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Exploring Brain Activity in Different Mental Cognitive Workloads

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Abstract

Objective: Understanding neural mechanisms underlying cognitive workload is crucial for advancing our knowledge of human cognition and mental processes. In this study, we utilized electroencephalography (EEG) analysis to investigate brain activity associated with varying mental cognitive workloads from a psychological perspective.
Method: We employed a publicly accessible EEG dataset consisting of a cohort of 36 healthy volunteers (75% female), aged 18 to 26 years, while the participants were at rest or engaged in an arithmetic task to explore mental cognitive workload. After preprocessing to reduce noise and various artifacts and to obtain a clean signal for every subject, functional connectivity and complexity features were calculated from EEGs through the coherence and permutation entropy algorithms, respectively. Then, repeated measures analysis of variance (ANOVA) was conducted to assess the differences in complexity and connectivity measures across various brain regions between the rest and task states.
Results: Brain sites showed significant within-subject effects, and the interaction between states and channels was significant for connectivity values ($F = 3.68$, $P = 0.034$). Post hoc comparisons indicated that FP1-F7, FP1-F8 and FP1-Fz connectivity were significantly lower during the task state compared to the rest state ($P < 0.05$). Moreover, F4-P3, F4-P4, FP1-O1, FP2-O2, F3-O1, F4-O1, F8-O1, C4-O1, F3-O2, F4-O2, F7-O2, F8-O2, Fz-O1, Fz-O2, Cz-O1 and Fz-P4 connectivity were significantly higher during the arithmetic task state ($P < 0.05$). Furthermore, brain sites showed significant within-subject effects and the interaction between states and channels was significant for entropy values ($F = 3.50$, $P = 0.041$). Post hoc comparisons indicated that the permutation entropy was significantly higher in the FP1, T3, T4, P4 and Pz channels during the arithmetic task compared to the rest state ($P < 0.05$).
Conclusion: During arithmetic tasks, the increased connectivity in the frontoparietal and frontooccipital networks and heightened complexity in the prefrontal, temporal and parietal lobes reflect the collaborative engagement of brain areas specialized in numerical processing, attention, working memory, cognitive control, and visual-spatial cognition. These changes in connectivity and complexity facilitate the integration of multiple cognitive processes essential for effective arithmetic problem-solving.

Key words: *Brain; Complexity Analysis; Cognition; Electroencephalography*

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Understanding the intricate workings of the human brain during various cognitive tasks has been a longstanding endeavor in neuroscience. The ability to elucidate how different mental activities elicit distinct patterns of brain activity holds profound implications for various fields ranging from education to clinical psychology (1). Understanding the dynamic interplay between brain activity and cognitive workload is essential for unraveling the neural mechanisms underlying human cognition (2). Cognitive workload refers to the mental effort exerted during tasks, encompassing a spectrum from routine activities to complex problem-solving scenarios. The brain's ability to adaptively allocate resources in response to varying cognitive demands underscores its complexity and efficiency in supporting cognitive functions (3, 4).

Thus far, assessments of cognitive workload have been divided into two distinct types: subjective and objective measures. Subjective measures depend on operators' personal perceptions and self-assessment, commonly employing questionnaires such as the Subjective Workload Assessment Method to evaluate mental workload. Despite their ease of use, these tools are criticized for their lack of objectivity, real-time feedback, and precise outcomes (5). In contrast, objective measures predominantly utilize task performance data and diverse biological signals, aiming to reduce task interference and overcome the limitations associated with subjective methods (6). Recent advancements in neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), magnetoencephalography (MEG), and near-infrared spectroscopy (NIRS), have revolutionized our ability to investigate brain activity with high spatial and temporal resolution (7, 8). These technologies enable researchers to map neural networks and identify specific brain regions involved in different cognitive processes (9, 10). For example, studies utilizing fMRI have shown that tasks requiring sustained attention activate the dorsal attention network involving the frontal and parietal cortices, whereas memory tasks recruit the hippocampus and surrounding medial temporal lobe structures (11, 12), reflecting their roles in executive functions and information processing (13). Commonly utilized physiological signals fall into categories such as heart rate, respiration, electroencephalogram (EEG), eye tracking, and electromyogram (14). Among these, EEG is popular because of its convenience, excellent temporal resolution, availability, safety, and affordability (15, 16). EEG allows for the measurement of electrical activity in the brain, offering real-time monitoring and detailed assessment of cognitive processes (17-19). Therefore, our study concentrates on the comparison of different mental workload states using EEG-based methods.

Different cognitive tasks elicit unique EEG signatures, such as theta and alpha rhythms, which vary depending on the nature of the task (20). Tasks requiring higher cognitive demand, such as problem-solving or decision-making, typically show increased frontal cortex activation in EEG studies (21). EEG studies have highlighted specific oscillatory patterns, such as theta and gamma oscillations, during memory encoding and retrieval processes (22-25). Attentional processes are often associated with modulations in the alpha band, reflecting changes in cognitive workload and attentional allocation (26, 27). Furthermore, multitasking scenarios are characterized by fluctuations in theta and alpha band activity, indicating varying levels of cognitive load and task-switching demands (28). Prolonged cognitive tasks lead to changes in EEG patterns, such as increased theta activity and reduced alpha power, indicating cognitive fatigue (29). In addition, emotional stimuli influence EEG patterns, with distinct changes in alpha asymmetry and gamma oscillations depending on emotional valence and arousal levels (30). EEG studies have also identified age-related changes in brain activity during cognitive tasks, reflecting alterations in neural efficiency and cognitive decline (31). These findings illustrate the diverse applications of EEG in understanding brain activity across different cognitive tasks and conditions, offering insights into neural mechanisms underlying human cognition.

The field has progressed towards understanding how cognitive workload modulates functional connectivity between brain regions. Functional connectivity analyses reveal synchronized activity patterns among distant brain areas, providing insights into network dynamics during task performance (32). For instance, increased cognitive load has been associated with enhanced connectivity within task-specific networks and decreased connectivity between task-negative and task-positive networks (33). EEG analysis reveals that working memory tasks involve increased theta and alpha band synchronization, especially in frontal and parietal regions (34). Moreover, investigations into brain activity across different cognitive workloads have highlighted the dynamic nature of neural networks involved in task performance. Variations in workload intensity and complexity often result in corresponding changes in neural recruitment patterns, underscoring the brain's adaptive capacity to meet varying cognitive demands (35).

Previous studies have relatively focused on the analysis of EEG frequency bands, and little research has been done on EEG connectivity and complexity characteristics under different mental workloads. This is while the integration of connectivity and complexity analyses in EEG studies offers a promising avenue for advancing our understanding of brain activity across varied cognitive workloads. By examining how different brain regions communicate and synchronize during tasks of differing complexity, researchers can elucidate the underlying neural networks that support cognitive processes. This paper aims to delve into recent findings using these analytical approaches, exploring how connectivity patterns and complexity measures in EEG signals provide insights into the dynamic nature of cognitive workload.

Materials and Methods

This section presents a comprehensive outline of the methods and techniques utilized to meet the research goals. It details the dataset selection and analysis approaches employed in this study. Each phase is systematically laid out, highlighting key variables, tools, and statistical methods applied. It should be noted that this research was approved through the Institutional Ethics Committee of the UCSI University (Kuala Lumpur, Malaysia).

EEG Dataset

In this study, we employed a publicly accessible EEG dataset to explore mental cognitive workload (36). A cohort of 36 healthy volunteers (75% female), aged 18 to 26 years, with normal vision and no history of cognitive disorders, mental illness, or learning disabilities, participated in the investigation. Participants performed an arithmetic task involving continuous subtraction while EEG data was collected. EEG signals were acquired using Ag/AgCl electrodes placed on the scalp according to the 10-20 system. 19 specific electrode positions were selected: FP2, FP1, F4, F3, Fz, F7, C3, F8, Cz, C4, O1, T3, O2, T5, T4, T6, P3, P4, Pz. A reference was established by connecting channels to A1 and A2 positioned on the earlobes. Electrode impedance was kept below 5 kOhm, and data were sampled at a rate of 500 Hz. To minimize noise and artifacts, the EEG signals were filtered using a 45 Hz low-pass filter, a 0.5 Hz high-pass filter, and a 50 Hz notch filter. Prior to EEG recording, participants underwent a relaxation period in a resting state, and during the arithmetic task they silently counted numbers without verbalizing them. Each trial began with the verbal delivery of a 4-digit number (the minuend) followed by a 2-digit number (the subtrahend), such as 4753 minus 17 or 3141 minus 42. Mental arithmetic tasks are widely acknowledged as a reliable means of inducing stress in experimental contexts. Engaging in continuous subtraction tasks for 15 minutes is associated with inducing psychosocial stress. As a result, the protocol required considerable cognitive effort from the participants. During EEG recording, participants were seated in a dimly lit, soundproof room, comfortably reclined in an armchair. The recording session commenced with a three-minute adaptation phase, followed by a three-minute resting-state session with closed eyes, and concluded with a four-minute period of performing the arithmetic task. Figure 1 illustrates the timeline of the recording procedure.

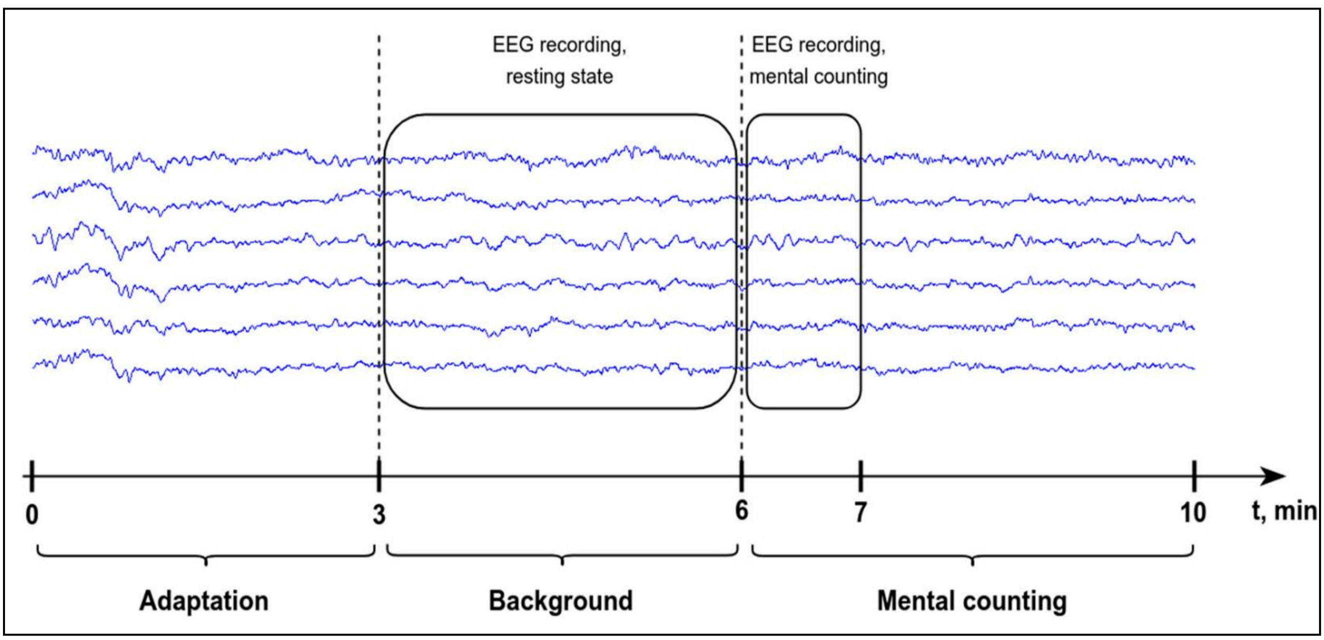

Figure 1. The Time Course of the Electroencephalogram Recording Procedure To Explore Mental Workloads (36)

Data Preprocessing

We adhered to the preprocessing recommendations specified in the literature accompanying the dataset. This process included several key steps: (I) We applied a high-pass filter set at 1 Hz to the raw data, which helped to remove low-frequency noise from sources such as scalp sweat, head movements, and electrode connections, as well as gradual changes in the EEG signal over time; (II) A 50 Hz notch filter was used to eliminate electrical interference from external sources like power lines, which can introduce electromagnetic noise into the EEG recordings; (III) We implemented Artifact Subspace Reconstruction (ASR) to automatically detect and eliminate noise or artifacts from the EEG data; (IV) The data was then re-referenced to an average reference, shifting from a fixed reference to this method—this approach is favored by some researchers, especially when electrode placement covers a significant area of the scalp. We emphasized the use of ASR due to the presence of notable amplitude artifacts in the datasets. ASR is an adaptive technique for removing high-amplitude disturbances. Finally, 10 epochs of 10 seconds of clean signal for each individual were selected for subsequent analyses. The preprocessing steps were carried out using the EEGLAB toolbox within the MATLAB environment (version 2015b).

Connectivity Analysis

Brain connectivity elucidates the network of structural and functional connection across different brain areas. These functional connections among brain areas depend on neural oscillations, and might vary in different workload conditions including rest and task (37). Coherence is a well-known mathematical algorithm to evaluate the amount of similar neural oscillatory activity between two or more brain sites. The coherence algorithm in EEG connectivity analysis is a fundamental method used to quantify the degree of synchronization in neural activity between different brain regions. It provides insight into how strongly two or more brain areas oscillate in harmony, indicating functional connectivity (38). Essentially, coherence measures the consistency of phase relationships between EEG signals across channels, offering a mathematical approach to understanding the coordinated activity of neuronal networks (39). By examining these patterns, researchers can discern meaningful correlations in brain function and how they may change under various conditions or cognitive tasks. This method plays a crucial role in advancing our understanding of brain dynamics and their implications for cognitive processes and neurological disorders.

Complexity Analysis

Complexity EEG analysis refers to the study of EEG signals using methods that assess the intricacies and patterns within brain activity (40). Unlike traditional EEG analysis that focuses on basic features like amplitude and frequency, complexity analysis delves deeper into the non-linear dynamics of neural signals. It explores how EEG signals exhibit complex behaviors such as fractal patterns, self-similarity, and irregular fluctuations that traditional methods may overlook (41, 42). This approach provides insights into the richness and adaptability of brain function, offering a more nuanced understanding of neurological processes and their variations across different states, such as wakefulness and sleep or during cognitive tasks. Complexity EEG analysis is pivotal in uncovering the underlying mechanisms of brain function and in developing more refined diagnostic and therapeutic approaches for neurological disorders.

In this study, permutation entropy is utilized to measure EEG complexity in different states. Permutation entropy is a measure of the complexity of a time series based on the idea of quantifying the frequency of occurrence of ordinal patterns in the time series. An ordinal pattern is a sequence of values that preserves the order of the original time series (43). Permutation entropy is calculated by first dividing the time series into overlapping windows of a fixed length. Then, for each window, the ordinal pattern of the time series is computed and transformed into a symbolic sequence. The frequency of occurrence of each symbolic sequence is then calculated and used to compute the permutation entropy feature (44). A higher permutation entropy value indicates a more complex time series with a higher degree of irregularity or unpredictability, while a lower value indicates a simpler time series with less irregularity or unpredictability (45). We chose this algorithm to calculate EEG complexity because of its sensitivity to temporal patterns, robustness to noise, simple interpretation, nonparametric nature, and computational efficiency.

Statistical Analysis

As data distribution was normal according to the Shapiro-Wilk test, we employed repeated measures analysis of variance (ANOVA) to assess the differences in complexity and connectivity measures across various brain regions between the rest and task states. The between-subject factor was the group, while the within-subject factors included 19 EEG channels. Whenever necessary, we applied the Bonferroni correction to account for multiple comparisons. Additionally, we utilized paired-samples t test to identify the EEG channels where complexity or connectivity significantly differed between the two states as the post-hoc comparison. In cases where the assumption of sphericity was breached, as determined by Mauchly's test, we reported the estimates based on the Greenhouse-Geisser correction. These analyzes were performed separately for each of the connectivity and complexity features. All statistical analyzes were done through the IBM SPSS statistics 21.0 software. A P-value of 0.05 was considered as a significant level in statistical analysis.

Results

Figure 2 shows an example of raw EEGs recorded at rest and task conditions. After EEG preprocessing, functional connectivity between all electrode pairs was first calculated through the coherence algorithm. Figure 3 shows the grand average of coherence values for all electrode pairs in both rest state and task condition. As mentioned, there were 36 cases in each research group. As can be seen, the functional connectivity between different brain regions seems to be different in the task condition compared to the rest condition. According to the repeated measures analysis, a significant main effect was observed between states for functional connectivity values (F = 3.92, P = 0.025). Brain sites showed significant within-subject effects and the interaction between states and channels was significant for connectivity values (F = 3.68, P = 0.034). Post hoc comparisons indicated that FP1-F7, FP1-F8 and FP1-Fz connectivity were significantly lower during the task state compared to rest (P < 0.05). Moreover, F4-P3, F4-P4, FP1-O1, FP2-O2, F3-O1, F4-O1, F8-O1, C4-O1, F3-O2, F4-O2, F7-O2, F8-O2, Fz-O1, Fz-O2, Cz-O1 and Fz-P4 connectivity were significantly higher during the arithmetic task state (P < 0.05).

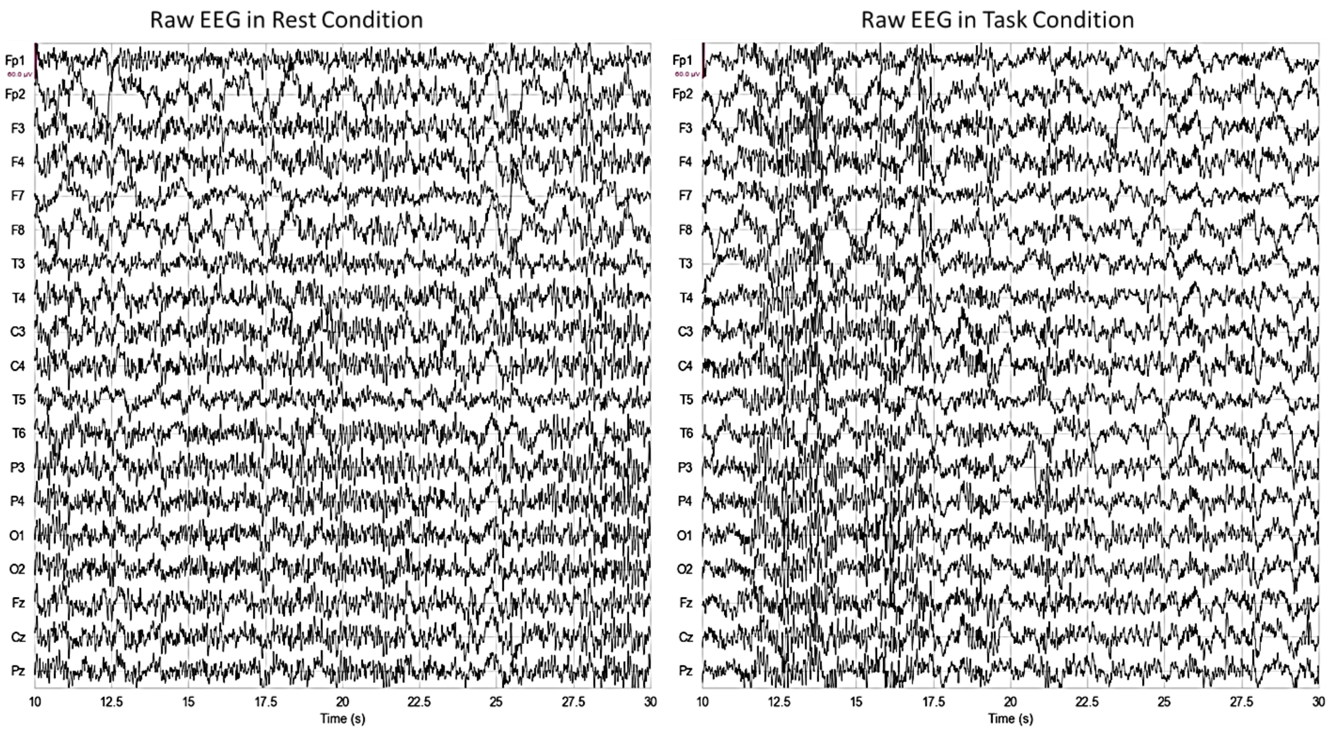

Figure 2. An Example of Raw EEGs Recorded at Rest (Left) and Task (Right) Conditions

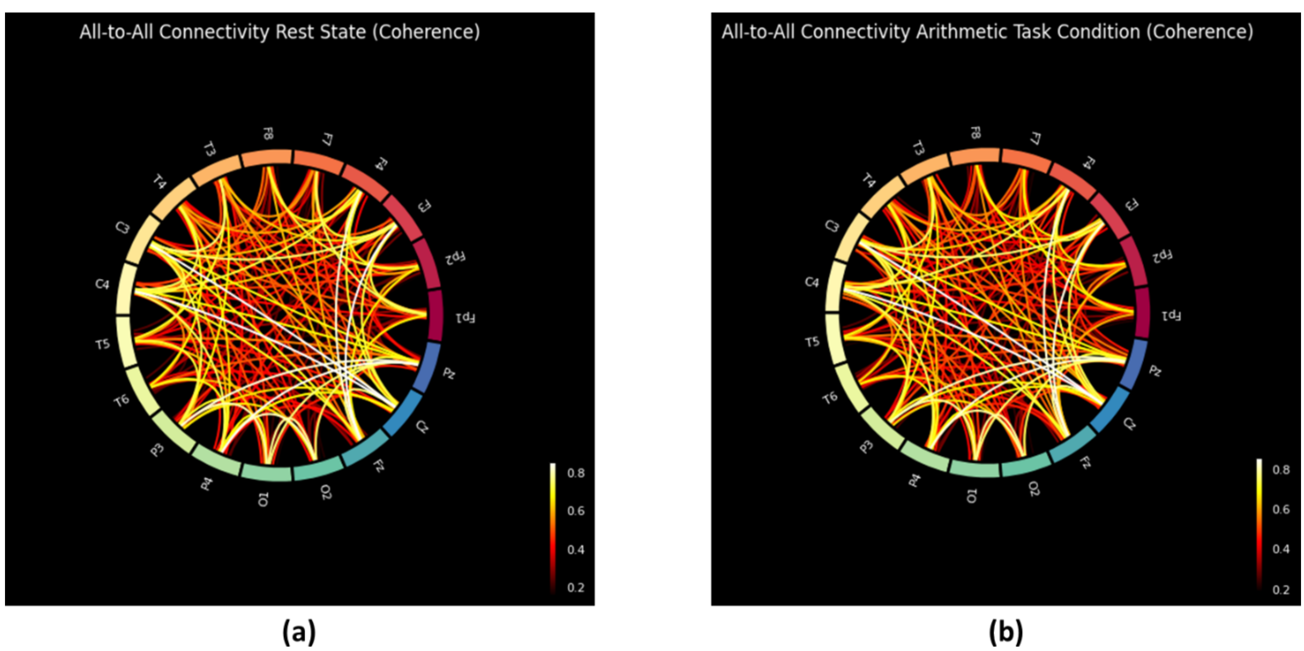

Figure 3. The Grand Average of Functional Connectivity Obtained through the Coherence Algorithm for All EEG Channel Pairs in the (a) Rest State, and (b) Task Condition

Table 1 shows the coherence values of the pairwise channels with significant differences between the two states of rest and arithmetic task.

Table 1. Significant Differences between Functional Connectivity Measures of Rest and Task States through the Post Hoc Comparison

Pairwise Channel	Rest State (n = 36) (m ± SD)	Task State (n = 36) (m ± SD)	T-value (P-value)	Mean Difference	Standard Error	95% Confidence Interval	
						Lower	Upper
FP1-F7	0.742 ± 0.135	0.669 ± 0.130	2.327 (0.023)	0.072	0.031	0.0104	0.135
FP1-F8	0.472 ± 0.135	0.410 ± 0.111	2.112 (0.038)	0.061	0.029	0.003	0.120
F4-P3	0.373 ± 0.086	0.424 ± 0.094	2.381 (0.020)	0.050	0.021	0.008	0.093
F4-P4	0.437 ± 0.082	0.486 ± 0.100	2.265 (0.027)	0.049	0.021	0.005	0.092
FP1-O1	0.178 ± 0.058	0.213 ± 0.079	2.152 (0.035)	0.035	0.016	0.002	0.068
FP2-O1	0.163 ± 0.070	0.199 ± 0.071	2.132 (0.037)	0.035	0.016	0.002	0.069
F3-O1	0.270 ± 0.079	0.327 ± 0.092	2.846 (0.006)	0.057	0.020	0.017	0.097
F4-O1	0.241 ± 0.066	0.297 ± 0.083	3.135 (0.003)	0.055	0.017	0.020	0.091
F8-O1	0.159 ± 0.042	0.205 ± 0.080	3.032 (0.003)	0.045	0.015	0.015	0.076
C4-O1	0.432 ± 0.078	0.473 ± 0.093	2.000 (0.049)	0.040	0.020	0.001	0.081
F3-O2	0.250 ± 0.081	0.302 ± 0.085	2.651 (0.010)	0.052	0.019	0.012	0.091
F4-O2	0.256 ± 0.072	0.317 ± 0.090	3.161 (0.002)	0.061	0.019	0.022	0.099
F7-O2	0.177 ± 0.062	0.211 ± 0.065	2.249 (0.028)	0.033	0.015	0.003	0.064
F8-O2	0.186 ± 0.051	0.231 ± 0.087	2.663 (0.010)	0.044	0.016	0.011	0.078
FP1-Fz	0.668 ± 0.114	0.609 ± 0.122	2.095 (0.040)	0.058	0.027	0.002	0.114
Fz-O1	0.258 ± 0.067	0.310 ± 0.088	2.802 (0.007)	0.052	0.018	0.014	0.089
Fz-O2	0.259 ± 0.073	0.311 ± 0.091	2.675 (0.009)	0.053	0.019	0.013	0.091
Cz-O1	0.444 ± 0.070	0.482 ± 0.090	2.006 (0.049)	0.038	0.019	0.002	0.076
Fz-P4	0.416 ± 0.074	0.458 ± 0.102	1.996 (0.049)	0.042	0.021	0.002	0.084

Figure 4 shows the box plots for permutation entropy in rest and task conditions. As can be seen, there are some differences in the nonlinear measures among different brain regions between resting and task conditions. According to the repeated measures analysis, a significant main effect was observed between rest and task states for permutation entropy values ($F = 3.81$, $P = 0.032$). Brain sites showed significant within-subject effects and the interaction between states and channels was significant for entropy values ($F = 3.50$, $P = 0.041$). Post hoc comparisons indicated that the permutation entropy was significantly higher in the FP1, T3, T4, P4 and Pz channels during the arithmetic task compared to the rest state ($P < 0.05$). Table 2 shows the post hoc comparisons between permutation entropy measures of rest and task states. As can be seen, the entropy values in all brain regions are higher in the task state than in the rest state, and their P-values are close to significance ($P < 0.1$).

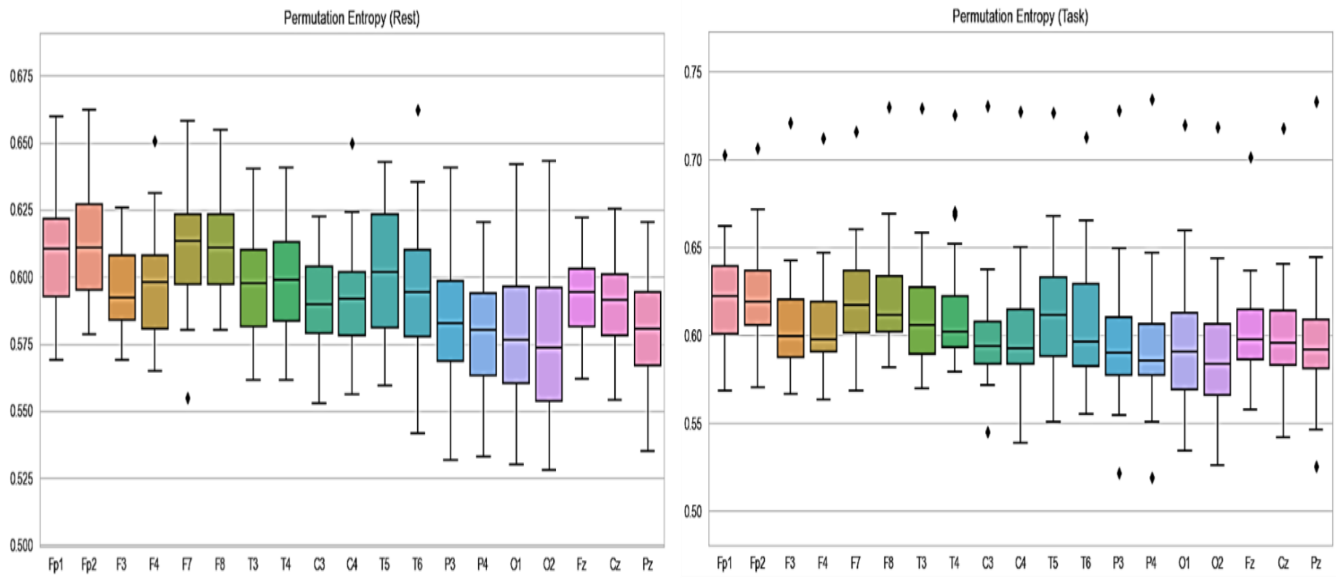

Figure 4. Box Plots for Permutation Entropy in Rest and Task Conditions

Table 2. Post Hoc Comparison between Permutation Entropy Measures of Rest and Task States

EEG Channel	Rest State (n = 36) (m ± SD)	Task State (n = 36) (m ± SD)	t-value (P-value)	Mean difference	Standard error	95% Confidence interval	
						Lower	Upper
FP1	0.610 ± 0.021	0.621 ± 0.026	1.968 (0.048)*	0.011	0.005	0.001	0.022
FP2	0.611 ± 0.020	0.622 ± 0.026	1.825 (0.072)	0.010	0.004	-0.021	0.009
F3	0.595 ± 0.017	0.605 ± 0.029	1.772 (0.081)	0.010	0.004	-0.021	0.001
F4	0.595 ± 0.019	0.605 ± 0.028	1.707 (0.092)	0.009	0.005	-0.021	0.001
F7	0.610 ± 0.021	0.619 ± 0.027	1.642 (0.105)	0.009	0.005	-0.020	0.002
F8	0.612 ± 0.019	0.620 ± 0.029	1.485 (0.142)	0.008	0.006	-0.020	0.003
T3	0.597 ± 0.020	0.611 ± 0.030	2.147 (0.035)*	0.013	0.006	0.001	0.025
T4	0.600 ± 0.020	0.613 ± 0.031	2.088 (0.040)*	0.012	0.006	0.001	0.025
C3	0.590 ± 0.018	0.600 ± 0.030	1.699 (0.094)	0.009	0.005	-0.021	0.001
C4	0.590 ± 0.019	0.601 ± 0.031	1.714 (0.091)	0.010	0.006	-0.022	0.001
T5	0.601 ± 0.023	0.614 ± 0.032	1.914 (0.060)	0.012	0.007	-0.026	0.001
T6	0.592 ± 0.025	0.604 ± 0.032	1.797 (0.077)	0.012	0.006	-0.027	0.001
P3	0.582 ± 0.024	0.595 ± 0.033	1.914 (0.060)	0.013	0.006	-0.027	0.001
P4	0.578 ± 0.028	0.593 ± 0.038	2.147 (0.035)*	0.014	0.007	0.001	0.028
O1	0.577 ± 0.029	0.595 ± 0.034	1.901 (0.061)	0.015	0.008	-0.031	0.001
O2	0.576 ± 0.027	0.589 ± 0.037	1.661 (0.101)	0.013	0.007	-0.028	0.002
Fz	0.591 ± 0.016	0.601 ± 0.025	1.766 (0.082)	0.009	0.005	-0.019	0.001
Cz	0.590 ± 0.017	0.600 ± 0.028	1.821 (0.073)	0.010	0.005	-0.021	0.001
Pz	0.579 ± 0.022	0.594 ± 0.034	2.217 (0.030)*	0.015	0.007	0.001	0.028

* Indicates P < 0.05

Discussion

By uncovering the specific brain regions and networks involved in different cognitive tasks, researchers gain a deeper understanding of how the human brain processes information, makes decisions, and solves problems. This knowledge contributes to the fields of neuroscience and cognitive psychology, advancing our theoretical understanding of human cognition. In this study, we investigated and compared the connectivity and complexity features of EEG signals recorded during rest and arithmetic task conditions. The results demonstrated reduced functional connectivity within frontal regions in the arithmetic task, which may reflect a compensatory mechanism to facilitate connectivity between the frontal lobe and other cortical regions in order to perform a specific cognitive task. Accordingly, we observed that the functional connectivity between the frontal lobe and the occipital and parietal regions increased significantly during the arithmetic task. Previous studies showed that during arithmetic tasks, there is increased connectivity between the frontal and parietal lobes (frontoparietal connectivity) (46, 47). The frontal lobes, associated with executive functions and cognitive control, become more actively connected to the parietal lobes, which are involved in numerical processing, spatial cognition, and attention (48). This enhanced connectivity indicates that the coordination needed for cognitive functions, such as working memory and attention, should be integrated seamlessly with numerical processing and problem-solving strategies (21). Furthermore, literature shows that in the context of arithmetic tasks, frontooccipital connectivity also undergoes change (49). The frontal lobes, particularly involved in higher-order cognitive functions and attentional control, show increased connectivity with the occipital lobes, responsible for visual processing and spatial perception (50). This enhanced connectivity suggests the integration of numerical information with visual-spatial representations, such as when dealing with arithmetic problems involving visual stimuli or spatial manipulation (51).

Previous studies showed that the cortical regions associated with arithmetic tasks include the parietal lobe, particularly the intraparietal sulcus, the prefrontal cortex that is involved in working memory and executive functions, and areas within the temporal lobe such as the angular gyrus (52, 53). These brain regions play crucial roles in processing numerical information, calculation, and problem-solving tasks. Our findings showed that EEG complexity significantly increased in these brain areas during the arithmetic task. Previous studies showed that this heightened complexity in the prefrontal region reflects the recruitment of working memory, strategic planning, and inhibitory control mechanisms required for manipulating numerical information, selecting appropriate problem-solving strategies, and maintaining task-relevant information (54). Moreover, the temporal regions, involved in auditory and visual processing, language comprehension, and memory, undergo changes in complexity during arithmetic tasks, consistent with previous findings (55, 56). The temporal cortex may exhibit increased activity and complexity to support the integration of auditory and visual representations of numerical information, especially in tasks involving verbal and symbolic elements, as well as the retrieval of arithmetic facts from long-term memory (57). As shown in previous studies, the complexity of the parietal cortex, which plays a crucial role in numerical processing, spatial cognition, and attention, is also affected during arithmetic tasks (58). The parietal regions may show increased engagement and complexity as they are involved in numerical manipulation, mental arithmetic, and spatial representations required for solving arithmetic problems. Overall, during arithmetic tasks, the prefrontal, temporal, and parietal regions exhibit changes in complexity to accommodate the demands of working memory, attention, and the manipulation of numerical and spatial information. The dynamic modulation of complexity in these brain regions reflects the intricate interplay of cognitive processes essential for effective arithmetic problem-solving.

Limitation

The study primarily included a homogeneous group of young adults. This limited range of age and demographic features may restrict the generalizability of the findings across different age groups and populations. Moreover, the arithmetic task used may not fully capture the range of cognitive workloads encountered in everyday life. Future studies could benefit from incorporating a variety of tasks to assess how different cognitive demands affect brain activity. While EEG provides an excellent temporal resolution, its spatial resolution is limited. This might hinder the ability to identify specific brain regions involved in complex cognitive processes by overlooking subtle differences in localized brain activity. Although efforts were made to control for artifacts, individual differences in factors such as fatigue, motivation, and stress levels were not explicitly accounted for, which could impact the EEG results. These limitations highlight areas for further exploration and indicate the need for additional studies to build on the findings.

Conclusion

In summary, during arithmetic tasks, the increased connectivity in the frontoparietal and frontooccipital networks and heightened complexity in the prefrontal, temporal and parietal lobes reflect the collaborative engagement of brain areas specialized in numerical processing, attention, working memory, cognitive control, and visual-spatial cognition. These changes in connectivity and complexity facilitate the integration of multiple cognitive processes essential for effective arithmetic problem-solving. Enhancing our comprehension of these neurophysiological mechanisms not only furthers basic neuroscience but also holds implications for applications in cognitive enhancement strategies, neurofeedback interventions, and the development of adaptive learning technologies. By understanding how the brain responds to cognitive demands, we can ultimately improve human performance and well-being across a broad spectrum of activities and contexts.

Conflict of Interest

None.

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