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STRESS LEVEL AND COGNITIVE LOAD TEST OF HIGH SCHOOL STUDENTS BASED ON THE ANALYSIS OF CONSUMER-GRADE EEG SIGNAL AND NASA-TLX QUESTIONNAIRE

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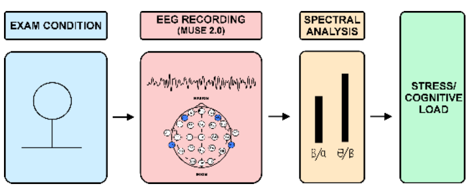
Graphic abstract



Abstract

Brain wave data collection had been conducted on 35 students from SMAN 2 Cikarang Selatan, Indonesia, during their physics exam between August and September 2024. This research aimed to process brain wave activity experienced by students three minutes before the exam, during the 40-minute exam period, and three minutes after the exam, focusing on stress management that may affect brain activity through amplitude changes and frequency shifts using the consumer-grade EEG device Muse 2.0. Mental demand and frustration can be objectively measured using EEG through Beta/Alpha (β/α) power ratio and Theta/Beta (θ/β) power ratio. In addition to using EEG, students' cognitive load is also assessed subjectively using the NASA-TLX questionnaire. The analysis of β/α power ratio differences after and before the exam categorized subjects into five groups: Positive 2, Positive 1, Neutral, Negative 1, and Negative 2. The results indicate that a certain level of increased cognitive load during the exam led to lower test scores than neutral cognitive load conditions. A rise in β wave power during the exam provides insight into individuals striving to engage with cognitive tasks optimally. The β/α power ratio difference has a moderate positive correlation (0.263) with increased mental demand, suggesting that subjects experienced excessive cognitive load during the exam. Higher mental demand is associated with an increase in the power of β frequency in the frontal lobe. Additionally, a weak positive correlation (0.077) was found between the frustration indicator in NASA-TLX and the (θ/β) power ratio difference.

Keywords: Brain waves, cognitive load, mental demand, frustration, theta/beta power ratio, beta/alpha power ratio, NASA-TLX

1.0 INTRODUCTION

Stress is a mental health phenomenon affecting individuals due to various causal factors. The brain plays a critical role in stress management because stress can influence brain activity by altering the processing of information provided [1]. Acute stress levels are associated with changes in the prefrontal cortex, responsible for decision-making, memory, and attention modulation. Stress also affects the hippocampus, which is related to memory and learning functions [1]. There are two types of stress: positive stress, which enhances learning abilities, and negative stress, which suppresses learning abilities [2].

An educational journey is one of the triggers of stress for students during the learning process [3]. Packed schedules often cause excessive anxiety at school due to diverse demands, a multitude of stressors, including academic workload, exams, peer pressure, and academic expectations from parents or teachers, which can lead to anxiety, depression, and burnout [4] [5]. Academic accomplishments are a significant life goal for students and can be severely impacted if students succumb to depression, which induces cognitive burdens [6] [7] .

The 2015 PISA (Programme for International Student Assessment) revealed that 64% of female students and 47% of male students experienced excessive anxiety when facing exams [8]. This anxiety arises from the fear of failure or making mistakes, affecting students' performance during exams. Physics, a subject demanding high concentration and cognitive ability, often requires literacy and numeracy skills to analyze problems. Students' perception about physics and its nature, such as being cumulative and hence missing one concept makes it hard to grasp the subsequent one, too much material to learn, being abstract and theoretical with many laws and rules, and being abundant with many formulas requiring mathematical background etc., makes them feel physics is difficult [9]. Consequently, physics often becomes a daunting subject for students, increasing their cognitive load.

Measuring academic stress levels among students is particularly challenging since there are variations in individual mental conditions. Electroencephalography (EEG) is a technique used to measure electrical activity generated by brain neuron firing, also known as cerebral electrical activity [10]. Electroencephalograms (EEGs) measure the brain's electrical activity, which is often employed for quantitative methods to study stress. Due to its ability to reflect both normal and abnormal brain electrical activity, EEG is a powerful tool in neurology and clinical neurophysiology [11]. EEG is a non-invasive and painless procedure widely used to study the brain's cognitive processes [11]. EEGs show variations in amplitude and frequency of brain waves, which are associated with mental states and psychological disorders [12].

Under stress, the brain responds with changes in electrical signals observable through EEG. An increase in β activity has been found in stressful conditions, which is associated with alertness, focus, and concentration [13]. At the same time, the brain also typically exhibits a decrease in α activity during stress, suggesting that stress can suppress the α rhythm. This relation forms the basis of the β/α ratio, where higher values indicate stress and lower values indicate relaxation [14], [15]. The β/α power ratio can indicate the cognitive load experienced by students [16]. The analysis of this ratio provides insights into the relative balance between relaxation and mental alertness. An elevation of α to β activity in the frontal area can reflect increased cognitive load [17]. The EEG results showed significant decrease in alpha rhythm power ($p<0.01$) and increase in beta rhythm power ($p<0.02$) on the PFC under stress condition [18].

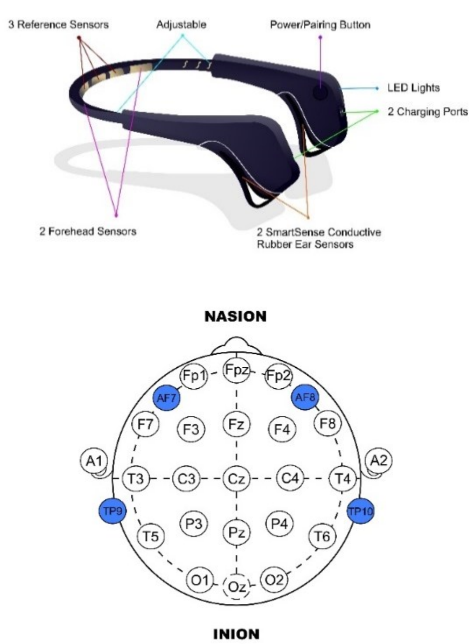
The α band often shows sensitivity to mental workload experiments [19] [20], cognitive fatigue [21], attention and alertness [22]. Continuous suppression in the α band appears linked to increased task difficulty [23]. The β band is associated with visual attention [24], short-term memory tasks [25], and working memory [26]. Increased β band activity correlates with heightened task engagement [27] and concentration levels [28]. Reduced α activity corresponds with increased frontal-parietal activity, indicated by higher β power and decreased θ, reflecting heightened vigilance [29]. The theta/beta (θ/β) power ratio is another indicator of student stress. The θ/β ratio aids the study of emotional-cognitive interactions and their biological functioning [30]. Apart from EEG's objective methods, students' cognitive load can be measured subjectively through the NASA-TLX questionnaire, with quantitative results to measure human performance objectively. The questionnaire consists of primary and secondary task measures [31].

This study aims to measure high school students' cognitive load and stress levels due to physics exams. The objective measurement uses EEG data through β/α and θ/β ratios, and the subjective measurement uses the NASA-TLX questionnaire. A more comprehensive analysis is conducted by examining the correlation between EEG results and NASA-TLX.

2.0 METHODOLOGY

Based on data completeness and the health status of participants, 35 male students were selected from 41 volunteers at SMAN 2 Cikarang Selatan, Indonesia. The participants, aged 15 to 17 years, were chosen to facilitate practical access and ensure the efficient use of equipment. The research site was determined by the approval granted for data collection. EEG recordings were conducted for 46 minutes per participant between August and September 2024. Prior to participation, all students provided written informed consent, confirming their voluntary involvement in the study. The study began with the preparation of tools, namely Muse 2.0 (InteraXon Inc., Canada; RRID: SCR_014418) (Figure 1a) and an Android tablet equipped with the Mind Monitor application. The equipment was a consumer-based EEG device with electrodes AF-7, AF-8, TP-9, TP-10, and references CMS/DRL (Figure 1b), and it is not intended for diagnostic or clinical use in this study. Previous validation studies demonstrate that the Muse system can reliably record ERP components such as the N200, P300, and reward positivity [32], and more recent work has confirmed its capability to measure the N400 effect with acceptable reliability [33].

(a)



(b)

Figure 1 (a) Muse 2.0 (b) Electrode's position [34]

EEG data recording consists of three stages: before, during, and after the exam. The data collection process for three minutes before the exam was conducted by asking subjects to sit quietly and remain relaxed. During the 40-minute exam, the subjects were instructed to answer 30 physics exam questions sequentially, with a maximum score of 100. The method of answering followed the real exam activities conducted in school, using Google Forms as the medium and paper with pens for calculations. Subjects were asked to minimize movements that could affect the data. After completing the exam, EEG recording was conducted for three minutes with the subjects in a relaxed state. Following this, subjects were asked to complete the NASA-TLX questionnaire based on their feelings. Finally, a brief verbal interview was conducted for confirmation.

EEG data were acquired using the Muse 2 headband (InteraXon Inc., Toronto, Canada; RRID: SCR_014418). To ensure full access to raw EEG signals at the native sampling rate (256 Hz), we used the third-party application Mind Monitor (mind-monitor.com; James Clutterbuck, Toronto, Canada), which is not bundled with the Muse hardware and must be purchased separately. Brain wave frequencies can be classified into five categories for further analysis: delta δ (0.5–4 Hz), theta θ (4–8 Hz), alpha α (8–13 Hz), beta β (14–30 Hz), and gamma γ (30–50 Hz) [12].The EEG spectrum can be expressed in absolute terms as the energy within the selected frequency bands. Absolute Band Power (ABP) represents the total power within a specific frequency range and is presented on a logarithmic scale with units called Bels [34]. Data is provided for AF-7, AF-8, TP-9, TP-10 electrode channels in Muse 2.0.

Data in (.csv) format from Mind Monitor only provides a sampling rate of 1-2 data points per second, which does not meet the tool's specifications (256 Hz). Therefore, data processing is conducted through the Mind Monitor website. Data from the Mind Monitor website includes average comparisons of ABP, brain waves in the left and right hemispheres, frontal and temporal lobes, and average values for each frequency band of brain waves.

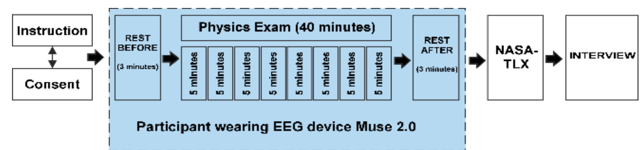


Figure 2 Data recording flow

The data obtained during the 40-minute exam is divided manually every five minutes and then processed through the Mind Monitor website to see the average ABP data. The data was processed using Microsoft Excel to show changes in brain wave condition before, during, and after the exam.

$$\Delta = \left(\frac{ABP_\beta}{ABP_\alpha}\right)_{after} - \left(\frac{ABP_\beta}{ABP_\alpha}\right)_{before} \quad (1)$$

The β/α power ratio was calculated in the frontal lobe of the brain to analyze the cognitive load condition and the θ/β ratio for the indication of the stress experienced by the subject. Then, the difference (Δ) of the β/α power ratio before and after the exam (equation 1) was calculated. The difference in β/α power ratio results was grouped into five categories (Figure 3): neutral, positive 1 (P1), positive 2 (P2), negative 1 (N1), and negative 2 (N2). The criteria were performed after calculating the mean value (-0.026) and standard deviation (SD = 0.138) of 35 subjects.

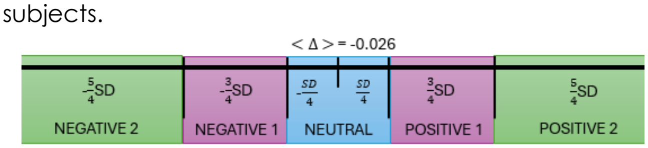


Figure 3 Data grouping

The processing of NASA-TLX questionnaire data begins with calculating the weighted values of six indicators listed on the first page of the questionnaire. The NASA Task Load Index is a multidimensional rating procedure that provides an overall workload assessment based on the average of six indicators: Mental Demands, Physical Demands, Temporal Demands, Own Performance, Effort, and Frustration [35]. The weight of each indicator is determined by asking the subject to choose between two indicators, identifying which one is perceived as more dominant in contributing to mental workload for the given task. The total weight amounts to fifteen.

Subsequently, rating calculations are performed for each indicator on the second page of the questionnaire. These ratings are scaled from 1 to 100, with five-unit intervals. The rating values are then multiplied and summed by their respective weights. The NASA-TLX score is obtained by dividing the total value by fifteen, after which the cognitive workload experienced by the subject is classified accordingly.

The categorization results from both EEG and NASA-TLX are then correlated to determine the relationship between the two methods using Pearson correlation. The Pearson correlation coefficient ranges from -1 to +1, measuring the strength and direction of the relationship between two statistical categories. A negative coefficient suggests that an increase in one variable is accompanied by a decrease in the other, and vice versa. A correlation coefficient close to zero indicates a weak relationship between variables. A positive correlation coefficient indicates that both variables tend to increase, or both tend to decrease. Values approaching -1 or +1 signify a strong linear relationship between them.

3.0 RESULTS AND DISCUSSION

The increase in the β/α power ratio in the frontal lobe is associated with a rise in cognitive load [16]. Greater engagement in cognitive processes during decision-making leads to an elevated β/α ratio, indicating a less relaxed state and increased stress [36].

The classification of the differences in the β/α power ratio is presented in Table 1. The neutral category suggests that the cognitive load of the subjects did not undergo significant changes after being given the stimulus of completing 30 physics exam questions within 40 minutes. The negative category indicates that the subjects' cognitive load tended to decrease following the exam process, whereas the positive category signifies an increase in cognitive load during the exam. The p-value was derived using the Shapiro-Wilk test, confirming that the data satisfied the assumption of normality.

Table 1 Difference in the β/α power ratio and exam scores for each category

Δ β/α	Category	Exam Score	Number of Subjects	P-value
($\Delta \geq 0.103$)	Positive 2	23.5±6.9	6	0.223
($0.034 \leq \Delta < 0.103$)	Positive 1	28.0±9.1	5	0.389
($-0.034 \leq \Delta < 0.034$)	Neutral	27.2±8.4	9	0.273
($-0.034 \leq \Delta < -0.103$)	Negative 1	31.7±7.3	7	0.391
($\Delta \geq -0.103$)	Negative 2	20.9±6.1	8	0.473

Excessive increases (p = 0.223) or decreases (0.273) in the difference in the β/a power ratio (positive 2 or negative 2) result in lower average exam scores compared to other categories. Six individuals were identified as experiencing an increase in cognitive load after the physics exam, with an average ± SD exam score is 23.5±6.9 out of 100. For subjects in the positive 2 (P2) category, cognitive overload occurs when task demands exceed the available resources of an individual, rendering them unable to accurately process relevant information or generate appropriate responses. Cognitive load is a fundamental concept in human performance studies, arising from the observation that the human cognitive system has a limited capacity for executing cognitive tasks. This limitation reduces efficiency and drastically increases the likelihood of errors [37]. This phenomenon can be explained by the hypothesis that students in the P2 category experienced an increase in cognitive load due to time constraints during the exam, a competitive learning environment that hindered their comprehension of the material, ultimately leading to a decline in their performance.

In the negative 2 (N2) category, a decrease in cognitive load and a decline in the average exam score to 20.9±6.1 out of 100 were observed, indicating that the subjects did not put forth optimal effort during the examination process and demonstrated insufficient concentration in utilizing working memory to complete cognitive tasks. Working memory functions as the central processing unit of the nervous system, serving as a temporary storage mechanism that depends on individual capacity [11]. It is defined as a structural component of the human brain responsible for temporarily storing and manipulating specific information [38]. The quantitative data from this study aligns with previous research conducted by other scholars, which has demonstrated a significant decline in student performance during timed tests compared to untimed tests, despite both assessments having identical levels of difficulty [39]. These experimental findings suggest that time constraints may be a key factor contributing to the decline in student performance in real exam scenarios.

The Positive 1 (P1 and Negative 1 (N1) categories have higher average exam scores and higher p-value because the subjects tried to focus on the questions and enhance their memory in completing cognitive tasks. The Neutral category indicates that the subjects' mental load did not undergo significant changes after taking the exam, allowing them to accurately process relevant information.

The β frequency band, operating at 13-30Hz in the frontal lobe, provides insights into cognitive processes such as thinking, task focus, problem-solving, and decision-making [40]. Alpha α waves exhibit sensitivity to mental workload and cognitive fatigue, with increased a wave activity being associated with reduced attention and alertness [31]. The frontal lobe plays a crucial role in high-level cognitive processes, prospective memory, speech and language functions, as well as the ability to make decisions related to reasoning, learning, and creativity [41]. Investigative findings suggest that the frontal region of the brain is the dominant area in representing stress [42].

Figure 3 shows data on the β/α power ratio in the frontal lobe for one subject chosen randomly, representing each category during the exam. The frontal brain region is connected to sensor electrodes AF-7 and AF-8, which correspond to the left and right foreheads, in the Muse 2.0 device. Completing physics exam questions is a cognitive task performed to observe the subject's brain wave conditions

The quantitative data of three subjects in categories P2, P1, and neutral show a fluctuating and increasing trend at the end of the exam session, indicating that all three subjects were trying to focus on the questions and enhance memory in completing cognitive tasks. The high and stable β/α power ratio condition for S13-Neutral provides information about an individual striving to fully engage with the cognitive task with $p = 3.69\,x\,10^{-8}$ as shown in Table 2.

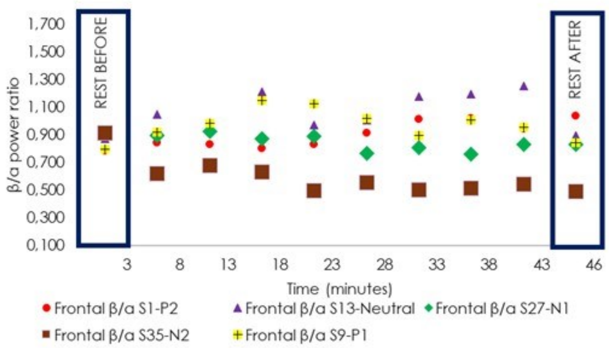


Figure 3 β/α power ratio for one subject per each category during the exam

A Shapiro–Wilk test was conducted to examine the normality of the β/α power ratio distributions across one representative subject in each experimental categories as shown in Table 2 number one to five. The results indicated that all subjects demonstrated normally distributed data (all $p > 0.05$). Subsequent significance testing revealed that the β/α power ratio was highly significant across each subject in all categories, including Positive 1, Positive 2, Neutral, Negative 1, and Negative 2 (all $p < 1.2 \times 10^{-8}$). These findings suggest that the β/α power ratio is a stable and robust neural marker during the exam, regardless of emotional category.

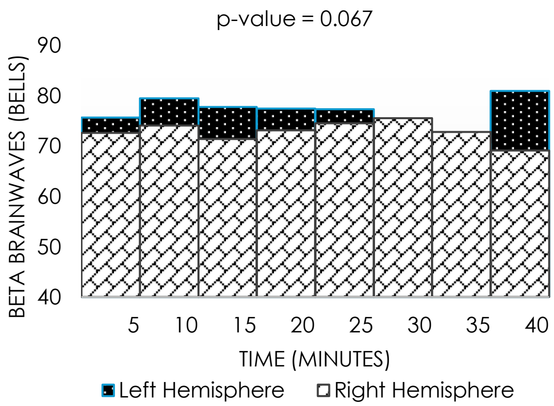
However, for S27 in category N1, the β/α power ratio decreased during the exam process ($p = 1.98\,x\,10^{-9}$). Similar data was also observed for S35 in category N2, which had the lowest β/α power ratio among all subjects and showed a declining trend ($p = 5.82\,x\,10^{-8}$). Research from other studies suggests that β waves are associated with visual attention, short-term memory tasks, and working memory enhancement [31]. Based on this, it can be concluded that during the physics exam, S35 did not experience excessive cognitive load and made little effort to concentrate to activate working memory for completing the cognitive task.

Table 2 Data statistics of β/α power ratio per each category during the exam

No	Category	Normality	P_value
1	S1-Positive 2	0.165	1.18×10^{-8}
2	S9-Positive 1	0.494	7.65×10^{-9}
3	S13-Neutral	0.263	3.69×10^{-8}
4	S27-Negative 1	0.468	1.98×10^{-9}
5	S35-Negative 2	0.300	5.82×10^{-8}
6	All-Positive 2	0.015	1.91×10^{-27}
7	All-Positive 1	0.865	7.88×10^{-40}
8	All-Neutral	0.095	6.98×10^{-58}
9	All- Negative 1	0.164	6.22×10^{-37}
10	All-Negative 2	0.083	2.05×10^{-42}

When comparing across categories for all subjects (number 6 to 10), the results indicated that all conditions yielded extremely significant β/α power ratios (all $p < 10^{-27}$). Among them, the neutral condition demonstrated the strongest effect ($p = 6.98 \times 10^{-53}$), followed by negative 2 ($p = 2.05 \times 10^{-42}$), positive 1 ($p = 7.88 \times 10^{-40}$), negative 1 ($p = 6.22 \times 10^{-37}$), and positive 2 ($p = 1.91 \times 10^{-27}$). Although positive 2 showed a significant deviation from normality ($p = .015$), the overall trend suggests that the neutral condition elicited the most pronounced β/α ratio differences, whereas positive 2 produced the weakest—though still highly significant—effect. These results highlight variation in the magnitude of neural responses depending on emotional category, with neutral yielding the strongest statistical evidence.

The brain wave conditions of five selected representative subjects are shown in Figure 4 for the β frequency band in the left and right hemispheres. In the cognitive task of solving physics exam questions, the left hemisphere is associated with reasoning processes for solving numerical and scientific problems and the ability to use and understand language. Meanwhile, the right hemisphere manages spatial perception and patterns, generating mental images to compare spatial relationships [41]. During cognitive tasks, attention focus, and the central nervous system interact, particularly in maintaining and manipulating relevant information, which is commonly modelled by the concept of working memory [37].



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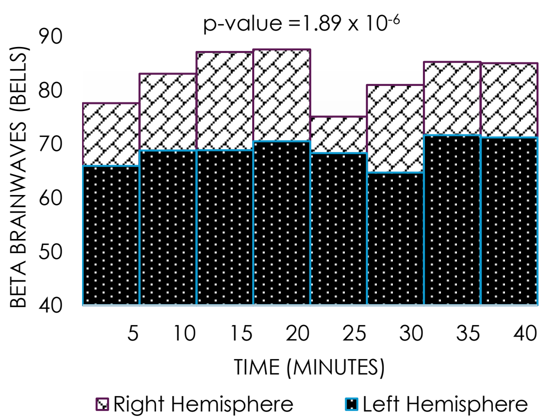

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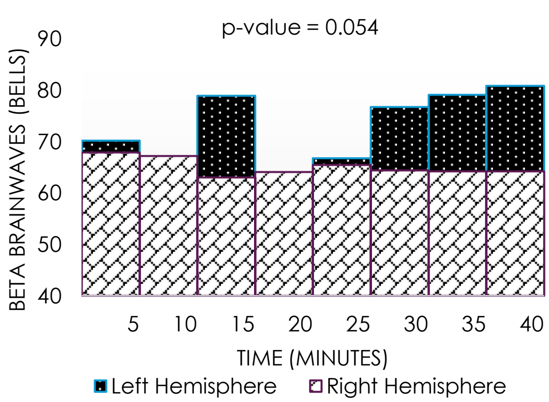

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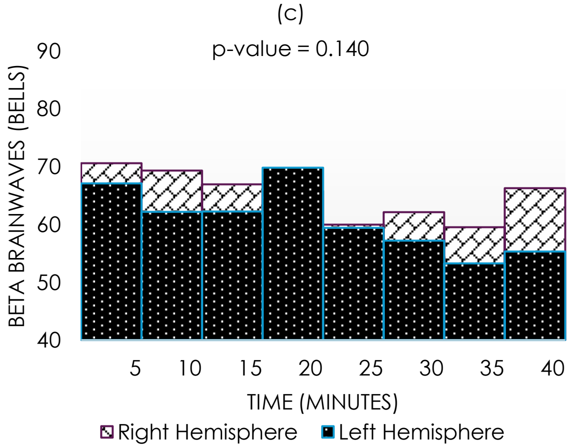

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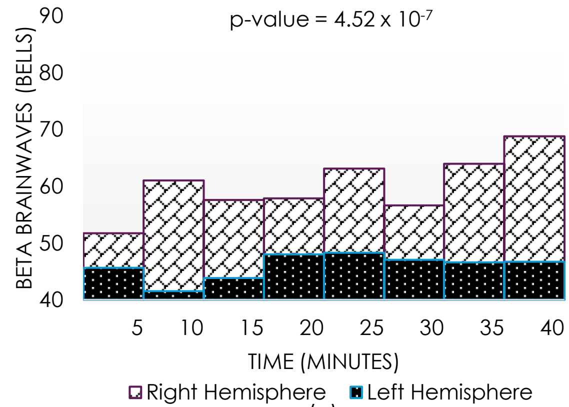

(e)

Figure 4 ABP in beta frequency band for left and right hemisphere (a) S1-P2 (b) S9-P1 (c) S13-Neutral (d) S27-N1 (e) S35-N2

Based on Figure 4(a), EEG recordings indicate that S1-P2 tends to use the left hemisphere of the brain more than the right hemisphere. This suggests that S1-P2 approaches the physics exam questions using numerical and scientific reasoning processes. However, the difference in Absolute Brain Power (ABP) for β frequency between the left and right hemispheres for this subject is relatively small, with $p = 0.067$. This value indicates relatively balanced β activity over the 40-minute session. A High amplitude of ABP (≥75 B) indicates that the subject experiences an increase in cognitive load during the exam. This aligns with the previously established β/α category, where S1-P2 undergoes excessive cognitive load, decreasing performance during the exam, with a lower exam score. Similarly, Figure (c) ($p = .054$) and Figure (d) ($p = .140$) revealed no statistically significant hemispheric asymmetry, suggesting that in these conditions, β/α power was distributed comparably across both hemispheres.

S9, categorized as positive 1, demonstrated a highly significant effect ($p = 1.89 \times 10^{-6}$), with consistently stronger β activity in the right hemisphere relative to the left across all time intervals. ($p = 1.89x\ 10^{-6}$). Relevant research indicates that β frequency brain waves in the left hemisphere show increased activity when solving complex arithmetic problems [43]. This aligns with the data shown for S9 in Figure 4(b), as the physics exam questions presented increased in difficulty sequentially. This implies that S9 heightened attention and focus on an effort to complete the cognitive task.

A comparable pattern was observed in Figure 4(e), where the right hemisphere exhibited greater beta activity than the left, supported by a robust level of significance ($p = 4.52 \times 10^{-7}$). Taken together, these findings suggest that while β activity was largely symmetrical in some conditions, specific experimental contexts elicited pronounced hemispheric differences, particularly favouring the right hemisphere.

S35-N2 exhibited dominance of the right hemisphere of the brain, which was more active during the exam process. According to relevant research, β brain waves are typically higher in the left hemisphere than in the right, and an increase in right hemisphere β asymmetry is an indicator of anxiety or stress [44]. However, S35 falls into the negative 2 category based on the previously conducted β/α power ratio classification. The interpretation of this phenomenon could suggest that S35-N2 did not experience excessive cognitive load due to a lack of understanding of the physics exam questions and instead relied more on mental recall by processing memory images using the right hemisphere of the brain to solve problems.

After the test, the researcher interviewed all subjects (based on Figure 2). The interview results show that out of 30 physics exam questions, all subjects were required to answer 20 questions within 40 minutes, with some not completing the entire exam. They resorted to guessing the answers as time ran out. On average, subjects attempted 15-25 questions.

Additionally, subjects were asked about their problem-solving methods: S1 solved questions directly using rough calculations, S13 skipped difficult questions and used rough calculations, while only recalling materials, formulas, or questions previously discussed in class. NASA-TLX is a subjective assessment of a subject's mental state based on six subscales: mental demand, physical demand, temporal demand, own performance, effort, and frustration. Before rating, the subject must choose between two indicators 15 times to determine the indicator weights, then provide a rating for each scale from 1 to 100. During the questionnaire completion, subjects were informed about the rating criteria for each indicator on a scale of 1 to 100.

The processed data is then classified based on Figure 5, which presents data from all 35 subjects. The quantitative scores obtained from the questionnaire analysis are categorized according to cognitive workload classification based on the NASA-TLX questionnaire. The workload classification is defined as follows: 1)$0 \le x \le 20$: very low, (2) $20 \le x \le 40$: low, (3) $40 \le x \le 60$: moderate, (4) $60 \le x \le 80$: high, and (5) $80 \le x \le 100$: very high [45].

Responses regarding problem-solving methods confirmed the categorization of subjects based on the β/α power ratio difference, with S35 ranking last in the negative 2 category due to not fully utilizing cognitive ability during the exam. The final question asked about the subjects' conditions after the exam, with most feeling relief and calm. However, S1 reported experiencing dizziness, which aligns with the increased β/α power ratio difference. In contrast, S35 reported feeling neutral, corresponding to a decreasing β/α power ratio difference.

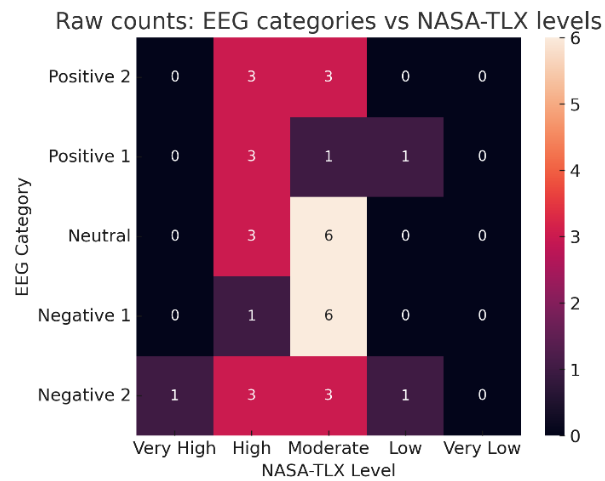

Figure 5 Number of subjects based on NASA-TLX with EEG results

Based on the data in Figure 5, eight subjects fall into the classifications of very high, high, moderate, and low cognitive workload according to NASA-TLX. Yet, they are categorized as N2 based on the β/α power ratio results from EEG. This discrepancy arises because the NASA-TLX questionnaire is subjective assessment of cognitive load, influenced by each subject's individual condition.

Subjects in the N2 category, according to EEG results, reported experiencing anxiety, stress, and frustration while working on the physics exam, but they did not utilize their brain's full capacity to solve the problems effectively. For subjects in category P2, three individuals were classified as experiencing high and moderate cognitive workload based on NASA-TLX. Literature reviews suggest that subjects with a high cognitive workload experience stress, leading to frustration while solving mental arithmetic tasks due to their lack of mastery in arithmetic concepts [45].

Subjects with a moderate cognitive workload face slight difficulties when solving arithmetic problems [45]. Meanwhile, subjects with a low cognitive workload do not experience stress or difficulty in solving mental arithmetic tasks because they have a strong grasp of arithmetic and feel confident [45]. Based on this research interpretation, subjects classified as experiencing high and moderate cognitive workload in category P2 have not yet mastered the physics exam material and struggle with problem-solving, which aligns with the β/α power ratio analysis, indicating excessive cognitive load. The physics exam material covered vectors and kinematics, which require mathematical comprehension and critical reasoning skills for proper understanding.

The raw data analysis between the difference in β/α power ratio and the mental demand of NASA-TLX was conducted on all 35 subjects, as shown in Table 3.

A similar analysis was performed on the difference in θ/β power ratio in the same table. Additionally, correlations between NASA TLX and EEG power ratio difference were statistically analyzed and the results are presented in Table 4.

Several studies using EEG to evaluate stress levels have indicated that brain waves with lower frequencies (δ, θ, α) can serve as features for distinguishing between stress-related and normal emotional states [42]. Theta (θ) activity shows signs of stress response, and an increase in θ oscillations suggests periodic memory representation retrieval [36]. Higher θ values are associated with increased cognitive resource demands, greater task difficulty, and enhanced memory. Specifically, θ levels appear to rise in situations requiring prolonged concentration during task execution [31].

Table 3 Data of ∆ Power Ratio and NASA-TLX for all subjects

Subject	∆ θ/β	∆ β/α	NASA-TLX	
			Mental Demand	Frustration
S1	-0.236	0.252	100	25
S2	-0.362	0.211	360	400
S3	-0.189	0.147	150	300
S4	-0.277	0.137	100	120
S5	-0.109	0.135	70	90
S6	-0.553	0.106	225	55
S7	-0.064	0.086	320	50
S8	-0.172	0.080	210	400
S9	-0.135	0.048	120	110
S10	-0.026	0.044	210	240
S11	-0.037	0.040	160	0
S12	-0.228	0.027	280	85
S13	-0.052	0.027	135	60
S14	0.051	0.023	195	340
S15	0.018	0.017	135	0
S16	-0.105	0.017	40	0
S17	-0.062	0.012	65	400
S18	-0.118	-0.001	70	300
S19	-0.120	-0.004	180	130
S20	-0.136	-0.006	60	30
S21	0.288	-0.037	45	150
S22	-0.067	-0.041	65	0
S23	0.003	-0.048	165	0
S24	0.026	-0.054	60	80
S25	0.012	-0.067	30	0
S26	0.164	-0.083	150	0
S27	0.118	-0.085	180	0
S28	0.448	-0.107	150	375
S29	0.377	-0.123	195	100
S30	0.065	-0.133	120	300
S31	0.162	-0.143	170	150
S32	0.055	-0.180	255	425
S33	0.747	-0.258	170	425
S34	0.227	-0.310	60	195
S35	1.132	-0.421	45	25

Based on research conducted using NASA-TLX for the mental demand indicator, a negative correlation (-0.270) was found with the difference in θ/β power ratio. Mental demand is a subscale related to the subject's mental state in completing the physics exam as a cognitive task [35]. The correlation coefficient indicates that high mental demand is associated with a lower difference in θ/β power ratio. Relevant studies have revealed a link between the θ/β ratio and cognitive load, which requires attentional control [46].

According to Table 4, a small positive correlation (p_value = 0.662) is observed between the frustration indicator in NASA-TLX and the difference in θ/β power ratio. Theta/beta (θ/β) power ratio has been positively correlated with stress levels as obtained previously by another study [36]. In NASA-TLX, frustration represents anxiety and feelings of pressure experienced by the subject during the exam process [35]. The correlation coefficient indicates a relationship wherein an increase in frustration corresponds to an increase in the difference in θ/β power ratio. However, the correlation coefficient (0.077) suggests that the data gives a weak linear relationship.

Table 4 Correlation between EEG results and NASA-TLX

NASA TLX Indicator	Correlation	
	Pearson	*P_value*
θ/β – *Frustration*	0.077	0,662
β/α – *Mental Demand*	0.263	0.127

An increase in θ spectral power correlates with rising cognitive resource usage [19] [47], task difficulty [48] , and working memory [21]. Theta (θ) waves have been linked to regulating motivational and emotional processes [49]. Higher θ/β ratios are associated with higher stress levels [50]. Conversely, lower θ/β ratios indicate stronger concentration capabilities [16]. These findings are consistent with increased stimulus-driven attention during anxiety and stress states [51]. Alpha (α) waves primarily appear when the brain is in a relaxed state, while β waves are present when the brain is in an active mode and under stress [36]. Table

4 concludes that the difference in β/α power ratio positively correlates (p_value = 0.127) with increased mental demand experienced by the subjects, indicating that they encountered excessive cognitive load during the exam. The correlation coefficient (0.263) suggests that the data gives a moderate linear relationship. A similar result was also obtained in another study [50], where a decrease in the α/β (or increase in the β/α) ratio occurs when decision-making requires greater cognitive engagement.

4.0 CONCLUSION

The difference in β/α power ratio between after and before the physics exam categorizes the research subjects (35 high school students) into five categories: positive 2 (P2), positive 1 (P1), neutral, negative 1 (N1), and negative 2 (N2). Excessive increases or decreases in the difference of β/α power ratio (P2 or N2) result in lower average exam scores compared to other categories. In the P2 category, cognitive overload occurs when task demands exceed the resources available to an individual. In the N2 category, cognitive load decreases because subjects do not exert maximum effort in the exam process. The P1, neutral, and N1 categories have better average exam scores because subjects strive to pay attention to the questions and enhance their memory for completing cognitive tasks.

Physics exams, which require numerical calculation and critical thinking, are associated with increased β waves in the left hemisphere. However, data from five representative subjects—each representing one of the five categories—show different tendencies in using the left and right hemispheres. This variation is due to individual differences in problem-solving approaches, as revealed through interviews, such as imagining solutions versus performing direct calculations.

A small positive correlation (0.077) is found between the frustration indicator in NASA-TLX and the θ/β power ratio difference, which is consistent with previous research [36]. A moderate positive (0.263) correlation also occurs between the β/α power ratio difference and the increased mental demand in NASA-TLX, per a prior study [16].

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

[1] Saffari, F., K. Norouzi, L. Bruni, S. Zarei, and T. Ramsoy. 2023. Impact of Varying Levels of Mental Stress on Phase Information of EEG Signals: A Study on the Frontal, Central, and Parietal Regions. *Biomedical Signal Processing and Control*. 86: 105236. https://doi.org/10.1016/j.bspc.2023.105236.

[2] Kumar, S. 2015. Examination Stress and Its Effect on EEG. *International Journal of Medical Science and Public Health*. 4(11). https://doi.org/10.5455/ijmsph.2015.23042015308.

[3] Jiménez-Mijangos, L., J. Rodríguez-Arce, and R. Martínez-Méndez. 2023. Advances and Challenges in the Detection of Academic Stress and Anxiety in the Classroom: A Literature Review and Recommendations. *Education and Information Technologies*. 28: 3637–3666. https://doi.org/10.1007/s10639-022-11324-w.

[4] Anupama, K., and D. Sarada. 2018. Academic Stress among High School Children. *IP Indian Journal of Neurosciences*. 4: 175–179. https://doi.org/10.18231/2455-8451.2018.0042.

[5] Kulakow, S., D. Raufelder, and F. Hoferichter. 2021. School-Related Pressure and Parental Support as Predictors of Change in Student Stress Levels from Early to Middle Adolescence. *Journal of Adolescence*. 87: 38–51. https://doi.org/10.1016/j.adolescence.2020.12.008.

[6] Abbas, J., K. Kumari, and W. M. Al-Rahmi. 2024. Quality Management System in Higher Education Institutions and Its Impact on Students' Employability with the Mediating Effect of Industry–Academia Collaboration. *Journal of Economic and Administrative Sciences*. 40(2): 325–343. https://doi.org/10.1108/JEAS-07-2021-0135.

[7] Akinola, M., C. Kapadia, J. G. Lu, and M. F. Mason. 2019. Incorporating Physiology into Creativity Research and Practice: The Effects of Bodily Stress Responses on Creativity in Organizations. *Academy of Management Perspectives*. 33(2). https://doi.org/10.5465/amp.2017.0094.

[8] OECD (Organisation for Economic Co-operation and Development). 2017. *PISA 2015 Results (Volume III): Students' Well-Being*. Paris: OECD Publishing. https://doi.org/10.1787/9789264273856-en.

[9] Ornek, F., W. R. Robinson, and M. R. Haugan. 2008. What Makes Physics Difficult? *International Journal of Environmental and Science Education*. 3(4): 165–172.

[10] Qayoom, A., A. Wahab, N. Kamaruddin, and Z. (incomplete). 2015. Artifacts Classification in EEG Signals Based on Temporal Average Statistics. *Jurnal Teknologi*. 77(7): 73–77. https://doi.org/10.11113/jt.v77.6251.

[11] Mohd Tumari, S. Z., and R. Sudirman. 2015. Working Memory Impairments Imitate Age-Related Behaviors in Children Using Visual Stimulation Based on Event-Related Potentials. *Jurnal Teknologi*. 74(6): 55–63. https://doi.org/10.11113/jt.v74.4668.

[12] Katmah, R., F. Al-Shargie, U. Tariq, F. Babiloni, F. Al-Mughairbi, and H. Al-Nashash. 2021. A Review on Mental Stress Assessment Methods Using EEG Signals. *Sensors*. 21. https://doi.org/10.3390/s21155043.

[13] Engel, A. K., and P. Fries. 2010. Beta-Band Oscillations—Signalling the Status Quo? *Current Opinion in Neurobiology*. 20(2): 156–165. https://doi.org/10.1016/j.conb.2010.02.015.

[14] Seo, S. H., and J.-T. Lee. 2010. Stress and EEG. In *Convergence and Hybrid Information Technologies*. 410–426. https://doi.org/10.5772/9651.

[15] Mireille, V.-M., S.-G. Alina, and V.-P. Luis. 2022. Electroencephalographic Response to a Casual Video

Game Played on Stress and Anxiety Patients: A Study of Beta/Alpha and Theta/Beta Ratios. In *IEEE EMBS R9 Conference*. https://doi.org/10.1109/IEEECONF60929.2023.10525292.

[16] Wen, T. Y., and S. Armiza M. A. 2020. Electroencephalogram (EEG) Stress Analysis on Alpha/Beta Ratio and Theta/Beta Ratio. *Indonesian Journal of Electrical Engineering and Computer Science*. 17: 175–182. https://doi.org/10.11591/ijeecs.v17.i1.pp175-182.

[17] Griffiths, B. J., S. D. Mayhew, K. J. Mullinger, J. Jorge, I. Charest, M. Wimber, and S. Hanslmayr. 2019. Alpha/Beta Power Decreases Track the Fidelity of Stimulus-Specific Information. *eLife*. 8. https://doi.org/10.7554/eLife.49562.

[18] Al-Shargie, F. M., M. Kiguchi, N. Badruddin, S. Dass, A. F. M. Hani, and T. B. Tang. 2016. Mental Stress Assessment Using Simultaneous Measurement of EEG and fNIRS. *Biomedical Optics Express*. 7(10): 3882–3898. https://doi.org/10.1364/BOE.7.003882.

[19] Xie, J., G. Xu, J. Wang, M. Li, C. Han, and Y. Jia. 2016. Effects of Mental Load and Fatigue on Steady-State Evoked Potential-Based Brain–Computer Interface Tasks. *PLoS ONE*. 11. https://doi.org/10.1371/journal.pone.0163426.

[20] Puma, S., N. Matton, P. Paubel, E. Raufaste, and R. El-Yagoubi. 2018. Using Theta and Alpha Band Power to Assess Cognitive Workload in Multitasking Environments. *International Journal of Psychophysiology*. 123: 111–120. https://doi.org/10.1016/j.ijpsycho.2017.10.004.

[21] Borghini, G., G. Vecchiato, J. Toppi, L. Astolfi, A. Maglione, and R. Isabella. 2012. Assessment of Mental Fatigue during Car Driving by Using High-Resolution EEG Activity and Neurophysiologic Indices. In *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. https://doi.org/10.1109/EMBC.2012.6347469.

[22] Kamzanova, A. T., A. M. Kustubayeva, and G. Matthews. 2014. Use of EEG Workload Indices for Diagnostic Monitoring of Vigilance Decrement. *Human Factors*. 56: 1136–1149. https://doi.org/10.1177/0018720814526617.

[23] Mazher, M., A. Abd Aziz, A. Malik, and H. U. Amin. 2017. An EEG-Based Cognitive Load Assessment in Multimedia Learning Using Feature Extraction and Partial Directed Coherence. *IEEE Access*. 5: 14819–14829. https://doi.org/10.1109/ACCESS.2017.2731784.

[24] Wrobel, A. 2000. Beta Activity: A Carrier for Visual Attention. *Acta Neurobiologiae Experimentalis*. 60: 247–260. https://doi.org/10.55782/ane-2000-1344.

[25] Palva, S., S. Kulashekhar, M. Hämäläinen, and J. M. Palva. 2011. Localization of Cortical Phase and Amplitude Dynamics during Visual Working Memory Encoding and Retention. *Journal of Neuroscience*. 31: 5013–5025. https://doi.org/10.1523/JNEUROSCI.5592-10.2011.

[26] Spitzer, B., and S. Haegens. 2017. Beyond the Status Quo: A Role for Beta Oscillations in Endogenous Content (Re)activation. *eNeuro*. 4(4). https://doi.org/10.1523/ENEURO.0170-17.2017.

[27] Coelli, S., R. Sclocco, R. Barbieri, G. Reni, C. Zucca, and A. M. Bianchi. 2015. EEG-Based Index for Engagement Level Monitoring during Sustained Attention. In *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. https://doi.org/10.1109/EMBC.2015.7318658.

[28] Kakkos, I., G. N. Dimitrakopoulos, L. Gao, Y. Zhang, P. Qi, and G. K. Matsopoulos. 2019. Mental Workload Drives Different Reorganizations of Functional Cortical Connectivity between 2D and 3D Simulated Flight Experiments. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 27: 1704–1713. https://doi.org/10.1109/TNSRE.2019.2930082.

[29] MacLean, M. H., K. M. Arnell, and K. A. Cote. 2012. Resting EEG in Alpha and Beta Bands Predicts Individual Differences in Attentional Blink Magnitude. *Brain and Cognition*. 78: 218–229. https://doi.org/10.1016/j.bandc.2011.12.010.

[30] Putman, P., J. van Peer, I. Maimari, and S. van der Werff. 2010. EEG Theta/Beta Ratio in Relation to Fear-Modulated Response Inhibition, Attentional Control, and Affective Traits. *Biological Psychology*. 83(2): 73–78. https://doi.org/10.1016/j.biopsycho.2009.10.008.

[31] Raufi, B., and L. Longo. 2022. An Evaluation of the EEG Alpha-to-Theta and Theta-to-Alpha Band Ratios as Indexes of Mental Workload. *Neuroinformatics*. 16. https://doi.org/10.3389/fninf.2022.861967.

[32] Krigolson, O. E., C. C. Williams, A. Norton, C. D. Hassall, and F. L. Colino. 2017. Choosing MUSE: Validation of a Low-Cost, Portable EEG System for ERP Research. *Frontiers in Neuroscience*. 11: 109. https://doi.org/10.3389/fnins.2017.00109.

[33] Hayes, H. B., and C. Magne. 2024. Exploring the Utility of the Muse Headset for Capturing the N400: Dependability and Single-Trial Analysis. *Sensors*. 24: 7961. https://doi.org/10.3390/s24247961.

[34] Clutterbuck, J. 2018. Muse Developer Archive. Archived webpage. https://web.archive.org/web/20181105231756/http://developer.choosemuse.com/tools/available-data#Absolute_Band_Powers (accessed June 2024).

[35] NASA. 1986. *NASA Task Load Index (TLX) v. 1.0 Manual*. https://ntrs.nasa.gov/api/citations/20000021488/downloads/20000021488.pdf (accessed May 2024).

[36] Rajendran, V. G., S. Jayalalitha, and K. Adalarasu. 2022. EEG-Based Evaluation of Examination Stress and Test Anxiety among College Students. *IRBM*. 43: 349–361. https://doi.org/10.1016/j.irbm.2021.06.011.

[37] Chikhi, S., N. Matton, and S. Blanchet. 2022. EEG Power Spectral Measures of Cognitive Workload: A Meta-Analysis. *Psychophysiology*. 59: e14009. https://doi.org/10.1111/psyp.14009.

[38] Vugs, B., M. Hendriks, J. Cuperus, and L. Verhoeven. 2014. Working Memory Performance and Executive Function Behaviors in Young Children with SLI. *Research in Developmental Disabilities*. 35(1): 62–74. https://doi.org/10.1016/j.ridd.2013.10.022.

[39] Hafeez, M. A., S. Shakil, and S. Jangsher. 2018. Stress Effects on Exam Performance Using EEG. In *14th International Conference on Emerging Technologies (ICET)*. https://doi.org/10.1109/ICET.2018.8603652.

[40] Kumar, J. S., and P. Bhuvaneswari. 2012. Analysis of Electroencephalography (EEG) Signals and Its Categorization – A Study. *Procedia Engineering*. 38. https://doi.org/10.1016/j.proeng.2012.06.298.

[41] Tortora, G. J., and B. Derrickson. 2015. *Principles of Anatomy and Physiology*. 14th ed. Wiley.

[42] Sahroni, A., H. Setiawan, F. Mahananto, and H. Zakaria. 2020. Objective Stress Measurement: Studi Korelasi Parameter Saliva Amylase dan Aktivitas Gelombang Otak Menggunakan Electroencephalograph (EEG). *Transmisi*. 22(1). https://doi.org/10.14710/transmisi.22.1.22-29.

[43] Kwon, H., J. Cho, and E. Lee. 2009. EEG Asymmetry Analysis of the Left and Right Brain Activities during Simple versus Complex Arithmetic Learning. *Journal of Neurotherapy*. 13: 109–116. https://doi.org/10.1080/10874200902885852.

[44] Attar, E. T. 2022. Review of Electroencephalography Signals Approaches for Mental Stress Assessment. *Neurosciences*. 27(4): 209–215. https://doi.org/10.17712/nsj.2022.4.20220025.

[45] Awanis, R. F., S. Khabibah, and E. M. Imah. 2023. Analisis Beban Kerja Kognitif Siswa SMP pada Tugas Aritmetika Mental. *EDUKASIA: Jurnal Pendidikan dan Pembelajaran*. 4(1): 509–520. https://doi.org/10.62775/edukasia.v4i1.290.

[46] Putman, P., B. Verkuil, E. Arias-Gracia, I. Pantazi, and C. van Schie. 2014. EEG Theta/Beta Ratio as a Potential Biomarker for Attentional Control and Resilience against Deleterious Effects of Stress on Attention. *Cognitive, Affective, & Behavioral Neuroscience*. 14: 782–791. https://doi.org/10.3758/s13415-013-0238-7.

[47] Tsang, P. S., and M. A. Vidulich. 2006. Mental Workload and Situation Awareness. In *Proceedings of the Human Factors*

and Ergonomics Society Annual Meeting. https://doi.org/10.1002/0470048204.ch9.

[48] Antonenko, P., F. Paas, R. Grabner, and T. van Gog. 2010. Using Electroencephalography to Measure Cognitive Load. *Educational Psychology Review*. 22: 425–438. https://doi.org/10.1007/s10648-010-9130-y.

[49] Knyazev, G. G. 2007. Motivation, Emotion, and Their Inhibitory Control Mirrored in Brain Oscillations. *Neuroscience & Biobehavioral Reviews*. 31(3): 377–395. https://doi.org/10.1016/j.neubiorev.2006.10.004.

[50] Salma, N., B. Mai, K. Namuduri, R. Mamun, Y. Hashem, H. Takabi, N. Parde, and R. Nielsen. 2018. Using EEG Signal to Analyze IS Decision-Making Cognitive Processes. *Information Systems and Neuroscience*. 25. https://doi.org/10.1007/978-3-319-67431-5_24.

[51] Sanger, J., L. Bechtold, D. Schoofs, M. Blaszkewicz, and E. Wascher. 2014. The Influence of Acute Stress on Attention Mechanisms and Its Electrophysiological Correlates. *Frontiers in Behavioral Neuroscience*. 8: 353. https://doi.org/10.3389/fnbeh.2014.00353.