; 13; 26]. In this sense, increased beta network density may reflect greater engagement of sensorimotor communication processes necessary for maintaining MI in a more complex visual context.

Conversely, the higher connectivity observed in the alpha band during right-hand MI is consistent with alpha-mediated control models, which posit that alpha synchronization supports selective suppression of task-irrelevant activity and protects internally generated representations from competing sensory or motor programs [11, 10, 12]. Within this model, increased alpha connectivity during right-hand MI may reflect stronger top-down control and suppression of competing representations, thereby facilitating the formation of a stable motor image for the dominant effector.

For the development of BCIs, it is important to understand how accurately users can self-assess the success of their mental efforts. The prevailing assumption is that if a person believes that he or she performed a vivid mental image, this should be reflected in the brain activity. Testing this relationship is necessary to determine whether subjective experience can be relied upon during BCI training [7, 29]. In our study, participants rated the quality of imagery using VAS.

To assess the relationship between subjective task performance ratings and objective neural activity, we conducted

RMCorr analysis in the beta band. The correlation was statistically significant, but very weak ($r=0.07$, $p=0.014$). In our paradigm, participants rated the quality of their images, and the small association with beta-band functional connectivity suggests that subjective perceptions may reflect certain aspects of large-scale network interactions during MI. At the same time, the minimal effect size is consistent with previous studies showing that people only partially evaluate their ability to modulate BCI-relevant signals [29]. This likely occurs because self-assessment relies on broader cognitive processes (such as attention, confidence, and internal monitoring) that extend beyond activity limited to primary sensorimotor areas.

Discussion

In the present study, we investigated the neurophysiological mechanisms of MI using a graph theoretic approach to analyze functional connectivity patterns across multiple frequency bands. Using ImCoh, a metric that minimizes spurious zero-lag synchrony due to volume conduction and common-reference effects [23, 14], we identified frequency-specific network reorganization associated with MI laterality and examined the relationship between objective connectivity measures and subjective ratings of task performance.

The results of the analysis showed that imagining left vs. right hand movements exerts differential effects on connectivity in the alpha and beta frequency bands. In the beta frequency band (13–30 Hz), we observed significantly higher network density during left (non-dominant) hand imagery with a medium effect size (Cohen's $d=0.496$). In contrast, connectivity in the alpha band (8–13 Hz) was enhanced during right (dominant) hand imagery (Cohen's $d=-0.461$). This crossover pattern suggests that alpha and beta oscillations support complementary mechanisms during MI.

Enhanced connectivity in the beta band during non-dominant hand imagery is consistent with the status quo hypothesis, which suggests that beta oscillations reflect the active maintenance of the current sensorimotor state [13]. Imagery of the less-practiced non-dominant hand is likely a more demanding task requiring the continued engagement of sensorimotor circuits to maintain a stable internal motor representation. Our results expand on previous studies regarding the influence of handedness on MI [15] by demonstrating that this asymmetry manifests not only in local ERD/ERS patterns but also in the large-scale organization of functional networks. The topological concentration of the beta cluster in central and parietal regions further supports its role in sensorimotor integration, which is consistent with evidence that beta synchronization facilitates long-range connectivity within motor circuits [26].

The opposite pattern in the alpha band, where increased connectivity is observed during imagery of the dominant hand, is consistent with current models of alpha-mediated inhibitory control [10, 11, 12]. According to the gating by inhibition concept, alpha synchronization serves to suppress task-irrelevant neural populations, thereby protecting task-relevant representations from interference. For a well-practiced dominant hand, motor representation may be more accessible, allowing attentional resources to be directed toward suppressing competing motor programs and irrelevant sensory input. The long-range fronto-occipital topology of the alpha cluster supports this interpretation, as it indicates networks involved in top-down attentional control rather than primary sensorimotor processing.

Notably, we did not observe statistically significant laterality effects in the theta band. Although theta oscillations were linked to cognitive control and working memory processes, their contribution to MI lateralization appears to be secondary within this paradigm. This null result may reflect the predominantly sensorimotor (rather than mnemonic) demands of our task.

A secondary goal of this study was to assess whether participants' subjective ratings of image quality correspond to objective measures of brain connectivity. RMCorr revealed a statistically significant but weak relationship between global beta-band connectivity and VAS scores ($r=0.07$, $p=0.014$), indicating that subjective assessments explain less than 0.5% of the variance in network dynamics. This is consistent with previous findings regarding the fact that users have limited introspective access to BCI-relevant neural signals [29], which suggests that subjective confidence is not a reliable indicator of actual brain state modulation. At the same time, the presence of even a weak relationship inspires cautious optimism: connectivity-based metrics may serve as potential indicators that will help users gradually learn to recognize and better understand their own imagery-related states in the course of MI training. Such metrics could complement real-time feedback and support more effective self-monitoring as users acquire MI skills.

Several limitations of this study should be considered. First, functional connectivity was analyzed at the sensor level using 18 electrodes. Although ImCoh reduces volume conduction artifacts, sensor-level analysis does not allow for unambiguous localization of neural sources, and the observed fronto-occipital connectivity patterns should be interpreted with caution. Future studies using high-density EEG with source reconstruction methods will provide a more precise spatial characterization of MI networks.

Second, subjective experience was assessed using a unidimensional VAS scale, which reflects only an overall assessment of perceived effectiveness. This approach does not distinguish between various components of imagery experience, such as vividness of visual imagery, kinesthetic intensity, or perceived exertion. Multidimensional assessment tools, such as the Movement Imagery Questionnaire, may reveal more nuanced relationships between specific aspects of MI and neural connectivity.

Third, although we manipulated the type of visual stimulus (abstract vs. realistic), the present analysis focused on combined experimental settings to maximize statistical power to detect laterality effects. The independent contribution of stimulus abstraction to network organization remains to be explored in future studies.

Fourth, our sample consisted exclusively of healthy young adults, limiting the generalizability of our results to clinical populations. Given that MI-based BCIs are particularly relevant for the neurorehabilitation of stroke patients, it is crucial to determine whether the observed frequency-specific lateralization patterns are preserved or altered in individuals with motor impairments.

Finally, a cross-sectional study precludes conclusions about training-related changes. Future studies should monitor connectivity changes over training sessions. This would clarify whether practice improves the correspondence between subjective and objective assessments.

Hence, the present study demonstrates that MI engages frequency-specific patterns of functional connectivity in the brain that systematically vary depending on the imagined hand

laterality. The dual dissociation between alpha- and beta-band networks suggests that these oscillatory systems perform distinct complementary functions: beta connectivity supports challenging maintenance of MI for less automated actions, while alpha connectivity reflects top-down inhibitory control during the imagery of well-practiced movements. The weak correspondence between network connectivity and subjective assessments highlights the fundamental disconnect between brain physiology and conscious experience, which has direct implications for the design of BCI training protocols.

Future research should expand on these findings by examining source-level connectivity, incorporating multivariate measures of imagery experience, and tracking network reorganization during learning. Understanding how individual differences in underlying network architecture predict BCI ability and how targeted interventions can alter these networks represents a promising direction for optimizing MI-based neurorehabilitation [31].

Conclusion

This study demonstrates that MI is based on distinct patterns of functional connectivity in the brain, which vary depending on which hand is imagined. Increased connectivity in the beta band for the non-dominant hand suggests that the brain forms a more integrated network to perform less practiced motor tasks. Furthermore, we found only a weak relationship between objective brain connectivity and users' self-reported performance. This reveals a significant gap between the brain's physiological state and a person's conscious perception indicating that the sense of control when using a BCI is a complex mental phenomenon rather than a direct reflection of sensorimotor network activity. These results highlight the need to incorporate real-time feedback based on connectivity metrics into BCI training, as users cannot rely solely on their own perceptions to improve performance. Future research should focus on understanding the higher-order cognitive mechanisms underlying this sense of control and adapting these principles for clinical rehabilitation.

Acknowledgments

This study was supported by the Russian Federation Ministry of Healthcare as part of the research project No. 123020600127-4, "Development of a Biofeedback-Based Multimodal Computer Appliance for the Rehabilitation of Patients with Cognitive and Motor Disorders of Various Origins", completed at the National Medical Research Center for Therapy and Preventive Medicine in 2023-2025.

Conflict of interest

The authors declare that they have no conflicts of interest.

Ethical approval

The study was approved by Local Independent Ethic Committee of National Medical Research Center for Therapy and Preventive Medicine compliant with the ethical principles of the 1964 Helsinki Declaration (Approval No: 06-05/25, date of registration: 15.10.2025).

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