Electro Encephalography and BMI The role of BETA Cortical Oscillations in Body Mass Index: A pilot study in human EEG related to BMI

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Abstract

Body mass index (BMI) is a major indicator for diagnosing overweight and obesity. We aimed to explain the neural bases of BMI. Participants consisted of twenty-five undergraduate students (mean age of 21.36 years SD= 23.39) Beta band activity on electroencephalogram (EEG) was positively associated with BMI ($P<0.05$). Stepwise regression analysis showed that the central region of beta band could predict variances of BMI ($P<0.05$). In conclusion, increased beta activity on the EEG appears to be a neural markers for predicting overweight and obesity.
Keywords: body mass index, brain oscillations, EEG.

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Introduction

Obesity and overweight has increased dramatically in economically developed countries and in urbanized populations and there is a growing global childhood obesity epidemic, with a large variation in secular trends across countries (1). About 70% of obese adolescents grow up to become obese adults (2). In 1998, The World Health Organization project monitoring of cardiovascular diseases (MONICA) reported Iran as one of the seven countries with the highest prevalence of childhood obesity (2). Over the past decade, there was an increasing in prevalence of weight discrimination by 66% and this percent is comparable to rates of racial discrimination, especially among women (3). An index that is used for recognizing overweight and obesity is body mass index (BMI). The BMI is calculated by dividing weight in kilograms by the square of height in meters (kg/m2). The BMI is a simple indication of the ratio between weight and height that is commonly used to identify overweight and obese adult individuals and populations. The WHO defines being overweight as having a BMI equal to or greater than 25, and obese when the BMI is over 30, which implies the gravest consequences for health. High BMI is an important risk factor for cardiovascular disease, diabetes, hypertension, locomotive syndrome, and some cancers (4).

Recently, researchers have reported that there is a neuro-biological bases for predicting BMI (5, 6, 7). The EEG is a methodology that can be used to investigate the neural bases of psychological and neurological variables. EEG activity is reported in frequency bands: delta (δ: 1 – 4 Hz), theta (θ: 4 – 8 Hz), alpha (α: 8 – 13 Hz), beta (β: 13 – 30 Hz) and gamma (ϒ: 30 – 60 Hz) (8). Imperatori et al. (9) investigated the EEG power spectra in overweight and obese patients. They showed that patients with three or more food addiction symptoms showed an increase of functional connectivity in the fronto-parietal region of the brain in both the theta and alpha band. Moreover, Hume et al. (10) showed that obese women exhibit lower relative delta band power and higher relative beta band power over the right frontal cortex. De Ridder et al. (11) showed that the 'obesity neural brain activity' consisted of dorsal and pre-genual anterior cingulate cortex, posterior cingulate extending into the precuneus/cuneus as well as the parahippocampal and inferior parietal area. It has also been shown that the anterior cingulate cortex EEG theta activity (12) is related to negative emotions and depression (13, 14).

In summary, understanding how neural activity may be associated with BMI may be important in our understanding of the pathophysiology of obesity (15). EEG frequency bands appear to be related to overweight and obesity (9, 10); therefore, we hypothesized that it is expected cortical oscillations using EEG, especially beta, delta and alpha, are related to body mass index.

Methods

We used a correlation analysis to investigate the research questions. The participants consisted of twenty-five males' undergraduate students from Ferdowsi University of Mashhad, Iran (age mean= 21.36, SD= 23.39) that were selected as volunteers. Inclusion criteria included participants are right-handed and has normal or corrected-to-normal visual acuity and without history of epilepsy.

Tools

Body mass index: Body mass index (BMI) is a measure of body fat based on height and weight that applies to adult men and women. BMI was calculated by weight (kg) divided by height (m) squared (kg/m^2). BMI Categories: underweight = <18.5, normal weight = 18.5–24.9, overweight = 25–29.9, obesity = BMI of 30 or greater.

EEG: In order to record brain activity, a Mitsar EEG-201 (Mitsar Co. Ltd. Saint Petersburg, Russia) was used. The device includes 19 main electrodes (Fp1, Fp2, F3, F4, F7, F8, Fz, C3, C4, Cz, P3, P4, Pz, T3, T4, T7, T8, O1, O2), two reference electrodes (A1 and A2) and a ground electrode (Fpz) according to the 10-20 system of electrode placement. The data were collected using a sampling rate of 250 Hz and filtered using WINEEG software with a frequency band 1 to 100 Hz. Linked Ear references were used with all EEG. Electrolytic gel was applied and each site gently abraded until impedances were below 10 kΩ. Eye-closed and eye open conditions were used for recording signals that were 3 minutes each in duration. So as to decrease interferences, we control interferences variables such as non-using of medication in the last 48 hours, registration in the morning, right-handedness of the participants, clean skin, and, suitable environmental conditions (air conditioning and comfortable chair). During eye-closed condition, we requested the participants to place their hands on the knees, half-open their mouths, and avoid blinking and opening the eyes; and during eyes open condition we requested them to additionally fixate a central point (24, 25).

After recording the signals, the data were saved in EDF+ file format using WINEEG and opened in Neuroguide software. Artifacts were rejected by automatic rejection (1-s epoch, 75 % overlapping) .Artifact-free epochs of 250 samples were extracted through Neuroguide software and submitted to Fast Fourier Transform (FFT, 1 Hz resolution). Considering the aims of the study, the frequency bands were delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–25 Hz) and gamma (>30 Hz). We computed the mean of absolute power (μV^2) of EEG bands in eyes-closed condition.

Procedure

The first step, participants were selected (25 males). After completing consent letter, participants filled BMI form and then entered into the EEG session. For entering the QEEG laboratory, researchers advised participants about the experimental requirement of the study. After consenting, participants were investigated at the Polyclinics of Clinical Psychology (the QEEG laboratory). Recording was made with eyes open and eye-closed under resting conditions (3 minutes each in duration). EEG signals were obtained using the FFT method. Finally, in terms of cortical oscillations, we considered absolute power (μV^2) of delta 1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–25 Hz) and gamma (>30 Hz). Accordingly, the sites from the 19 EEG channels were computed as the mean of absolute power for each frequency band.

Data Analysis

After collecting the information, the data were analyzed using SPSS 22 software (SPSS Inc., Chicago, Illinois, USA). In order to analyze the data, we used descriptive statistic (arithmetic mean, standard deviation) and inferential statistic (a two-tailed Pearson correlation, Stepwise regression).

Results

Table 1. Descriptive Indexes for EEG Oscillations and BMI

Variables	Delta	Theta	Alpha	Beta	Gamma	BMI
Mean	18.44	11.63	32.84	10.84	0.62	23.80
SD	3.85	4.41	17.78	6.90	0.17	3.95
Sig. of data normality	.200	.002	.010	.008	.200	.022

Table 1 shows the data about descriptive indexes of EEG bands and BMI. The mean (SD) of delta, theta, alpha, beta, gamma and BMI were 18.44 (3.85), 11.63 (4.41), 32.84 (17.78), 10.84 (6.90), 0.62 (0.17) and 23.80 (3.95) respectively. In order to check for data normality, one-sample

Kolmogorov-Smirnov test was applied. As it is seen, delta and gamma bands were normally distributed while theta, alpha, beta bands and BMI were not normally distributed.

Table 2. Pearson Correlation between EEG Oscillations and BMI

BMI	Delta	Theta	Alpha	Beta	Gamma
Correlation coefficient	-.09	-.08	-.15	.43*	.16
Bootstrap CI 95 %, lower (upper)	-.633 (.313)	-.392 (.437)	-.471 (.341)	-.032 (.686)	-.254 (.481)
Significant	.64	.68	.47	.03	.43

*P<.05

To apply a two-tailed Pearson correlation, we used the percentile bootstrap (95 % confidence interval, p value .05). The bootstrap method is a resampling multiple comparisons procedure that assigns measures of accuracy (26). We expressed upper and lower correlations in the table 2.

Pearson correlation showed that there is a positive and significant relationship between EEG beta activity and BMI (P<.05). While there was no any significant relationship between BMI and other bands.

After recognizing the relationship between EEG oscillations and BMI, we computed regions of beta band for predicting BMI. In order to achieve the goal, Stepwise regression was applied. Frontal, central, parietal, temporal and occipital regions in beta band were selected as independent variables for predicting BMI. As it is seen in table 3, central region of beta band could significantly predict BMI (P<.05) while other regions were excluded because of lack of predicting BMI. In detail, the beta (T, P value) of frontal, parietal, occipital and temporal were -.57 (-1.13, P=.270), -.31 (-.75, P=.458), -.21 (-.57, P=.570), and -.17 (-.37, P=.712) respectively.

Table 3. Stepwise Regression

Model	adjusted R	Beta	T	Significant
Central region	.257	.507	2.759	.011

Discussion

The primary results showed that beta band activity is related to increasing BMI. Moreover, regression analysis showed that the central region of beta band can predict variances of BMI. As Table 1 shows the data about descriptive indexes of EEG bands and BMI. The mean (SD) of delta, theta, alpha, beta, gamma and BMI were 18.44 (3.85), 11.63 (4.41), 32.84 (17.78), 10.84 (6.90), 0.62 (0.17) and 23.80 (3.95) respectively. In order to check for data normality, one-sample eating women more vulnerable or sensitive to food and the environmental cues. In addition to these findings, researchers have shown that beta activation is related to disinhibition of behaviors, especially in alcoholics (17, 18).

Increased beta activity of the alcoholics has been stated to indicate an imbalance in the excitation–inhibition homoeostasis in the cortex (16, 19). Moreover, Li et al. (20) showed that beta oscillations in major depression – signaling a new cortical circuit for central executive function such as working memory and attention. It seems that people with a high-level of BMI has a disinhibition of behaviors to tackle with overeating and also they may has a problem in executive control.

Li et al. (21) revealed that resting-state beta activity might be involved in the neuropathology of emotional control in adults with attention/hyperactivity disorder. Also, it was revealed that the prefrontal cortex (PFC) might be an adaptation at least partly induced by the higher grey matter volume in the ventral striatum and may help to increase cognitive control over gambling impulses (22). In fact, that beta oscillations may facilitate communication between the PFC and striatum during such learning (23).

We could not find any relationships between BMI and other EEG bands, though Imperatori et al. (9) found a higher of functional connectivity in both the theta and alpha bands; therefore, our finding are partially consistent with previous studies. As a limitation of present study, all our study subjects were men. Therefore, it is recommended for further implications the future studies ought to participate females.

Conclusion

In the context of the study, we speculated that increasing activity in the beta frequency reflects enhancing body mass index. As a result, it may has an implication for people with a high-level of BMI may has pathological emotional and cognitive control, and disinhibition in their eating behaviors. Thus, increased beta activity is a neural markers for predicting overweight and obesity.

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Conflict of Interest: Authors declare they have no conflict of interest.

Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the department of psychology's research committee at Ferdowsi University of Mashhad, Iran and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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