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Exploring the link between cognitive load and brain activity during calculus learning through electroencephalogram (EEG): Insights from visualization and cluster analysis

Rina Oktaviyanthi*, Ria Noviana Agus, Khotimah

Department of Mathematics Education, Universitas Serang Raya, Serang, Indonesia
*Correspondence: rinaokta@unsera.ac.id

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Abstract

Understanding the relationship between cognitive load and brain activity is essential for enhancing learning outcomes, particularly in complex subjects such as calculus. Despite its significance, empirical research examining the manifestation of cognitive load in brain activity patterns remains sparse, indicating a notable gap in the literature. This study aims to investigate the correlation between brain activity and cognitive load in a cohort of 30 mathematics education students enrolled in a calculus course, utilizing electroencephalogram (EEG) recordings. A quantitative descriptive research design was employed, integrating cluster analysis and data visualization techniques to facilitate an in-depth examination. EEG recordings of theta, alpha, and beta wave activity were collected during calculus sessions, followed by the administration of a cognitive load questionnaire. Descriptive statistics were utilized to analyze the distribution of cognitive load and brain activity, while correlation analysis was conducted to explore the relationships between cognitive load and EEG parameters across the different brainwave bands. The results revealed that higher cognitive load was positively correlated with increased frequency and amplitude in the alpha and beta bands, while a negative correlation was observed with theta frequency. Furthermore, cluster analysis effectively categorized participants based on distinct EEG signal patterns associated with varying levels of cognitive load. These findings offer valuable insights for the development of personalized learning interventions tailored to individual brain activity profiles, providing a foundation for future research on adaptive learning environments.

Keywords: Brain Wave Frequency, Calculus, Cluster Analysis, Cognitive Load, Electroencephalogram

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In the context of higher education, students encounter substantial cognitive demands, particularly in the field of mathematics, where the development of critical thinking and analytical skills is paramount (González-Hernández et al., 2021; Sachdeva & Eggen, 2021; Trinidad, 2020). To evaluate cognitive load and its influence on learning outcomes, researchers employ Electroencephalography (EEG), a non-invasive method for monitoring brain activity through scalp electrodes. EEG offers valuable insights into brain activity patterns (Cheng et al., 2022), enabling the exploration of cognitive processes and the dynamic relationship between cognitive demands and mental capacity (Pei et al., 2023). Students with higher cognitive abilities tend to exhibit more efficient information processing, which is reflected in structured brainwave patterns during complex tasks. Specifically, alpha waves (8-12 Hz) are associated with a state of relaxed alertness, facilitating memory retrieval, while beta waves (12-30 Hz) are indicative of active engagement and problem-solving. The prominence of these waves during task-focused activities suggests effective management of mathematical challenges. Additionally, optimal cognitive performance is characterized by reduced theta wave activity (4-8 Hz), as lower theta levels are indicative of efficient cognitive load management, preventing mental overload (Lapomarda et al., 2022; Ramírez-Moreno et al., 2021; Tan et al., 2024). Conversely, heightened theta wave activity may signal disengagement, potentially impairing task performance. Thus, the interplay of alpha, beta, and theta waves is vital for student engagement with demanding academic material. By incorporating EEG data, educators can gain a deeper understanding of students' cognitive states, thereby informing the development of tailored instructional strategies that cater to diverse cognitive profiles.

Many students experience excessive cognitive load in demanding subjects such as mathematics, often due to the complexity of the material exceeding their cognitive capacity (Chen et al., 2023; Oktaviyanthi et al., 2024). EEG analyses indicate that students under high cognitive load typically show increased theta wave activity, which is associated with mental strain and potential stress (Kramer, 2020; Liu et al., 2023). However, it is noteworthy that students with lower cognitive load may perform equally well academically, challenging the assumption that higher cognitive load always correlates with greater engagement (Souza & Naves, 2021; Xiong et al., 2020). In fact, some students can process information efficiently with minimal cognitive load, achieving high performance despite lower brainwave activity. Clustering analyses of EEG signals reveal significant individual variability in brain activity patterns (Apicella et al., 2022; Bashir et al., 2021; Forbes et al., 2022), further demonstrating that cognitive responses to academic challenges differ among students (Gao et al., 2023). These findings underscore the importance of recognizing individual differences, as not all students respond uniformly to cognitive demands. Consequently, this variability suggests the need for differentiated instructional approaches to cater to diverse cognitive profiles.

This study questions the conventional assumption that higher cognitive load is directly correlated with superior academic performance. EEG data reveals diverse responses among students, with some achieving optimal academic outcomes despite lower cognitive load. These findings suggest that factors such as study strategies, time management, and stress levels may play a more significant role in academic performance than cognitive load alone. Current instructional practices often adopt a one-size-fits-all approach, which overlooks individual differences in cognitive responses (Ke et al., 2023). This gap between educational expectations and students' actual needs may contribute to suboptimal learning experiences (Mangaroska et al., 2022). Although EEG-based clustering has the potential to identify diverse learning needs, its application in educational settings remains limited (Christodoulides et al., 2022; Kalantari et al., 2021). Despite the promise of EEG technology in enhancing our understanding of cognitive processes (Tang et al., 2024), its widespread use in education is hindered by the need for specialized equipment and expertise (Zhang et al., 2022). Additionally, the interpretation of EEG data requires a combination of neuropsychological and statistical knowledge, presenting challenges to the integration of these insights into everyday teaching practices.

Furthermore, this study introduces an innovative approach by combining EEG signal visualization with cluster analysis to deepen our understanding of the relationship between cognitive load and brain activity in students. Techniques such as brainwave graphs and heatmaps facilitate real-time monitoring of brain activity during calculus learning (Gashaj et al., 2024; Mendoza-Armenta et al., 2024), providing clear representations of shifts in frequency and amplitude that help identify mental fatigue or heightened cognitive engagement (Wang et al., 2020). Cluster analysis complements this by categorizing students based on their EEG patterns (Al-Salman et al., 2023; Alyasseri et al., 2021), revealing individual differences in cognitive responses that traditional methods often fail to capture (Dalmaijer et al., 2022; Finn et al., 2020). For example, while some students exhibit increased alpha and beta wave activity under cognitive strain (Qu et al., 2020), others show elevated theta wave activity (Ikotun et al., 2023). The integration of visualization with cluster analysis provides novel insights into cognitive load and brain activity, opening avenues for personalized learning (Xu et al., 2021). A deeper understanding of individual cognitive responses enables educators to design interventions that address each student's unique cognitive needs (Chew & Cerbin, 2021), ultimately enhancing the learning experience and academic performance in challenging subjects such as calculus.

This research contributes to the advancement of learning and teaching by integrating EEG technology, cognitive load analysis, and clustering, offering new perspectives on effective educational practices. Its interdisciplinary approach—spanning educational science, neuropsychology, and data mining—uniquely investigates cognitive load and brain activity within the context of higher education (Das Chakladar & Roy, 2023; Niso et al., 2023). EEG emerges as a critical tool for monitoring brain activity (Wang et al., 2022), providing more comprehensive data on cognitive responses compared to traditional surveys or tests (Zhou et al., 2022). This enables more adaptive learning (Budin et al., 2016; Devi et al., 2021), where instructional decisions are informed by real-time cognitive data (Hernández-Mustieles et al., 2024; Srinivasa et al., 2022). Additionally, cluster analysis introduces a novel methodology for grouping students based on EEG profiles (Bradley et al., 2022), supporting differentiated instruction by tailoring strategies to the specific cognitive needs of each group (Pereira et al., 2020; Wang et al., 2020). This study not only deepens our understanding of cognitive load and brain activity but also offers practical, actionable strategies for enhancing educational quality.

METHODS

To investigate the relationship between cognitive load and students' brain activity during calculus learning, this study employs a descriptive quantitative research design, enabling a comprehensive analysis of these variables. Data will be collected from Mathematics Education students to identify patterns of cognitive engagement that emerge throughout the learning process. The research methodology begins with the selection of a representative sample, followed by data collection utilizing validated instruments, including a cognitive load questionnaire and EEG to record brain activity. The collected data will then undergo systematic processing and analysis to provide a detailed understanding of the cognitive dynamics involved. The subsequent sections will provide a detailed description of each stage in the research process, including sample selection, data collection methods, data processing techniques, and the analytical procedures employed to explore the relationship between cognitive load and brain activity. An overview of the research flow is presented in Figure 1.

The research methodology diagram, illustrated in Figure 1, delineates the steps involved in analyzing cognitive load using a quantitative descriptive approach. Data collection incorporates two primary techniques: EEG experiments for frequency band analysis and the administration of a cognitive load questionnaire. In the data processing phase, clustering and visualization methods are employed to organize and present the data, thereby revealing underlying patterns. The subsequent analysis phase utilizes descriptive statistics and correlation analysis to investigate the relationships between cognitive load and brain activity. Finally, data interpretation facilitates the drawing of conclusions regarding cognitive load patterns and their association with brain activity in the context of learning. This structured approach offers a comprehensive framework for examining cognitive load within educational settings.

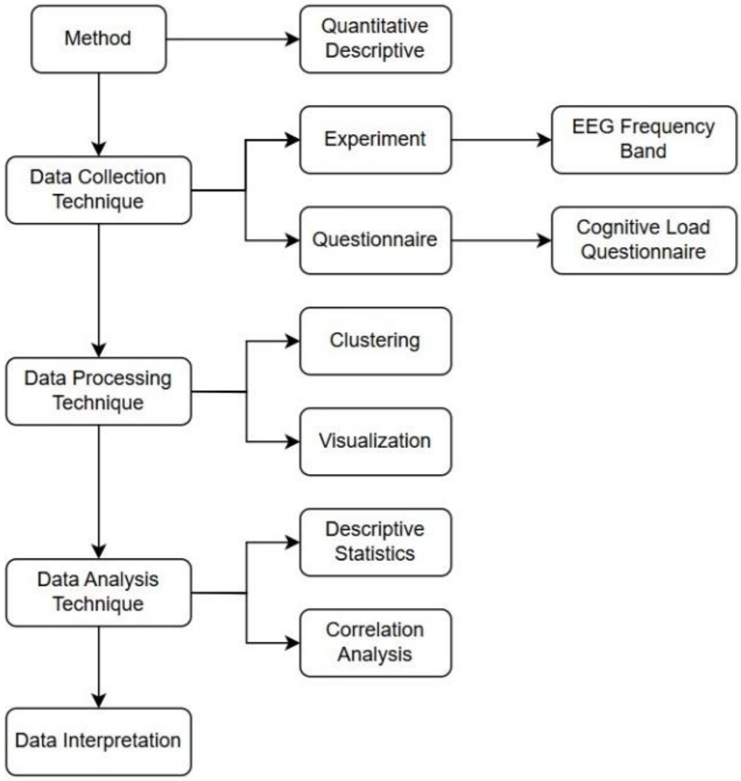


Figure 1. Research flow

Research Objectives

The primary objective of this study is to examine the relationship between brain activity and cognitive load among 30 Mathematics Education students enrolled in a calculus course. Using EEG, the research aims to capture real-time brainwave activity and quantify cognitive load, providing insights into how students process complex information during the learning of calculus.

Research Approach

This study adopts a descriptive quantitative approach, incorporating visualization techniques and cluster analysis (Denis, 2020; Grekousis, 2020). This methodology is selected for its efficacy in elucidating the relationships between variables—specifically, cognitive load and brain activity. It offers a clear, data-driven representation of how cognitive load is experienced by students within a controlled learning environment.

Research Subjects

The participants in this study comprise 30 first-year Mathematics Education students from Universitas Serang Raya, all of whom are enrolled in a calculus course. Purposive sampling was employed to select participants at a comparable stage of learning, ensuring consistency in the measurement of cognitive load and brain activity. During the calculus learning session, each student was fitted with an EEG device to record their brain signals in real time. Following the session, participants completed a questionnaire to assess their perceived cognitive load.

Data Collection Instruments

Two primary instruments were utilized in this study. The first instrument, EEG, was employed to record brain activity signals during the learning session. The EEG captured the frequency and amplitude of brain waves, particularly theta, alpha, and beta waves, which are associated with varying cognitive levels (Khosla et al., 2020; Morales & Bowers, 2022). The second instrument was a Cognitive Load Questionnaire, designed to assess the cognitive load experienced by students while learning the concept of limits. This questionnaire measured intrinsic, extraneous, and overall cognitive load using a validated Likert scale (Oktaviyanthi et al., 2024). A sample of the questions used to assess mathematical cognitive load is provided in Table 1.

Table 1. Sample questions assessing cognitive load

Type Cognitive Load	Indicator	Sample Question
Intrinsic Cognitive Load (ICL)	Assesses students' perception of the inherent complexity of the formal limit concept, including the difficulty of understanding it without prior knowledge. It reflects the cognitive load experienced as students navigate the concept's interconnected and challenging content within calculus.	- Do I find the formal limit concept challenging to comprehend? - Is the explanation of the formal limit difficult for me to understand? - Do I consider the content of the formal limit concept to be highly complicated?
Extraneous Cognitive Load (ECL)	Measures the effectiveness of learning media in helping students understand the structure, interrelationships, and information related to the formal limit concept. It also evaluates whether the design of the learning media facilitates or hinders cognitive processing, access to relevant information, and focus on the formal limit concept.	- Does the learning media help me understand the overall structure of the formal limit concept? - Does the design of the learning media for the formal limit concept make it challenging for me to recognize the relationships between concepts?
Germane Cognitive Load (GCL)	Measures students' engagement in cognitive processing to understand the formal limit concept through learning media. It focuses on the mental effort required to integrate new information with prior knowledge and build a comprehensive understanding, contributing to deep learning.	- Do I actively visualize the formal limit concept? - Do the learning media encourage me to actively think about the formal limit concept? - Do I strive to understand the formal limit concept? - Do I find it challenging to fully understand the formal limit concept?

Data collection was conducted by placing EEG devices on each participant to record brain signals throughout the controlled calculus learning session. Following the session, students completed the cognitive load questionnaire. The EEG data were processed using Python programming to extract the frequency and amplitude of the recorded brain signals. These data were then visualized and analyzed using cluster analysis techniques, which grouped subjects based on their EEG signal characteristics. This approach allowed for the identification of variations in cognitive responses corresponding to different levels of cognitive load.

Data Analysis

The analysis consisted of four main steps aimed at understanding the relationship between cognitive load and brain activity, as well as identifying groups of students based on their EEG signal patterns:

1. Descriptive Statistics
   The initial step involved calculating the mean, standard deviation, and distribution of data related to cognitive load and brain activity (Rahman et al., 2020; Choubey & Pandey, 2021). This provided a preliminary overview of the data characteristics and facilitated the identification of distribution patterns, including potential outliers.
2. Correlation Analysis
   Correlation analysis was conducted to examine the relationship between cognitive load, as assessed by the questionnaire, and various brain activity indicators, including the frequency and amplitude of theta, alpha, and beta waves (Kästle et al., 2021; Šverko et al., 2022). Depending on the normality of the data distribution, either Pearson or Spearman correlation was employed.
3. Data Visualization
   Visualization techniques were utilized to enhance the interpretation of the relationship between cognitive load and brain activity (Fu et al., 2021; Magnotti et al., 2020). These visual representations helped identify general trends (Wang et al., 2022) and specific patterns that might not be readily apparent through numerical analysis alone (Donohoe & Costello, 2020).
4. Cluster Analysis
   The K-means clustering method was applied to group subjects based on their EEG signal patterns (Bablani et al., 2020; Wen & Aris, 2022). This analysis enabled the identification of clusters of subjects with similar brain activity profiles, allowing for the determination of significant differences in cognitive responses to calculus learning.

Data Interpretation Techniques

Each analytical step provides layered insights into the relationship between cognitive load and brain activity. Descriptive statistics offer a comprehensive understanding of the data characteristics, while correlation analysis identifies significant associations. Data visualization helps to elucidate underlying trends, and cluster analysis uncovers individual differences in cognitive responses (Atiomo, 2020; Cabañero et al., 2020; Cezar & Maçada, 2023; Qin et al., 2024). Collectively, these analytical methods illustrate the influence of cognitive load on brain activity, providing valuable insights for the development of adaptive learning strategies tailored to individual cognitive profiles.

RESULTS AND DISCUSSION

The study collected data from 30 students, focusing on two primary variables: cognitive load and three types of brainwave frequencies—Theta (Hz), Alpha (Hz), and Beta (Hz). Figure 2 illustrates the distribution of the collected data and reveals variations in relaxation levels and mental activity among the participants. Cognitive load ranges from 50 (low) to 97 (high), while Theta frequencies span from 1.15 Hz (minimal relaxation) to 3.50 Hz (enhanced relaxation). Alpha frequencies fall between 12.50 Hz and 14.85 Hz, reflecting mostly stable or heightened states of relaxation, and Beta frequencies range from 20.0 Hz to 24.7 Hz, with higher values associated with intense mental activity. Participants with elevated cognitive load generally exhibit high Beta and low Theta frequencies, indicative of a focused mental state, whereas those with lower cognitive load demonstrate higher Theta frequencies, signaling greater relaxation.

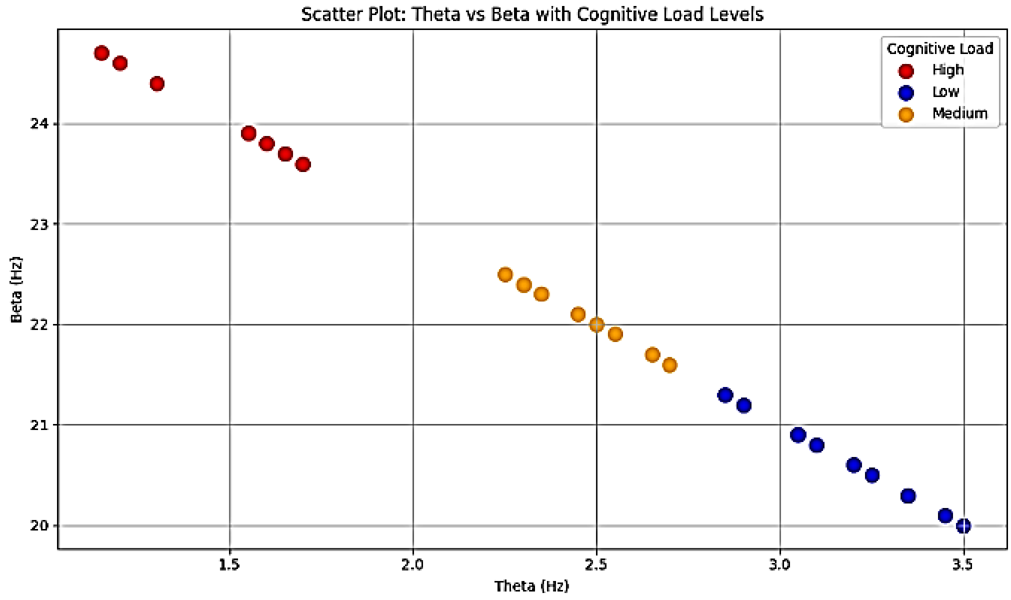


Figure 2. Distribution of cognitive load and brainwave frequencies

Furthermore, in Figure 2 also shows participants with high cognitive load (represented by red dots, n=9) consistently display low Theta frequencies (1–2 Hz) and very high Beta frequencies (23–25 Hz), characteristic of intense focus and elevated cognitive effort. The moderate cognitive load group (orange dots, n=9) exhibits medium Theta frequencies (2–3 Hz) and relatively high Beta frequencies (21–23 Hz), suggesting a balanced focus level. The low cognitive load group (blue dots, n=12) is characterized by higher Theta frequencies (3–4 Hz) and lower Beta frequencies (20–21 Hz), indicative of reduced engagement and greater relaxation.

Descriptive Statistics

This study involved 30 participants, with the key variables consisting of cognitive load and brainwave frequencies in the Theta, Alpha, and Beta bands. Table 2 provides the descriptive statistics for the collected data.

Table 2. Descriptive Statistics of Research Data

	Subject	Cognitive Load	Frequency (Hz)	Amplitude	Theta (Hz)	Alpha (Hz)	Beta (Hz)
count	30	30	30	30	30	30	30
mean	15.50	71.03	12.10	0.71	2.45	13.55	22.10
std	8.80	14.28	1.43	0.14	0.71	0.71	1.43
min	1	50	10	0.50	1.15	12.50	20
25%	8.25	59	10.90	0.59	1.84	12.95	20.90
50%	15.50	70.50	12.05	0.71	2.48	13.53	22.05
75%	22.75	83.25	13.33	0.83	3.05	14.16	23.33
max	30	97	14.70	0.97	3.50	14.85	24.7

The mean cognitive load of the participants was 71.03 as presented in Table 2, indicating a relatively high overall cognitive load. The standard deviation of 14.28 highlights considerable variability in cognitive load across individuals. The cognitive load scores ranged from 50 (low) to 97 (high), further demonstrating substantial variation in the cognitive load experienced by the participants.

Regarding brain activity frequencies, the mean Theta frequency was 2.45 Hz, with values ranging from 1.15 Hz (indicating minimal relaxation) to 3.50 Hz (representing greater relaxation) (Basharpoor et al., 2021; Finley et al., 2024). The average Alpha frequency was 13.55 Hz, reflecting that most participants were in a stable or heightened mental state. The Alpha frequency range, from 12.50 Hz to 14.85 Hz, illustrates the variation in mental stability across participants (Basharpoor et al., 2021; Dos Anjos et al., 2024).

The mean Beta frequency was 22.10 Hz, with a minimum of 20.00 Hz and a maximum of 24.70 Hz, typically associated with heightened mental activity. The average amplitude was 0.71, indicating a relatively consistent brain signal across participants. The amplitude range, from 0.50 to 0.97, reflects variability in the intensity of brain activity (Basharpoor et al., 2021; Curham & Allen, 2022).

Overall, the findings suggest that participants with higher cognitive load tend to exhibit higher Beta frequencies and lower Theta frequencies, indicating a more focused mental state. In contrast, participants with lower cognitive load generally show higher Theta frequencies, signifying a more relaxed state.

Correlation Analysis and Data Visualization

A correlation analysis was performed to examine the linear relationships between cognitive load and various brain activity indicators, including EEG frequency (in Hz), amplitude, and brainwave frequencies (Theta, Alpha, and Beta). A correlation matrix was utilized to assess the strength and direction of the relationships between these variables, with correlation coefficients ranging from -1 to 1 (Moscarelli, 2023). A coefficient of 1 represents a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 denotes no linear relationship (Armitage et al., 2013; Hadd & Rodgers, 2020). The results are presented in Table 3.

Table 3. Correlation Matrix of Cognitive Load and EEG Variables

	Cognitive Load	Frequency (Hz)	Amplitude	Theta (Hz)	Alpha (Hz)	Beta (Hz)
Cognitive Load	1	0.83	0.88	-0.93	0.86	0.91
Frequency (Hz)	0.83	1	0.76	-0.77	0.63	0.73
Amplitude	0.88	0.76	1	-0.81	0.80	0.82
Theta (Hz)	-0.93	-0.77	-0.81	1	-0.82	-0.81
Alpha (Hz)	0.86	0.63	0.80	-0.82	1	0.78
Beta (Hz)	0.91	0.73	0.82	-0.81	0.78	1

The correlation data presented in Table 3 reveals several notable relationships. Cognitive load shows strong positive correlations with EEG frequency (0.83), amplitude (0.88), as well as Alpha (0.86) and Beta (0.91) wave frequencies. These results indicate that as cognitive load increases, EEG frequency, brainwave amplitude, and brain activity at Alpha and Beta frequencies also increase proportionally. In contrast, Theta frequency exhibits a strong negative correlation with cognitive load (-0.93), amplitude (-0.81), and Beta waves (-0.81), suggesting that higher cognitive load is associated with a decrease in Theta activity (Curham & Allen, 2022). The negative correlation with Alpha waves (-0.82) further reinforces the idea that increased cognitive load corresponds with reduced Theta activity

(Gnambs, 2023).

Therefore, it can be concluded that cognitive load is positively correlated with enhanced brain activity at higher frequencies, particularly in the Alpha and Beta bands, as well as with increased amplitude. Conversely, it is negatively correlated with Theta activity, which is typically associated with lower mental engagement (Makowski et al., 2020). The visualization of the relationship map between cognitive load and EEG frequency, shown in Figure 3, further illustrates these findings.

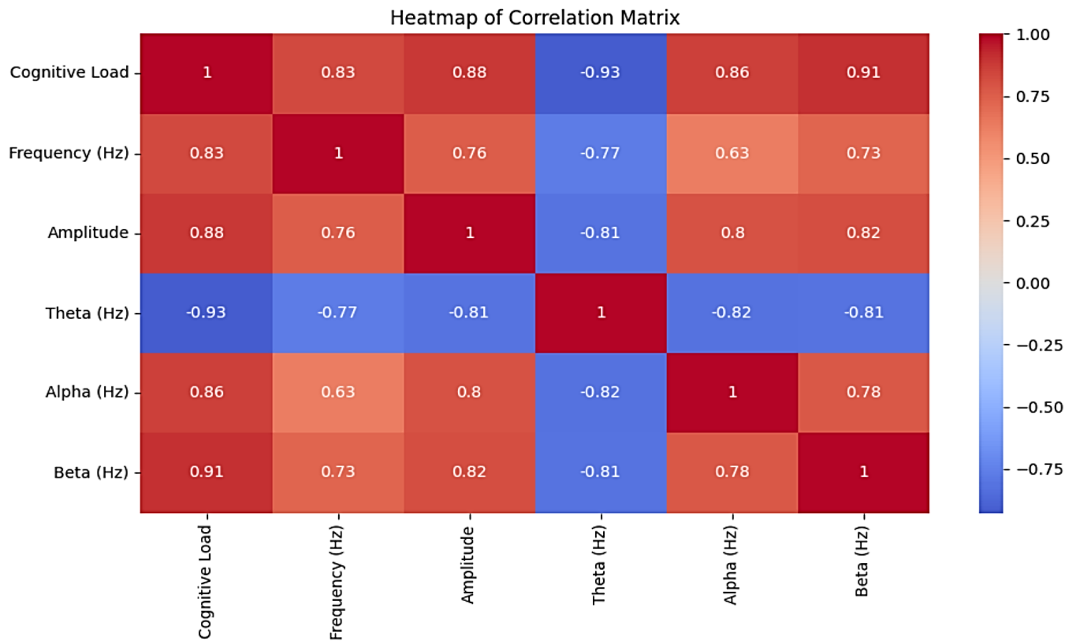


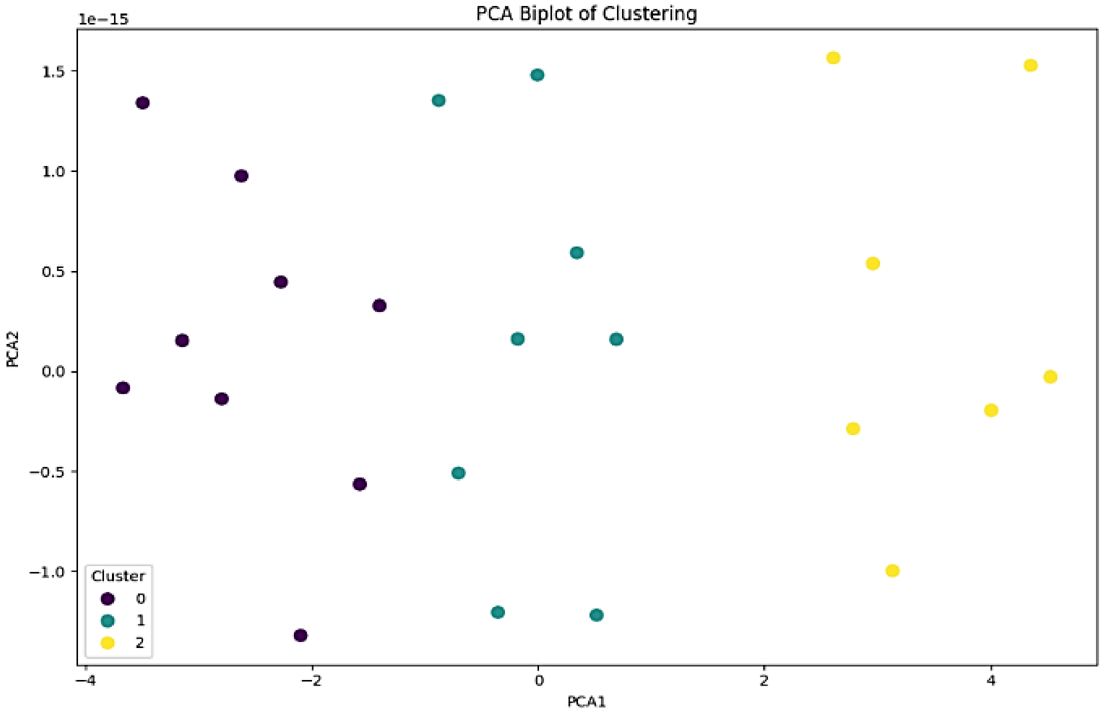
Figure 3. Relationship between cognitive load and EEG variables: Heatmap

Figure 3 presents a heatmap of the correlation matrix, offering a visual representation that highlights the strong relationships between cognitive load and EEG frequency variables, amplitude, and the Alpha and Beta frequencies. The red regions indicate a strong positive correlation (approaching 1), while the blue areas represent negative correlations (approaching -1) between Theta and the other variables. The heatmap reveals that cognitive load is strongly positively correlated with EEG frequency and amplitude, while it shows a negative correlation with Theta frequency (Fernandez et al., 2017; Gu, 2022). The strong correlations between cognitive load, frequency, and amplitude suggest that increased cognitive load is associated with heightened brain activity in both frequency and amplitude.

In conclusion, the analysis confirms a significant relationship between cognitive load and various brain activity indicators. Increased cognitive load consistently correlates positively with EEG frequency, amplitude, and brain activity in the Alpha and Beta frequency ranges, while it negatively correlates with Theta activity. Higher cognitive load, therefore, is closely associated with increased brain activity at higher frequencies, while Theta activity tends to decrease as cognitive load rises.

Cluster Analysis and Data Visualization

The cluster analysis conducted in this study examines the distribution patterns of EEG data, which have been dimensionally reduced through advanced statistical techniques. The primary visualization method used to present the clustering results is the PCA (Principal Component Analysis) plot. This approach aims to reveal the relationship between cognitive load and brain activity patterns based on EEG characteristics, while also validating the clustering outcomes. The clusters are illustrated in Figure 4, which provides a comprehensive depiction of these relationships. The findings from Figure 4 can be described as follows.



(a) (b)

Figure 4. Visualization of EEG cluster analysis: PCA

Figure 4 illustrates the results of the Principal Component Analysis (PCA), which reduced the dimensionality of the EEG data into two primary components, PCA1 and PCA2. The plot shows the distribution of EEG data, which has been grouped into three distinct clusters. Firstly, in cluster 0 (Purple), subjects in this cluster are located on the negative side of PCA1, indicating that their EEG characteristics are significantly different from those of other clusters, suggesting unique cognitive responses under cognitive load (Demšar et al., 2013). This cluster includes Subjects 1, 4, 7, 8, 12, 14, 15, 17, 18, 21, 22, 24, 26, and 27. Furthermore, in cluster 1 (Teal), the EEG data from this cluster are distributed around the center of the plot, indicating balanced and stable EEG features that reflect moderate levels of cognitive engagement (Gewers et al., 2021). This cluster includes Subjects 2, 5, 6, 9, 11, 13, 16, 19, 20, 23, 25, 28, and 30. Finally, in cluster 2 (Yellow), positioned on the positive side of PCA1, this cluster exhibits distinct EEG characteristics compared to the other clusters, suggesting unique cognitive responses within this group. This cluster includes Subjects 3, 10, and 29.

The results of this cluster analysis provide valuable insights into the distinctive brain activity patterns associated with varying cognitive load levels. Each cluster represents a group of subjects with similar EEG characteristics, allowing for the categorization of individuals based on their brain activity patterns. By mapping these brain activity patterns to cognitive load, the study contributes to a deeper understanding of how brain activity correlates with cognitive load levels. These findings offer a foundation for the development of personalized learning strategies, where instructional approaches can be tailored to the unique brain activity patterns of individual learners.

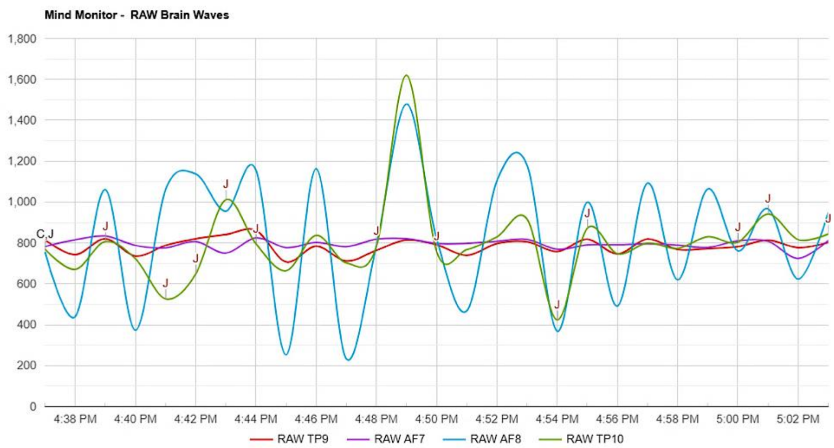
EEG Analysis of Subject Calculus Task

The EEG analysis conducted during the calculus tasks confirms the relationship between cognitive load and brain activity. Participants were categorized into high, moderate, and low cognitive load groups based on their Theta and Beta frequencies. In the high cognitive load group, low Theta (1-2 Hz) and high Beta (23-25 Hz) frequencies were observed, indicating focused mental effort. Conversely, the low cognitive load group exhibited higher Theta (3-4 Hz) and lower Beta (20-21 Hz) frequencies, which are indicative of a more relaxed state. Clustering analysis further identified three distinct groups: Cluster 0, which exhibited unique EEG patterns; Cluster 1, characterized by balanced EEG features; and Cluster 2, displaying distinct traits that suggest varying cognitive responses. These findings underscore the influence of cognitive load on Beta and Theta frequencies, which in turn impact task performance.

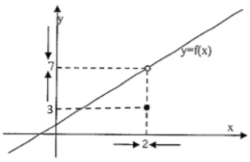
This section presents EEG recordings from subjects exhibiting different levels of cognitive load—high, moderate, and low—while performing a calculus problem-solving task. It investigates how varying cognitive states, as indicated by EEG patterns, are associated with task performance, as shown in Table 4.

Table 4. EEG Recording and task solution of subject 3 and subject 10

Subject 3

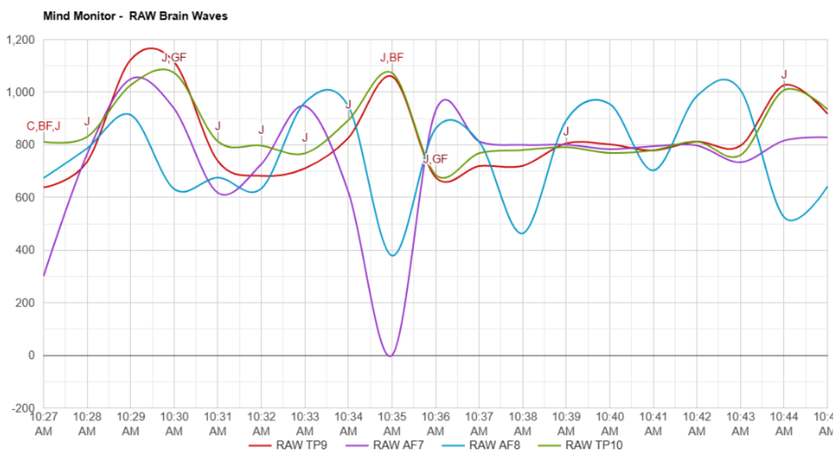


Question:
Based on the following figure, can I find the values of $f(2)$ dan $\lim_{x\to 2} f(x)$?

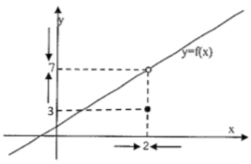


Answer:
"I find this question quite complex because there's a lot of information to process from the graph. But after looking at it in detail, I can see that the function's value at $x = 2$ is 3, since there's a point there. However, for the limit, I need to check how the graph approaches $x = 2$ from both sides. From this, I'm confident that $\lim_{x\to 2} f(x)$ is actually 7, as that's the value the graph approaches. So, the answer is $f(2) = 3$ and $\lim_{x\to 2} f(x) = 7$."

Subject 10



Question:
Based on the following figure, can I find the values of $f(2)$ dan $\lim_{x \to 2} f(x)$?



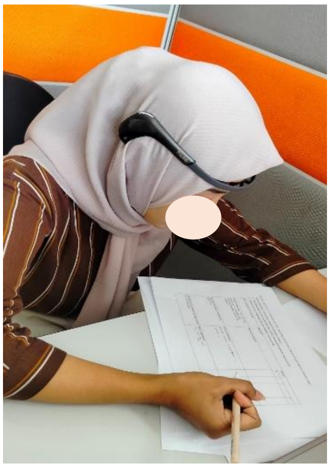
Answer:
"This question makes me dizzy because the graph is a bit confusing. I see there's a point at $y = 3$ when $x = 2$, so maybe $f(2) = 3$? But it also asks for the limit. Since the graph seems to rise toward 7 as it approaches $x = 2$, maybe the limit is 7? I'm not too sure."

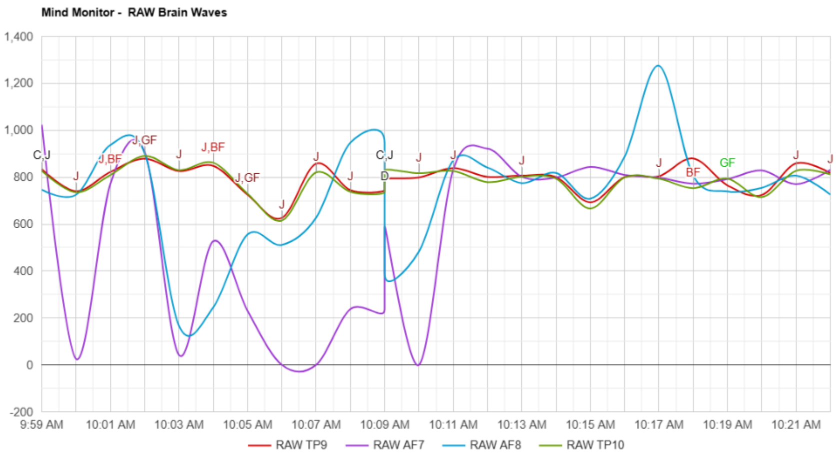
Table 4 presents the EEG signal recordings for Subject 3 and Subject 10, both of whom exhibit high cognitive load, as evidenced by increased Beta wave activity within the green frequency band, indicative of concentrated mental effort. Simultaneously, both subjects demonstrate low Theta wave activity within the purple frequency band, which is typically associated with relaxation, further emphasizing their focused cognitive state. Despite these similar EEG patterns—high Beta (green) and low Theta (purple)—Subject 3 performs more effectively in problem-solving tasks and displays higher confidence compared to Subject 10. This performance disparity may be attributed to several factors, including Subject 3's greater familiarity with calculus tasks, stronger cognitive strategies, or an enhanced ability to maintain focus under conditions of high cognitive load. These factors likely enable Subject 3 to better utilize the heightened Beta frequency state to optimize task performance.

Table 5 presents the EEG recordings for Subject 4 and Subject 1, both of whom exhibit low cognitive load, primarily indicated by their Theta frequency band (purple frequency band). Elevated Theta activity is typically associated with a more relaxed or less focused mental state, common in situations with lower cognitive demands. While both subjects share this low-load Theta characteristic, Subject 4 outperforms Subject 1 in problem-solving tasks and displays higher confidence. This performance difference may be attributed to factors such as Subject 4's deeper understanding of the calculus material or a greater adaptability in problem-solving. These attributes likely enable Subject 4 to maintain effective performance, even in a low cognitive load state.

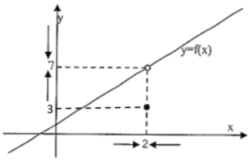
Table 5. EEG Recording and Task Solution of Subject 4 and Subject 1

Subject 4



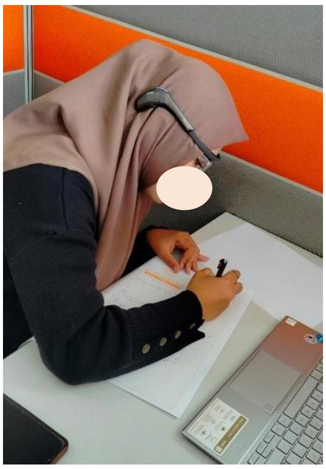


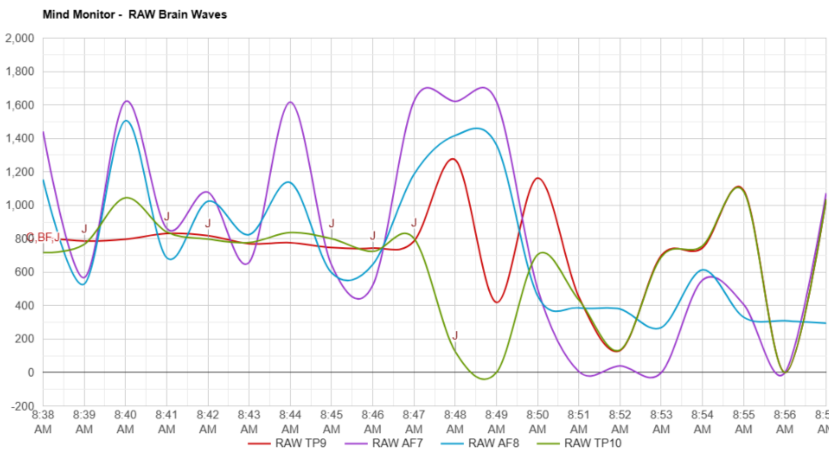
Question:
Based on the following figure, can I find the values of $f(2)$ dan $\lim_{x\to 2} f(x)$?



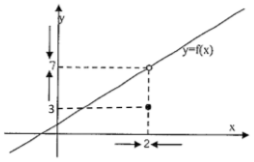
Answer:
"This question is quite easy for me, and the graph is clear. I can immediately see that $f(2) = 3$ because the point at $x = 2$ is at $y = 3$. For the limit, I see that the graph approaches y=7 from both directions as x approaches 2. So, the answer is $f(2) = 3$ and $\lim_{x\to 2} f(x) = 7$. This answer seems quite clear to me."

Subject 1





Question:
Based on the following figure, can I find the values of $f(2)$ dan $\lim_{x\to 2} f(x)$?

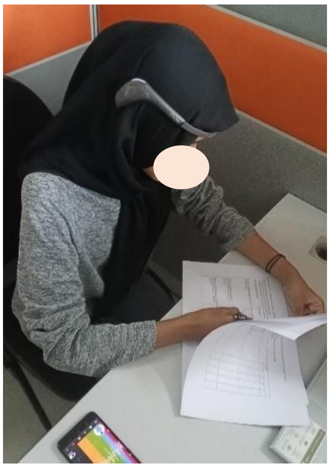


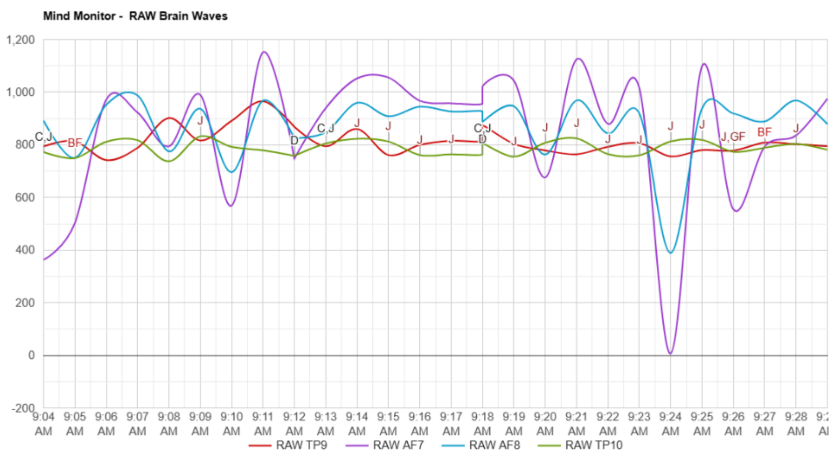
Answer:
"I don't find it too hard to look at the graph, but I'm still confused about what I need to find. At $x = 2$, there's a point at $y = 3$, so I think $f(2) = 3$. But the question also asks for the limit, and I don't really understand how that's different from the function value at that point."

Table 6 presents the EEG recordings for Subject 2 and Subject 6, both of whom are experiencing a moderate cognitive load, as indicated by their Alpha frequency band (blue frequency band). The moderate level of Alpha activity reflects a state of mental alertness and engagement, typical of tasks requiring sustained focus without overwhelming cognitive strain. Despite exhibiting similar cognitive load characteristics, Subject 2 provided an incorrect answer, whereas Subject 6 answered correctly and with greater confidence. This performance discrepancy may be due to factors such as Subject 6's familiarity with the specific type of calculus problem, which may have facilitated more effective information processing. Additionally, Subject 6's higher resilience under moderate cognitive demands or more refined problem-solving strategies could have contributed to their ability to achieve both accuracy and confidence within the same cognitive load range.

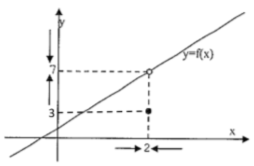
Table 6. EEG recording and task solution of Subject 2 and Subject 6

Subject 2





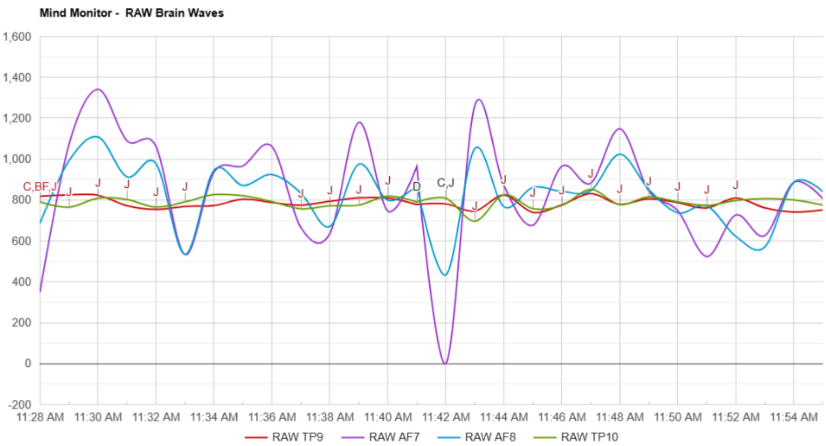
Question:
Based on the following figure, can I find the values of $f(2)$ dan $\lim_{x \to 2} f(x)$?



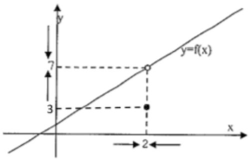
Answer:
"I'm trying to understand the graph. From what I see, when $x = 2$, there's a point at $y = 3$, so I think $f(2) = 3$. But the question also asks for the limit, and I'm not too sure about that. Maybe the limit is the

same as the function value, so I'll answer $\lim_{x \to 2} f(x) = 3$. I know this might not be entirely correct, but that's what I can conclude from the graph."

Subject 6



Question:
Based on the following figure, can I find the values of $f(2)$ dan $\lim_{x \to 2} f(x)$?



Answer:
"I feel focused enough to solve this question without feeling too pressured. Looking at the graph, I can quickly see that the function value at $x = 2$ is 3 because there's a point there. For the limit, I notice the graph approaches $x = 7$ as x approaches 2 from both sides. So, I'm confident the answer is $f(2) = 3$ and $\lim_{x \to 2} f(x) = 7$. I'm quite sure this is the correct answer."

These findings underscore the significance of EEG recordings in elucidating the relationship between cognitive load and brain performance. By monitoring brainwave activity across Beta, Theta, and Alpha frequency bands, EEG data offers an objective, real-time perspective on cognitive states, such as focus, relaxation, or mental engagement (Apicella et al., 2022). For example, high Beta activity is typically indicative of concentrated mental effort, while Theta waves are more closely associated with relaxed, less focused states (Liu et al., 2023). This neurophysiological data enhances our understanding of cognitive load, providing insights that go beyond subjective self-reports and revealing how brain activity patterns correlate with cognitive demands in problem-solving scenarios.

EEG recordings are therefore essential in illustrating how different levels of cognitive load—high, moderate, or low—affect brain performance (Wirth et al., 2020). In high cognitive load states, increased Beta activity (green frequency band) is commonly linked to focused attention. However, individual performance may still vary, influenced by factors such as task familiarity or cognitive resilience, as observed in Subjects 3 and 10. Similarly, in low cognitive load conditions, characterized by higher Theta activity (purple frequency band), the absence of high engagement does not necessarily indicate a lack of task involvement, especially when individuals utilize effective problem-solving strategies.

Discussion

Brain Response Patterns Based on EEG Cluster Analysis

This study illustrates a meaningful connection between cognitive load and brain activity as captured through EEG signals. The utilization of visualization and cluster analysis techniques allowed the identification of distinct brain activity patterns among participants based on their cognitive load levels. Through the EEG cluster analysis, three primary clusters of brain activity were observed:

1. Low Cognitive Load - Theta Dominant Cluster
   Cluster 0, characterized by dominant Theta activity, reflects a relaxed mental state, conducive to efficient information processing and indicating a lower cognitive load. This aligns with Gruzelier's Brain State-dependent Learning (BSL) theory, which posits that optimal brain states are essential for effective learning (Horwitz et al., 2000; Kunze et al., 2016). The heightened Theta activity observed in this cluster correlates with internalization and memory consolidation, emphasizing the importance of relaxation in facilitating learning. Educational environments that promote relaxation could foster enhanced cognitive engagement and processing.
2. Moderate Cognitive Load - Alpha Dominant Cluster
   Cluster 1, marked by prominent Alpha activity, indicates a state of mental alertness and focused attention, reflecting a moderate cognitive load. Increased Alpha activity enhances the brain's ability to receive and process information effectively, supporting the notion that a balance between relaxation and engagement is optimal for learning. These findings align with those of Chikhi et al. (2022), Emami & Chau (2020), and Wang et al. (2024), who suggest that moderate cognitive load, characterized by Alpha activity, plays a pivotal role in maintaining cognitive engagement while avoiding strain.
3. High Cognitive Load - Beta Dominant Cluster
   Cluster 2, characterized by dominant Beta activity, represents heightened mental alertness and concentration, but also signals a risk of cognitive overload. This observation aligns with Sweller's Cognitive Load Theory (2011, 2020), which argues that excessive cognitive load reduces working memory capacity and impairs learning efficiency. Increased Beta activity, often seen during complex cognitive tasks, underscores the delicate balance needed in learning environments. While Beta waves reflect focused attention, prolonged high Beta activity could hinder cognitive processing and task performance, indicating the need for careful management of cognitive load during demanding tasks.

Broader Implications and Practical Applications

This study contributes to the growing body of research linking cognitive load and brain activity, particularly by demonstrating the utility of EEG-based cluster analysis in educational contexts. The identification of distinct brainwave clusters—especially Beta-dominant clusters associated with high cognitive load—provides valuable insights for adaptive learning. By enabling real-time assessments of students' cognitive states, EEG-based clustering offers a dynamic way to tailor learning strategies to individual cognitive conditions (da Silva, 2022; Tetzlaff et al., 2021). This aligns with previous studies that highlighted the importance of monitoring Beta activity and its relationship to cognitive load (Feldmann et al., 2022), emphasizing the role of real-time feedback in alleviating cognitive strain and improving learning outcomes (Skulmowski & Xu, 2021).

Moreover, the combination of visualization and cluster analysis in EEG research represents a methodological advancement, enhancing the understanding of cognitive load's impact on brain activity patterns. This approach, used in recent EEG studies (Gao et al., 2020), allows for the mapping of specific EEG patterns to distinct cognitive states, offering deeper insights into how brain responses vary under different cognitive demands (Hassan et al., 2024). By identifying clusters with similar brain activity, this method also supports the identification of unique response profiles, allowing for a more individualized understanding of cognitive engagement in complex tasks (Ismail & Karwowski, 2020). Given the study's focus on university students, these insights are particularly valuable in the context of higher education, providing actionable information for effective cognitive load management and adaptive learning strategies.

Furthermore, the practical implications of this research are far-reaching. The integration of EEG-based assessments into adaptive learning systems holds significant promise for personalizing instructional materials based on real-time cognitive states (Fuentes-Martinez et al., 2023). EEG technology provides educators with direct insights into students' mental states, enabling tailored interventions that support cognitive resilience, emotional regulation, and sustained task engagement (Zanetti et al., 2022). This personalized approach to learning could enhance overall learning effectiveness, particularly in complex and high-stakes cognitive tasks.

Finally, this study paves the way for further exploration into how EEG-driven insights can inform adaptive education models. By incorporating real-time cognitive load assessments into educational practices, it may be possible to optimize learning environments, supporting students at various cognitive load levels. Future research could expand on these findings by examining the long-term impact of EEG-based interventions on student performance, as well as exploring the potential for cross-disciplinary applications of EEG in educational settings. Such investigations could provide valuable evidence for integrating EEG monitoring as a tool for enhancing cognitive performance and learning outcomes in diverse contexts.

CONCLUSION

This research successfully explored the relationship between cognitive load and brainwave activity among 30 mathematics education students enrolled in a calculus course. Using EEG signals and employing visualization and cluster analysis techniques, the study identified three distinct brain activity patterns. One cluster, characterized by Beta wave dominance, reflected high alertness and concentration, potentially indicating cognitive overload. A second cluster, dominated by Theta waves, represented a more relaxed state conducive to efficient information processing and lower cognitive load. The third cluster, exhibiting prominent Alpha waves, suggested a balanced state of relaxation and focus, associated with moderate cognitive load. These findings highlight a clear correlation between brainwave frequencies and cognitive load, providing valuable insights into how brain activity patterns can inform the optimization of learning strategies in educational settings. Tailoring interventions based on individual EEG profiles may enhance cognitive efficiency and improve learning outcomes for students.

While the findings offer substantial contributions to understanding cognitive load dynamics, several limitations should be considered. The study's relatively small sample size (n=30) may limit the generalizability of the results, and future research should aim to include larger, more diverse participant groups to enhance the applicability of the findings. Additionally, the research focused exclusively on isolated learning tasks, overlooking other factors such as emotional, environmental, and social influences, which could also impact cognitive load. Incorporating these variables in future investigations would provide a more holistic understanding of cognitive load and its interaction with brainwave activity. Moreover, the use of advanced analytical methods, such as machine learning, could further refine the detection of complex brainwave patterns and offer more accurate real-time insights into student engagement and cognitive processes.

Future studies should also explore the longitudinal evolution of brain activity patterns in response to repeated exposure to challenging learning material, such as calculus concepts. Investigating the influence of individual learning styles, prior knowledge, and cognitive resilience on cognitive load could yield valuable insights into personalized learning approaches. Furthermore, addressing factors like emotional state and task familiarity, which can influence performance under cognitive load, is crucial. Examining EEG pattern shifts over time may also provide insights into cognitive fatigue and guide the development of adaptive learning interventions that support student well-being and enhance academic performance. Ultimately, this research sets the foundation for further studies into the interplay between cognitive load and brain activity, with potential applications in adaptive learning technologies and the improvement of educational outcomes.

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REFERENCES

Al-Salman, W., Li, Y., Oudah, A. Y., & Almaged, S. (2023). Sleep stage classification in EEG signals using the clustering approach based probability distribution features coupled with classification algorithms. *Neuroscience Research*, *188*, 51–67. https://doi.org/10.1016/J.NEURES.2022.09.009

Alyasseri, Z. A. A., Abasi, A. K., Al-Betar, M. A., Makhadmeh, S. N., Papa, J. P., Abdullah, S., & Khader, A. T. (2021). *EEG-Based Person Identification Using Multi-Verse Optimizer as Unsupervised Clustering Techniques*. 89–110. https://doi.org/10.1007/978-981-33-4191-3_4

Apicella, A., Arpaia, P., Frosolone, M., Improta, G., Moccaldi, N., & Pollastro, A. (2022). EEG-based measurement system for monitoring student engagement in learning 4.0. *Scientific Reports 2022, 12*(1), 1–13. https://doi.org/10.1038/s41598-022-09578-y

Armitage, P., Berry, G., & Matthews, J. N. S. (2013). *Statistical methods in medical research*. John Wiley & Sons.

Atiomo, W. (2020). Emotional Well-Being, Cognitive Load and Academic Attainment. *MedEdPublish*, *9*, 118. https://doi.org/10.15694/MEP.2020.000118.1

Bablani, A., Edla, D. R., Kuppili, V., & Ramesh, D. (2020). A multi stage EEG data classification using k-means and feed forward neural network. *Clinical Epidemiology and Global Health*, *8*(3), 718–724. https://doi.org/10.1016/J.CEGH.2020.01.008

Basharpoor, S., Heidari, F., & Molavi, P. (2021). EEG coherence in theta, alpha, and beta bands in frontal regions and executive functions. *Applied Neuropsychology: Adult*, *28*(3), 310–317. https://doi.org/10.1080/23279095.2019.1632860

Bashir, F., Ali, A., Soomro, T. A., Marouf, M., Bilal, M., & Chowdhry, B. S. (2021). Electroencephalogram (EEG) Signals for Modern Educational Research. *Innovative Education Technologies for 21st Century Teaching and Learning*, 149–171. https://doi.org/10.1201/9781003143796-10

Bradley, C., Nydam, A. S., Dux, P. E., & Mattingley, J. B. (2022). State-dependent effects of neural stimulation on brain function and cognition. *Nature Reviews Neuroscience*, *23*(8), 459–475. https://doi.org/10.1038/s41583-022-00598-1

Budin, G., Gavrilova, M. L., Shell, D. F., Wang, Y., Fiorini, R. A., Widrow, B., ... & Chan, C. (2016). Cognitive Intelligence: Deep Learning, Thinking, and Reasoning by Brain-Inspired Systems. *International Journal of Cognitive Informatics and Natural Intelligence, 10*(4), 1-20. https://doi.org/10.4018/IJCINI.2016100101

Cabañero, L., Hervás, R., González, I., Fontecha, J., Mondéjar, T., & Bravo, J. (2020). Characterisation of mobile-device tasks by their associated cognitive load through EEG data processing. *Future Generation Computer Systems*, *113*, 380–390. https://doi.org/10.1016/J.FUTURE.2020.07.013

Cezar, B. G. da S., & Maçada, A. C. G. (2023). Cognitive Overload, Anxiety, Cognitive Fatigue, Avoidance Behavior and Data Literacy in Big Data environments. *Information Processing & Management*, *60*(6), 103482. https://doi.org/10.1016/J.IPM.2023.103482

Chen, O., Paas, F., & Sweller, J. (2023). A Cognitive Load Theory Approach to Defining and Measuring Task Complexity Through Element Interactivity. *Educational Psychology Review*, *35*(2), 1–18. https://doi.org/10.1007/S10648-023-09782-W/FIGURES/3

Cheng, B., Fan, C., Fu, H., Huang, J., Chen, H., & Luo, X. (2022). Measuring and Computing Cognitive Statuses of Construction Workers Based on Electroencephalogram: A Critical Review. *IEEE Transactions on Computational Social Systems*, *9*(6), 1644–1659. https://doi.org/10.1109/TCSS.2022.3158585

Chew, S. L., & Cerbin, W. J. (2021). The cognitive challenges of effective teaching. *The Journal of Economic Education*, *52*(1), 17–40. https://doi.org/10.1080/00220485.2020.1845266

Chikhi, S., Matton, N., & Blanchet, S. (2022). EEG power spectral measures of cognitive workload: A meta-analysis. *Psychophysiology*, *59*(6), e14009. https://doi.org/10.1111/PSYP.14009

Choubey, H., & Pandey, A. (2021). A combination of statistical parameters for the detection of epilepsy and EEG classification using ANN and KNN classifier. *Signal, Image and Video Processing*, *15*(3), 475–483. https://doi.org/10.1007/S11760-020-01767-4/METRICS

Christodoulides, P., Miltiadous, A., Tzimourta, K. D., Peschos, D., Ntritsos, G., Zakopoulou, V., Giannakeas, N., Astrakas, L. G., Tsipouras, M. G., Tsamis, K. I., Glavas, E., & Tzallas, A. T. (2022). Classification of EEG signals from young adults with dyslexia combining a Brain Computer Interface device and an Interactive Linguistic Software Tool. *Biomedical Signal Processing and Control*, *76*, 103646. https://doi.org/10.1016/J.BSPC.2022.103646

Curham, K. J., & Allen, J. J. B. (2022). Logic Behind EEG Frequency Analysis: Basic Electricity and Assumptions. *The Oxford Handbook of EEG Frequency*, 15. https://global.oup.com/academic/product/the-oxford-handbook-of-eeg-frequency-9780192898340

da Silva, F. L. (2022). EEG: Origin and Measurement. *EEG-FMRI: Physiological Basis, Technique, and Applications, Second Edition*, 23–48. https://doi.org/10.1007/978-3-031-07121-8_2

Dalmaijer, E. S., Nord, C. L., & Astle, D. E. (2022). Statistical power for cluster analysis. *BMC Bioinformatics*, *23*(1), 1–28. https://doi.org/10.1186/S12859-022-04675-1/TABLES/5

Das Chakladar, D., & Roy, P. P. (2023). Cognitive workload estimation using physiological measures: a review. *Cognitive Neurodynamics*, *18*(4), 1445–1465. https://doi.org/10.1007/S11571-023-10051-3/METRICS

Demšar, U., Harris, P., Brunsdon, C., Fotheringham, A. S., & McLoone, S. (2013). Principal Component Analysis on Spatial Data: An Overview. *Annals of the Association of American Geographers*, *103*(1), 106–128. https://doi.org/10.1080/00045608.2012.689236

Denis, D. J. (2020). Univariate, bivariate, and multivariate statistics using R: Quantitative tools for data analysis and data science. *Univariate, Bivariate, and Multivariate Statistics Using R: Quantitative Tools for Data Analysis and Data Science*, 1–366. https://doi.org/10.1002/9781119549963

Devi, D., Sophia, S., & Boselin Prabhu, S. R. (2021). Deep learning-based cognitive state prediction analysis using brain wave signal. *Cognitive Computing for Human-Robot Interaction: Principles and Practices*, 69–84. https://doi.org/10.1016/B978-0-323-85769-7.00017-3

Donohoe, D., & Costello, E. (2020). Data visualisation literacy in higher education: An exploratory study of understanding of a learning dashboard tool. *International Journal of Emerging Technologies in Learning (iJET)*, *15*(17), 115-126. https://doi.org/10.3991/ijet.v15i17.15041

Dos Anjos, T., Di Rienzo, F., Benoit, C. E., Daligault, S., & Guillot, A. (2024). Brain wave modulation and EEG power changes during auditory beats stimulation. *Neuroscience*, *554*, 156–166. https://doi.org/10.1016/J.NEUROSCIENCE.2024.07.014

Emami, Z., & Chau, T. (2020). The effects of visual distractors on cognitive load in a motor imagery brain-computer interface. *Behavioural Brain Research*, *378*, 112240. https://doi.org/10.1016/J.BBR.2019.112240

Feldmann, L. K., Lofredi, R., Neumann, W. J., Al-Fatly, B., Roediger, J., Bahners, B. H., Nikolov, P., Denison, T., Saryyeva, A., Krauss, J. K., Faust, K., Florin, E., Schnitzler, A., Schneider, G. H., & Kühn, A. A. (2022). Toward therapeutic electrophysiology: beta-band suppression as a biomarker in chronic local field potential recordings. *Npj Parkinson's Disease, 8*(1), 1–9. https://doi.org/10.1038/s41531-022-00301-2

Fernandez, N. F., Gundersen, G. W., Rahman, A., Grimes, M. L., Rikova, K., Hornbeck, P., & Maayan, A. (2017). Clustergrammer, a web-based heatmap visualization and analysis tool for high-dimensional biological data. *Scientific Data, 4*(1), 1–12. https://doi.org/10.1038/sdata.2017.151

Finley, A. J., Angus, D. J., van Reekum, C. M., Davidson, R. J., & Schaefer, S. M. (2024). Correction to "Periodic and aperiodic contributions to theta-beta ratios across adulthood." *Psychophysiology*, *61*(7), e14555. https://doi.org/10.1111/PSYP.14555

Finn, E. S., Glerean, E., Khojandi, A. Y., Nielson, D., Molfese, P. J., Handwerker, D. A., & Bandettini, P. A. (2020). Idiosynchrony: From shared responses to individual differences during naturalistic neuroimaging. *NeuroImage*, *215*, 116828. https://doi.org/10.1016/J.NEUROIMAGE.2020.116828

Forbes, O., Schwenn, P. E., Wu, P. P. Y., Santos-Fernandez, E., Xie, H. B., Lagopoulos, J., McLoughlin, L. T., Sacks, D. D., Mengersen, K., & Hermens, D. F. (2022). EEG-based clusters differentiate psychological distress, sleep quality and cognitive function in adolescents. *Biological Psychology*, *173*, 108403. https://doi.org/10.1016/J.BIOPSYCHO.2022.108403

Fu, B., Li, F., Niu, Y., Wu, H., Li, Y., & Shi, G. (2021). Conditional generative adversarial network for EEG-based emotion fine-grained estimation and visualization. *Journal of Visual Communication and Image Representation*, *74*, 102982. https://doi.org/10.1016/J.JVCIR.2020.102982

Fuentes-Martinez, V. J., Romero, S., Lopez-Gordo, M. A., Minguillon, J., & Rodríguez-Álvarez, M. (2023). Low-Cost EEG Multi-Subject Recording Platform for the Assessment of Students' Attention and the Estimation of Academic Performance in Secondary School. *Sensors, 23*(23), 9361. https://doi.org/10.3390/S23239361

Gao, X., Huang, W., Liu, Y., Zhang, Y., Zhang, J., Li, C., Chelangat Bore, J., Wang, Z., Si, Y., Tian, Y., & Li, P. (2023). A novel robust Student's t-based Granger causality for EEG based brain network analysis. *Biomedical Signal Processing and Control*, *80*, 104321. https://doi.org/10.1016/J.BSPC.2022.104321

Gao, Z., Dang, W., Wang, X., Hong, X., Hou, L., Ma, K., & Perc, M. (2020). Complex networks and deep learning for EEG signal analysis. *Cognitive Neurodynamics, 15*(3), 369–388. https://doi.org/10.1007/S11571-020-09626-1

Gashaj, V., Trninić, D., Formaz, C., Tobler, S., Gómez-Cañón, J. S., Poikonen, H., & Kapur, M. (2024). Bridging cognitive neuroscience and education: Insights from EEG recording during mathematical proof evaluation. *Trends in Neuroscience and Education*, *35*, 100226. https://doi.org/10.1016/J.TINE.2024.100226

Gewers, F. L., Ferreira, G. R., De Arruda, H. F., Silva, F. N., Comin, C. H., Amancio, D. R., & Costa, L. D. F. (2021). Principal component analysis: A natural approach to data exploration. *ACM Computing Surveys*, *54*(4), 1-34. https://doi.org/10.1145/3447755/SUPPL_FILE/GEWERS.ZIP

Gnambs, T. (2023). A Brief Note on the Standard Error of the Pearson Correlation. *Collabra: Psychology*, *9*(1), 1-8. https://doi.org/10.1525/collabra.87615

González-Hernández, H. G., Medina-Pozos, J. M., Cantú-González, V., Amozurrutia-Elizalde, A., Flores-Amado, A., & Mora-Salinas, R. J. (2021). Looking for experimental evidence of critical thinking through EEG. *International Journal on Interactive Design and Manufacturing*, *15*(2–3), 333–351. https://doi.org/10.1007/S12008-021-00761-5/METRICS

Grekousis, G. (2020). Spatial Analysis Methods and Practice: Describe-Explore-Explain through GIS. *Spatial Analysis Methods and Practice: Describe-Explore-Explain through GIS*, 1–518. https://doi.org/10.1017/9781108614528

Gu, Z. (2022). Complex heatmap visualization. *IMeta*, *1*(3), e43. https://doi.org/10.1002/IMT2.43

Hadd, A., & Rodgers, J. L. (2020). *Understanding correlation matrices*. Sage Publications.

Hassan, I., Zolezzi, M., Khalil, H., Mohmood, R., Pedersen, S., & Chowdhury, M. E. H. (2024). Cognitive load estimation using a hybrid cluster-based unsupervised machine learning technique. *IEEE Access, 12*, 118785-118801. https://doi.org/10.1109/ACCESS.2024.3428691

Hernández-Mustieles, M. A., Lima-Carmona, Y. E., Pacheco-Ramírez, M. A., Mendoza-Armenta, A. A., Romero-Gómez, J. E., Cruz-Gómez, C. F., ... & Lozoya-Santos, J. D. J. (2024). Wearable Biosensor Technology in Education: A Systematic Review. *Sensors, 24*(8), 2437. https://doi.org/10.3390/S24082437

Horwitz, B., Friston, K. J., & Taylor, J. G. (2000). Neural modeling and functional brain imaging: An overview. *Neural Networks*, *13*(8–9), 829–846. https://doi.org/10.1016/S0893-6080(00)00062-9

Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Abuhaija, B., & Heming, J. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences*, *622*, 178–210. https://doi.org/10.1016/J.INS.2022.11.139

Ismail, L. E., & Karwowski, W. (2020). Applications of EEG indices for the quantification of human cognitive performance: A systematic review and bibliometric analysis. *PLOS ONE*, *15*(12), e0242857. https://doi.org/10.1371/JOURNAL.PONE.0242857

Kalantari, S., Rounds, J. D., Kan, J., Tripathi, V., & Cruz-Garza, J. G. (2021). Comparing physiological responses during cognitive tests in virtual environments vs. in identical real-world environments. *Scientific Reports*, *11*(1), 1–14. https://doi.org/10.1038/s41598-021-89297-y

Kästle, J. L., Anvari, B., Krol, J., & Wurdemann, H. A. (2021). Correlation between Situational Awareness and EEG signals. *Neurocomputing*, *432*, 70–79. https://doi.org/10.1016/J.NEUCOM.2020.12.026

Ke, J., Liao, P., Li, J., & Luo, X. (2023). Effect of information load and cognitive style on cognitive load of visualized dashboards for construction-related activities. *Automation in Construction*, *154*, 105029. https://doi.org/10.1016/J.AUTCON.2023.105029

Khosla, A., Khandnor, P., & Chand, T. (2020). A comparative analysis of signal processing and classification methods for different applications based on EEG signals. *Biocybernetics and Biomedical Engineering*, *40*(2), 649–690. https://doi.org/10.1016/J.BBE.2020.02.002

Kramer, A. F. (2020). Physiological metrics of mental workload: A review of recent progress. *Multiple-Task Performance*, 279–328. https://doi.org/10.1201/9781003069447-14

Kunze, T., Hunold, A., Haueisen, J., Jirsa, V., & Spiegler, A. (2016). Transcranial direct current stimulation changes resting state functional connectivity: A large-scale brain network modeling study. *NeuroImage*, *140*, 174–187. https://doi.org/10.1016/J.NEUROIMAGE.2016.02.015

Lapomarda, G., Valer, S., Job, R., & Grecucci, A. (2022). Built to last: Theta and delta changes in resting-state EEG activity after regulating emotions. *Brain and Behavior*, *12*(6), e2597. https://doi.org/10.1002/BRB3.2597

Liu, Y., Yu, Y., Ye, Z., Li, M., Zhang, Y., Zhou, Z., Hu, D., & Zeng, L. L. (2023). Fusion of Spatial, Temporal, and Spectral EEG Signatures Improves Multilevel Cognitive Load Prediction. *IEEE Transactions on Human-Machine Systems*, *53*(2), 357–366. https://doi.org/10.1109/THMS.2023.3235003

Magnotti, J. F., Wang, Z., & Beauchamp, M. S. (2020). RAVE: Comprehensive open-source software for reproducible analysis and visualization of intracranial EEG data. *NeuroImage*, *223*, 117341. https://doi.org/10.1016/J.NEUROIMAGE.2020.117341

Makowski, D., Ben-Shachar, M. S., Patil, I., & Lüdecke, D. (2020). *Methods and Algorithms for Correlation Analysis in R*. https://doi.org/10.21105/joss.02306

Mangaroska, K., Sharma, K., Gašević, D., & Giannakos, M. (2022). Exploring students' cognitive and affective states during problem solving through multimodal data: Lessons learned from a programming activity. *Journal of Computer Assisted Learning*, *38*(1), 40–59. https://doi.org/10.1111/JCAL.12590

Mendoza-Armenta, A. A., Blanco-Téllez, P., García-Alcántar, A. G., Ceballos-González, I., Hernández-Mustieles, M. A., Ramírez-Mendoza, R. A., Lozoya-Santos, J. de J., & Ramírez-Moreno, M. A. (2024). Implementation of a Real-Time Brain-to-Brain Synchrony Estimation Algorithm for Neuroeducation Applications. *Sensors*, *24*(6), 1776. https://doi.org/10.3390/S24061776

Morales, S., & Bowers, M. E. (2022). Time-frequency analysis methods and their application in developmental EEG data. *Developmental Cognitive Neuroscience*, *54*, 101067. https://doi.org/10.1016/J.DCN.2022.101067

Moscarelli, M. (2023). Correlation. In: Biostatistics With 'R': A Guide for Medical Doctors. Springer, Cham. https://doi.org/10.1007/978-3-031-33073-5_7

Niso, G., Romero, E., Moreau, J. T., Araujo, A., & Krol, L. R. (2023). Wireless EEG: A survey of systems and studies. *NeuroImage*, *269*, 119774. https://doi.org/10.1016/J.NEUROIMAGE.2022.119774

Oktaviyanthi, R., Agus, R. N., Garcia, M. L. B., & Lertdechapat, K. (2024). Cognitive load scale in learning formal definition of limit: A rasch model approach. *Infinity Journal*, *13*(1), 99–118. https://doi.org/10.22460/INFINITY.V13I1.P99-118

Pei, Y., Yang, J., Boubchir, L., Yoo, G., Kim, H., & Hong, S. (2023). Prediction of Cognitive Load from Electroencephalography Signals Using Long Short-Term Memory Network. *Bioengineering*, *10*(3), 361. https://doi.org/10.3390/BIOENGINEERING10030361

Pereira, T. D., Shaevitz, J. W., & Murthy, M. (2020). Quantifying behavior to understand the brain. *Nature Neuroscience*, *23*(12), 1537–1549. https://doi.org/10.1038/s41593-020-00734-z

Qin, T., Fias, W., Van de Weghe, N., & Huang, H. (2024). Recognition of map activities using eye tracking and EEG data. *International Journal of Geographical Information Science*, *38*(3), 550-576. https://doi.org/10.1080/13658816.2024.2309188

Qu, X., Liukasemsarn, S., Tu, J., Higgins, A., Hickey, T. J., & Hall, M. H. (2020). Identifying Clinically and Functionally Distinct Groups Among Healthy Controls and First Episode Psychosis Patients by

Clustering on EEG Patterns. *Frontiers in Psychiatry*, *11*, 541659. https://doi.org/10.3389/FPSYT.2020.541659/BIBTEX

Rahman, M. A., Hossain, M. F., Hossain, M., & Ahmned, R. (2020). Employing PCA and t-statistical approach for feature extraction and classification of emotion from multichannel EEG signal. *Egyptian Informatics Journal*, *21*(1), 23–35. https://doi.org/10.1016/J.EIJ.2019.10.002

Ramírez-Moreno, M. A., Díaz-Padilla, M., Valenzuela-Gómez, K. D., Vargas-Martínez, A., Tudón-Martínez, J. C., Morales-Menendez, R., Ramírez-Mendoza, R. A., Pérez-Henríquez, B. L., & Lozoya-Santos, J. de J. (2021). Eeg-based tool for prediction of university students' cognitive performance in the classroom. *Brain Sciences*, *11*(6), 698. https://doi.org/10.3390/BRAINSCI11060698/S1

Sachdeva, S., & Eggen, P.-O. (2021). Learners' Critical Thinking About Learning Mathematics. *International Electronic Journal of Mathematics Education*, *16*(3), em0644. https://doi.org/10.29333/IEJME/11003

Skulmowski, A., & Xu, K. M. (2021). Understanding Cognitive Load in Digital and Online Learning: a New Perspective on Extraneous Cognitive Load. *Educational Psychology Review*, *34*(1), 171–196. https://doi.org/10.1007/S10648-021-09624-7

Souza, R. H. C. e., & Naves, E. L. M. (2021). Attention Detection in Virtual Environments Using EEG Signals: A Scoping Review. *Frontiers in Physiology*, *12*, 727840. https://doi.org/10.3389/FPHYS.2021.727840/BIBTEX

Srinivasa, K. G., Kurni, M., & Saritha, K. (2022). *Adaptive Teaching/Learning*. 201–240. https://doi.org/10.1007/978-981-19-6734-4_9

Šverko, Z., Vrankić, M., Vlahinić, S., & Rogelj, P. (2022). Complex Pearson Correlation Coefficient for EEG Connectivity Analysis. *Sensors*, *22*(4), 1477. https://doi.org/10.3390/S22041477

Sweller, J. (2011). Cognitive Load Theory. *Psychology of Learning and Motivation - Advances in Research and Theory*, *55*, 37–76. https://doi.org/10.1016/B978-0-12-387691-1.00002-8

Sweller, J. (2020). Cognitive load theory and educational technology. *Educational Technology Research and Development*, *68*(1), 1–16. https://link.springer.com/article/10.1007/s11423-019-09701-3

Tan, E., Troller-Renfree, S. V., Morales, S., Buzzell, G. A., McSweeney, M., Antúnez, M., & Fox, N. A. (2024). Theta activity and cognitive functioning: Integrating evidence from resting-state and task-related developmental electroencephalography (EEG) research. *Developmental Cognitive Neuroscience*, *67*, 101404. https://doi.org/10.1016/J.DCN.2024.101404

Tang, H., Dai, M., Du, X., Hung, J. L., & Li, H. (2024). An EEG study on college students' attention levels in a blended computer science class. *Innovations in Education and Teaching International*, *61*(4), 789–801. https://doi.org/10.1080/14703297.2023.2166562

Tetzlaff, L., Schmiedek, F., & Brod, G. (2021). Developing Personalized Education: A Dynamic Framework. *Educational Psychology Review*, *33*(3), 863–882. https://doi.org/10.1007/S10648-020-09570-W/FIGURES/3

Trinidad, J. E. (2020). Understanding student-centred learning in higher education: students' and teachers' perceptions, challenges, and cognitive gaps. *Journal of Further and Higher Education*, *44*(8), 1013–1023. https://doi.org/10.1080/0309877X.2019.1636214

Wang, C. C., Cheng, P. K. H., & Wang, T. H. (2022). Measurement of Extraneous and Germane Cognitive Load in the Mathematics Addition Task: An Event-Related Potential Study. *Brain Sciences 2022, Vol. 12, Page 1036*, *12*(8), 1036. https://doi.org/10.3390/BRAINSCI12081036

Wang, G., Tian, L., Liu, J., Nie, S., & Yu, S. (2024). Neural mechanisms of cognitive load in Multimedia Learning: a Meta-analysis of EEG frequency Band Modulation. *Current Psychology 2024*, 1–17. https://doi.org/10.1007/S12144-024-06577-2

Wang, M., Hu, J., & Abbass, H. A. (2020). BrainPrint: EEG biometric identification based on analyzing brain connectivity graphs. *Pattern Recognition*, *105*, 107381. https://doi.org/10.1016/J.PATCOG.2020.107381

Wen, T. Y., & Aris, S. A. M. (2022). Hybrid Approach of EEG Stress Level Classification Using K-Means Clustering and Support Vector Machine. *IEEE Access*, *10*, 18370–18379. https://doi.org/10.1109/ACCESS.2022.3148380

Wirth, J., Stebner, F., Trypke, M., Schuster, C., & Leutner, D. (2020). An Interactive Layers Model of Self-Regulated Learning and Cognitive Load. *Educational Psychology Review*, *32*(4), 1127–1149. https://doi.org/10.1007/S10648-020-09568-4/FIGURES/5

Xiong, R., Kong, F., Yang, X., Liu, G., & Wen, W. (2020). Pattern Recognition of Cognitive Load Using EEG and ECG Signals. *Sensors*, *20*(18), 5122. https://doi.org/10.3390/S20185122

Xu, K. M., Koorn, P., de Koning, B., Skuballa, I. T., Lin, L., Henderikx, M., Marsh, H. W., Sweller, J., & Paas, F. (2021). A Growth Mindset Lowers Perceived Cognitive Load and Improves Learning: Integrating Motivation to Cognitive Load. *Journal of Educational Psychology*, *113*(6), 1177–1191. https://doi.org/10.1037/EDU0000631

Zanetti, R., Arza, A., Aminifar, A., & Atienza, D. (2022). Real-Time EEG-Based Cognitive Workload Monitoring on Wearable Devices. *IEEE Transactions on Biomedical Engineering*, *69*(1), 265–277. https://doi.org/10.1109/TBME.2021.3092206

Zhang, Y., Zhou, T., Wu, W., Xie, H., Zhu, H., Zhou, G., & Cichocki, A. (2022). Improving EEG Decoding via Clustering-Based Multitask Feature Learning. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(8), 3587–3597. https://doi.org/10.1109/TNNLS.2021.3053576

Zhou, Y., Huang, S., Xu, Z., Wang, P., Wu, X., & Zhang, D. (2022). Cognitive Workload Recognition Using EEG Signals and Machine Learning: A Review. *IEEE Transactions on Cognitive and Developmental Systems*, *14*(3), 799–818. https://doi.org/10.1109/TCDS.2021.3090217