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Assessing the Relationship Between Body Mass Index and Neural Activity of Prefrontal Cortex in Overweight Adults Using EEG-Resting State Data: A Wavelet Transform Analysis

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ABSTRACT

Neuroscientific evidence suggests that weight gain may be associated with changes in brain lobes' volume and function, as well as impulsive behaviour related to eating. However, it remains unclear whether impulsivity behaviour in overweight subjects is linked to abnormal activity in the resting state. To address this question, we propose a novel method to assess the relationship between different levels of body mass index (BMI) and neural activity of the prefrontal cortex (PFC) using electroencephalography (EEG) resting state data. EEG signals recorded during open-eye resting state from 36 subjects were divided into two groups based on BMI: overweight and normal weight subjects. We applied wavelet transform technique to compute the power for decomposed EEG bands and extracted coherence maps to assess the functional connectivity of the PFC. The one-way analysis of variance (ANOVA) was employed to assess the difference in EEG variables between the study groups. The results show a significant increase in the power of the sub-Theta band (4.49-5.34) Hz in overweight subjects compared to normal weight subjects (p-value = 0.001), as well as dysfunctional connectivity between left-right prefrontal sites in the overweight group with decreasing coherence function. These outcomes suggest that the specific PFC-EEG signals observed in overweight individuals are consistent with EEG patterns seen in other impulsivity-related diseases. Therefore, our findings reveal a specific EEG pattern in overweight adults that could be potentially utilized in developing neurotherapy-based treatment methods for overweight management.

1. Introduction

BMI is a common parameter used in screening the individuals' weight categories such as normal weight, overweight, and obesity, based on mass and height of individuals (kg/m²). Recently, the

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World Health Organization (WHO) has reported that more than 1.9 billion adults are overweight (BMI ≥ 25 kg/m²), and more than 650 million are obese (BMI ≥ 30 kg/m²) worldwide [1]. The increase in BMI (more than 25 kg/m²) may lead to health problems such as diabetes and cardiovascular disease. The Global Burden of Disease in 2017 reported that 4 million people die each year because of being overweight or obese [2]. Thus, managing BMI in adolescence is warranted to reduce metabolic syndromes, such as diabetes and cardiovascular disease.

The overweight and obesity individuals have an impulsive behaviour in eating or craving for overeating of high-calorie foods, which is considered the key to weight gain [3]. The impulsive eating behaviour might have independent or overlapping effects on neurocognitive health. Therefore, overweight reduction could in turn improve aspects of neurocognitive health. Recent evidence in neurosciences suggests that weight gain may be linked to adverse changes in brain lobes volume and function, as well as weakness in cognitive behaviour [5,7]. In contrast, the weakness in brain functions and cognitive disorders such as impulsivity behaviours could be the cause of weight gain. However, these suggestions remain a matter of speculation, but it is important to note their evidence for causal links between overweight and adverse changes in brain structure and function.

The prefrontal cortex (PFC) is essential for impulse control and decision-making [30], particularly in the context of eating behaviours and weight management. Obesity and overweight are associated with impaired decision-making and cognitive inflexibility, with opposing patterns of impulsive behaviour. Specific areas of the PFC show alterations in activation and extent of dysfunction in these conditions [20,29]. Modulating excitability in the dorsolateral prefrontal cortex (DLPFC) influences the liking but not the wanting of highly palatable foods, implying involvement in the hedonic experience of eating [21]. Accordingly, it is reasonable that overweight adolescence may accelerate the onset of other brain diseases such as Alzheimer's or depression in the long term. Therefore, neuroscientists have conducted research to understand how high-BMI affects brain health. Accordingly, it is reasonable that overweight adolescence may accelerate the onset of other brain diseases such as Alzheimer's or depression in the long term. Therefore, several neuroscience studies have aimed to investigate how high-BMI affects brain health.

Generally, functional magnetic resonance imaging (fMRI) is one of the neuroimaging modalities used to estimate neuronal activity based on indirect signals that reflect the fluctuation in brain blood flow and blood oxygenation levels, called blood-oxygen-level-dependent (BOLD) [4]. The BOLD signals produce images of brain structure that can be used for clinical analysis. In BMI studies, fMRI is widely used to assess the relationship between overweight and brain based on structural analysis. For instance, *Kakoschke et al.,* [5] applied fMRI to scan the association between high-BMI and volumes in brain regions linked to obesity. Their results illustrated high-BMI related to larger cerebellar white matter, medial orbitofrontal cortex (OFC), and nucleus accumbent volume, and impulsive eating behaviour related to smaller amygdala and larger frontal pole volumes. Park *et al.,* [6] used dynamic analysis method with fMRI data to improve the assessment outcomes between overweight and brain functional activity. The authors inferred that executive control brain network showed a strong correlation with impulsive eating behaviour and high-BMI. These studies applied fMRI under task experiment related to food-cue stimuli. In contrast, *Li et al.,* [7] used the fMRI to test the relation between hippocampus and amygdala brain regions with a food-cue task and resting state. The authors showed that brain activity of these regions in resting state is higher in overweight than normal weight individuals.

Electroencephalography (EEG) is another neuroimaging modality applied to determine brain activity based on direct electrical signals from surface electrodes placed on the scalp [8]. EEG signals include information about brain activity in several frequency bands, and these can be decomposed into frequency bands such as Delta, Theta, Alpha, and Beta. Apart from fMRI, EEG data has good temporal resolution, an affordable price, and is easy to set up. However, there are only a few published studies on EEG-BMI data in the literature. More details on the recent studies that aimed to assess the relation between EEG and overweight subjects are provided in the following section.

1.1 Related Work

The EEG data provides a more objective assessment of impulsive eating behaviours. The EEG experiments based on event-related potential (ERP) are used to assess the association between EEG signals of selected regions and food-cue performance in overweight and obesity cases. Recent studies [9,10] have shown similar spike (P300) amplitudes for high- and low-calorie food and the strongest food-cue related EEG-alpha band desynchronization for low-calorie stimuli. *Bauer et al.,* [11] have analysed the EEG power in female adolescents with obesity under a working memory task and revealed that frontal beta increased in obesity compared to control. *Dubbelink et al.,* [12], on the other hand, have used magnetoencephalographic (MEG) data and demonstrated that functional connectivity in the delta and beta bands increased in overweight during close-eyes resting state. The studies mentioned above acquired EEG signals from specific scalp sites under a task experiment related to food-cue stimuli. However, it remains unclear whether impulsive behaviour in overweight subjects might relate to their abnormal activity in the resting state. Resting-state data would be valuable to figure out the neural mechanisms behind impulsive eating behaviours, which is a critical marker of weight gain. The brain activities of specific regions as measured by resting-state EEG are mostly stable over time. Therefore, the EEG-resting state may be a good index of cognitive activation analysis and mental disorders diagnosis [13,14].

To date, the relation between overweight and neural activity based on EEG-resting state is poorly understood. Only three studies reported in the literature have employed the EEG resting state to assess the relationship between neural activities and overweight or obesity in specific terms. Babiloni *et al.,* [15] have analysed the EEG power in overweight adults. Their analysis revealed that the alpha band of the parieto-occipital site decreased compared with normal weight as control during eyes-closed resting state and alpha band of the posterior site had abnormal fluctuations during eyes-open resting state [16]. Schmidt *et al.,* [17] examined the EEG spectral power in 12 overweight children and compared that with 22 normal weight children as control. Their results showed significantly increased delta and decreased alpha band power in overweight children compared to control during eye-close resting state. As mentioned, recently cited studies have focused on examining the relation between neural activities at resting state and children's weight status. As EEG signals differ depending on age, their results would not be adopted for adults older than 15 years [18]. However, the neurophysiological indicators in general and their association with adults' weight status are still fuzzy and have not yet been investigated.

Despite the evidence of the studies mentioned earlier, EEG studies in overweight have not explicitly considered EEG analysis methods. The above-cited studies [15-17] have employed the frequency domain technique to extract the spectral power of EEG signals, leaving the question of whether the time-frequency domain in EEG analysis is effective to extract important information for the proper examination of neural activities among overweight subjects. Immense amounts of EEG data have been acquired experimentally, and it is not possible to analyse EEG data visually [19]. Therefore, there is a solid demand to extract relevant information from EEG signals accurately. Several methods have been described for EEG informative features extraction, which involve the frequency domain, such as relative spectral power in different frequency bands [15-17], and recently the time-frequency domain, including wavelet transformation coefficients [23,24]. From the studies, effective EEG features to examine the neural activities' association with high-BMI are required.

In this work, the relation between the difference in BMIs (normal and overweight) and EEG activity based on a time-frequency processing scheme is investigated. First, the EEG signals are recorded from scalp sites according to the 10/20 international system in a bio-polar montage. Then, the EEG signals are inspected visually to remove the noise and artifacts. After that, continuous wavelet transform (CWT) is applied to visualize and compute the power of EEG signals in several frequency bands. Finally, one-way analysis of variance (ANOVA) with a probability (*p*-value) < 0.05 is used to compare between study groups and find significant variance in EEG bands between normal and overweight subjects. The research assesses the relation between EEG-resting-state data and high-BMI subjects based on the time-frequency domain.

The rest of the paper is structured as follows. Section 2 describes the proposed data collection and data analysis methods, including participant recruitment, EEG data acquisition, pre-processing, EEG features extraction, and statistical analysis. Section 3 presents the results and analysis. Finally, section 4 presents the discussion and conclusion.

2. Methodology

The objective of this study is to assess the relationship between high BMI and EEG-PFC features using time-frequency analysis. The statistical analysis is implemented through ANOVA testing with a (p-value) < 0.05. The main steps of this study are illustrated in Figure 1. Additionally, Algorithm 1, presented herein, assumes a central role within this process, facilitating the effective discrimination and assessment of EEG-PFC features among individuals with distinct BMI classifications.

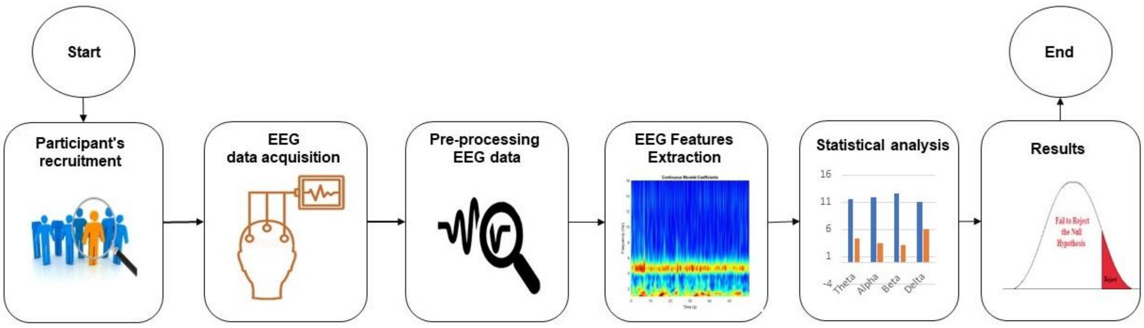

Fig. 1. Methods to find correlation between difference in BMIs (normal and overweight) based on statistical analysis of EEG components.

2.1 Participants Recruitment

The study was performed at the Clinical Neurophysiology Clinic at Medical Lab-Faculty of Medicine and Health Sciences, Universiti Putra Malaysia (UPM). Participants were recruited from UPM through advertisements in student social media groups, library boards, and the main entrance of the faculties. The potential participants are from different ethnic groups, including local and international students, who were asked to undergo a screening test to assess their eligibility according to inclusion and exclusion criteria. Participants must have a body mass index more than or equal to 18 kg/m²; participants must be within the defined age limit (18 – 45) years, participants must not have any head injury or brain disorders. While the exclusion criteria include those currently undergoing treatment with drugs evoking weight variation, currently pregnant, currently smoking, and left-handed. The enrolment process took one month (between May-June 2018).

Thirty-six respondents managed to fulfil the inclusion criteria and after receiving information about the aims of the study, each participant provided a written consent form to participate in the study. Then, all participants were divided into two main groups; eighteen participants with BMI less than or equal to 18 kg/m² as the normal weight group, and eighteen participants with BMI more than 25 kg/m² as the overweight group, their characteristics are summarized in Table 1.

Table 1
Participants characteristics based on BMI groups and EEG parameters

Details	Normal weight Group	Overweight Group
Subject umber	18	18
BMI average ±std (Kg/m^2)	22.9 ± 1.5	30.7 ± 3.5
Age average ±std (Years)	28.7 ± 3.8	27.5 ± 7.5
Gender (Male, Female)	(12, 6)	(11, 7)
Number of EEG channels	2 electrodes (Fp1, Fp2)	
Sampling frequency	256 (Hz)	

Algorithm 1: Extracting time-frequency components of EEG-PFC signals in discriminating normal and overweight groups using mean value of power for each EEG frequency bands

i. Input filtered EEG signals = matrix $(m \times n)$
m = 18 (number of subjects), *n = 2* (number of groups)
ii. Fp$_i$ signals = $i \times t$
i = scalp site number (1,2) *, t* = timepoints (15360)
iii. *[CWT$_i$, Frq]* = estimate CWT coefficients for each EEG-PFC signal
i = Fp scalp site number (1,2) , Frq = frequency bands ranged (1-16) Hz
iv. P_{Dn} = the sum of the absolute squares of wavelet coefficients divided by the signal length based on decomposition levels (D$_n$= decomposition levels)
v. G_j = cluster the outcome of (4) into matrix $(m \times n)$
vi. *p*-value = run ANOVA test for each cluster *(G_j)*
While *j* ≤ 2 repeat step (6)
If *p*-value ≤ 0.05
Save *p*-value at *T*
else *T* = empty
vii. *F* = find the most significant EEG bands based on *T*-index

2.2 EEG Data Acquisition

The Prefrontal Cortex (PFC) plays a main role in controlling the executive brain networks, especially in restraint the impulsive behaviours such as craving for overeating in overweight and obesity cases [20,21]. The EEG signals of PFC have been applied in several mental health analyses such as depressive symptoms [22], and neuropsychological performance in healthy [8]. In the current study, EEG signals are acquired from prefrontal Fp1, Fp2 by placing two surface gold electrodes to measure the brain signal on the scalp sites with ear-clip electrodes measuring the reference signals according to the 10-20 system, EEG parameters are illustrated in Table 1, and the head-size of the participant was measured to identify these positions.

The positioning steps of electrodes are illustrated in Figure 2 (a). The bipolar montage was used, the active electrodes were placed on the left and right prefrontal positions (Fp1-Fp2); the reference electrodes were placed on the left and right (A1-A2) earlobe as shown in Figure 2 (b). For EEG-resting state data, the participant is seated on a comfortable chair facing the digital screen, showing different color bands, helping the participant to relax. Then, electrodes are placed on their forehead and earlobes after skin preparation. Then, EEG recording played for 5 minutes, the participant asked to be relaxed and should keep eyes open during the recording session.

2.2.1 Pre-processing EEG data

The resting-state EEG data is collected from 36 subjects as mentioned above with sampling rate 256 Hz. Inspecting EEG signals by eye is deemed necessary here to remove artifacts such as eye-blinking, body motion, itching or other artifacts sourced from an EEG equipment or the electrodes. After that, only the first 60 seconds for each signal are extracted to avoid any unstable timepoints that may affect the signal quality, so the dimension of EEG signals for each individual, is 2-number of electrodes × 15360-timepoints. Then, each signal is treated by band-pass filter with range 1-42 Hz to remove artifact caused by electrical power supply (60-50 Hz) and smoothed by using Gaussian filter before CWT implementation.

2.2.2 EEG feature extraction

The PFC activity is analysed based on the power of sub-EEG frequency bands. In general, the EEG power bands computed in previous studies [15,17] are based on power spectral density (PSD). Technically, PSD requires the selection of a fixed sliding-window size for coefficient measurements and only frequency domain information is extracted with good resolution.

In contrast, implementing a time-frequency technique with continuous wavelet transform (CWT), provides a multi-resolution image of sub-EEG frequency bands called scalogram. Scalogram is a 2D matrix plotted as a function of time and frequency bands of the signal. Scalogram is advocated to use for better time visualization for a short-time period and high frequency or slow-frequency visualization for a longer period. Therefore, CWT is a more powerful method than the conventional cosine and Fourier transforms, as a time-frequency transform.

CWT has been implemented widely in signal processing [24,31] for time-frequency component extraction. Therefore, CWT is proposed as a good approach in this work to extract the time-frequency components of EEG-PFC signals. The CWT coefficient is defined as the convolution of the EEG signal $x(t)$ with the scaled and translated version of the mother wavelet φ as:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t).\varphi^* \left(\frac{t-b}{a}\right) dt \tag{1}$$

where *a* denotes wavelet scale, *b* denotes positions and * denotes the complex conjugate. The filtered EEG-signal for each PFC site is decomposed into Dn×15360 by using CWT based on Morse wavelet, where Dn is number of decomposition levels of the wavelet coefficients. Depending on the principal frequency components of filtered EEG signals, 49 is the maximum number of decompositions as listed in Table 2. As noted, the filtered EEG signal is decomposed into specific wavelet coefficients for each level in a particular frequency range. For example, third level of Theta band is decomposed into 11 wavelet coefficients with frequency range 4.00-7.55 Hz. According to the decomposition levels, the power of sub-band relative frequency range is calculated.

The power is then calculated for each EEG-band by summing all values for each level. The average of the power for each decomposition level is estimated and applied with ANOVA to test the hypothesis and realize the most significant EEG-bands in comparison to normal and overweight.

In the subsequent step, the brain connectivity between the left-right hemisphere could assist in understanding dysfunctional neuroscientific causes. Therefore, the wavelet coherence method is applied to determine the similarity of neural activity between Fp1-Fp2 based on time-frequency contents of the EEG signals.

Table 2
Participants characteristics based on BMI groups and EEG parameters

EEG band	Levels	Wavelet coefficients	Frequency range
Beta	1	D1-4	13.45 – 16.00 Hz
Alpha	2	D5-13	8.00 – 12.69 Hz
Theta	3	D14-25	4.00-7.55 Hz
Delta	4	D26-49	1.00 – 3.55 Hz

The common power $C_{Fp1-Fp2}$ between the pairwise C_{Fp1}, C_{Fp2} is measured at various scales *a* and time *b* using

$$C_{Fp1-Fp2}(a,b) = S(C^*_{Fp1}(a,b)C_{Fp2}(a,b)) \tag{2}$$

Then, the coherence map $Coh_{Fp1-Fp2}$ between two-sites is calculated using:

$$Coh_{Fp1-Fp2} = \frac{\left|C_{Fp1-Fp2}(a,b)\right|^2}{\left(S\left|C_{Fp1}\,(a,b)\right|^2\right).\left(S\left|C_{Fp2}\,(a,b)\right|^2\right)} \tag{3}$$

The coherence map dimension (49×15360) is factored using singular value decomposition (SVD). SVD is one of the factorization methods used to extract the top decomposition value of rectangular matrices such as the coherence map [27]. The *SVD* of the coherence map $C_{Fp1-Fp2}$ is expressed as:

$$SVD\ (Coh_{Fp1-Fp2}) = \mathrm{U}.\Sigma.V^T \tag{4}$$

Where V (15360×15360) and U (49×49) are orthonormal matrices, and Σ (49×15360) is a diagonal matrix of singular values. The first element in Σ (1,1) matrix is the Top-SVD value and carries more fundamental information of the original matrix [28]. In this study, the Top-SVD represents the important part of the coherence map and is used with ANOVA test to assess the difference in functional connectivity between study groups.

The EEG data is collected based on two-independent groups; Group-1 comprises normal weight subjects with BMI ≥ 18 kg/m^2, and Group-2 comprises overweight subjects with BMI ≥ 25 kg/m^2. Based on the EEG features, the hypothesis is $\mu1 \neq \mu2$, where µ1 is the mean of sub-EEG frequency bands power in Group-1 and µ2 is the mean of sub-EEG frequency bands power in Group-2. The null hypothesis is $\mu1 = \mu2$. The analysis of variance (ANOVA) is applied to test the hypothesis that is appropriate to compare between two groups with significant variance based on *p*-value < 0.05.

3. Results

In this section, we evaluate the relationship between different BMI classifications and EEG-PFC activities using Continuous Wavelet Transform (CWT). Mean values for each group are calculated, and the variance between the two groups is assessed through ANOVA test parameters, including F-values and p-values. The F-value provides insight into the effect size of different BMIs on EEG feature variations. Higher effect size values suggest an increase in F-values and a decrease with a more modest effect size. The *p*-value evaluates the significance level of the effect size. This study explores three frameworks: correlations between different BMIs and EEG-Fp1 features, EEG-Fp2 features, and asymmetric values between Fp1-Fp2.

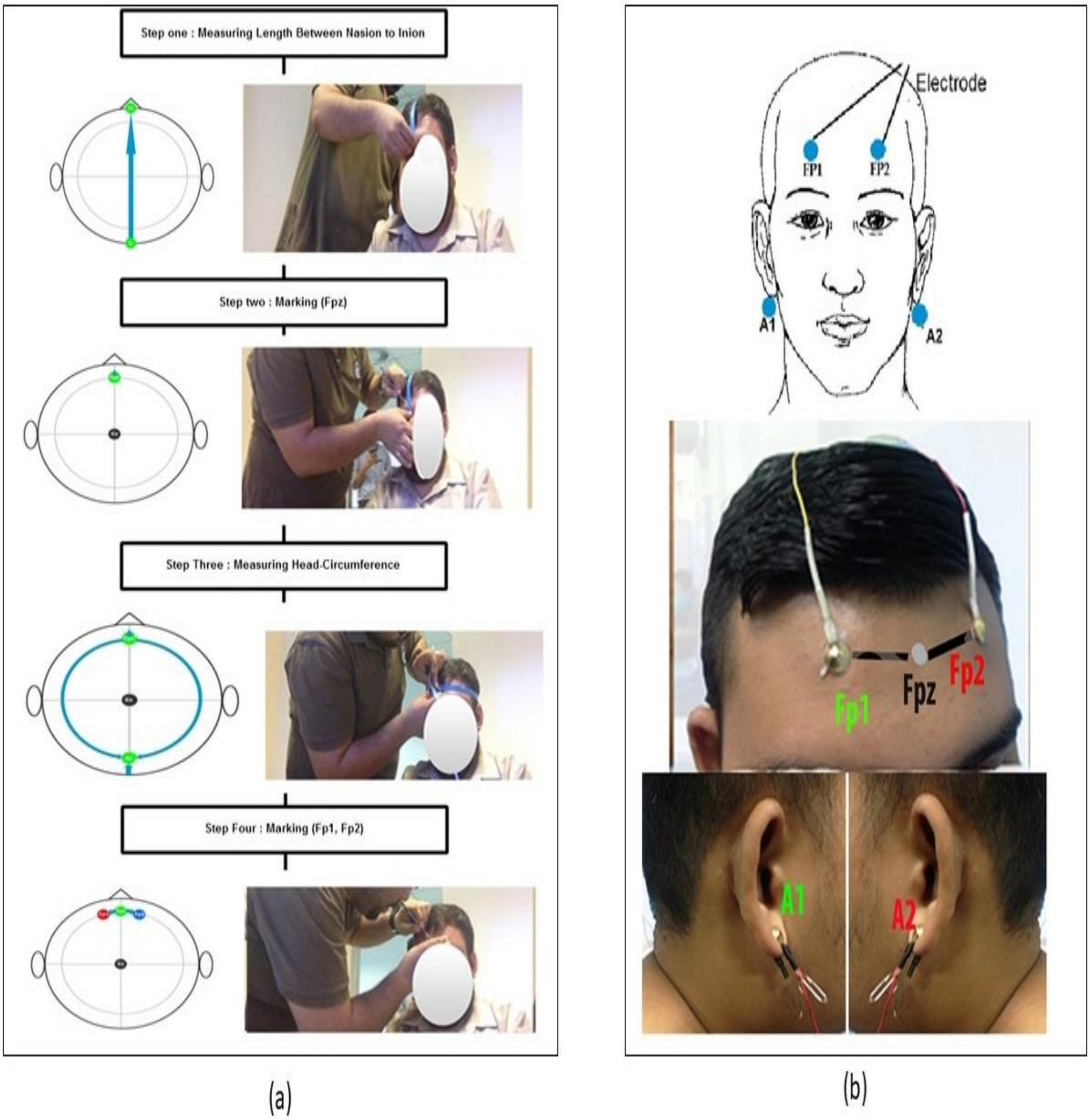

Fig. 2. (a) Determination of the position of Fp1, Fp2 scalp site based on 10/20 international system, (b) placement of the EEG-electrode on Fp1 and Fp2 as active electrodes and A1, A2 as reference for bipolar EEG montage

3.1 Correlations Between Different BMIs and EEG-Fp1 Components

The mean wavelet energy of the four frequency bands of EEG-Fp1 was calculated for both normal and overweight groups. The results are presented in Figure 3. Notably, the power values are highest for the overweight group (Group 1) across the four frequency bands, while the lowest values are observed for the normal weight group (Group 2).

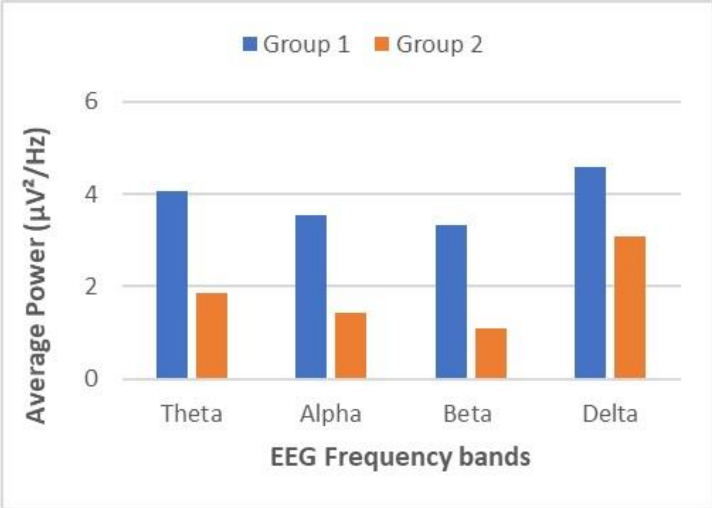

Fig. 3. Average power (µV²/Hz) for EEG frequency bands of Fp1 site for overweight group (Group 1) and normal weight group (Group 2)

The variance results between the two groups and the ANOVA test parameters are tabulated in Table 3. The F and p-values suggest that the wavelet energy of the Theta band holds the most significant correlation between different BMIs and Fp1 activities.

Table 3
ANOVA test parameters of average power (µV²/Hz) for EEG frequency bands of Fp1 site for overweight group (G1) and normal weight group (G2)

EEG bands	G1	G 2	Variance (G1-G2)	*F*	*p*-value
Delta	4.57	3.09	1.48	6.93	0.01
Theta	**4.05**	**1.86**	**2.19**	**11.83**	**0.001**
Alpha	3.54	1.42	2.12	9.63	0.003
Beta	3.34	1.09	2.25	9.94	0.003

Further analysis of the wavelet coefficients for EEG frequency bands (1-16) Hz, averaged across group subjects, is shown as a scalogram for both normal and overweight groups in Figure 4. There is notably high power in the sub-theta bands (4-5) Hz of the EEG-Fp1 signal for the overweight group compared to the normal weight subjects, indicating significant variance in power (2.19) with a p-value < 0.005.

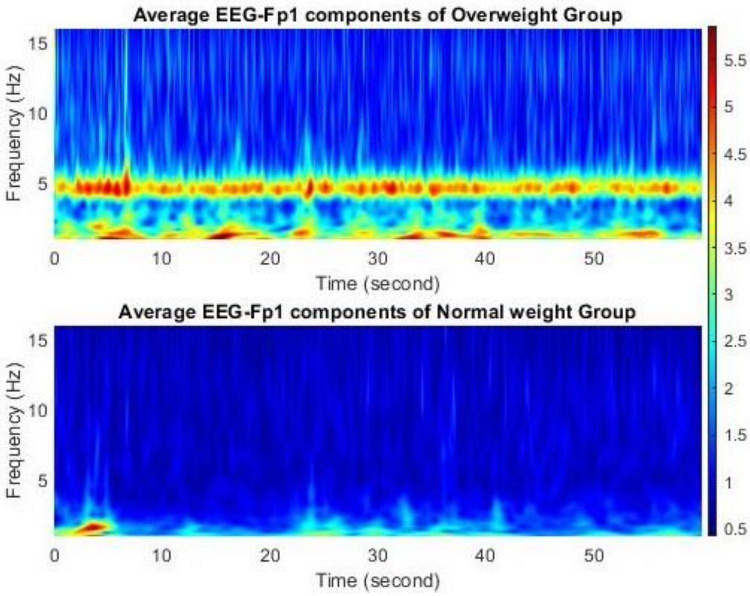

Fig. 4. Scalograms of EEG-Fp1 time-frequency components for overweight (top) and normal weight groups(bottom)

For a more detailed representation, the power of sub-Theta bands for each group, along with ANOVA test parameters, is tabulated in Table 4. Based on F and P-values, the Theta bands in the range of 5.34 to 4.49 Hz show the most significant variance in values between the two groups, with a p-value of 0.001.

Table 4
ANOVA Test Parameters of Sub-Theta Bands Power ($\mu V^2/Hz$) for Overweight Group (Group 1) and Normal Weight Group (Group 2) of Fp1 Site

Theta Bands (Hz)	Group 1	Group 2	*F*	*p*-value
5.34	3.98	1.76	11.85	0.001
5.04	4.07	1.82	12.01	0.001
4.76	4.17	1.91	12.04	0.001
4.49	4.26	2.01	12.15	0.001

3.2 Correlations Between Different BMIs and EEG-Fp2 Components

The average power for the four decomposition levels of EEG-Fp2 was determined for both normal and overweight groups, and the results are presented in Figure 5.

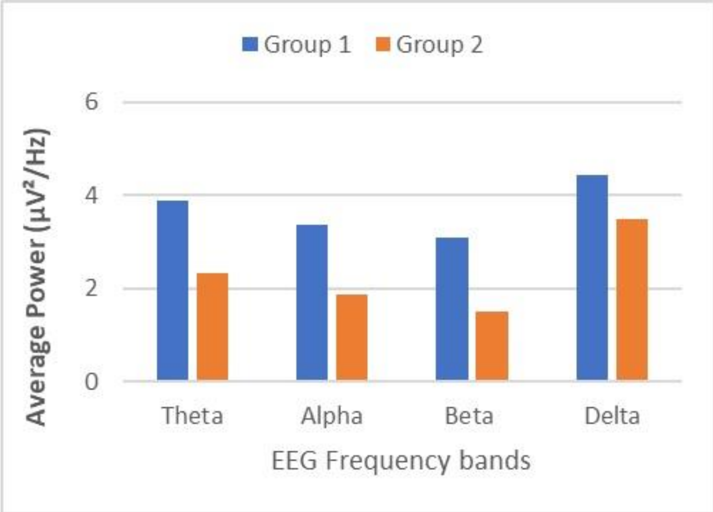

Fig. 5. Average power (µV²/Hz) for EEG frequency bands of Fp2 site for overweight group (Group 1) and normal weight group (Group 2)

Similar to the previous analysis, the power is highest in the overweight group across the four frequency bands, and lowest in the normal weight group. The variance results and ANOVA test parameters are displayed in Table 5. Based on the F and p-values, it can be inferred that power in the Theta band holds the most significant correlation between different BMIs and EEG-Fp2 activities.

Table 5
ANOVA test parameters of average power (µV²/Hz) for EEG frequency bands of Fp2 site for overweight group (G1) and normal weight group (G2)

EEG bands	G1	G 2	Variance (G1-G2)	*F*	*p*-value
Delta	5.57	3.23	2.34	14.20	0.001
Theta	5.09	1.98	3.11	18.92	0.001
Alpha	4.62	1.57	3.05	17.48	0.001
Beta	4.31	1.16	3.15	18.36	0.001

Further analysis of the Wavelet Transform of the EEG-Fp2 signal, averaged across group subjects, is shown in Figure 6. This analysis identifies specific frequency bands that exhibit significant changes between normal and overweight subjects.

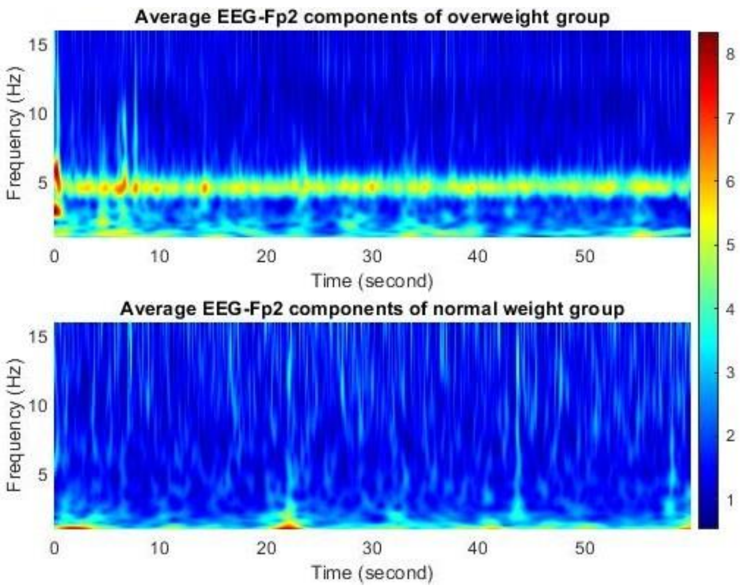

Fig. 6. Scalograms of EEG-Fp2 time-frequency components for overweight (top) and normal weight groups(bottom)

The results, as presented in Table 6, indicate that sub-theta bands 5.34 to 4.49 Hz show significant differences between the two study groups, with a p-value of 0.004. These findings emphasize the significant correlation between different BMIs and theta bands of EEG-PFC, suggesting that BMI classifications impact the functional connectivity between the left and right prefrontal cortex.

Table 6
ANOVA Test Parameters of Sub-Theta Bands Power (μV²/Hz) for Overweight Group (Group 1) and Normal Weight Group (Group 2) of Fp2 Site

Theta Bands (Hz)	Group 1	Group 2	*F*	*p*-value
5.34	17.35	11.09	7.89	0.008
5.04	17.92	11.15	8.76	0.005
4.76	18.4	11.32	9.25	0.004
4.49	18.66	11.60	9.28	0.004

3.3 Correlations Between Different BMIs and Fp1-Fp2 Coherence

High coherence values indicate similarity in neural activity between Fp1 and Fp2, reflecting the integrity of functional connectivity in the prefrontal area. Figure 7 represents the average wavelet coherence between Fp1 and Fp2 for the overweight and normal weight groups. The x-axis represents time, and the y-axis indicates EEG sub-frequency bands (1-16) Hz. The color-coded areas in the figure denote coherence status. The red colour signifies strong coherence (in-phase), green represents weak coherence (anti-phase), and shades of blue indicate no coherence. Differences between the groups are evident, with stronger coherence observed in the normal weight group compared to the overweight group.

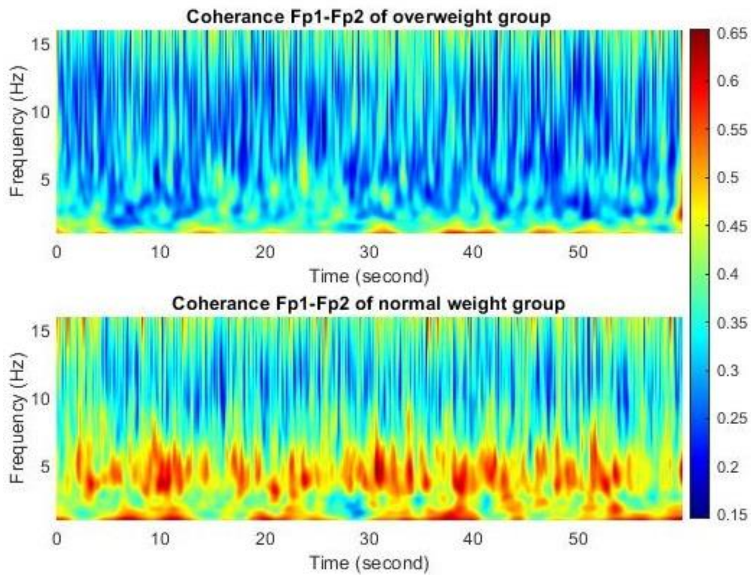

Fig. 7. Coherence of Fp1-Fp2 based on time-frequency contents of EEG signals for overweight (top) and normal weight groups(bottom)

The results of the ANOVA test are presented in Table 7, indicating a significant difference in coherence maps between the two groups (F = 9.28, p-value = 0.004). These findings suggest that overweight status impacts the functional connectivity between the left and right prefrontal cortex, potentially affecting cognitive functions associated with overeating behaviours [5,29].

Table 7
ANOVA Test Parameters of Top-SVD Values of Coherence Maps (Fp1-Fp2) for Overweight Group and Normal Weight Group

Top-SVD	Overweight Group	Normal Weight Group
Mean	311.03	425.30
Variance	114.26	
F	9.28	
p-value	0.004	

4. Discussion

The present study assessed the relationship between high BMI status and neural activity of the PFC based on EEG-resting state data, providing insights into the underlying neurophysiological mechanisms of how weight gain impacts brain functions. According to the outcomes, the null hypothesis that the mean of sub-EEG frequency band power in the overweight group is equal to the mean of sub-EEG frequency band power in the normal weight group was rejected. The following main points summarize the results: Firstly, the power of the sub-Theta band (4.49-5.34 Hz) in EEG signals for Fp1 and Fp2 increased in overweight compared to normal weight subjects. Secondly, the functional connectivity based on wavelet coherence between Fp1 and Fp2 decreased significantly among overweight subjects compared with the normal weight group. These findings suggest that overweight-specific PFC-EEG signals are characterized by higher slow-band activity (Theta) during the resting state, akin to EEG signals observed in other impulsivity-related disorders such as ADHD [25]. Additionally, the study suggests that frontal cortical dysfunction, as observed in individuals with ADHD, might explain deficits in self-eating regulation in adults with overweight and obesity.

Direct comparison of this study's outcomes with previous research on resting-state activities in overweight subjects was challenging due to the variations in neuroimaging acquisition terms and feature extraction methods. However, a brief comparison with previous studies is outlined in Table 1. Notably, while there were some differences in experimental terms, all studies hypothesized the same concept. For instance, in the study by *Babiloni et al*., [15], encoded EEG signals during the resting state with closed eyes, revealing abnormal EEG-Alpha band activity in parietal, occipital, and temporal scalp sites related to overweight status. Similarly, *Del Percio et al.,* [16] aimed to assess the EEG-Alpha band in parietal, occipital, and temporal scalp sites with eyes open during the resting state. However, their findings may not directly correlate with understanding impulsivity behaviour in overweight subjects due to the absence of direct cognitive function control over parietal, occipital, and temporal scalp sites [20]. Another study by *Schmidt et al.,* [17] focused on examining the relationship between neural activities during the resting state and children with overweight status, but EEG signals differ based on age, rendering their results inapplicable to adults aged over 15 years [18]. *Stephan et al*., [29] observed that overweight individuals exhibit altered resting-state functional connectivity (rsFC) in the medial frontal cortex (MFC) using fMRI data acquisition. Furthermore, the previous studies employed the power spectral density technique for EEG feature extraction and applied the ANOVA test to identify the most significant band related to overweight subjects compared to the normal weight group as controls. However, the wavelet transform technique is highly effective in nonstationary signal analysis such as EEG [23,24].

The primary contribution of this study lies in the utilization of resting-state EEG, combined with the wavelet transform method, for the assessment of brain activity in overweight individuals, as an alternative to fMRI. When comparing EEG and fMRI, it becomes evident that EEG offers superior time resolution compared to fMRI, providing more precise and time-localized information about brain activity. The wavelet transform plays a crucial role in providing time-localized information about the EEG signal, enabling the identification of specific events or patterns within the signal. This capability underscores the significance of decomposing the EEG signals into multiple levels, facilitating the visualization of the sub-EEG frequency bands, and ensuring an accurate assessment of the relationship between EEG mechanisms and the subjects under study. As demonstrated in the results section, the sub-Theta bands of the prefrontal cortex (PFC) were found to be heightened in overweight subjects compared to those with a normal weight. This significant finding can potentially be seamlessly integrated with other research focusing on behaviour control in overweight individuals, offering valuable insights into sensory-driven behaviours that contribute to overeating and subsequent weight gain.

5. Conclusion

This study successfully assessed the relationship between body mass index and neural activity in the prefrontal cortex of overweight adults using EEG resting state data. Our findings demonstrate a significant increase in the power of the sub-Theta band and dysfunctional connectivity between prefrontal sites in overweight subjects, highlighting potential neurophysiological factors associated with impulsivity behaviour related to overeating. These specific EEG patterns observed in overweight individuals provide valuable insights for developing targeted neurotherapy courses, such as EEG-neurofeedback, to influence neural processes underlying impulsive behaviour and support overweight management. By integrating neuroscientific approaches with weight management strategies, we aim to pave the way for more effective and personalized interventions for individuals struggling with overweight and obesity.

Table 8
Summary of existing resting-state studies for overweight and obesity

Methods	Hypothesis	Features	Outcome
Babiloni et al., [15]	EEG activities differ among different BMIs as a reflection of the relationship between neural activity and body weight.	Power spectral density-based frequency domain.	Overweight subjects are related to abnormal alpha activity in parietal, occipital, and temporal scalp sites.
Del Percio et al., [16]	Abnormal Alpha-EEG activity related to overweight during resting state eyes open.	Power spectral density-based frequency domain.	Decreasing of alpha-EEG activity among overweight subjects in parietal, occipital, and temporal scalp sites.
Schmidt et al., [17]	Abnormal EEG activity related to an increase in food intake and weight gain of children with overweight status.	Power spectral density-based frequency domain.	Significant increase in delta band activity and a decrease in alpha band activity during the eyes-closed resting state among the group of children with overweight.
Stephan et al., [29]	Overweight individuals are expected to exhibit altered resting-state functional connectivity (rsFC) in the regions of the frontal cortex, as compared to normal-weight individuals.	Resting state functional connectivity	Alerting in functional connections between the MFC and regions associated with reward and maladaptive eating may be key neural mechanisms of food-specific intentional inhibition in overweight individuals.
Our method	PFC-EEG activities differ among different BMIs as a reflection of the relationship between neural activity and body weight.	Wavelet power and coherence maps-based time-frequency domain.	Significant increasing of sub-theta band (4.49-5.34) Hz and low coherence between PFC sites during eyes-open resting state among adults with overweight compared with the normal weight group.

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