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Comparison of Attention Levels During Morning and Afternoon Learning Sessions Using Electroencephalography

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ABSTRACT

Attention is a key cognitive function influencing learning, memory and problem-solving, yet it is affected by circadian rhythms and study time preferences. This study aimed to compare attention levels between morning and afternoon study sessions among university students using a portable EEG device, the NeuroSky MindWave. Twenty volunteers from final-year undergraduate students (10 males, 10 females) participated in the study to complete two cognitive tasks which are the Stroop Color and Word Test (SCWT) and a comprehension test under controlled laboratory conditions. The EEG recordings include NeuroSky attention scores, low beta power and theta/beta ratios were then analyzed using the Wilcoxon Signed-Rank Test, Mann–Whitney U Test, and k-means clustering. Results showed significantly higher attention scores and low beta activity, as well as lower theta/beta ratios in morning sessions compared to afternoon ($p < 0.001$), which indicate greater cognitive alertness earlier in the day. Additionally, no statistically significant gender differences were observed. K-means clustering also supported these findings, showing clear separation between morning and afternoon sessions, with most morning data points clustering in the "focused/alert" group and afternoon data points in the "less focused/drowsy" group. These results highlight the influence of study time on cognitive performance and demonstrate the utility of consumer-grade EEG devices for real-time monitoring of attention in educational settings.

INTRODUCTION

Attention is the capacity to selectively focus on task-relevant stimuli while filtering out distractions and irrelevant information (Li et al., 2024). As one of the most fundamental cognitive functions, attention underpins learning, memory formation and higher-order problem solving. Sustained attention is the ability to maintain a consistent behavioral response during continuous and repetitive activity to support persistence and cognitive effort over extended periods and enable learners to process and retain information effectively. In modern educational contexts, maintaining attention is increasingly challenging. A recent empirical study measured the maximum time an individual can sustain focused attention during a continuous performance task. Results showed a clear lifespan pattern in which children maintained attention for about 29.6 seconds, young adults peaked at 76.2 seconds and older adults maintained around 67.0 seconds. These data highlight the developmental and age-related changes in attention span (Simon et al, 2023). A student's ability to sustain attention depends on both intrinsic and extrinsic factors. Internally, the brain's attentional control is governed by

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three core neural networks: the alerting network, responsible for maintaining a state of readiness; the orienting network, which prioritizes sensory input; and the executive control network, which resolves conflicts and manages goal-directed tasks (Giovannoli et al., 2021). Externally, environmental distractions, task complexity and study scheduling can profoundly impact attentional performance.

Traditional approaches to measure attention have relied heavily on behavioral assessments such as questionnaires or cognitive tests, including the Stroop Color and Word Test. Although these are useful, they capture overt performance and are susceptible to bias (Nasiri et al., 2023). Cognitive neuroscience methods such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) provide direct insights into brain activity, to enable the detection of covert attentional states that may not manifest in behavior (Morales & Bowers, 2022). EEG, in particular, offers millisecond-level temporal resolution, making it well-suited for tracking rapid fluctuations in attentional engagement during tasks. EEG measures neuronal oscillations across frequency bands, each linked to specific cognitive states. Theta waves are implicated in memory encoding and retrieval to support the integration of new information with existing knowledge (Xiao et al., 2024). Alpha waves are associated with retention, relaxation, and attentional disengagement (Klimesh, 2012), while beta waves are linked to active concentration, problem solving and decision-making (Nayak & Anilkumar, 2019; Magazu et al., 2024). Additionally, an elevated theta/beta ratio has been correlated with mind-wandering, reduced working memory and diminished attentional control (Picken et al., 2020). This neurophysiological basis makes EEG a valuable tool for objectively assessing attention in educational and research settings.

Historically, EEG studies have relied on laboratory-grade multi-electrode systems (Dikker et al., 2020, Apicella et al., 2022, Cao et al., 2019). While these systems offer high spatial resolution, they require extensive preparation, controlled environments and trained personnel which limit their applicability in routine educational contexts. In contrast, portable consumer-grade EEG devices, such as the NeuroSky MindWave, have made brainwave monitoring more accessible. This single-electrode, dry-sensor headset uses ThinkGear technology to process signals in real time, filter out environmental noise, and transmit data wirelessly (Matamoros et al., 2020). Its proprietary attention index, validated against self-reported measures (Ni et al., 2020; Morshad et al., 2020), offers a practical, non-invasive way to monitor cognitive engagement during authentic learning activities. The device's affordability and ease of use also make it suitable for large-scale studies and real-world educational applications (Rieiro et al., 2019; Derdiyok et al., 2024).

One critical factor influencing attention is the timing of study sessions. Circadian rhythms and individual chronotypes can cause significant variation in cognitive performance throughout the day. While early morning sessions are often associated with mental freshness and better memory retention (Dikker et al., 2020), a recent review reported that a person's mental performance can change depending on the time of day and whether that time matches their natural body clock (chronotype). It also found that the pattern of these daily changes is not the same for everyone in which young people and older adults often reach their peak alertness at different times of the day (Gabay et al., 2022). Conversely, late-night study can lead to reduced concentration due to accumulated fatigue and diminished cognitive resources. Despite this, most prior studies have relied on indirect measures such as login data or task completion rates (Ebeling et al., 2025), which do not necessarily reflect real-time neural engagement Furthermore, few have systematically compared attention across study times using portable EEG technology in ecologically valid settings (Wiłkość-Dębczyńska et al., 2023; Valdez et al, 2023**).** This study addresses these gaps by employing the NeuroSky MindWave to measure and compare attention levels during daytime, between morning and afternoon study sessions among university students. EEG recordings will be analyzed using both proprietary attention scores and power band ratios, complemented by statistical methods and k-means clustering to identify patterns in attentional engagement. By linking study-time preferences to objective neurophysiological indicators, the findings will provide evidence-based insights to help students optimize study schedules, inform educators on curriculum planning, and demonstrate the utility of portable EEG systems in educational neuroscience. Ultimately, this research bridges the fields of cognitive neuroscience, educational psychology, and medical device technology in advancing the integration of low-cost EEG systems into everyday learning environments.

MATERIALS AND METHOD

The research protocol was designed and conducted in strict adherence to internationally recognized ethical principles for research involving human participants. The study conformed to the principles outlined in the Declaration of Helsinki and followed established standards of respect for persons, beneficence and justice. Participation was voluntary, informed consent was obtained from all participants prior to data collection and participants were informed of their right to withdraw at any time without penalty. No invasive procedures or interventions beyond minimal risk were involved. Confidentiality and anonymity of participant data were maintained throughout the study and all data were securely stored and accessible only to the research team. The study procedures were implemented with due consideration for participant safety, dignity, and privacy.

This study adopted a comparative experimental design to evaluate attention levels across different study time preferences using a portable EEG device. Attention and EEG data were recorded during morning (08:00) and afternoon (14:00) sessions under controlled laboratory conditions, with each participant completing the same set of cognitive tasks in both sessions. Twenty final-year undergraduate students (10 males, 10 females) from the Faculty of Electrical Engineering, Universiti Teknologi Malaysia, participated voluntarily in this study. Eligible participants were right-handed, physically healthy on the day of the experiment and had no history of neurological or psychiatric disorders affecting attention (Ko et al., 2017). Recruitment was conducted via a pre-study online survey, which included an information sheet describing the purpose, procedures, and potential risks of the study. Written informed consent was obtained from all participants prior to data collection.

The NeuroSky MindWave, a single-electrode, dry-sensor EEG headset, was used to record attention data. The active sensor was positioned at Fp1 (left frontal pole) according to the International 10–20 system, while an ear clip on the left earlobe

(A1) served as the reference electrode. The headset's ThinkGear™ chip pre-processed EEG signals, removed noise and artifacts, and transmitted data wirelessly to the MyndPlay Pro software for recording. Two learning tasks were administered during each session. The first was the Stroop Color and Word Test (SCWT), which measures selective and focused attention by requiring participants to identify the ink color of a word while ignoring the semantic meaning of the word itself, particularly in incongruent conditions where interference must be overcome (Rahmaniyah Dwi Astuti et al., 2023). The second was a comprehension test designed to assess selective, sustained, and divided attention by evaluating the participant's ability to read, process, and interpret written material under time constraints. Each task lasted approximately 12 minutes, and the order of administration was consistent between sessions.

The NeuroSky MindWave was selected for this study due to several advantages that make it suitable for attention monitoring in ecologically valid settings. Unlike conventional multi-channel EEG systems, which often require extensive electrode preparation and restrict participant mobility, the NeuroSky MindWave is a lightweight, wireless, and non-invasive single-channel device that enables data collection in naturalistic learning environments with minimal disruption to participants. In addition, its relatively low cost and portability facilitate repeated measurements and improve accessibility for large-scale studies. Previous studies have demonstrated that the device provides reliable estimates of attention-related EEG parameters and exhibits acceptable agreement with research-grade EEG systems for cognitive and attentional assessments. Consequently, the NeuroSky MindWave represents a practical and cost-effective solution for investigating attention dynamics outside highly controlled laboratory environments.

Before each session, the headset was connected to the recording computer and signal quality was verified. Participants were seated comfortably and instructed to blink, relax and regulate breathing to establish a stable baseline. The meditation index was confirmed to be at least 50 and baseline attention scores were expected to fall within the range of 40 to 60 to indicate a neutral state of brain activity. EEG data were recorded continuously during each task, after which the data were exported as CSV files for analysis. In addition to EEG measurements, participants completed two self-report questionnaires. Before the first session, they answered a 10-item Attention Control Scale (ACS) to assess their general ability to focus and shift attention in daily life. After each session, they completed a 15-item self-report attention (SRA) questionnaire adapted from Derryberry & Reed's ACS and the Moss Attention Rating Scale (MARS). The SRA questionnaire measured attention focusing, attention shifting, and the influence of environmental factors such as distractions, learning materials, and motivation. Responses were rated on a four-point Likert scale, and scores for environmental factors were calculated separately for each learning period.

The primary EEG variables analyzed were the NeuroSky eSense attention scores, ranging from 0 to 100, and the processed EEG power bands for theta and low beta frequencies. Raw EEG values were pre-processed onboard by the device and categorized by session (morning or afternoon) before normalization to a 0–1 scale. Statistical analyses were performed using IBM SPSS Statistics (v29, IBM Corp.). Data normality was assessed with the Shapiro–Wilk test and Q–Q plots. As the data did not meet normality assumptions, the Wilcoxon Signed-Rank Test was applied to compare attention levels between morning and afternoon sessions, and the Mann–Whitney U Test was used to examine gender differences (Sainani, 2012). To complement statistical testing, an unsupervised k-means clustering algorithm was applied using Python in Google Colab to visualize the distribution of attention scores and EEG power bands across sessions. Data were pre-processed by labeling morning sessions as "0" and afternoon sessions as "1" and normalizing all variables to a common scale. Clusters were generated to identify patterns associated with study time and gender, and scatterplots were produced to illustrate the groupings. This combined approach provided both statistical and visual insights into the influence of study time on attention levels.

The Mann–Whitney U Test was used to determine whether there were significant differences between male and female participants. The Mann–Whitney U statistic is given by:

$$U_1 = R_1 - \frac{n_1(n_1+1)}{2}, U_2 = R_2 - \frac{n_2(n_2+1)}{2}.$$

(equation 1)

where (n_1) and (n_2) denote the sample sizes of the two groups, and (R_1) and (R_2) represents the sum of ranks for the first and second group, respectively

To compare measurements obtained from the same participants during the morning and afternoon sessions, the Wilcoxon Signed Ranks Test was employed. The test statistic is based on the sum of the positive and negative ranks of the paired differences and The Wilcoxon Signed-Rank Sum test compares the medians of two dependent distributions.

RESULT AND DISCUSSION

This section reports the quantitative findings from the EEG data analysis and questionnaire responses, organized by the main study objectives. The results focus on the three key EEG-derived variables which are NeuroSky attention score, low beta power, and theta/beta ratio to examine the differences between morning (08:00) and afternoon (14:00) study sessions, as well as gender comparisons. Both statistical methods and k-means clustering were employed to interpret the data patterns.

Descriptive Analysis of EEG Measures

Table 1 presents representative processed EEG data obtained from a single participant containing the raw attention values and the corresponding EEG frequency bands recorded during the experiment. Table 2 summarizes the mean attention scores, low beta power and theta/beta ratios for all 20 participants across the morning (8 AM) and afternoon (2 PM) learning sessions. The overall descriptive statistics for each EEG parameter are presented in Table 3.

As shown in Table 3, the mean attention score decreased from 59.38 ± 6.24 in the morning session to 45.98 ± 3.32 in the afternoon session. This represents a reduction of approximately 22.6% which suggests that participants generally exhibited lower levels of attention during the afternoon compared with the morning. Similarly, low beta activity, which is associated with cortical activation, alertness and active cognitive processing, demonstrated a noticeable decline across the two learning periods. The mean low beta power decreased from 40,432.65 ± 26,595.10 μV² in the morning to 29,261.83 ± 16,420.94 μV² in the afternoon, which correspond to a reduction of approximately 27.6%. This decrease indicates reduced neural activity related to vigilance and cognitive engagement as the day progressed.

In contrast, theta activity increased from 140,230.34 ± 51,696.66 µV² in the morning session to 168,514.56 ± 50,628.23 µV² in the afternoon session. The higher theta values observed during the afternoon suggest increased mental fatigue and reduced alertness, as theta oscillations are commonly associated with drowsiness and decreased cognitive efficiency. Consistent with these observations, the mean theta/beta ratio increased from 4.07 ± 1.94 in the morning to 6.65 ± 3.40 in the afternoon, which represent an increase of approximately 63.3%. Since the theta/beta ratio is widely used as an indicator of attentional regulation, the higher ratio observed during the afternoon implies reduced attentional efficiency and greater cognitive load during the later learning period.

Furthermore, the larger standard deviations observed for theta and low beta power indicate considerable inter-individual variability among participants. Despite these variations, a consistent trend was observed across the group, characterized by decreased attention and low beta activity together with increased theta activity and theta/beta ratio during the afternoon session. Overall, the descriptive findings suggest that cognitive alertness and attentional performance were generally higher during the morning learning period compared with the afternoon session.

Table 1 Processed attention value and EEG frequency bands of a single subject

Observation	Attention	Theta	Low Beta
1	57	124327	40954
2	57	121220	5794
3	57	162582	41763
4	57	41405	7823
5	57	39913	7335
6	57	1697	13911
7	57	43517	56665
8	57	28542	97019
9	57	2375	10915
10	77	136794	22205
11	84	64776	19966
12	80	108666	63650
13	88	22974	10113
14	69	41638	31609
15	50	269604	2150
16	66	18100	1360
17	50	145338	21651

Table 2 The mean values of attention, low beta and theta/beta ratio of 20 subjects across 2 learning periods

Participant_ID	Attention_8AM	Attention_2PM	Low_Beta_8AM	Low_Beta_2PM	Theta_Beta_8AM	Theta_Beta_2PM
1	53.96	48.34	25153.65	24563.53	4.63	7.95
2	65.50	48.95	26316.18	25704.22	4.07	6.28
3	61.44	41.44	32311.83	28273.21	2.52	6.41
4	65.93	48.58	121430.33	24372.38	1.85	9.45
5	67.89	40.18	26717.63	15328.74	8.36	18.37
6	54.32	47.87	23671.74	21825.56	5.52	8.80
7	68.39	40.25	102115.08	94356.44	2.05	2.33
8	56.01	46.25	27681.14	25581.98	3.22	4.87
9	67.34	48.91	25578.50	20477.26	3.20	7.15
10	58.17	48.13	24330.14	21912.90	2.97	6.18
11	58.43	45.21	23772.61	22167.24	5.19	5.84
12	55.84	46.32	26297.53	25944.50	3.69	4.55
13	70.44	41.40	23603.86	23449.28	9.29	9.48
14	55.72	49.63	45529.36	28453.28	3.49	5.68
15	51.31	44.39	27160.68	24865.24	4.52	5.01
16	50.83	48.14	35986.90	34092.39	5.16	2.83
17	52.17	50.15	46893.13	17574.24	2.31	6.70
18	62.06	47.43	51238.92	33003.81	3.45	7.07
19	56.52	46.76	35333.34	32380.23	2.88	3.44
20	55.41	41.35	57618.36	40820.23	3.03	4.57

Table 3 Descriptive Statistics of EEG data in morning and afternoon session

Time	Parameter	N	Minimum	Maximum	Mean	Std. Deviation
Morning	Attention	20	50.83	70.44	59.3840	6.24015
Morning	Theta	20	72144.25	224677.48	140230.3405	51696.65847
Morning	Low Beta	20	23603.86	121430.33	40432.6455	26595.10464
Morning	Theta/Beta Ratio	20	1.85	9.29	4.0700	1.93683
Afternoon	Attention	20	40.18	50.15	45.9840	3.31524
Afternoon	Theta	20	96507.97	281622.34	168514.5630	50628.23066
Afternoon	Low Beta	20	15328.74	94356.44	29261.8330	16420.93698
Afternoon	Theta/Beta Ratio	20	2.33	18.37	6.6480	3.40367

Normality Testing and Comparison Between Study Times

Prior to hypothesis testing, the normality of the data was assessed using the Shapiro–Wilk test. While the morning attention scores satisfied the assumption of normality ($p = 0.09$), all other variables, including afternoon attention scores, low beta power, and theta/beta ratio, exhibited non-normal distributions ($p \leq 0.05$). Therefore, non-parametric statistical methods were employed for subsequent analyses. Differences between the morning and afternoon sessions were evaluated using the

Wilcoxon Signed Ranks Test, and the results are summarized in Table 4. Significant differences were observed for all variables investigated ($p < 0.001$). Specifically, attention scores decreased significantly from the morning to the afternoon session ($Z = -3.920$, $p < 0.001$), indicating reduced attentional performance during the later study period. Likewise, low beta power showed a significant reduction in the afternoon session ($Z = -3.920$, $p < 0.001$), suggesting diminished neural activity associated with alertness and active cognitive processing.

In contrast, the theta/beta ratio increased significantly from morning to afternoon ($Z = -3.509$, $p < 0.001$), implying reduced attentional regulation and increased mental fatigue as the day progressed. Overall, these findings indicate that study time significantly influenced both behavioural and neurophysiological measures of attention. Participants generally exhibited higher attention levels and greater low beta activity during the morning session, whereas the afternoon session was characterized by lower attentional performance and elevated theta/beta ratios, reflecting reduced vigilance and cognitive efficiency.

Table 4 The result of Wilcoxon Signed Ranks Test

Variable	Z	p-value
Attention	-3.209^{b}	<0.001
Low Beta	-3.209^{b}	<0.001
Theta/Beta	-3.509^{b}	<0.001

Notes: a. Wilcoxon Signed Ranks Test, b. Based on positive ranks, c. Based on negative ranks

Gender Comparisons

The mean ranks and sums of ranks for attention scores and EEG variables according to gender are presented in Table 5, while the corresponding Mann–Whitney U test results are summarized in Table 6. Overall, female participants exhibited slightly higher mean ranks than male participants for attention scores measured in the afternoon (12.30 versus 8.70) and low beta power measured during both the morning (11.60 versus 9.40) and afternoon sessions (12.20 versus 8.80). In contrast, male participants showed marginally higher mean ranks for attention scores in the morning (11.80 versus 9.20) and theta/beta ratios in both the morning (10.70 versus 10.30) and afternoon sessions (11.50 versus 9.50).

Despite these differences in mean ranks, the Mann–Whitney U test revealed no statistically significant differences between male and female participants for any of the variables examined. Specifically, the p-values ranged from 0.174 to 0.880, all exceeding the significance level of 0.05. For attention scores, the Mann–Whitney U statistics were 32.000 and 37.000 for the afternoon and morning sessions, respectively, corresponding to p-values of 0.174 and 0.326. Similarly, low beta power showed no significant gender differences in either the morning ($U = 39.000$, $p = 0.406$) or afternoon session ($U = 33.000$, $p = 0.199$). Furthermore, theta/beta ratios did not differ significantly between male and female participants, with p-values of 0.880 and 0.450 for the morning and afternoon sessions, respectively.

These findings indicate that gender did not have a significant influence on attention levels or EEG measures in the present study. Moreover, the observed changes between morning and afternoon sessions appeared to be consistent across both male and female participants.

Table 5 Mean Rank and Sum of Ranks for Attention and EEG Variables According to Gender

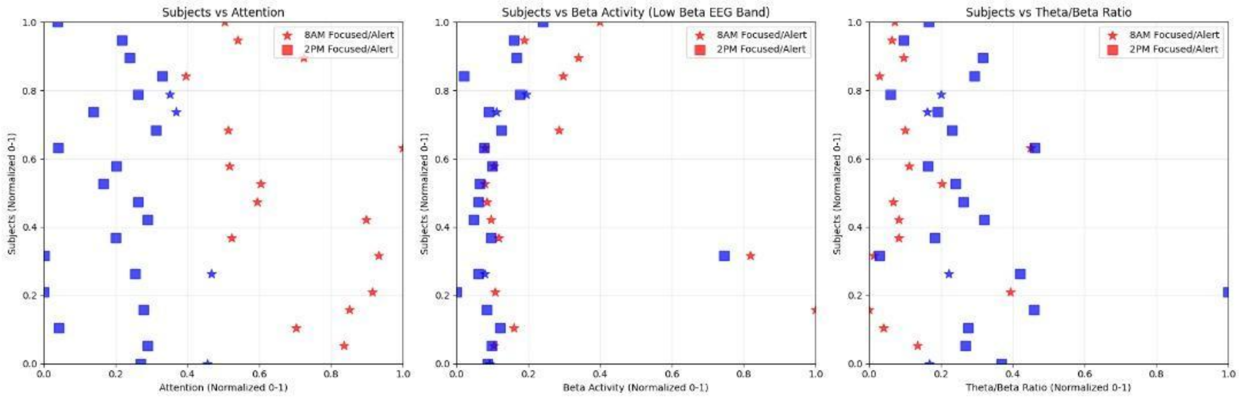
Variable	Gender	N	Mean Rank	Sum of Ranks
Attention (2 PM)	Male	10	8.70	87.00
	Female	10	12.30	123.00
	Total	**20**	–	–
Attention (8 AM)	Male	10	11.80	118.00
	Female	10	9.20	92.00
	Total	**20**	–	–
Low Beta (8 AM)	Male	10	9.40	94.00
	Female	10	11.60	116.00
	Total	**20**	–	–
Low Beta (2 PM)	Male	10	8.80	88.00
	Female	10	12.20	122.00
	Total	**20**	–	–
Theta/Beta (8 AM)	Male	10	10.70	107.00
	Female	10	10.30	103.00
	Total	**20**	–	–
Theta/Beta (2 PM)	Male	10	11.50	115.00
	Female	10	9.50	95.00
	Total	**20**	–	–

Table 6 Mann–Whitney U Test Statistics for Attention and EEG Variables According to Gender

Test Statistic	Attention (2 PM)	Attention (8 AM)	Low Beta (8 AM)	Low Beta (2 PM)	Theta/ Beta (8 AM)	Theta/ Beta (2 PM)
Mann–Whitney U	32.000	37.000	39.000	33.000	48.000	40.000
Wilcoxon W	87.000	92.000	94.000	88.000	103.000	95.000
Z	−1.361	−0.983	−0.832	−1.285	−0.151	−0.756
Asymp. Sig. (2-tailed)	0.174	0.326	0.406	0.199	0.880	0.450
Exact Sig. [2 × (1-tailed Sig.)]	0.190^{b}	0.353^{b}	0.436^{b}	0.218^{b}	0.912^{b}	0.481^{b}

Notes: a. Grouping variable: Gender, b. Not corrected for ties.

The absence of significant gender differences observed in the present study is consistent with previous findings reported by Cave and Barry (2021), who demonstrated sex-related differences in resting EEG amplitudes but suggested that these differences primarily reflected variations in neural oscillatory characteristics rather than substantial differences in cognitive functioning. Similarly, recent reviews have emphasized that sex-related differences in brain activity are generally subtle and highly dependent on biological and environmental factors, which results in heterogeneous findings across cognitive



(a) (b) (c)

Fig 1 Graphs of three variables against 20 subjects in a normalized range

domains (Kim, 2024; Yener et al., 2024). Therefore, the present findings suggest that circadian modulation of attention and EEG activity occurs similarly in both male and female participants.

K-Means Clustering of EEG Variables

K-means clustering was used to provide a complementary, visual understanding of the data patterns. The normalized range plots in Fig 1 summarize the data distribution across the three EEG variables for all participants. Attention Scores (Figure 4.1(a)) shows that two clear clusters emerged. Cluster 0 comprised mostly morning data points with higher attention scores, while Cluster 1 contained more afternoon data points with moderate-to-lower attention scores. The separation between morning and afternoon points was visually distinct and reinforcing the statistical results.

From the Low Beta Power (Fig 1(b)), the data points were predominantly grouped within a single primary cluster (Cluster 0), which indicate a relatively homogeneous low beta activity among participants. Nevertheless, a slight shift towards lower low beta values was observed during the afternoon session compared with the morning session. Since beta oscillations are associated with cortical activation, vigilance and active cognitive processing, this reduction may reflect a decline in alertness and cognitive engagement later in the day.

Similarly, the Theta/Beta Ratio (Fig 1(c)) showed that most observations were concentrated within Cluster 0, which suggest a relatively consistent attentional regulation among participants. However, the afternoon session exhibited a tendency towards higher theta/beta ratios compared with the morning session. Elevated theta activity and higher theta/beta ratios have been associated with poorer attentional control and reduced cognitive performance. Therefore, the higher theta/beta ratios observed in the afternoon may indicate increased cognitive load and diminished attentional engagement as the day progressed.

These findings are consistent with recent evidence showing that higher resting-state theta activity is associated with lower cognitive functioning (Tan et al., 2024). Furthermore, Wei et al. (2024) demonstrated that the spontaneous theta/beta power ratio is related to attentional control, with higher ratios reflecting weaker attentional control abilities. Collectively, these findings support the present observation that reduced low beta activity and increased theta/beta ratios during the afternoon are indicative of decreased vigilance and attentional efficiency relative to the morning session.

It should be noted that participants' activities on the night preceding the experiment and their dietary intake before the morning and afternoon sessions were not strictly controlled in the present study. Participants were allowed to maintain their usual daily routines in order to minimise disturbances to their natural circadian patterns. Consequently, variations in sleep quality, physical activity, meal composition, and caffeine consumption may have contributed to individual differences in attention and EEG measures. Previous studies have demonstrated that sleep deprivation can significantly alter EEG connectivity and cognitive performance (Ma et al., 2023), while caffeine intake has been shown to affect sleep architecture and neurophysiological activity (Clark and Landolt, 2017). Therefore, these factors should be considered as potential confounding variables when interpreting the findings. Nevertheless, the repeated-measures design employed in this study enabled each participant to serve as his or her own control, thereby reducing the influence of inter-individual variability. Future studies should incorporate more rigorous monitoring of sleep duration, dietary intake, stimulant consumption, and physical activity to further clarify the effects of circadian variation on attention and EEG dynamics.

CONCLUSION

This study demonstrated that study time significantly affects EEG-derived measures of attention in university students, with higher attention scores and low beta activity and lower theta/beta ratios observed during morning sessions compared to the afternoon. These differences were statistically significant and consistently visualized using k-means clustering, which classified most morning sessions in a focused/alert state and most afternoon sessions in a less focused/drowsy state. Gender did not significantly influence these outcomes, indicating that the time-of-day effect was consistent across male and female participants. The findings align with existing literature on circadian influences on cognitive function and provide empirical evidence to support scheduling cognitively demanding learning activities in the morning. Furthermore, the results validate the NeuroSky MindWave as a practical and accessible tool for real-time cognitive monitoring in educational research. Future studies could extend this work to larger populations, varied academic disciplines, and real-world learning environments, as well as explore longitudinal monitoring of attention to optimize academic performance and well-being.

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