Accepted Manuscript

Accepted Manuscript (Uncorrected Proof)

Title: Effect of Smartphone Distractions on Cognitive Performance in Adolescents: An Electroencephalography Approach

Running Title: Problematic Phone Use and Cognition

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To appear in: *Basic and Clinical Neuroscience*

Received date: 2021/02/9

Revised date: 2021/07/30

Accepted date: 2021/09/11

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Please cite this article as:

Suhail, T. A., Indiradevi, K. P., Suhara, E. M., Poovathinal, S. A., Anitha, A. (In Press). Effect of Smartphone Distractions on Cognitive Performance in Adolescents: An Electroencephalography Approach. *Basic and Clinical Neuroscience*. Just Accepted publication Sep. 21, 2021. Doi: http://dx.doi.org/10.32598/bcn.2021.2295.2

DOI: http://dx.doi.org/10.32598/bcn.2021.2295.2

Highlights

- Investigated the effect of media multitasking on cognitive performance during learning tasks.
- A questionnaire survey and EEG analysis have been adopted for evaluating cognitive performance in a phone-use group and control group.
- Various EEG features such as band ratios, attention index, and sample entropy have been used in this work
- A significant decline in cognitive performance indices was found in phone-use group.

Plain Language Summary

The current study examined the impact of smartphone use on cognitive task performance and mental health in adolescents using a questionnaire survey and EEG spectral analysis. It has been observed that smartphone use in between studies/work affects cognitive performance of individuals. EEGs of twenty-two subjects were recorded during a reading task before and after smartphone use. Recent studies have detected variations in EEG rhythms due to electromagnetic fields generated by phone calls, while the present study focuses on EEG variations during cognitive task due to frequent use of mobile applications such as social media, etc. The analysis revealed a significant decline in cognitive performance due to uncontrolled use of smartphone or media multitasking during learning/working hours.

Abstract

Introduction: The dependence on smartphones has become widespread among all age groups in every realm of daily life. There has been increased concern about the adverse effects of problematic smartphone use and media multitasking among adolescents. Recent studies used various performance measures like questionnaire surveys to examine the association between smartphone addiction and learning performance, and such studies have yielded mixed findings. The current study investigates the effects of media multitasking on cognitive performance using Electroencephalography (EEG) features and a self-report questionnaire survey.

Methods: The patterns of smartphone use among adolescents in South India were investigated in this study, using a questionnaire survey. Further, the impact of smartphone usage on cognitive task performance was examined using EEG features. For this, EEGs of twenty-two healthy subjects were recorded during learning tasks before and after using a social networking site on smartphones. Subsequently, various EEG features were extracted, including ratios of wavelet decomposed EEG bands, attention index, and Sample entropy. Finally, these cognitive performance indices were evaluated and compared with a control group.

Results: A total of 600 healthy individuals (341 males, 259 females) participated in the survey among whom, 310 (50.91%) belonged to the high-user group. Performance degradation (p=0.005), sleep problems (p=0.040) and mental stress (p=0.049) were more prevalent among the high-user group. A significant decline in EEG-based cognitive performance indices was also observed in the phone-use group compared to the control group.

Conclusion: The findings of this study highlight the importance of controlling phone use when engaged in cognitive tasks. The study also offers an insight to develop neurofeedback techniques that enhance cognitive skills.

Keywords: Smartphone Addiction, EEG, Cognitive Skill, Spectral Analysis, Attention, Mental Health

1. Introduction

Cognitive skills play a vital role in learning capacity and task performance. Attention, memory, perception, and logical reasoning represent various levels of cognitive functions. Studies on human cognition have revealed several biological, behavioral, and environmental factors that contribute to the augmentation or deterioration of cognitive skills. One such factor is the indiscriminate use of smartphones that adversely affects cognitive capacities, impacting physical and mental health (Shaffer, 1996). In recent years, smartphones have become embedded in almost every domain of human life, such as social networking, education, business, entertainment, etc. However, excessive use of smartphones can sometimes lead to addiction, which has emerged as a prevalent social problem that disrupts daily life. Smartphone addiction indicates the inability to control smartphone use despite negative effects on users (Shaffer, 1996). Recent studies have shown that the prevalence of smartphone addiction among children and adolescents is rapidly increasing (Soni et al., 2017). The younger population is more addicted to social media platforms, and they tend to use social networking sites during their study or work hours (Chiang et al., 2019). Such kind of heavy media multitasking or switching between tasks may result in cognitive decline and poor academic outcomes (Abi-Jaoudeet al., 2020; van der Schuur, 2015; Uncapher et al. 2017). Furthermore, it has been implicated in anxiety, impatience, withdrawal, mood changes, and lack of concentration in tasks, in addition to physical health problems such as pain in the wrist, neck and joints, nervous disturbances, and fatigue (Hou et al., 2019; Thomée et al., 2011; Van Deursen, 2015). Hence, the current study attempts to investigate the effects of smartphone use or media multitasking on adolescents' cognitive performance.

Researchers have used several techniques for estimating the cognitive performance of individuals, including behavioral, subjective, and neurophysiological measures (Tattersall et al., 1996; Hart et al., 1988; Borghini et al., 2016). Behavioral measures rely on the performance of the subjects in experimental tasks while subjective measures rely on self-reports and questionnaires (Tattersall et al., 1996; Hart et al., 1988). Neurophysiological techniques measure cognitive performance using variations of physiological signals such as brain activity, cardiac activity, skin conductance, etc. (Borghini et al., 2016; Mühl et al., 2014; Gevins and Smith, 2003). Neurophysiological measures have been demonstrated as effective tools for real-time monitoring and thereby enhancing the cognitive performance of individuals. Electroencephalography (EEG), a very convenient and low-cost technique that records the electrical activity of the brain, is being widely used to measure various cognitive assessment factors such as attention (Peng et al., 2020), mental workload (Gevins and Smith, 2003), working memory (Missonnier et al., 2006), etc. EEG reflects the neuronal changes occurring due to cognitive engagement or fatigue, and hence EEG is widely used for assessing the cognitive performance of individuals. EEG is composed of several rhythms based on the frequency- delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (31-50 Hz) (Britton et al., 2016; Noachtar et al., 1999). Several neurocognitive experiments have showed that the cognitive state of attention is linked with theta, alpha, beta, and gamma bands of EEG (Freeman et al., 1999; Liu et al., 2013; Peng et al., 2020). Attention is a complex neural phenomenon comprising different brain regions (Rosenberg et al., 2016; Posner and Petersen, 1990) coupled with several frequencies (Clayton et al., 2015). Researchers have used various EEG features based on temporal, power spectral density (Liu et al., 2013), wavelet transform (Djamal et al., 2016), and Hilbert- Huang Transform (Peng et al., 2020) for deriving neuro markers that detect attention from neural signals. Gruzelier (2009) showed that the ratio of the alpha band to theta band reflects the performance enhancement index of individuals during cognitive tasks. Freeman et al. (1999) demonstrated that the ratio of the beta band to theta band indicates neural activity and is a potential biomarker for attentional assessment. Rabbi et al. (2009) reported that the ratio of the beta to (alpha + theta) is indicative of cognitive performance and attentional resource index. Ming et al. (2009) used sample entropy of EEG samples to discriminate mental states of attention and inattention. This study reported a higher sample entropy during attentive tasks compared to the mental state of inattention. Cognitive workload (CWL) is another term used for measuring task complexity while performing a task. It indicates a measure of the human ability to maintain focus and rational reasoning while processing multiple activities and facing various distractions (Recarte and Nunes, 2003). Several recent studies have shown that cognitive workload or task complexity is positively correlated with theta activity over the frontal region of the brain (Gevins and Smith, 2003) and inversely correlated with the alpha band over the parietal region (Borghini et al., 2014; Gevins et al., 1997).

With the advent of the internet and smartphone technologies, social networking sites (SNS) have become very popular among people of different ages and professions. The investigation of the impact of problematic smartphone use on learning performance and work efficacy has gained more attention in recent years (Abi-Jaoudeet al., 2020; Darcin et al., 2015). Several studies have revealed the regions of brain activation during the use of social networking sites. Neuroimaging studies based on functional Magnetic Resonance Imaging (fMRI) demonstrated that the task of social networking activates a network of brain regions such as the dorsomedial prefrontal cortex, bilateral temporoparietal junction, anterior temporal lobes, inferior frontal gyri, and posterior cingulate cortex/precuneus (Schurz et al., 2014; Saxe et al., 2003; Wolf et al., 2010).

Numerous studies have investigated the effects of phone use or media multitasking on cognitive performance in adolescents. However, most of them were based on self-report questionnaire surveys while a few utilized changes in physiological signals like brain activity, heart rate, etc. Moreover, neuroimaging studies using fMRI revealed the adverse effects of media multitasking on cognitive functioning (Moisala et al., 2016). Some EEG-based studies have examined the variations in EEG frequency bands induced by electromagnetic fields due to mobile phone radiation (Arns et al., 2007; Croft et al., 2008; Krause et al., 2006; Parmar et al., 2019). Out of these studies, only a few (Krause et al., 2006; Parmar et al., 2019) investigated the impact of phone usage on cognitive tasks. Moreover, such works used a limited number of EEG features such as average amplitudes, frequencies, etc. The changes in brain activity patterns during cognitive tasks induced due to media multitasking (or switching between learning and social media use) have not been investigated in detail. The main objective of the current study was to investigate the effects of smartphone distractions or media multitasking on adolescents' cognitive performance using a large set of EEG indices. To achieve this, the study examined the patterns of smartphone use among adolescents using a questionnaire survey. Following this, the impact of smartphone distractions on cognitive performance was assessed using a diverse set of EEG-based cognitive performance indices such as band ratios, attention index, cognitive workload, and Sample entropy. It is hypothesized that uncontrolled use of smartphones could negatively be associated with mental health and task performance.

2. Methods

Ethical clearance: The study was approved by the Institutional Ethics Committee duly constituted according to the guidelines of the Indian Council of Medical Research (ICMR). The procedure was explained in detail, and written informed consent was obtained from all the participants.

Survey on smartphone use: A self-report questionnaire was used to conduct a survey on the pattern of smartphone use among adolescents in South India. The questionnaire included data on demography, duration of phone use, frequency of phone use during study/work, the most-used feature on phone, and performance outcome in academics or job. Data on stress and sleep pattern among phone users were also collected. The respondents were divided into the low-user group and the high-user group based on the duration of phone use. The participants who indulged in the use of their smartphones for more than three hours per day were grouped into the high-user group and others into the low-user group.

Data Used

The current study used EEG data of healthy subjects recorded using EBNeuro Galileo BE Plus LTM 128 channel EEG acquisition system during various mental tasks such as resting, reading before and after smartphone usage, etc. Twenty-two healthy subjects (fourteen males and eight females) aged 18-32 years (21.73 ± 2.78; mean ± SD) participated in the EEG experiment. The subjects included undergraduate students and research staff from the institute. The subjects were ruled out of any medical or psychiatric conditions, and they were divided into two groups: phone-use group (experimental group) and control group. There were 11 subjects in each group with mean age and standard deviation 21.0 ± 1.48 (phone-use group) and 22.45 ± 3.58 (control group) with four females in each group.

EEG recording: In this work, EEG signals were recorded using BE Plus LTM 128 channel EEG acquisition system. All the EEG channels were recorded with an averaged reference, and electrode impedance was kept lower than 5 Kohm. The subjects were comfortably seated in an electrically shielded room. For the experimental group, the recording consisted of four sessions-resting or relaxation phase, the reading task phase (named pre-use task phase), the smartphone use phase, and the reading task phase following the smartphone use (named post-use task phase). EEG was continuously recorded from each subject during rest state (3 minutes duration) and each of the remaining three states (5 minutes duration). During the resting state, the participants were instructed to remain in an idle state for three minutes without making any movements. During the reading stage, they had to read a scientific article related to the basics of brain functions (Farnsworth, 2018) for five minutes. During the phase of smartphone use, they were instructed to use the social media platform "Facebook" for five minutes during which they viewed their profile photos and posts, including comments received. After five minutes of smartphone use, the subjects were asked to read the remaining part of the article. After five minutes of smartphone use, the subjects were asked to read the remaining part of the article. For the control group, the experiment was conducted in a similar manner but without smartphone use. Instead, the subjects were instructed to sit in an idle state between the two reading phases. The participants were asked to answer the questions related to the reading content and also to express their mental state whether they had felt any state of inattentive or fatigue during each task. Accordingly, the subject's mental state was verified based on the subject's feedback in the form of answering questions and self-expression of the emotional state they felt during the task. Figure. 1 illustrates the sequence of operations performed for the assessment of cognitive performance using EEG-based indices.

Figure 1. Block diagram of the proposed work for cognitive performance assessment using EEG features

64 channels from different brain regions including Frontal (F), Parietal (P), Temporal (T), and Occipital (O) were selected for EEG analysis. EEG data were online digitized with a sampling frequency of 128 Hz and exported to MATLAB-compatible format for further processing. Then, EEG was segmented into several epochs of one-second duration, which had been reported as an optimal epoch duration to detect changes in neuronal activity during different mental states (Wang et al., 2014; Fraschini et al., 2016). The first five seconds in each trial were considered as task preparation time for each subject and excluded those epochs from the analysis. EEG data were bandpass filtered between 1 Hz and 60 Hz, and an additional notch filtering was performed for eliminating 50 Hz power line noise interference. Amplitude thresholding was also performed to minimize movement artifacts, in which EEG samples with amplitudes greater than ±80 µV were excluded (Gotlib et al., 1998; Poppy and Speckens, 2015).

EEG Feature Extraction: EEG features were extracted from the pre-processed EEG in the frequency domain for interpreting brain activity. Wavelet transform was used for decomposing EEG into various rhythms such as delta, theta, alpha, beta, and gamma. Wavelet transform is a very effective technique for the time-frequency analysis of non-stationary signals like EEG (Mallat, 1998; Polikar, 1999). It can detect any transient events occurring in the signal, and it decomposes the given signal using a set of oscillating functions known as wavelets. Different families of wavelet functions '$\boldsymbol{\psi_{a,b}(t)}$' are formed as scaled and shifted versions of a unique mother wavelet '$\boldsymbol{\psi(t)}$' according to (1).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi(\frac{t-b}{a}) \qquad (1)$$

where, a, b ∈ $R, a \neq 0$, 'a' is the scaling parameter, 'b' is the shifting parameter and 't' is the time variable. Discrete wavelet transform (DWT) is a discrete version of continuous wavelet transform, defined by assigning discrete values to wavelet parameters 'a' and 'b' ($a = 2^{-j}$ and $b = k\ 2^{-j}$, where j and k are integers representing the scale and translation). The current work performed four-level DWT decomposition for decomposing the digitized EEG samples into different frequency components. The wavelet family chosen was Daubechies-4 (db4) wavelet owing to its resemblance to the EEG waveform (Indiradevi, et al., 2008). DWT decomposes the EEG signal to detail (high frequency) and approximation (low frequency) coefficients from which various EEG bands- delta, theta, alpha, beta, and gamma were selected as indicated in Figure 2.

Figure 2. Four-level Wavelet decomposition of EEG signal into five bands. D indicates detail (high frequency) component and A represents approximation (low frequency) component.

Based on the neuroscientific literature, various kinds of EEG features were extracted in this experiment. They included band ratios, attention index, and sample entropy of EEG samples. EEG band ratios have been reported as effective neuro markers for recognizing the mental state of attentive tasks (Freeman et al., 1999; Gruzelier, 2009; Rabbi et al., 2009). The current experiment used different band ratios such as alpha to theta ratio (ATR), alpha to beta ratio (ABR), beta to theta ratio (BTR), and theta to gamma ratio (TGR). These were computed as the ratio of the absolute power of respective bands according to Equations (2)-(5). Another ratio beta to (alpha + theta) ratio (BATR) was estimated as the ratio of theta absolute power to the sum of alpha absolute power and beta absolute power (6).

$$ATR = \frac{AP_\alpha}{AP_\theta} \tag{2}$$

$$ABR = \frac{AP_\alpha}{AP_\beta} \tag{3}$$

$$BTR = \frac{AP_\beta}{AP_\theta} \tag{4}$$

$$TGR = \frac{AP_\theta}{AP_\gamma} \tag{5}$$

where $AP_\theta, AP_\alpha, AP_\beta \; and \; AP_\gamma$ represent absolute power of theta (θ), alpha (α), beta (β), and gamma (γ) bands respectively.

$$BATR = \frac{AP_\beta}{AP_\alpha + AP_\theta} \tag{6}$$

Attention index defined by a combination of band ratios (Suhail et al., 2021) was computed as

$$AITAB = \frac{AP_\theta}{AP_\alpha} + \frac{AP_\alpha}{AP_\beta} \tag{7}$$

As EEG is a complex non-linear phenomenon, different kinds of entropies have been utilized in this work for assessing the mental states of cognitive tasks. Sample entropy is a powerful tool that measures the amount of regularity in the signal. It was computed based on the algorithm proposed by Richman and Moorman (2000) with parameters, $m = 2$ and $r = 0.2\times\sigma$, where m is subseries length, r is similarity tolerance, σ standard deviation of EEG samples.

Cognitive workload (CWL), which is a measure of task complexity, was estimated by the ratio of theta power across the frontal region to alpha power across the parietal region (7) (Holm et al., 2009).

$$CWL = \frac{Theta\ Power\ across\ Frontal\ region}{Alpha\ Power\ across\ Parietal\ region} \quad (8)$$

EEG features were normalized into a common scale [0 1] using the min-max normalization technique (Li et al., 2016). The normalized version of ith sample xi from a feature set X was computed using equation (9).

$$x_i{}' = \frac{x_i - min(X)}{max(X) - min(X)} \quad (9)$$

All the features were computed across two hemispheres (right and left) of different lobes of the brain (frontal, parietal, temporal, and occipital) by averaging feature values over the channels in respective lobes. For example, the feature BATR across the left frontal region (FL) was computed by averaging the values of BATR over F1, F3, F5, and F7 channels. In this way, all features were evaluated lobe-wise for each group.

Statistical analysis: The Chi-square test was used to examine the impact of smartphone use (high-user and low-user groups) on task performance based on responses of the survey. The Chi-square test is generally conducted for testing statistical independence or association between two or more categorical variables. The Wilcoxon Signed-Rank test was used to examine the significant differences in EEG patterns before and after smartphone use. Wilcoxon Signed-Rank test is a non-parametric test used to compare related samples or matched pairs and is suitable for evaluating two different conditions of the same subjects (Scheff, 2016). The significance level was set to $P < 0.05$ for examining the significant difference in performance indices between pre-use and post-use tasks.

3. Results

Questionnaire survey on smartphone use: The pattern of smartphone usage among adolescents and its impact on task performance and health were examined using the survey. A total of 600 individuals, which included 341 males and 259 females, participated in this survey. Among the total participants of the survey, 310 (50.91%) belonged to the high-user group. Multiple parameters, including the most using feature in the phone, duration of phone use, phone use during studies/work, academic/work performance, sleep, and stress problems, were compared between high-user and low-user groups (Table 1). A significant difference (P=0.005) was observed in task performance between the high-user group and the low-user group. Performance degradation was more in the high-user group (49.03%) than in the low-user group (32.55%). Sleep problems (p=0.040) and mental stress (P=0.049) were also more prevalent in the high-user group.

Table 1. Comparison of the impact of smartphone use on task performance and health between high- and low-user groups (The results of Chi-Square test are shown with X2 and P values).

EEG experimental results: EEG rhythmic variations during the cognitive task before and after smartphone use were investigated in this experiment, following the survey. Firstly, the changes in various EEG-based cognitive performance indices during rest and attentive states were examined for all subjects. Finally, the variations in these EEG indices occurring due to phone use were evaluated by dividing the subjects into experimental (phone-use) and control groups. For the experimental group, EEG features were evaluated for the learning task before phone use (pre-use task) and the learning task after phone use (post-use task). For the control group, EEG features were evaluated for two phases of the learning task (phase-I and phase-II) with an idle state (without phone use) between the two phases. The variations in theta, alpha, beta, and gamma bands during the two learning tasks for each group are shown in Figure 3.

Figure 3. Variations in theta, alpha, beta, and gamma rhythms during the two learning tasks for a representative subject from each group. EEG bands extracted from EEG samples averaged over frontal channels are shown. For the phone use group, Task-I and Task-II are learning tasks before and after the smartphone usage. For the control group, Task-I and Task-II represent two learning tasks with an idle state between them.

EEG variations during the state of attentiveness

The variations in different kinds of EEG features during rest and attentive states are shown in Figure 4. During the mental state of attention, EEG band ratios BATR increased (59.91%), ATR increased (71.35%), BTR increased (59.97%), ABR decreased (42.39%), and TGR decreased (58.21%) across all lobes of the brain. A decrease in the attention index AITAB (35.79%) was also noticed during the attentive state. It observed an increase in Sample entropy (68.56%) and cognitive workload (35.08%) during the attentive state in comparison with the rest state. The results signify that the cognitive state of attention is characterized by the increases of BATR, ATR, BTR, and Sample entropy. The decreases of ABR, TGR, and attention index are also associated with the attentive state.

Figure 4. EEG features during resting and attentive states. Mean values (averaged across brain lobes over 22 subjects) with standard deviations are shown.

Effects of phone use on cognitive performance

The cognitive performances of phone-use (experimental) and control groups have been evaluated based on various EEG-based indices. The variations in EEG-based indices for the phone-use group and control group are shown in Figure 5. The ratio BATR decreased in the phone-use group. This ratio decreased in all lobes of the brain during the learning task after smartphone use. It has been demonstrated that BATR is associated with attentional resource index and the decrease in BATR represents a decline in cognitive performance (Rabbi et al., 2009). The mean values of BATR during the learning task before and after phone use for the experimental group are shown in Figure 5. The decrease was larger in the right frontal (60.18%), left frontal (57.96%), and left occipital (56.02%) regions. The mean values of BATR during the learning task for the control group are shown in Figure 5. For the control group, the ratio BATR increased during the learning task over the left frontal (10.67%) and right occipital (50.92%) regions while decreased in all other lobes. As the frontal lobe is responsible for various cognitive functions like attention, memory, planning, and problem-solving, etc., the changes in BATR across this region indicate variations in the cognitive task performance of individuals.

Figure 5. Beta to (alpha + theta) ratio (BATR) across brain lobes in phone-use group and control group. Mean values with standard deviations are shown.

The variations in EEG-based cognitive performance indices for the phone-use group and control group are shown in Figure 6. Alpha to theta ratio (ATR), representing the performance enhancement index (Gruzelier, 2009), decreased (39.57%) in the phone-use group while increased (64.37%) in the control group. The ratio ABR (alpha to beta ratio) increased in the phone-use group (37.79%) and decreased in the control group (16.37%). As the increase of beta band power and the decrease of alpha band power are associated with a higher level of certain cognitive skills such as alertness, the decrease in ABR indicates a higher cognitive performance (Jap et al., 2009).

Figure 6. Variations in EEG based cognitive performance indices in phone-use group and control group. Mean values with standard deviations are shown.

The ratio BTR (beta to theta ratio) decreased (36.15%) in the phone-use group while it increased (36.34%) in the control group. BTR decreased in all lobes during the learning task following phone use. The decrease of the ratio BTR indicates a lower performance in cognitive functioning (Freeman et al., 1999). For the control group, the BTR increased across all brain regions. Theta to gamma ratio (TGR) increased in the phone-use group (73.04%) while decreased in the control group (14.22%). It was shown that an increase in TGR is associated with poor cognitive functioning (Moretti et al., 2009). The increase of TGR was high in the phone-use group indicating a cognitive decline as shown in Figure 6.

Cognitive workload, which is a measure of task complexity (Gevins and Smith, 2003), increased (58.80%) during the learning task following phone use (Figure 6). It decreased (21.33%) in the control group, indicating a lower mental workload. The current study also observed an increase (57.55%) in attention index AITAB during the learning task following the phone use as shown in Figure 6. For the control group, AITAB decreased (28.04%) in all lobes. It has been showed that an increase in attention index AITAB represents a lower attentive state (Suhail et al., 2021).

Figure 7. Sample entropy in phone-use group and control group. Mean values with standard deviations are shown.

A decrease in Sample entropy was observed during the learning task following phone use. The decrease was significantly larger in the right frontal (52.01%) and left occipital (47.83%) regions. It has been demonstrated that Sample entropy increases during the attentive state (Ming et al., 2009). For the control group, Sample entropy increased in frontal and left occipital regions (2.47-4.88%) while decreased in all other lobes (18.51-36.48%) as indicated in Figure 7.

The statistical analysis revealed that BATR and cognitive workload exhibited a statistically significant difference ($P < 0.05$) in the phone-use group (between the learning tasks before and after smartphone use). For the control group, the features exhibited no significant differences. The evaluation of various cognitive performance indices between the phone-use group and control group suggests that smartphone use (or distractions) during cognitive tasks adversely affects the cognitive performance of individuals.

4. Discussion

The present study examined the patterns of smartphone use among adolescents and the impact of smartphone usage on cognitive performance. Several studies have addressed the negative effects of heavy media multitasking on the cognitive functioning of the brain. Most of them relied on self-report questionnaire surveys (Abi-Jaoudeet al., 2020; Uncapher et al., 2017) while a few utilized neuroimaging techniques like fMRI (Moisala et al., 2016). The current study adopted two techniques- a questionnaire survey and EEG-based analysis for measuring the effects of smartphone use on cognitive performance. Compared to the fMRI technique, EEG provides a very high temporal resolution in the order of milliseconds so that any minute variation in brain waves can be captured using EEG. In this work, the patterns of smartphone usage among different groups of people, such as students and working professionals, were investigated using a questionnaire survey. The survey responses indicated that 71.87% of total respondents were frequently involved in using their smartphones (other than study/work purposes) during their studies or working hours. Among these multitaskers, 55.01% expressed that their academic/job performance was degraded by smartphone use. Excessive use of smartphones has been also implicated in stress and sleep problems. The results are consistent with previous studies (Abi-Jaoudeet al., 2020; Hou et al., 2019; Kim et al., 2018) that showed the adverse effects of heavy media multitasking or excessive use of smartphones on academic performance and mental/physical health. In addition, EEG spectral analysis also indicated a significant difference in cognitive performance indices during tasks following smartphone use. The study used various EEG-based cognitive performance indices, including band ratios, Sample entropy, cognitive workload, and attention index. All these features were first evaluated during resting and attentive states. The increases of alpha to theta ratio, beta to (alpha + theta) ratio, and beta to theta ratio were observed during the attentive state, consistent with the neuroscientific literature (Freeman et al., 1999; Gruzelier, 2009; Rabbi et al., 2009).

The analysis of EEG-based cognitive performance indices in the phone-use group and control group signified that multitasking or switching between learning and phone use negatively affects cognitive performance. In a neuroimaging study using fMRI, Moisala et al. (2016) demonstrated that media multitasking is associated with behavioral distractibility and poor task performance in adolescents. Various mental and physical ill-effects such as headache, mental fatigue, and sleep problems were reported due to cell-phone use in an EEG-based study (Parmar et al., 2019). However, EEG-based performance indices have not been widely explored for analyzing the impact of smartphone distractions on cognitive performance. Various EEG features representing attentional resource index, performance enhancement index, cognitive workload, etc. were utilized in this study. The experimental results of EEG analysis revealed a decrease in the beta to (alpha + theta) ratio in the phone-use group, indicating a lower cognitive performance and attentional resource index (Rabbi et al., 2009). A decrease in alpha to theta ratio (performance enhancement index) and beta to theta ratio (attentional control) have also been observed in the phone-use group. The variations in these indices occurring due to phone distractions or multitasking indicated a significant decline in cognitive performance.

The findings of the current study indicate that media multitasking during learning or working hours can negatively affect the cognitive functioning of the brain. The current study considered only one type of cognitive task and one smartphone application like social media, which is a limitation of this work. Future work will investigate the impact of various smartphone applications like social media, gaming, etc. on various cognitive tasks like working memory, attentive tasks, etc. It is also important to focus on developing neurofeedback-based recovery methods for maintaining and enhancing the cognitive performance of individuals with poor cognitive capabilities.

5. Conclusion

The present study investigated the acute impacts of smartphone distractions on cognitive task performance using a questionnaire survey and a set of EEG-based performance indices. Multiple EEG features, such as band ratios, Sample entropy, and attention index, were used in this experiment. The survey responses indicated that overuse of smartphones is related to declines in learning performance and work efficacy. Furthermore, the experimental results of EEG analysis showed that smartphone use (or media multitasking during learning) induces significant differences in cognitive performance indices. Taken together, the findings emphasize the need for controlling the use of smartphones during study/work hours. The current study focused on the impact of a social networking site on a learning task. Future work will focus on the effects of various smartphone applications on different cognitive tasks. The relevance of neurofeedback techniques in improving cognitive capabilities deserves a special mention in this context.

Acknowledgements

We are deeply grateful to Mr. Ananthakrishnan C G, Ms. Sumitha K P and Ms. Rahna Parakkal at Institute for Communicative and Cognitive Neuroscience, Shoranur, Kerala, India for their valuable support for recording EEG data.

Disclosure

Conflict of interest: None

Compliance with ethical guidelines

All ethical principles were considered in this article.

Authors' contributions

All authors contributed in preparing this article.

References

Abi-Jaoude, E., Naylor, K. T., & Pignatiello, A. (2020). Smartphones, social media use and youth mental health. Cmaj, 192(6), E136-E141. https://doi.org/10.1503/cmaj.190434

Arns, M., Van Luijtelaar, G., Sumich, A., Hamilton, R., & Gordon, E. (2007). Electroencephalographic, personality, and executive function measures associated with frequent mobile phone use. International Journal of Neuroscience, 117(9), 1341-1360. https://doi.org/10.1080/00207450600936882

Borghini, G., Aricò, P., Graziani, I., Salinari, S., Sun, Y., Taya, F., ... & Babiloni, F. (2016). Quantitative assessment of the training improvement in a motor-cognitive task by using EEG, ECG and EOG signals. Brain topography, 29(1), 149-161. https://doi.org/10.1007/s10548-015-0425-7

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. Neuroscience & Biobehavioral Reviews, 44, 58-75. https://doi.org/10.1016/j.neubiorev.2012.10.003

Britton, J. W., Frey, L. C., Hopp, J. L., Korb, P., Koubeissi, M. Z., Lievens, W. E., ... & St Louis, E. K. (2016). Electroencephalography (EEG): an introductory text and atlas of normal and abnormal findings in adults, children, and infants. https://doi.org/10.5698/978-0-9979756-0-4

Chiang, J. T., Chang, F. C., Lee, K. W., & Hsu, S. Y. (2019). Transitions in smartphone addiction proneness among children: The effect of gender and use patterns. PloS one, 14(5), e0217235. https://doi.org/10.1371/journal.pone.0217235

Clayton, M. S., Yeung, N., & Kadosh, R. C. (2015). The roles of cortical oscillations in sustained attention. Trends in cognitive sciences, 19(4), 188-195. https://doi.org/10.1016/j.tics.2015.02.004

Croft, R. J., Hamblin, D. L., Spong, J., Wood, A. W., McKenzie, R. J., & Stough, C. (2008). The effect of mobile phone electromagnetic fields on the alpha rhythm of human electroencephalogram. Bioelectromagnetics: Journal of the Bioelectromagnetics Society, The Society for Physical Regulation in Biology and Medicine, The European Bioelectromagnetics Association, 29(1), 1-10. https://doi.org/10.1002/bem.20352

Darcin, A. E., Noyan, C., Nurmedov, S., Yilmaz, O., & Dilbaz, N. (2015). Smartphone addiction in relation with social anxiety and loneliness among university students in Turkey. European Psychiatry, 30(S1), 1-1. https://doi.org/10.1016/s0924-9338(15)30398-9

Djamal, E. C., Pangestu, D. P., & Dewi, D. A. (2016). EEG-based recognition of attention state using wavelet and support vector machine. In 2016 International Seminar on Intelligent Technology and Its Applications (ISITIA) (pp. 139-144). IEEE. https://doi.org/10.1109/isitia.2016.7828648

Farnsworth, B. (2018). What is EEG (Electroencephalography) and How Does it Work?. imotions. https://imotions. com/blog/what-is-eeg, 8.

Fraschini, M., Demuru, M., Crobe, A., Marrosu, F., Stam, C. J., & Hillebrand, A. (2016). The effect of epoch length on estimated EEG functional connectivity and brain network organisation. Journal of neural engineering, 13(3), 036015. https://doi.org/10.1088/1741-2560/13/3/036015

Freeman, F. G., Mikulka, P. J., Prinzel, L. J., & Scerbo, M. W. (1999). Evaluation of an adaptive automation system using three EEG indices with a visual tracking task. Biological psychology, 50(1), 61-76. https://doi.org/10.1016/s0301-0511(99)00002-2

Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. Theoretical Issues in Ergonomics Science, 4(1-2), 113-131. https://doi.org/10.1080/14639220210159717

Gevins, A., Smith, M. E., McEvoy, L., & Yu, D. (1997). High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. Cerebral cortex (New York, NY: 1991), 7(4), 374-385. https://doi.org/10.1093/cercor/7.4.374

Gotlib, I. H. (1998). EEG alpha asymmetry, depression, and cognitive functioning. Cognition & Emotion, 12(3), 449-478. https://doi.org/10.1080/026999398379673

Gruzelier, J. (2009). A theory of alpha/theta neurofeedback, creative performance enhancement, long distance functional connectivity and psychological integration. Cognitive processing, 10(1), 101-109. https://doi.org/10.1007/s10339-008-0248-5

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In Advances in psychology (Vol. 52, pp. 139-183). North-Holland. https://doi.org/10.1016/s0166-4115(08)62386-9

Holm, A., Lukander, K., Korpela, J., Sallinen, M., & Müller, K. M. (2009). Estimating brain load from the EEG. TheScientificWorldJOURNAL, 9, 639-651. https://doi.org/10.1100/tsw.2009.83

Hou, Y., Xiong, D., Jiang, T., Song, L., & Wang, Q. (2019). Social media addiction: Its impact, mediation, and intervention. Cyberpsychology: Journal of psychosocial research on cyberspace, 13(1). https://doi.org/10.5817/cp2019-1-4

Indiradevi, K. P., Elias, E., Sathidevi, P. S., Nayak, S. D., & Radhakrishnan, K. (2008). A multi-level wavelet approach for automatic detection of epileptic spikes in the electroencephalogram. Computers in biology and medicine, 38(7), 805-816. https://doi.org/10.1016/j.compbiomed.2008.04.010

Jap, B. T., Lal, S., Fischer, P., & Bekiaris, E. (2009). Using EEG spectral components to assess algorithms for detecting fatigue. Expert Systems with Applications, 36(2), 2352-2359. https://doi.org/10.1016/j.eswa.2007.12.043

Krause, C. M., Björnberg, C. H., Pesonen, M., Hulten, A., Liesivuori, T., Koivisto, M., ... & Hämäläinen, H. (2006). Mobile phone effects on children's event-related oscillatory EEG during an auditory memory task. International journal of radiation biology, 82(6), 443-450. https://doi.org/10.1080/09553000600840922

Li, K. G., Shapiai, M. I., Adam, A., & Ibrahim, Z. (2016, October). Feature scaling for EEG human concentration using particle swarm optimization. In 2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE) (pp. 1-6). IEEE. https://doi.org/10.1109/iciteed.2016.7863292

Liu, N. H., Chiang, C. Y., & Chu, H. C. (2013). Recognizing the degree of human attention using EEG signals from mobile sensors. sensors, 13(8), 10273-10286. https://doi.org/10.3390/s130810273

Mallat, S. (1999). VI - Wavelet zoom, A wavelet tour of signal processing (pp. 163-219). Academic Press. https://doi.org/10.1016/B978-012466606-1/50008-8

Ming, D., Zhang, M., Xi, Y., Qi, H., Hu, Y., & Luk, K. D. K. (2009, May). Multiscale entropy analysis of attention ralated EEG based on motor imaginary potential. In 2009 IEEE International Conference on Computational Intelligence for Measurement Systems and Applications (pp. 24-27). IEEE. https://doi.org/10.1109/cimsa.2009.5069911

Missonnier, P., Deiber, M. P., Gold, G., Millet, P., Pun, M. G. F., Fazio-Costa, L., ... & Ibáñez, V. (2006). Frontal theta event-related synchronization: comparison of directed attention and working memory load effects. Journal of neural transmission, 113(10), 1477-1486. https://doi.org/10.1007/s00702-005-0443-9

Moisala, M., Salmela, V., Hietajärvi, L., Salo, E., Carlson, S., Salonen, O., ... & Alho, K. (2016). Media multitasking is associated with distractibility and increased prefrontal activity in adolescents and young adults. NeuroImage, 134, 113-121. https://doi.org/10.1016/j.neuroimage.2016.04.011

Moretti, D. V., Fracassi, C., Pievani, M., Geroldi, C., Binetti, G., Zanetti, O., ... & Frisoni, G. B. (2009). Increase of theta/gamma ratio is associated with memory impairment. Clinical Neurophysiology, 120(2), 295-303. https://doi.org/10.1016/j.clinph.2008.11.012

Mühl, C., Jeunet, C., & Lotte, F. (2014). EEG-based workload estimation across affective contexts. Frontiers in neuroscience, 8, 114. https://doi.org/10.3389/fnins.2014.00114

Noachter, S. (1999). A glossary of terms most commonly used by clinical electroencephalographers and proposal for the report form for the EEG findings. Electroenceph clin Neurophysiol, 52, 21-41. https://doi.org/10.1055/s-2003-812583

Parmar, K., Tandon, R., Kumar, N., & Garg, R. K. (2019). Variations in electroencephalography with mobile phone usage in medical students. Neurology India, 67(1), 235.

Peng, C. J., Chen, Y. C., Chen, C. C., Chen, S. J., Cagneau, B., & Chassagne, L. (2020). An EEG-Based Attentiveness Recognition System Using Hilbert–Huang Transform and Support Vector Machine. Journal of Medical and Biological Engineering, 40(2), 230-238. https://doi.org/10.1007/s40846-019-00500-y

Polikar, R. (1999). The story of wavelets. In Physics and Modern Topics in Mechanical and Electrical Engineering (pp. 192-197). World Scientific and Engineering Academy and Society.

Poppy PLS, Speckens AE (2015) Multi-dimensional modulations of α and γ cortical dynamics following mindfulness-based cognitive therapy in Major Depressive Disorder. Cogn Neurodyn 9:13–29. https://doi.org/10.1007/s11571-014-9308-y

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. Annual review of neuroscience, 13(1), 25-42. https://doi.org/10.1146/annurev.ne.13.030190.000325

Rabbi, A. F., Ivanca, K., Putnam, A. V., Musa, A., Thaden, C. B., & Fazel-Rezai, R. (2009). Human performance evaluation based on EEG signal analysis: a prospective review. In 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 1879-1882). IEEE. https://doi.org/10.1109/iembs.2009.5333877

Recarte, M. A., & Nunes, L. M. (2003). Mental workload while driving: effects on visual search, discrimination, and decision making. Journal of experimental psychology: Applied, 9(2), 119. https://doi.org/10.1037/1076-898x.9.2.119

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. American Journal of Physiology-Heart and Circulatory Physiology. https://doi.org/10.1152/ajpheart.2000.278.6.h2039

Rosenberg, M. D., Finn, E. S., Scheinost, D., Papademetris, X., Shen, X., Constable, R. T., & Chun, M. M. (2016). A neuromarker of sustained attention from whole-brain functional connectivity. Nature neuroscience, 19(1), 165-171. https://doi.org/10.1038/nn.4179

Saxe, R., & Kanwisher, N. (2003). People thinking about thinking people: the role of the temporo-parietal junction in “theory of mind”. Neuroimage, 19(4), 1835-1842. https://doi.org/10.1016/s1053-8119(03)00230-1

Schurz, M., Maliske, L., & Kanske, P. (2020). Cross-network interactions in social cognition: A review of findings on task related brain activation and connectivity. cortex, 130, 142-157. https://doi.org/10.1016/j.cortex.2020.05.006

Shaffer, H.J., 1996. Understanding the means and objects of addiction: Technology, the internet, and gambling. Journal of Gambling Studies, 12(4), pp.461-469. https://doi.org/10.1007/bf01539189

Scheff, S. W. (2016). Nonparametric statistics. Fundamental statistical principles for the neurobiologist. Elsevier, Amsterdam, 157-182. https://doi.org/10.1016/B978-0-12-804753-8.00008-7.

Soni, R., Upadhyay, R., & Jain, M. (2017). Prevalence of smart phone addiction, sleep quality and associated behaviour problems in adolescents. International Journal of Research in Medical Sciences, 5(2), 515-519. https://doi.org/10.18203/2320-6012.ijrms20170142

Suhail, T. A., Indiradevi, K. P., Suhara, E. M., Suresh, P. A., & Anitha, A. (2021). Electroencephalography based detection of cognitive state during learning tasks: An extensive approach. Cognition, Brain, Behavior, 25(2), 157-178. https://doi.org/10.24193/cbb.2021.25.08

Tattersall, A. J., & Foord, P. S. (1996). An experimental evaluation of instantaneous self-assessment as a measure of workload. Ergonomics, 39(5), 740-748. https://doi.org/10.1080/00140139608964495

Thomée, S., Härenstam, A., & Hagberg, M. (2011). Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults-a prospective cohort study. BMC public health, 11(1), 1-11. https://doi.org/10.1186/1471-244x-12-176

Uncapher, M. R., Lin, L., Rosen, L. D., Kirkorian, H. L., Baron, N. S., Bailey, K., ... & Wagner, A. D. (2017). Media multitasking and cognitive, psychological, neural, and learning differences. Pediatrics, 140(Supplement 2), S62-S66. https://doi.org/10.1542/peds.2016-1758d

Van Der Schuur, W. A., Baumgartner, S. E., Sumter, S. R., & Valkenburg, P. M. (2015). The consequences of media multitasking for youth: A review. Computers in Human Behavior, 53, 204-215. https://doi.org/10.1016/j.chb.2015.06.035

Van Deursen, A. J., Bolle, C. L., Hegner, S. M., & Kommers, P. A. (2015). Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. Computers in human behavior, 45, 411-420. https://doi.org/10.1016/j.chb.2014.12.039

Wang, X. W., Nie, D., & Lu, B. L. (2014). Emotional state classification from EEG data using machine learning approach. Neurocomputing, 129, 94-106. https://doi.org/10.1016/j.neucom.2013.06.046

Wolf, I., Dziobek, I., & Heekeren, H. R. (2010). Neural correlates of social cognition in naturalistic settings: a model-free analysis approach. Neuroimage, 49(1), 894-904. https://doi.org/10.1016/j.neuroimage.2009.08.060

Tables

Table 1

Comparison of the impact of smartphone use on task performance and health between high- and low-user groups (The results of Chi-Square test are shown with X^2 and *P* values).

Parameter	High-user Group (n= 310)	Low-user Group (n= 298)	X^2	P Value
Phone use during task	251 (80.96%)	198 (66.44%)	35.07	0.000
Performance degradation	152 (49.03%)	95 (32.55%)	12.54	0.005
Sleep Problems	130 (41.93%)	96 (32.21%)	8.32	0.040
Stress problems	191 (58.38%)	151 (50.67%)	9.45	0.049

Figures

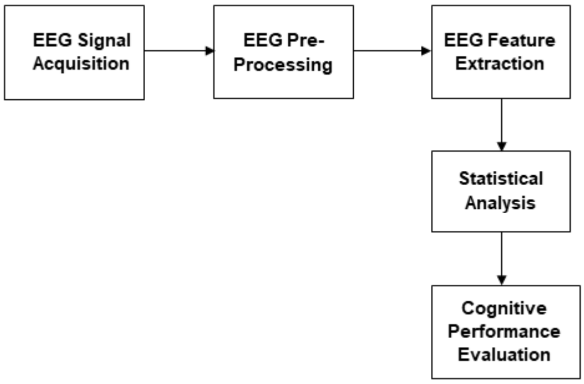


Figure 1. Block diagram of the proposed work for cognitive performance assessment using EEG features

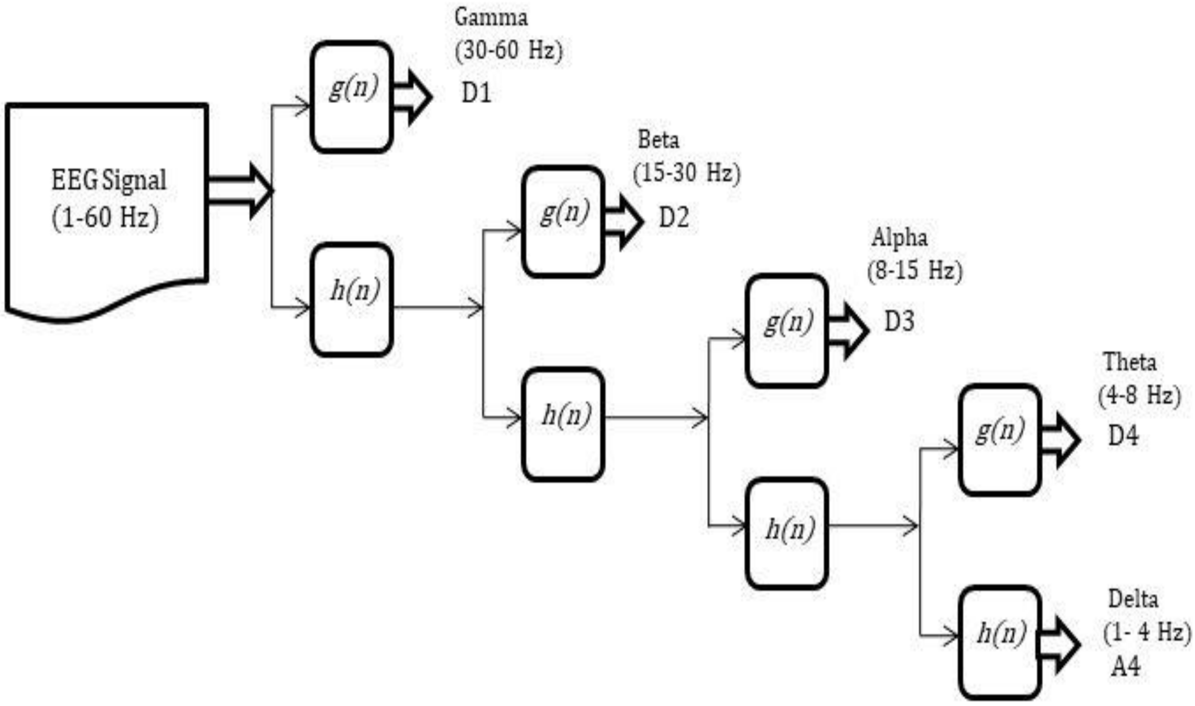


Figure 2. Four-level Wavelet decomposition of EEG signal into five bands. D indicates detail (high frequency) component and A represents approximation (low frequency) component.

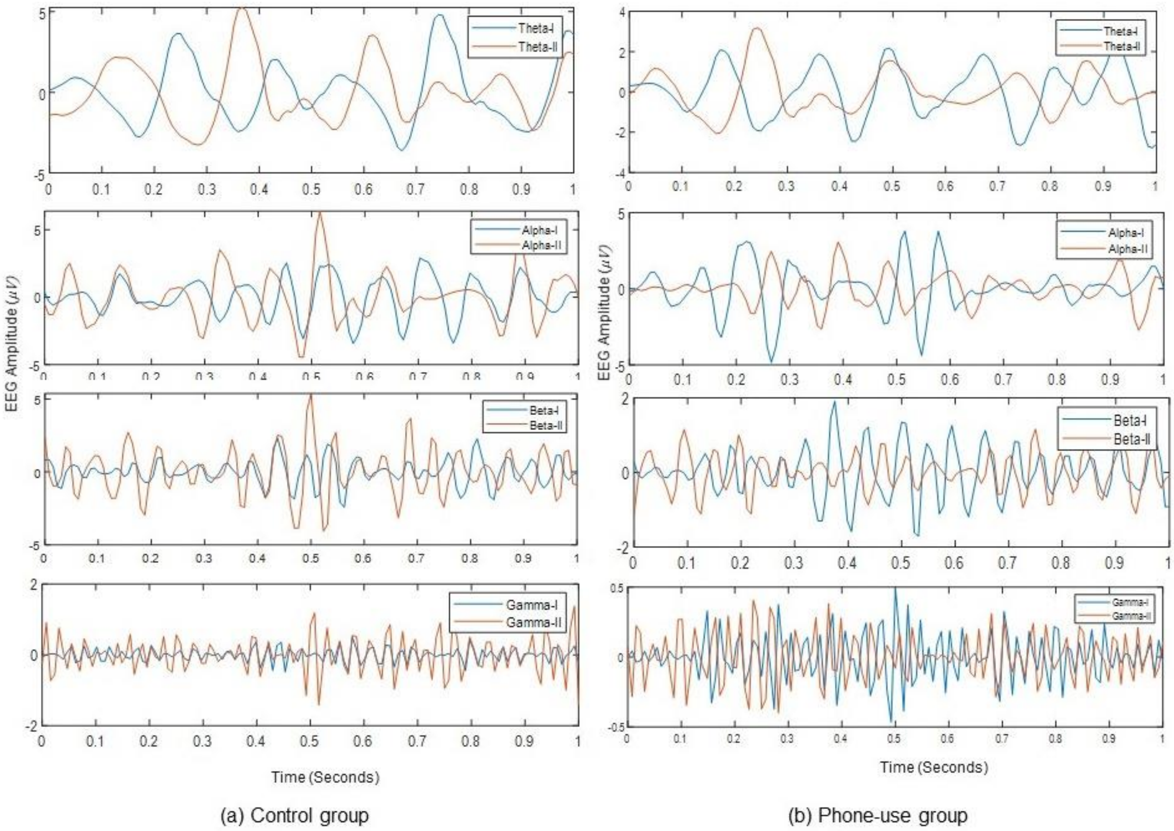
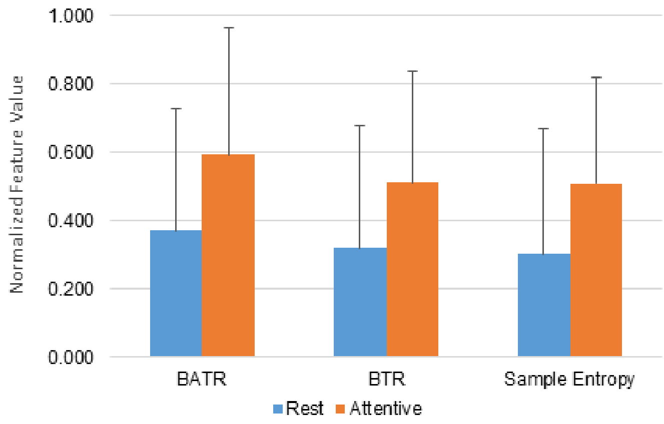
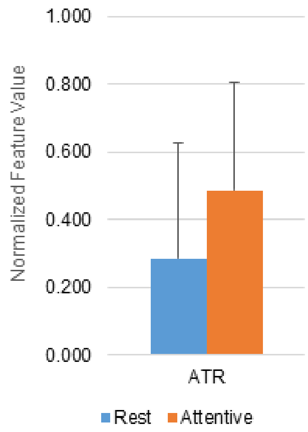


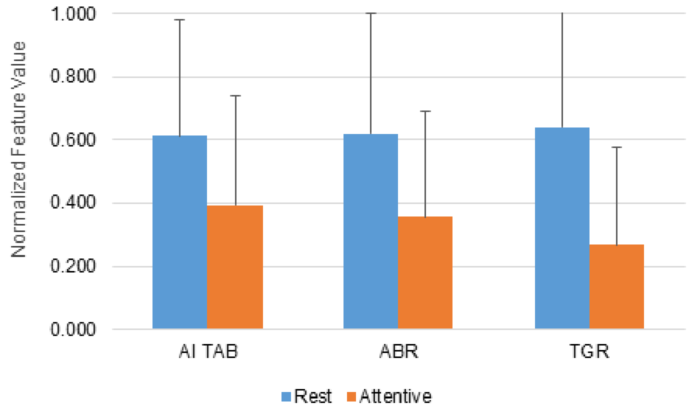
Figure 3. Variations in theta, alpha, beta, and gamma rhythms during the two learning tasks for a representative subject from each group. EEG bands extracted from EEG samples averaged over frontal channels are shown. For the phone use group, Task-I and Task-II are learning tasks before and after the smartphone usage. For the control group, Task-I and Task-II represent two learning tasks with an idle state between them.



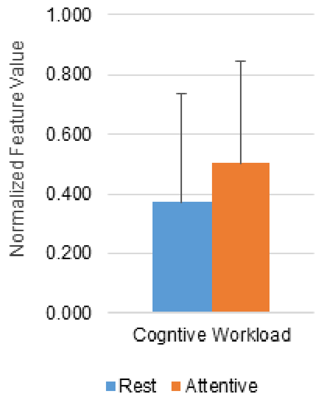
(a) Beta to (alpha+theta) ratio (BATR), beta to theta ratio (BTR), and Sample entropy



(b) Alpha to theta ratio (ATR)

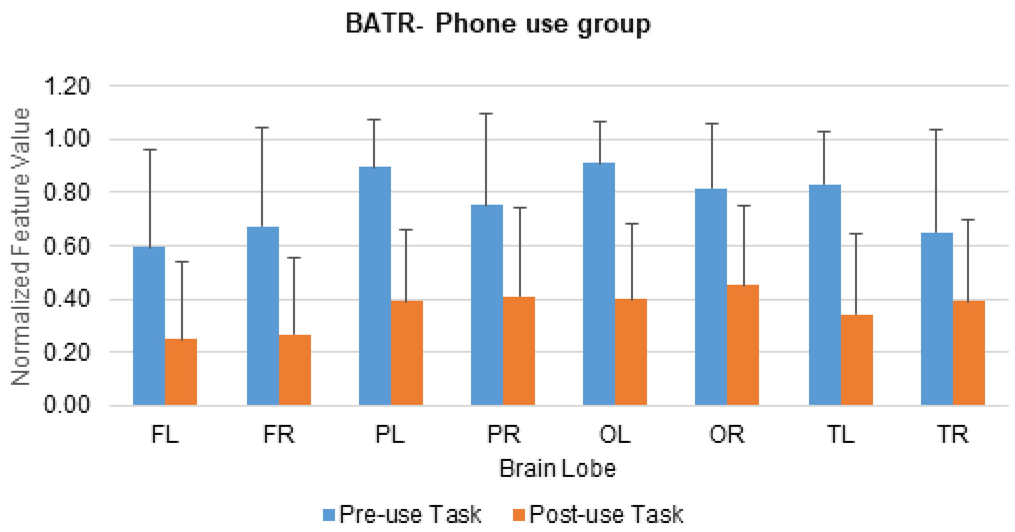


(c) Attention index AITAB, alpha to beta ratio (ABR), and Theta to gamma ratio (TGR)

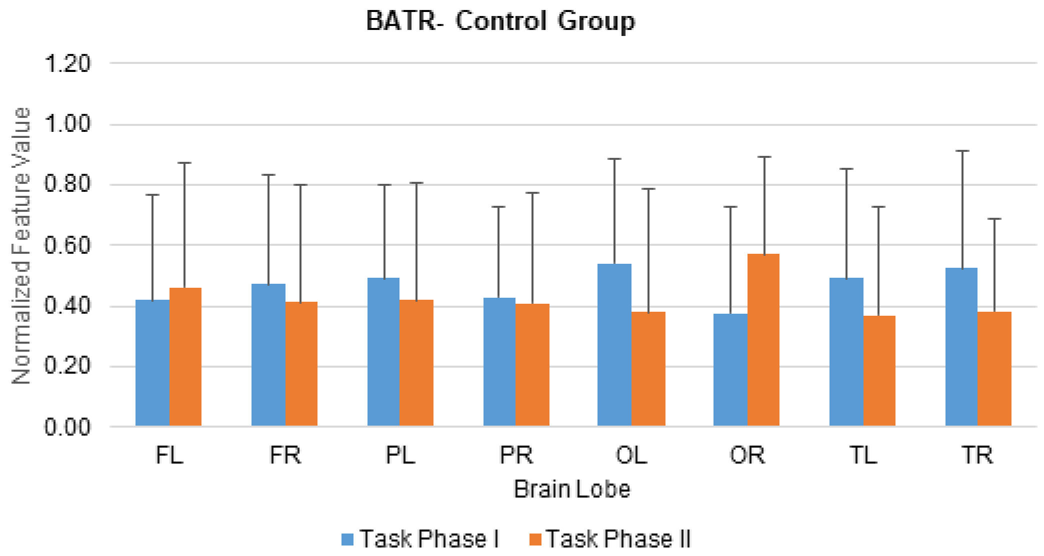


(d) Cognitive workload (CWL)

Figure 4. EEG features during resting and attentive states. Mean values (averaged across brain lobes over 22 subjects) with standard deviations are shown.

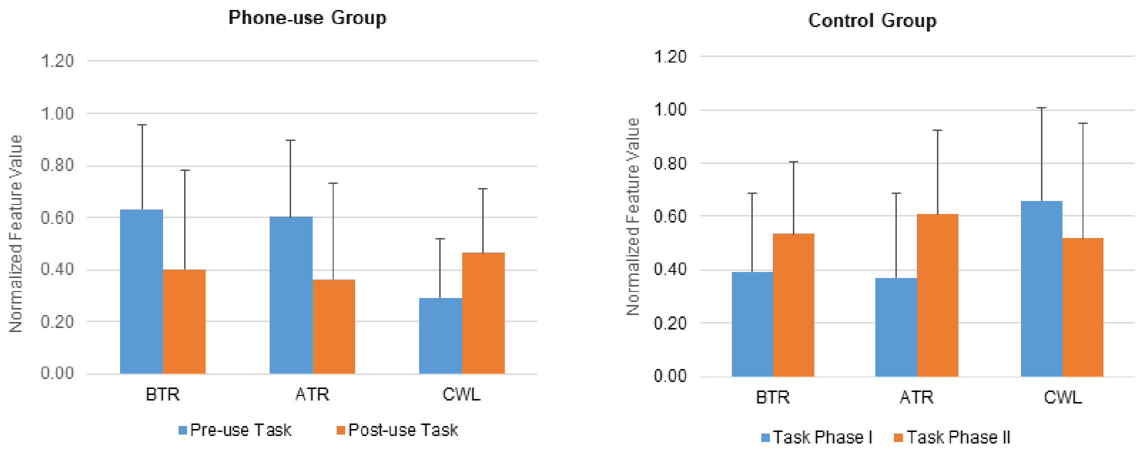


(a) Beta to (alpha+theta) ratio (BATR) in phone-use group

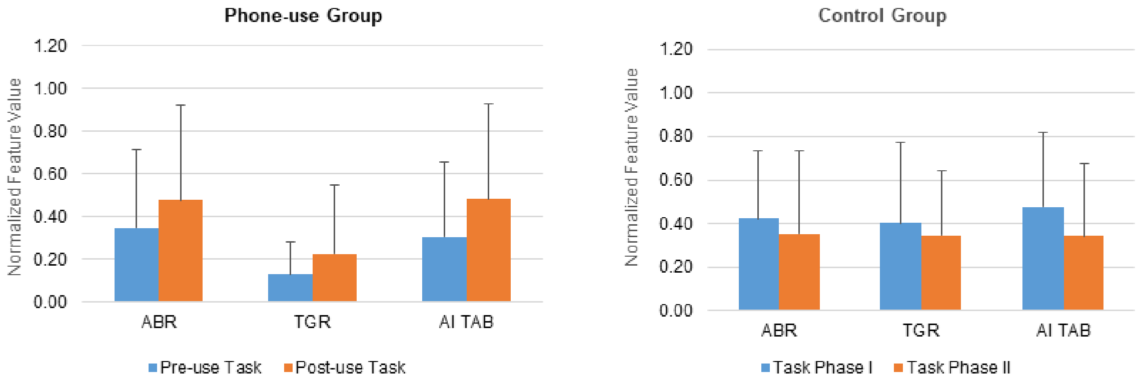


(b) Beta to (alpha+theta) ratio (BATR) in control group

Figure 5. Beta to (alpha + theta) ratio (BATR) across brain lobes in phone-use group and control group. Mean values with standard deviations are shown. (FL- frontal left, FR- frontal right, PL- parietal left, PR- parietal right, OL- occipital left, OR- occipital right, TL- temporal left, and TR- temporal right)

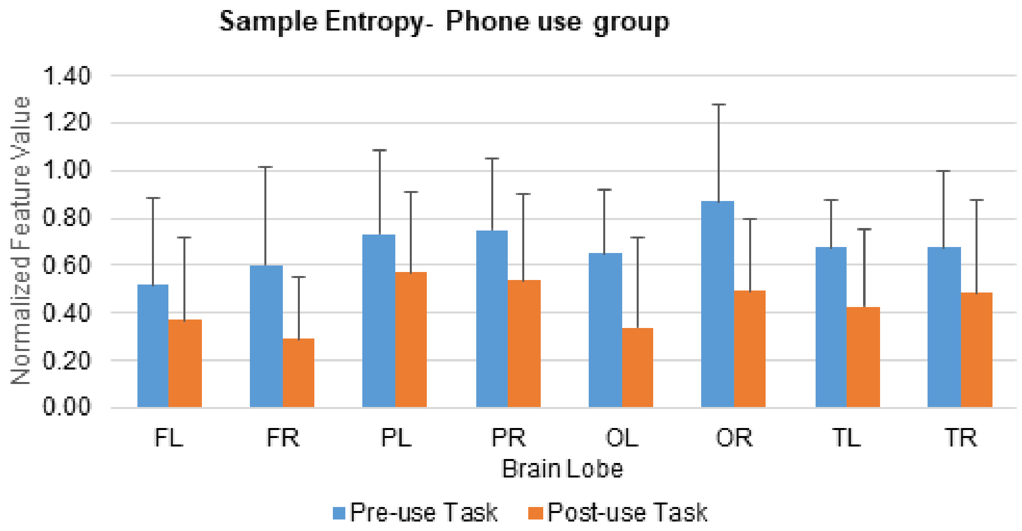


(a) Beta to theta ratio (BTR), alpha to theta ratio (ATR), and cognitive workload (CWL) in phone-use group and control group

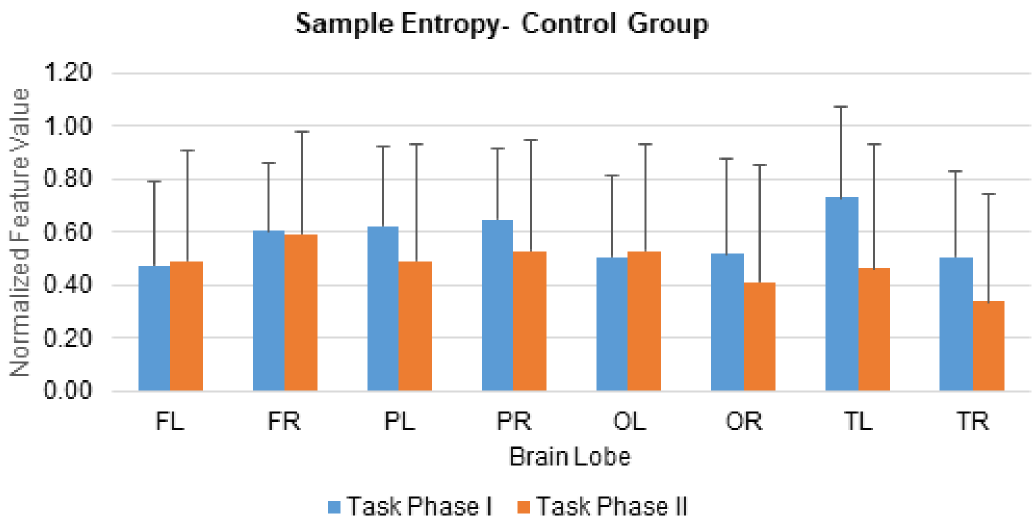


(b) Alpha to beta ratio (ABR), Theta to gamma ratio (TGR) and Attention index AITAB in phone-use group and control group

Figure 6. Variations in EEG based cognitive performance indices in phone-use group and control group. Mean values with standard deviations are shown.



(a) Sample entropy in phone-use group across different lobes



(b) Sample entropy in control group across different lobes

Figure 7. Sample entropy in phone-use group and control group. Mean values with standard deviations are shown. (FL- frontal left, FR- frontal right, PL- parietal left, PR- parietal right, OL- occipital left, OR- occipital right, TL- temporal left, and TR- temporal right)