Exploring EEG-Based Biomarkers of Attention in an Individual with Eating Disorders Using Non-Invasive Brain-Computer Interfaces

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Abstract

Eating disorders (ED) are complex health conditions characterised by abnormal eating behaviours, psychological distress, and often accompanied by cognitive impairments such as attention deficits. Understanding the neural mechanisms underlying these impairments is essential for developing targeted interventions. Electroencephalography (EEG), a non-invasive method for monitoring brain activity, has emerged as a promising tool to assess attention-related neural mechanisms in individuals with ED. This study explores the potential of using non-invasive brain-computer interfaces (BCIs) and EEG to identify attention-related biomarkers in individuals with ED. Specifically, the study investigates EEG correlates of attention in individuals experiencing recurrent binge eating episodes without significant weight gain, as defined by the DSM-5. A NeuroSky MindWave headset, equipped with a single dry electrode sensor placed on the frontal lobe was employed to capture EEG data during a steady-state condition of an individual with ED after sunset. The EEG data were analysed across the delta, theta, alpha, beta, and gamma frequency bands. The results revealed distinct EEG patterns associated with attention in the individual with ED. The study also suggests that meal timing, particularly avoiding dinner within five hours of bedtime may enhance attentional responses. These findings underscore the potential of EEG as a non-invasive tool for understanding attention-related neural mechanisms in ED. The simplicity and accessibility of using a basic EEG headset could inform future therapeutic approaches and further assist clinicians in developing personalised and effective treatments for individuals with ED which ultimately improve cognitive function and clinical outcomes.

Keywords: Attention Deficits, Eating Disorders (ED), Electroencephalography (EEG), Neural Biomarkers, Non-Invasive Brain-Computer Interfaces

1.0 Introduction

Brain-computer interfaces (BCIs) are advanced tools for detecting brain wave activity, particularly through non-invasive methods such as electroencephalogram (EEG) recordings. These devices can be utilised to assess cognitive states such as attention and meditation. So et al. [1] demonstrated the feasibility of using a wireless, single-channel BCI to capture short-term frontal EEG signals. The study successfully evaluated mental state changes during cognitive and motor tasks, such as performing arithmetic operations and finger tapping. Another study conducted by Blume et al. [2] provided a comprehensive review of the EEG signal differences in the brain activity observed in individuals with eating disorders (ED). The study revealed the identification of distinct patterns of abnormal brain activity associated with ED conditions, particularly in the theta wave band. This can be linked to the dynamic changes in mental conditions during cognitive tasks and motor tasks such as doing arithmetic operations, and finger tapping. This study also highlighted the potential of using the frontal EEG activity to further understand the neural mechanisms of ED.

Eating disorders (ED) are complex health conditions characterised by abnormal eating behaviours, and psychological distress, and often accompanied by cognitive impairments such as attention deficits. DSM-5 stated that individuals with ED exhibited significant alterations in EEG patterns as compared to those in normal individuals [3]. Individuals with ED often exhibit disrupted eating patterns such as overeating late at night, driven by a belief that such habits are not detrimental to their health. However, EEG-based assessments of attention reveal that bulimics struggle with attention tasks, particularly when they overeat during the day. This suggests that their focus is impaired due to these irregular eating patterns, as observed by Blume et al. [4]. Understanding the connection between eating behaviours and cognitive processes in ED is a crucial step toward improving diagnostic and therapeutic approaches [5].

Despite the significant impact of ED on both physical and cognitive health, the neural mechanisms underlying attention and response in individuals with ED remain poorly understood. One main issue is that attention becomes unstable, particularly after late dinners. Apart from that, bulimics often struggle to perform simple cognitive tasks, such as arithmetic, when eating late at night. Previous research has suggested that individuals should avoid eating for four to six hours before bedtime, but the effects of late eating on neural dynamics, especially attention and response processes, have not been thoroughly explored [4]. This study aims to fill that gap by comparing EEG activity during a quiet, restful state in participants with and without dinner after sunset. The primary objectives are to examine differences in EEG patterns between these conditions and investigate how late-night eating impacts attention and response processes. By examining these differences, the study seeks to deepen understanding of the neural underpinnings of attention and response in individuals with ED. These would potentially pave the way for improved diagnostic tools and targeted interventions.

To achieve this, EEG recordings were conducted in a controlled, semi-dark room for five minutes to minimize distractions and capture baseline brain activity in a quiet state [5]. This quiet state offers a unique opportunity to explore the intrinsic neural dynamics of attention and response without the confounding effects of task-related demands. By observing individuals with ED in this resting state, researchers can gain a clearer picture of their brain's functioning and identify any abnormal patterns in attention and response [6].

The findings of this study are expected to contribute valuable insights into the neural correlates of attention and response in ED. By using advanced statistical techniques such as cluster analysis and machine learning algorithms, this study aims to identify meaningful EEG patterns associated with these cognitive processes. These findings may lead to the development of more effective diagnostic tools and therapeutic interventions, ultimately enhancing the management of ED. Furthermore, by investigating attention and response processing in a quiet state, this study lays the groundwork for future research in the cognitive neuroscience of ED [7].

This research is built on the existing literature that has explored EEG responses to food-related stimuli in individuals with ED [7], [8]. Studies have examined EEG activity in semi-dark, quiet environments to assess brain function in those with binge eating disorders [5], [6]. Researchers such as Fairburn [7] and Lee et al. [8] have linked attention and response deficits to specific neural activity patterns in ED. The study conducted by Fiske et al. [9] suggests methodological approaches used in previous studies to assess the correlation between neural attention and response processing in ED. Additionally, studies by Abdurrohim et al. [10] and Ganin [11] have used EEG to investigate food-induced brain activity, revealing differences in neural responses to food stimuli [12], [13], [14], [15]. This study builds on these findings by exploring how late-night eating impacts attention and response processes in individuals with ED, which may provide valuable information about the underlying mechanisms of the disorder and potentially contribute to the advancement of novel treatment strategies [15[.

2.0 Methodology

Electroencephalogram (EEG) characteristics of eating disorders (ED) were performed on a participant meeting DSM-V-TR (text revision). The study examined the brainwave activities in terms of EEG signal in an individual with ED using a NeuroSky MindWave headset.

2.1 Participant

The EEG data acquisition was conducted at the laboratory at Universiti Teknologi MARA (UiTM), Shah Alam, Selangor, Malaysia. One subject participated in this study whose diagnosis of eating disorders (ED) was confirmed. The participant with ED (female, right hand) aged 60 years with a primary school educational level. She has been diagnosed by a general practitioner with the diagnostic criteria of eating disorder according to the Diagnostic and Statistical Manual of Mental Disorders Fifth Edition (DSM-5).

The data collection has received approval from the university's Research Ethics Committee (REC/05/2024).

2.2 Strategy of Using Headset

In this study, a NeuroSky MindWave headset is employed to record the brainwave activities of the participant. It is a consumer-grade EEG device which is specifically designed to measure brainwave activity through a dry sensor placed on the forehead. This device is used because it offers an affordable and accessible way for individuals to explore BCI applications, particularly in cognitive assessment and brainwave analysis [1]. The measurement was done using a single-channel brain-computer interface according to the research published by Salabun [16] and Gauttam [17].

Figure 1 shows the key components of a NeuroSky MindWave used in this study. The primary components include the adjustable headband (1), dry electrode of the EEG sensor (2), flexible ear arm (3), ear clip (4), power switch (5), and battery area (6). The single channel of this BCI device relies on the dry electrode of the sensor tip and a cell dry battery which typically lasts for several hours of continuous use. Figure 2 (a) presents the preparation of the EEG data acquisition procedure with the placement of the headband and the dry sensor on the specific anatomical landmarks on the head of an ED participant during the experimental procedure. The single placement of the dry electrode is called frontal pole (Fp1) which follows the International 10-20 System, a globally recognised method for placing electrodes on the scalp for recording EEG activity. Fp1 is referred to the reference of placement including the nasion point beside the nose, the inion points on the back of the head, and the pre-auricular points on both as shown in Figure 2 (b) and Figure 2 (c), respectively.

Figure 1: The Neurosky MindWave device

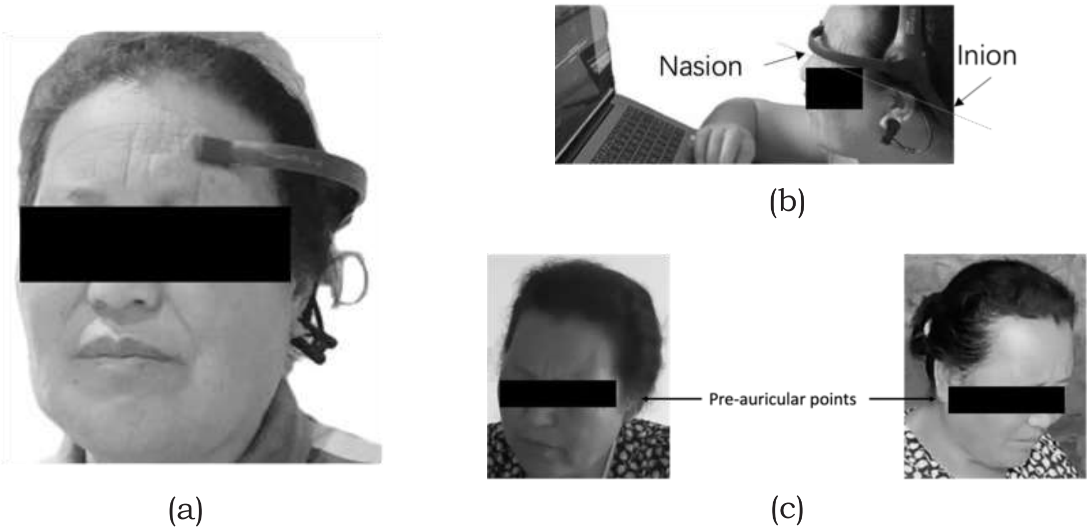

Figure 2: The preparation of EEG data acquisition procedure (a) placement of headband and the dry electrode for EEG data acquisition, (b) nasion and inion points, and (c) pre-auricular points

Figure 3 depicts the research framework using the BCI which consists of EEG visualisation for two experimental procedures with closed eyes and the amount of feedback for the experiment with opened eyes. The BrainWave Visualizer comprises the brainwave power spectrum graph and the attention meters. The number of feedback was realised using a Speed-Math Game Feedback containing a Math Game. This Math Game was used as a tool to measure the feedback of attention levels from the participant. Each game consists of simple arithmetic operations such as addition or subtraction involving two single-digit numbers.

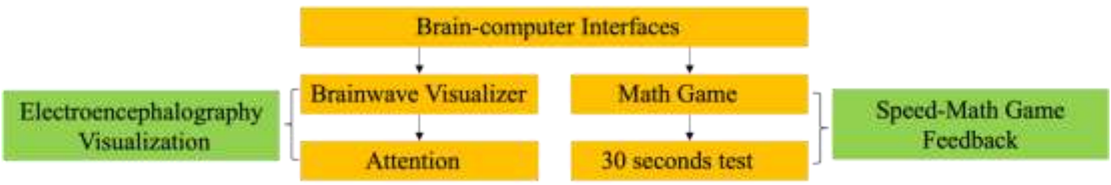

Figure 3: Research framework

During the EEG data experimental procedures, a participant was instructed to perform a simple mathematical calculation using a Math Game application for 30 seconds. The procedures for EEG data acquisition are shown in Figure 4. Both procedures were carried out for 30 seconds. In the beginning, the participant was required to close both of her eyes for 30 seconds for EEG visualization in her quiet state followed by a short break. Next, the participant was asked to open her eyes and focus on the Speed Math game for 30 seconds of duration as feedback of attention. The procedure was repeated until the EEG data was successfully obtained.

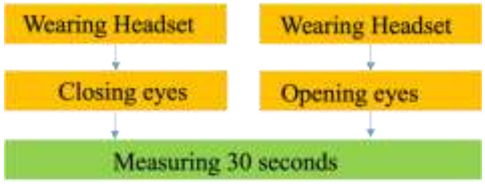

Figure 4: Procedure of EEG data acquisition

2.3 Electroencephalography Visualisation

EEG visualisation refers to the process of converting the raw electrical EEG signals from the brain into graphical or visual formats for interpretation and analysis using the brainwave visualiser. The EEG signals are decomposed into distinct frequency ranges to study specific brain activities. The frequency bands of EEG signals are typically recorded between 0 Hertz to 70 Hertz for 8 bands including delta, theta, low alpha, high alpha, low beta, high beta, low gamma, and high gamma band. The visualizer provides an interactive and comprehensive display of the EEG data which comes from the single-channel BCI headset when the headset device detects an EEG signal and connects to a laptop.

The visualizer graphically represents the brain's activity and includes features such as brainwave visualisation and attention meters. There are eight different frequency bands of brainwave on the visualizer ranging from 0 Hz to 70 Hz. The tallest column shape at any moment reflects the highest value among these bands which indicate dominant brain activity. The on-screen visualisations shift in response to changes in mental states. Distinct brainwave patterns will be displayed a bulimic person has a unique brain wave profile, visualizations will be different between the state of mind with dinner and without dinner.

The research was conducted using a laptop powered by Microsoft Windows 11 with minimum system requirements contain an operating system (OS), processor, and random-access memory (RAM). The EEG data of closed eyes were collected in three different quiet state as below:

i. Test before sunset. The participant had dinner before sunset. Before the dinner, we tested once using EEG.

ii. Test after dinner. After dinner, we tested EEG using the MindWave headset.

iii. Test after sunset without dinner. We test EEG at sunset in the state of the participant without dinner. The last meal of the participant before the test is lunch before midday. Then she had no food except drinking water after lunch.

2.4 Neural Feedback

When attending MathSpeed game suggests that the participant's attention levels (ranging from 0 to 100) were monitored during the MathSpeed game as shown in Figure 5. During the EEG test, the participant opened her eyes and took part in a simple number game related to math calculation as feedback for attention shown in Figure 6.

The given data represents a sequence of number games where participants are asked to perform simple math calculations within a 30-second time frame. Each game consists of an arithmetic operation (addition or subtraction) involving two single-digit numbers.

The EEG data of opened eyes was collected in three different quiet states as below:

i. MathSpeed game at sunset before dinner. Participant had dinner ahead of sunset. She attended the game before dinner.

ii. MathSpeed game around sunset after dinner. Participant attended the game after dinner.

iii. MathSpeed game at sunset without dinner. Participant did the number game when she had no food after midday. EEG was tested without the participant taking their dinner.

3.0 Results and Discussion

3.1 Analysis Following Dinner

The study aimed to investigate the effects of dinner on the behaviour and brain activity of the subject. The results revealed several interesting insights into the relationship between dietary habits and cognitive states. Analysis following dinner demonstrated that the subject had a strong inclination to lie down on the sofa or bed after eating. This behaviour could be attributed to the body's natural response to food intake, which is to rest and conserve energy for digestion. The concurrent EEG readings, which showed insufficient activity, supported this notion of relaxation.

The low brain activity levels indicated that the subject was not in a state of heightened alertness or excitement without a relaxed and tranquil state. This study highlights the potential of using non-invasive brain-computer interfaces and EEG to identify attention-related biomarkers in individuals with eating disorders. This study concluded that EEG is a useful non-invasive tool for assessing attention in individuals with eating disorders. This study also suggests that meal timing can significantly impact cognitive function in patients with eating disorders.

3.1.1 Attention Before Dinner

The participant had dinner at sunset. Before the dinner, we test EEG once using a MindWave headset at sunset. She closed her eyes and accepted the test in a quiet state.

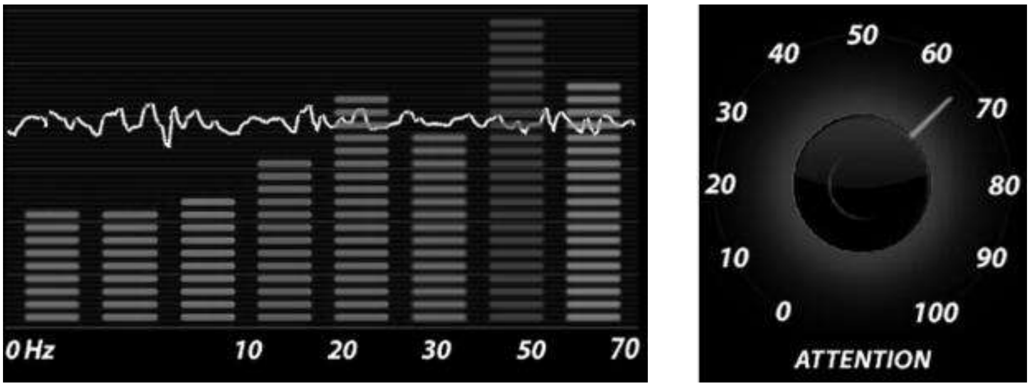

Figure 5: EEG visualizer based on MindWave headset with closed eyes

The single-channel EEG raw signal is shown in Figure 5. Both alpha and beta bands of EEG waves changed when the attention meter was at middle level with more than 50 scores on the meter. Next, the participant was allowed to take a rest. Then MathSpeed game was started once she prepared to press the keyboard when her eyes opened. The results of the MathSpeed game with monitoring on the visualizer are shown in Figure 6. She finished eight steps of calculation and scored 88 points in the game. The average attention scores are 62 which is a normal level.

Figure 6: Scores from the SpeedMath game based on the MindWave headset

The game process and seconds consumption are listed in Table 1. The given data represents a sequence of number games where participants are asked to perform simple math calculations within a 30-second time frame. For all games where a result was obtained, the participants accurately calculated the answer, as evidenced by the calculation result falling within the range of time taken (e.g., 0.00 seconds to 25.89 seconds) for the game. Notably, data were absent or a failure to provide an answer for the game where the operation was 9+2, indicated by an absence time range of 26.02 seconds to 30.00 seconds, suggesting that the participant did not respond or was unable to complete this task within the allotted time.

Table 1: Math calculation details every time during on number game

Sequence	Math	Result	Time in 30 Seconds (s)	Duration (s)	Correct or Incorrect
1	3+2	5	3.16	0.00-3.16	Correct
2	6-2	4	6.88	3.29-6.88	Correct
3	8-7	1	10.27	7.01-10.27	Correct
4	7-4	3	13.63	10.40-13.63	Correct
5	10-8	2	16.48	13.76-16.48	Correct
6	8-3	5	20.24	16.62-20.24	Correct
7	5-1	4	23.06	20.37-23.06	Correct
8	2+7	9	25.89	23.20-25.89	Correct
9	9+2	Absence	30.00	26.02-30.00	Absence

Overall, the findings suggest that the participants were capable of accurately performing the required calculations within the time constraints for most of the games.

3.1.2 Attention After Late Dinner

At first, we tested EEG once using the MindWave headset when she had a late dinner at sunset. After the late dinner, the subject expressed a desire to lie down on the sofa or bed. Concurrently, the electroencephalogram (EEG) readings indicated insufficient activity, suggesting a nervous state without relaxation where brain activity was not highly excited.

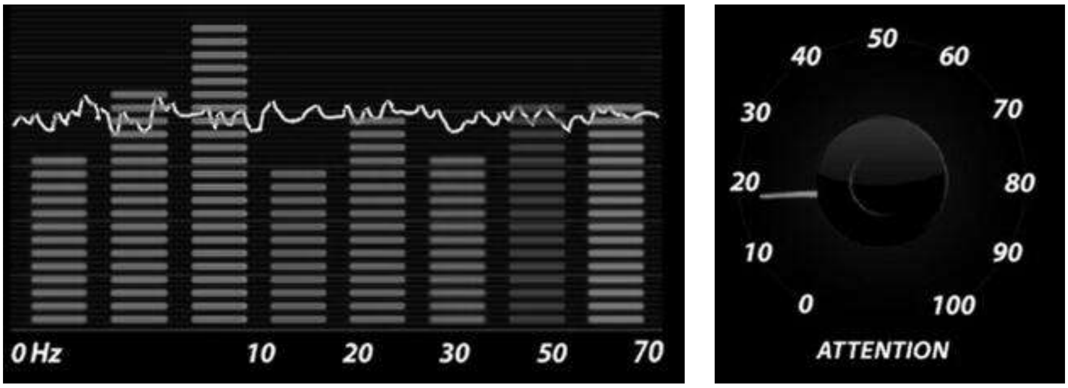

Figure 7: EEG visualizer based on MindWave with closed eyes

There are small waves during the EEG test. It is hard to pay attention during her EEG test. This meter showed a low level which means it is not easy to focus on the mind with low attention as shown in Figure 7.

Next, the participant took part in the MathSpeed game. During the test, she made more mistakes. She got seven correct steps of calculation. Her best performance is shown in the details listed in Table 2.

Table 2: Math calculation details every time during on number game

Sequence	Math	Result	Time in 30 Seconds (s)	Duration (s)	Correct or Incorrect
1	8+8	16	3.86	0.00-3.86	Correct
2	2+9	11	7.11	3.99-7.11	Correct
3	4+4	8	10.17	7.14-10.17	Correct
4	10-2	8	13.49	10.30-13.49	Correct
5	9+5	14	18.24	13.63-18.24	Correct
6	5+7	12	21.80	18.38-21.80	Correct
7	9-1	8	25.56	21.94-25.56	Correct
8	7+8	Absence	30.00	25.69-30.00	Absence

The attention scores from a simple number game based on the MindWave provide a quantitative measure of an individual's ability to focus and maintain concentration on a task that requires the processing of numerical information. In this game, participants are likely required to perform various tasks such as adding, subtracting, multiplying, or dividing numbers within a given time frame. The attention scores reflect how well participants can execute these tasks accurately and efficiently.

These scores can be used to assess the individual's attentional skills, which are crucial for everyday functioning and academic performance. A high attention score indicates that the individual can sustain their focus and process numerical information accurately, suggesting good cognitive health and efficient information processing abilities. Conversely, a low attention score may suggest difficulties with sustaining attention, potential cognitive impairments, or challenges related to a specific disorder or condition.

Moreover, the attention scores can be compared between different situations to identify any potential differences in attentional performance. For example, scores may vary between situations with dinner and without dinner because too late dinner affects attention. By analysing these scores, researchers and clinicians can gain valuable insights into the attentional profiles of individuals and develop targeted interventions or treatments to improve attentional abilities when necessary.

3.2 Results of Behaviour in the Absence of Dinner

By employing EEG recordings during a quiet state, a condition where participants are at rest and not engaged in any specific task, we aimed to capture the baseline brain activity in the individual with eating disorders. This allowed us to explore the intrinsic neural dynamics associated with attention and response without the confounding effects of task-related demands.

The problems that the study focused on were attention and feedback. The attention is unstable after sunset when the dinner of an individual is late. The response process was slow when the individual had dinner after sunset. In contrast, when dinner was absent, the subject exhibited a different behaviour pattern. They were able to sit quietly in a chair or enjoy the view from the window. The EEG recordings revealed a stable pattern of brain activity, suggesting a calm and focused cognitive state.

3.2.1 EEG Test at Sunset Without Dinner

We tested EEG at sunset in the state of the participant without dinner. The last meal of the woman before the test is lunch at midday. Then she had no food except drinking water after lunch.

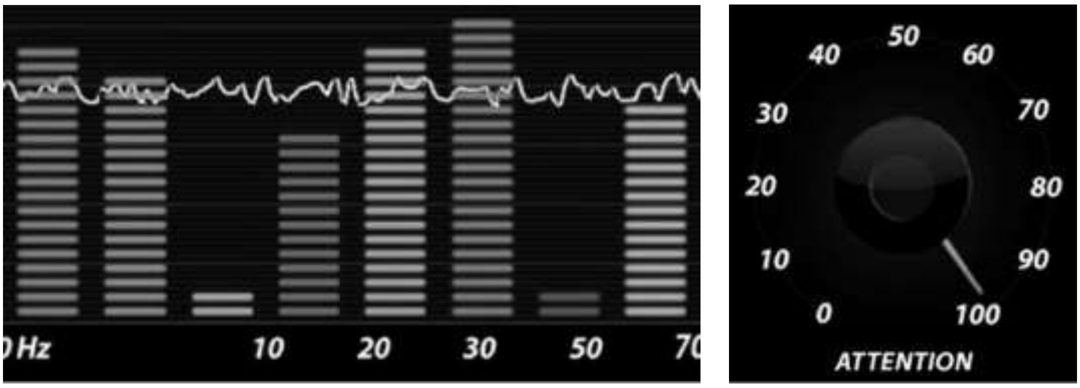

Figure 8: EEG visualizer based on MindWave with closed eyes

The single-channel EEG is shown in Figure 8. The beta band of EEG waves was high when the meter was changed to a high level by the participant. The participant could just take a short time to control the mind for focus once she lost the attention.

3.2.2 MathSpeed Game Without Dinner

The participant performed the SpeedMath game better when she had no meal after midday without dinner. The game scores were better than that with dinner. She finished 9 steps of calculation and scored 123 points in the game. Table 3 provides the details of the feedback. In the absence of dinner, the subject was able to sit quietly in a chair or enjoy the view from the window. The EEG demonstrated a stable pattern of brain activity, indicating a calm and focused state.

The findings of this study suggest that food intake influences the emotional state and brain activity of the subject. The post-dinner laying down behaviour is associated with lower levels of EEG activity, possibly indicating a need for rest and rejuvenation by both the body and the brain following meals. The MathSpeed game is an useful tool for examining the relationship between attention and response because it requires a participant to actively process and manipulate numerical information. In the context of an individual with an eating disorder, this game can help researchers understand how attentional processes may be affected by the disorder. By measuring the individual's performance on the game, along with their brain activity using an electroencephalogram (EEG) in a quiet state, researchers can identify any differences in attention and response that may be observed. For example, individuals with eating disorders may exhibit increased attentional bias towards numerical stimuli, or they may respond more slowly or less accurately due to cognitive impairments associated with the disorder. By analysing the EEG data during the quiet state, researchers can also explore the neural correlates of these attentional and responsive differences, providing valuable insights into the cognitive and emotional aspects of eating disorders.

Table 3: Math calculation details every time during on number game

Sequence	Math	Result	Time in 30 Seconds (s)	Duration (s)	Correct or Incorrect
1	7-6	1	2.83	0.00-2.83	Correct
2	9-7	2	2.93	2.93-5.83	Correct
3	8-1	7	5.93	5.93-8.60	Correct
4	9+3	12	8.67	8.67-11.88	Correct
5	2+1	3	12.02	12.02-14.39	Correct
6	1+5	6	14.52	14.52-18.19	Correct
7	7-4	3	18.33	18.33-21.48	Correct
8	8-3	5	21.61	21.61-25.44	Correct
9	2+1	3	25.54	25.54-29.14	Correct
10	8-7	Absence	29.25	29.25-30.00	Absence

Overall, the number game serves as an important tool for investigating the relationship between attention and response in individuals with eating disorders, and its use can contribute to a better understanding of the disorder and the development of effective treatments. The potential findings such as calculation speed and improvement could be inferred from the measurement of EEG.

i. Calculation Speed: The time taken by participants to complete each calculation can indicate their speed. Faster times may suggest quicker mental processing or familiarity with the types of calculations being presented.

ii. Improvement Over Time: If the data is collected over multiple sessions or trials, the trend in performance over time can be analysed. The improvement over time would suggest learning and skill development.

These finding indicates that the absence of food intake did not lead to restlessness or disquiet, but rather to a state of tranquillity and concentration. These findings suggest that food intake plays a significant role in shaping our cognitive states and behaviours. The post-dinner laying down behaviour and the associated decrease in brain activity reflect the body's natural inclination towards rest and digestion. On the other hand, the ability to sit quietly and maintain a stable EEG in the absence of dinner indicates that the absence of food does not necessarily result in restlessness, but rather can lead to a state of calm focus. The findings of this study suggest that food intake influences the emotional state and brain activity of the subject. The post-dinner laying down behaviour is associated with lower levels of EEG activity, possibly indicating a need for rest and rejuvenation by both the body and the brain following meals.

4.0 Conclusion

In conclusion, this study has successfully investigated EEG patterns in a female individual with an eating disorder (ED), utilising non-invasive, portable technology to assess attentional processes. Using the NeuroSky MindWave, a simple and efficient single-channel EEG device, the research focused on analysing key frequency bands (delta, theta, alpha, beta, and gamma) to evaluate cognitive responses. The findings indicate that avoiding dinner at least five hours before bedtime may enhance attentional performance and cognitive responsiveness in individuals with ED, highlighting the influence of dietary habits on mental clarity and emotional regulation. These results suggest that meal timing could serve as a practical strategy for managing cognitive and emotional health in ED populations. Additionally, the study underscores the utility of portable EEG devices for real-world applications, offering commercialisation potential for consumer-friendly tools that integrate EEG data analysis. Collaborations with health-tech industries could yield innovative apps providing personalised feedback on cognitive states and dietary habits. Despite its promising insights, the study is limited by a small sample size, reducing the generalisability of its findings. Future research should include a larger and more diverse participant group while exploring the long-term effects of dietary patterns on cognitive functioning. Integrating advanced EEG technologies with machine learning could further identify precise biomarkers for ED, enhancing diagnostic and therapeutic approaches. These advancements could contribute to a more integrated approach for managing eating disorders, benefiting both clinical treatments and innovative health-tech solutions.

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Author Contributions

Yunlong Xu: Conceptualization, Methodology, Software, Writing-Original Draft Preparation; **Marina Ismail**: Data Curation, Validation, Supervision; **Suzana Ahmad**: Validation, Supervision; **Qiang Li**: Writing-Reviewing and Editing; **Fang Chen**: Editing.

Conflicts of Interest

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission, and declare no conflict of interest in the manuscript.

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