Chapter

An Overview of Mindwave Applications: Study Cases

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Abstract

Brain-computer interfaces (BCIs) have diverse applications across various research domains. In healthcare, individuals with disabilities in communication and controlling prosthetic devices are aided. Beyond healthcare, BCIs integrate seamlessly into Internet of Things (IoT) and smart environments, enabling intuitive device control and interaction, enhancing user experiences. In neuromarketing and advertising, BCIs help decipher consumers' preferences and emotional responses to products and services, providing businesses with profound insights into consumer behavior. In education and self-regulation, BCIs monitor and regulate students' cognitive states. BCIs use sensors and hardware to capture brain signals, with non-invasive electroencephalography (EEG) technology being a pivotal component. Preliminary studies analyzing cognitive load using EEG signals and the Mindwave device pave the way for measuring student learning outcomes, shedding light on cognitive and neurological learning processes. Our research explores these parameters, particularly the Mindwave system, aiming to understand brain function across domains. To this end, we conduct a range of diversified studies, trying to better grasp parameters such as attention, concentration, stress, immersion, and fatigue during various tasks. Ultimately, our work seeks to harness BCIs' potential to improve our understanding of brain function and enhance various areas of knowledge.

Keywords: mindwave, attention, concentration, stress, immersion, fatigue, EEG, cognitive load, cognition, education

1. Introduction

Brain-computer interface (BCI) has been used in several research disciplines such as: medical, intelligent environments, neuromarketing & advertising, education & self-regulation, gaming & entertainment, and security or authentication domains. There are a variety of applications in the medical field, such as the prevention of smoking or alcoholism in the event of a loss of certain functions or a decrease in the alert level due to alcohol consumption or smoking [1, 2]. The prevention of traffic accidents and other type of incidents due to motion sickness could be avoided through a state monitoring and alertness system. It is feasible to identify a number of motion sickness prevision cues by analyzing EEG power responses in lateral, parietal, occipital, occipital midline brain regions and in the left and right motors [3]. Another aspect of the EEG utility in the medical area is related to the detection and diagnosis of several diseases such as tumors

[4], brain disorders such as forecasting epileptic seizure activity [5] or sleep disorders [6]. The physical or mental rehabilitation is other area of EEG intervention in the medical area. BCI can also be used to enable users to convert their thoughts into actions substituting motor movement for those with neuromotor disabilities or to offer rehabilitation in order to restore motor or cognitive functions that have been impaired due to disease or trauma. We can refer to Ref. [7] in terms of regaining mobility, for example, to be utilized to control tools like prostheses [8, 9], thinking that certain brain stroke injuries might be reorganized and the impaired motor functions could be recovered by neuroplasticity [10]. BCI may also be employed in rehabilitation in combination with virtual reality [11], augmented reality [12], and supervising and directing avatar motions from brain waves. Smart environments and the Internet of Things (IoT) could also benefit from BCIs in order to enable more comfortable and safety living standards [13, 14]. An application of BCIs in this field is related to smart environments that emit signals in order to demonstrate by their workers the important functions, for example, a doctor in an operating room [15] or a driver in an intelligent transportation [16]. Another strategy is to link a standard consumer BCI device to the IOT [17] or to enable a person with severe disabilities to remotely operate the household appliances around them [18]. BCIs can also be used to identify users in systems through bio-signals contributing to the security of the systems as these signals are difficult to synthesize, avoiding attacks and unauthorized accesses [19, 20]. The fields of neuromarketing and advertisement are other areas benefiting from the connection to BCI. It is usually done employing sophisticated high-resolution EEG statistical approaches in the temporal and frequency domains to analyze the capacity to trace brain activity while watching commercial TV advertisements [21]. BCI and EEG applications are becoming more popular, notably in educational settings. Nevertheless, the number of studies on this subject is rather modest, and the use of EEG-based systems in learning situations is currently uncommon [22]. Existing studies are primarily measuring students' levels of attention while completing mental activities, with a particular emphasis on attentional and motivational factors (such as reading assignments or seeing instructional material). Only 22 papers on this topic were found in a current search [22] leading researchers to the conclusion that the EEG is primarily used in online learning contexts rather than in traditional offline settings. They have been discussed in relation to motor abilities rather than intellectual abilities more frequently. The authors suggest using BCIs to evaluate students' reading proficiency in a variety of settings [23, 24], to research the best qualities of learning materials [25–27], and to learn more about how students interact with teachers and provide feedback on their inquiries [28, 29], in general research on e-learning [30, 31], to promote self-regulation of learning [32], the regulation of emotions in educational fields [33] and in sport competitions [34], through neurofeedback giving personalized interaction to each learner according to his/her responses [35] and improve cognitive performance [36], to assess an individual cognitive state [37] and analyze the impact of workload mental Fatigue [38]. The area of games and entertainment combined with BCI can also provide a multi-brain entertainment experience with several purposes [39, 40].

2. BCI contextualization

2.1 Concept

BCI is a method of controlling computers that involves no physical movement and instead uses brain activity that has been recorded using specialized equipment.

For Wolpaw et al. [41], BCI is a communication system with two adaptive elements that mutually complement one another. BCI has also been defined as a method of communication that enables a person to communicate her or his purpose to the outside world just by thinking, independent of the brain's normal nerve and muscle output channels [41]. BCI technology is a potent instrument for user-system communication, according to other writers, who note that it does not need any outside gadgets or human intervention to issue orders and complete interactions [42]. Current researchers believe that BCI provides a direct line of communication between the brain and an outside equipment [43–47]. BCIs quantify the activity of central nervous system (CNS) and transform it into artificial production that may subsequently be utilized to replace, improve, repair or complement genuine CNS output [41].

BCI allows users to interact with the world without the need of peripheral nerves and muscles by identifying patterns in brain signals and producing actions based on these patterns [48]. Brain electrical signals were first obtained from the cortical surface of animals in 1875 [49] and in 1929, Hans Berger described the first successful effort to capture the scalp's electroencephalography. Jacques Vidal created a computer-based device that gathered electrical impulses taken from the scalp and translated them into instructions in 1973, coining the phrase "brain-computer interface" [50]. Many BCI hardware components and software platforms have since been created, particularly in the early 2000s. While BCI software is crucial to the process of producing usable output and interpreting brain signals, BCI hardware is primarily utilized to capture brain signals. Receiving brain signals that have been directly recorded by the brain is necessary for BCI. BCIs employ the voltage changes in specific brain regions to record the user's brain activity. There are several ways to accomplish this: invasively, by implanting electrodes into the brain; partially invasively, by inserting electrodes into the skull without penetrating the brain; and non-invasively, by placing sensors on the scalp outside of the body.

2.2 Components

In BCI systems, active cortical neurons may be recorded in a variety of methods [51, 52], such as by EEG (electroencephalography), which involves placing multiple electrodes on the scalp. The most practical, least intrusive and easiest to use BCIs are non-invasive. Other approaches may be employed in these BCIs, but we focus on EEG because it is the least expensive, most widely utilized, and well suited for our needs. Measurement of the central nerve activity brought on by brain electrical impulses translates the associated identification of brain activity into a pattern that corresponds to a person's intended action [53]. These electrical impulses' magnitude is linked to certain brain areas. The electrodes/sensors are positioned in a certain manner, often categorized using recognized criteria like the 10–20 system or 10–10 system [54–56]. The spacing between electrode placements is indicated by the numbers 10 and 20, which correspond to 10% or 20% of the front-to-back or right-to-left distance, respectively. Usually, the following five regions are considered: frontal, central, parietal, temporal and occipital lobes. The potential locations for the electrodes to be placed in order to collect brainwaves are shown in **Figure 1**. A letter indicating the location of the electrode is associated with each location. These letters are: FP (Frontal Pole), F (Frontal lobe), C (Central region), P (Parietal lobe), T (Temporal lobe) and O (Occipital lobe) [54–56]. Also, there are places marked with the symbols "2″ and "L," which denote electrodes that are positioned between two areas and used to measure the voltage difference in that area. The letters may also be accompanied by a number, with an odd

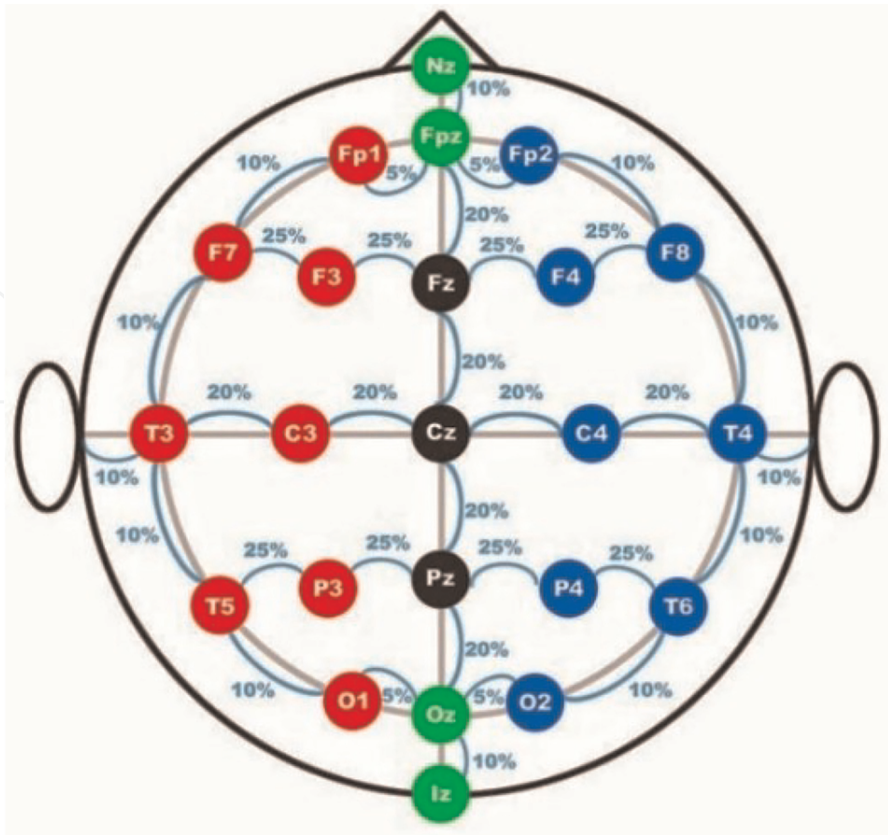

Figure 1.
EEG electrode placement [57]. These points are often also colored differently; the ones in black represent the 10–20 system, and the ones in black represent the 10–10 system.

number denoting the left half of the brain and an even number denoting the right side. The numbers for each side rise as the distance from the center (C) decreases [55, 56].

2.3 Frequency analysis

Through the EEG, it is possible to determine the amount of effort associated with an activity measuring several frequencies. Usually, to analyze the EEG signal we consider five distinct frequency bandwidths [53, 57, 58].

1. Delta (0.1 Hz or 0.5 to 4 Hz): As it usually happen in adults in deep sleep or coma states (occurring frequently in kids during the day), it is not very much used in that research area.

2. Theta (5–7 Hz or 4–8 Hz): is frequent in states of meditation, drowsiness, deep relaxation or specific sleep states.

3. Alpha (8–13 Hz): is the most common wave in adults and typically appears when people are relaxed, as when they are closed-eyed and not thinking at all.

4. Beta (13–25 Hz or 13–30 Hz): This is typically associated with states of alert. Concentration and anxiety. According to certain studies, this type of wave can be divided into Beta Low (13 to 17 Hz) and Beta High waves (17 to 30 Hz).

5. Gamma (30 to 100 Hz): These waves are also less researched; however, some authors say they are associated with hyper-vigilant mode, arousal, peak performance or visual perceptions of their surroundings [59].

The energy on nearly all other bands is directly connected with the activity in the brain, whereas the energy on the Alpha band is frequently thought to be negatively related to brain activity. For example, increased brain activity results in higher energy on the Theta, Beta and Gamma frequency bands [57, 58, 60]. EEG can be used to measure several aspects of interest (cognitive load, attention, concentration, among others combining several of the expressed above waves).

3. Types of devices for capturing EEG signals

Currently, there are various types of devices available for capturing EEG signals. Among the most commonly used and ones we have experienced are Emotiv **Figure 2**, Enobio **Figure 3**, MindWave **Figure 4** and Muse **Figure 5**. These headset portals are equipped with EEG (electroencephalography) technology. All the presented devices are compatible with several operating systems such as Android, Linux, iOS and Windows, and have some software compatible with them. These devices offer several key advantages, including their user-friendly nature, utilizing a minimal number of sensors for improved portability and inconspicuousness. Their discreet visual appearance helps users avoid attracting undue attention from others [62].

These aforementioned devices enable the study of various cognitive and emotional states, including levels of attention, concentration, frustration, stress and fatigue. They also facilitate the analysis of different brainwave frequencies such as Alpha, Beta, Delta, Gamma and Theta, which allow for the examination of parameters like the ERD/ERS complex and P100 or P300 potential. The availability of multiple channels provides more detailed insights into the spatial distribution of brain activity, enabling improved

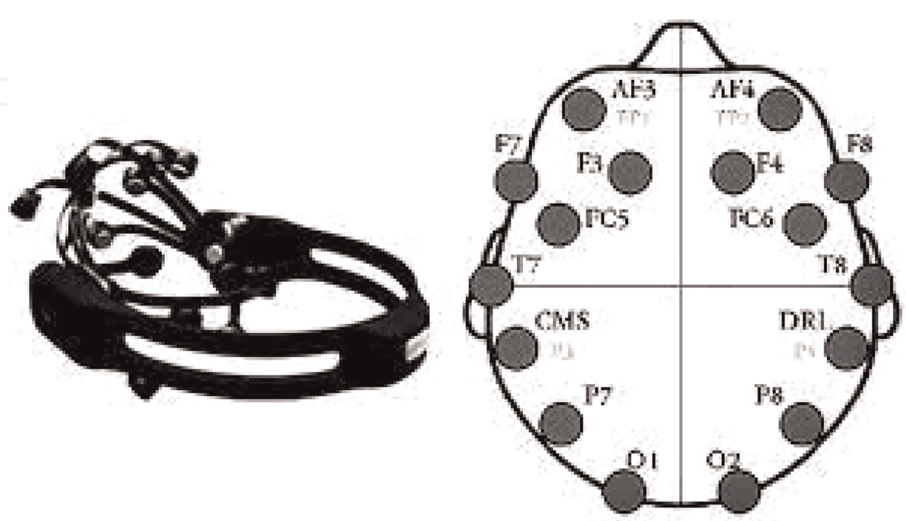

Figure 2.
Emotiv and electrodes placement. Emotiv is wireless Bluetooth EEG measurement equipment. It has 14 channels (wet electrodes, requiring saline water) to record and measure signals. Electrodes placed at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. It operates at a sampling rate of 2048 Hz with 14 bits. It is compatible with several operating systems such as Android, Linux, IOS and Windows, and has some software compatible with it.

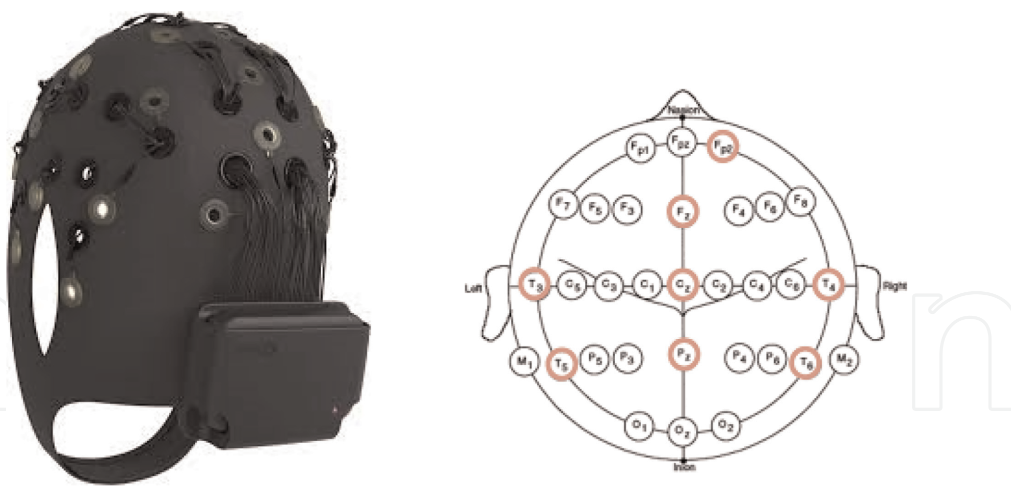

Figure 3.
Enobio and electrodes placement. Eight channels (8 simple-to-apply dry electrodes) and utilizes Bluetooth for real-time wireless communication with a computer. The positions of the F3, F4, T7, C3, Cz, C4, T8 and Pz electrodes were used. It operates at a sampling rate of 500 Hz. It provides Linux, Mac and Windows research tools in addition to Android, iOS and Windows SDKs.

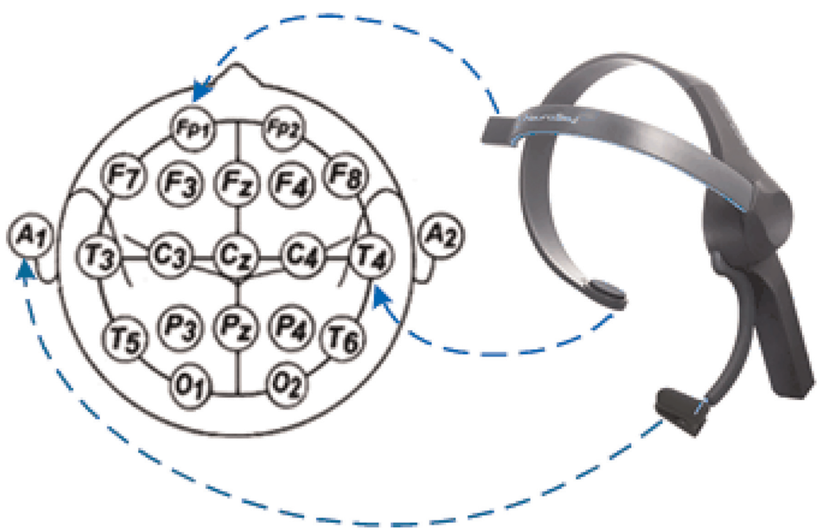

Figure 4.
*Mindwave and electrode placement. Mindwave [61] is a wireless Bluetooth EEG device in a form of headband. It has 4 channels (1 dry electrode—Fp1, 1 reference and 2 ground electrodes (T4 and A1)), **Figure 4**. One electrode, located at the AFz position (10–20 international standards), is included with the Muse headband. It operates at a sampling rate of 512 Hz and 12 bits. It provides Linux, Mac, and Windows research tools in addition to Android, iOS, and Windows SDK.*

localization of activity sources and neural analysis. A greater number of channels enhance brain coverage, thereby enhancing the accuracy of the study.

4. EEG studies

4.1 General studies

BCIs have applications in several areas. Respecting medical applications we can consider a variety of healthcare including prevention in cases of alcoholism or smoking [2, 63, 64], the detection and diagnosis of abnormalities associated with brain tumors, epilepsy seizures or dyslexia or sleep disorders [6, 65, 66], rehabilitation and

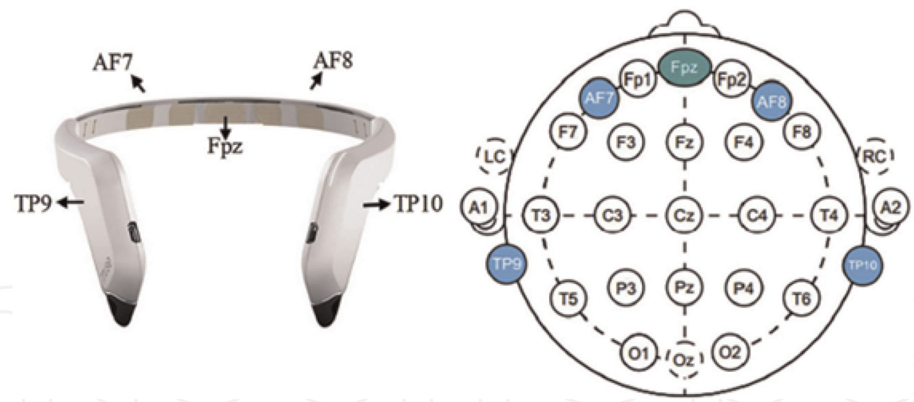

Figure 5.
Muse and electrodes placement. Headband-style wireless Bluetooth EEG with 5 channels (2 dry electrodes—Fp1 and Fp2; 2 ground electrodes—TP9 and TP10 and 1 reference (Fpz)). Electrodes are attached to the Muse headband at positions AF7 and AF8 (10–20 international standards). It works on a 256 Hz sampling rate with 12 bits. It provides Linux, Mac, and Windows research tools as well as Android, iOS, and Windows SDKs.

restoration especially in physical rehabilitation [11, 67–69]. The domain of Internet of Things and smart environments have also some systems developed using BCIs [13, 14, 70] as well as the fields of advertisement [21].

4.2 EEG in education and problem solving

The research conducted using various EEG devices in the field of education, which is our main focus, is presented in this part along with related work. As noted in Ref. [22] there are not many studies in the area of educational contexts, although some may be indicated, notably for the assessment of Concentration levels during reading tasks [23, 71–73]; Student engagement activities [74]; Feedback personalized [75]; Self-regulation [75]; to research the ideal qualities of learning resources [76–78]; to learn more about how students engage with professors and what feedback they provide to inquiries from professors [28, 74, 79] and in overall e-learning studies [30, 80, 81]. In Ref. [82] research was done in order to explore software developer's emotions while doing a task of making changes in software. The study had several goals; however, the main one was to understand and measure several psychological factors related to emotions occurring during the tasks and their correlation with the evolution of the task. We found yet another one related to program comprehension. The study [83] compares the programming comprehension between novice and expert programmers and observe the differences. Some studies evaluate students' emotions when engaged in computer programming activities [84–86]. The signals from the brain are processed in this study [62], to quantitatively examine, contrast and comprehend how emotions and/or cognitive load change when coders work with two different programming languages, C and Python.

4.3 Mindwave-EEG parameters

The EEG signal's major frequency range is [0.5 30] Hz, which may be separated into five major bands: Delta, Theta, Alpha, Beta and Gamma waves each with frequencies in the range of [0.5–4] Hz, [4–8] Hz, [8–13] Hz, [13–30] Hz and [30–40] Hz, respectively. This range carries information about mental states. Several brain wave fluctuations connected to various frequencies are mentioned in the literature as being connected to various levels of meditation and focus. Alpha waves correspond to levels of brain activity during meditation, while Beta and Gamma waves have been linked to attention, perception and cognition. The attention and meditation measure, which is listed on eSense with a scale from 1 to 100, is utilized in this study. The attention measure identifies the level of a user's mental "attention" or "focus," which occurs during intense concentration and intellectual activity, and the meditation measure is connected to reduction inactivity by the active mental processes in the brain. The eSense Attention indicator displays the level of mental focus or attention that a user is exerting in order to assess their level of concentration. The eSense Meditation measuring device tracks the brain's mental activity and displays how intense a user's mental relaxation is. **Table 1** describes the eSense meter values:

Values	eSense	Description
0	unable to calculate	excessive noise
[1–20]	"strongly lowered" levels	distractions, agitation
[20–40]	"reduced"	wandering thoughts, lack of focus
[40–60]	"neutral"/"baseline" levels	normal
[60–80]	"slightly elevated"/higher than normal levels	focus, concentration
[80–100]	"elevated"/"heightened" levels	elevated attention

Table 1.
Description of the eSense meter values.

Attention and meditation values ranging from 1 to 100, at a sampling rate of 1 Hz. These attention and meditation values are established using specialized algorithms. Levels amid 40 and 60 are regarded as "neutral" or baseline, 60 to 80 denote somewhat raised eSense levels, and 80 to 100 denote significantly elevated levels of attention/meditation. Values below 40 are interpreted as (slightly/strongly) lowered levels.

When the eSense value is 0, background noise prevents a reliable calculation of the signal. The blink strength is also saved as an integer number in the range of 0–255. The level of focus, meditation and blinking were all measured every second.

4.4 EEG analysis

To understand their correlation, the time of execution at each level for each participant can be calculated together with a study of the brain waves. It is crucial to remember that the results should be carefully interpreted, taking into consideration any additional factors that can have an impact on the correlation between brain waves and execution time. Because of it, several parameters in time and in frequency were used. It is also important to ensure that the data used for the analysis is reliable and valid, and that appropriate statistical techniques are used to address potential confounding factors or sources of bias.

4.4.1 Behavior data

Also, certain ratios of wave energy for each of the frequency characteristics were examined. Three alternative metrics were generated to characterize mental states using the frequency information bands, including:

1. Stress (S)

$$S = \frac{\beta}{\alpha} \tag{1}$$

2. Fatigue (F)

$$F = \frac{\alpha + \Theta}{\beta} \tag{2}$$

3. Immersion (I)

$$I = \frac{\Theta}{\alpha} \tag{3}$$

where Θ represents Theta activity, α represents Alpha activity and β represents the Beta activity. This Stress index, Eq. (1) has been previously used in other works. An example is [87], where the authors were able to relate the ratio's values to Stress scores reported by participants in a survey. It was also used to inverse version in Ref. [88], where it was found that Stressful situations resulted in an indicator of lower (therefore higher in the case of the ratio shown earlier). The second ratio Fatigue Eq. (2) has been used in various studies, in different forms [89]. In Refs. [90, 91], the inverse ratio is used in order to measure attention levels. As such, this version can be used as an indicator for mental fatigue. In Ref. [89], this ratio is tested, being compared to three other ratios in order to understand which is the most adequate for measuring Fatigue during driving. It was found that while there were significant differences for all ratios between the alert and fatigued states, this ratio was the one that showed the largest increase, and as such was able to best discriminate the two states. This is calculated only for the Pz signal, since that is where it has been proven to be more relevant. Finally, the last ratio is related to Immersion. It has been previously used in Ref. [92], where it was found that it was a valid indicator for states of high in-game Immersion. While this characteristic is related to concentration, it is still distinct from it, and these can occur at different times, which makes it an interesting variable for analysis [93].

The results are reported considering the minimum, maximum, average and standard deviation σ values. Significant level is reported at $p < 0.05$. The average of the parameter values were computed and compared. The time to conclude the tasks, as well as the energy of the various bands, was considered and related in this study.

4.4.2 ERS/ERD

In order to reflect the activation or inhibition of brain activity during the activity, an examination of the complex of event-related synchronization and desynchronization (ERD/ERS) was carried out to better characterize the data. The energy in the frequency band of interest during the activity interval is given by A, and the beginning reference interval is given by R, in order to derive values of the ERD/ERS complex. ERD/ERS is a metric used to calculate the amount of energy that is defined as:

$$\frac{ERD}{ERD}\% = \frac{R - A}{R} \tag{4}$$

Two values, ERS and ERD, can be distinguished using Eq. (4).

1. ERD: R > A (positive value) signifies that the band power of the test interval is lower than that of the reference, indicating a decline in the synchronization of the fluctuations (desynchronize).

2. ERS: R < A (negative values) signifies that the fluctuations' synchrony is increased by the test intervals' band power, which is higher than that of the fluctuations (synchronize).

5. Preliminary studies

In all these studies, we used the Mindwave device and the EEG Analyzer software (Android application).

5.1 Study1: assessing Mindwave capability to measure the attention mind states during car driving

This research paper presents the outcomes of a study conducted using the Mindwave headset to evaluate the levels of attention and mind states of drivers who were operating under side distraction tasks [94]. The primary objective of the research was to assess the quality and quantity of data collected by the headset while measuring the attention levels of drivers under different driving scenarios. The study aimed to test five different hypotheses:

1. H1—Driving and listening music implies reduced eSense Attention level (under 40) for all participants.

2. H2—Driving and eating implies low eSense reduced eSense Attention level (under 40) for all participants.

3. H3—Driving and talking on the mobile implies reduced eSense Attention level (under 40) for all participants.

4. H4—Driving in city center implies low eSense reduced eSense Attention level (under 40) for all participants.

5. H5—The study revealed a positive correlation between the eSense Attention levels measured by the Mindwave headset and the participants' self-reported driving experience.

A sample of four participants (3 females and 1 male) aged between 29 and 42 (M = 35,5) took part in the study. Participants were given standard instructions before each test like informing the group of side tasks to be executed and also that the purpose of the trial is not to evaluate their own performance. The participants were given the following tasks:

1. driving under real and moderate traffic conditions, like a motorway at approximately 100 km/h, during the daytime with given parallel tasks which decreases the attention level, such listening music, mobile talking, eating. Each task takes approx. 3 min.

2. driving in higher traffic conditions at approximately 50 Km/h, namely in a city center with highly traffic, without any other parallel task. This task takes approx. 3 min.

At the outset of the study, the participants were provided with a brief questionnaire to fill out, which solicited information regarding their identification, driving habits and frequency of driving. After completing each task, the participants were asked to complete a self-assessment form based on their experience. The findings from this investigation revealed a positive association between the attention levels that were measured objectively using the device and the attention levels that were subjectively reported by the participants themselves. This demonstrates the coherence between the attention levels recorded by the Mindwave device and the drivers' own perception of their attention state, thereby providing evidence to support the efficacy of BCI technology in assessing cognitive performance during driving.

- A one-sample t-test (df = 100) was run to test if the difference of the meter values between each of the participants for each single task was significantly different from 0. We observed a significant variability among participants, mainly by driving and listening music and then by driving and eating. For the remaining tasks, the comparison of the average of meter values between the participants was 50% equal.

- It was also executed a one sample t-test for tasks comparison. Just between driving and listening music and driving in city center with high traffic was not observed a difference of their average values. All other tasks comparisons show significant variability.

- The hypotheses tested produced slightly mixed results by different participants: Not all side tasks implied a reduced attention level, namely under 40 on eSense meter scale, but still the data average is on the interval of wandering thoughts, lack of focus and normal attention levels. Considering that all subjects have driving experience and periodically execute all these side tasks, it is understandable that attention levels are sometimes kept normal.

This investigation focuses on the evaluation of the Mindwave Mindset device to measure attention levels while driving and performing other tasks that may distract the driver. It proved the Mindwave Mindset capabilities regarding attention level analysis.

5.2 Study2: Attention and concentration in normal and deaf gamers

In a study, an experiment was conducted to compare the attention, concentration and eye blinking levels of hearing-impaired and normal hearing individuals while playing a computer game with and without sound [95]. The aim of the study was to understand the influence of sound on maintaining attention and concentration levels, and to explore how a brain-computer interface (BCI) could aid in recognizing these cognitive levels in two different populations: deaf and normal hearing individuals. The study also aimed to investigate the influence of music on attention and concentration levels in computer games and the relationship between blinking level and its impact on attention and concentration levels.

Fifteen individuals participated in the study, with 10 individuals having normal hearing and five individuals being deaf. All participants were male and between the ages of 18 and 20. The group of individuals without hearing problems was divided into two subgroups, with one subgroup playing the game with sound and the other without sound. For deaf individuals, only one test was conducted due to their hearing impairment. The game used in the study was Outlast, a first-person survival horror game developed by Red Barrels. The data obtained from the experiment was divided into three groups:

- Normal Hearing Sound (NHsound)—individuals without hearing problems playing with sound

- Normal Hearing (NH)—individuals without hearing problems playing without sound

- Impaired Hearing (IH)—deaf individuals

The results revealed that normal hearing individuals playing with sound exhibited higher levels of concentration compared to when playing without sound. Impaired hearing individuals showed a similar level of concentration. Additionally, there was a strong correlation between sound and the level of blinking, with sound inducing higher levels of blinking. The attention and meditation levels were also found to be influenced by blinking. The presence of sound increased blinking levels, while impaired hearing individuals exhibited the lowest levels of blinking. Among the normal hearing individuals, the group playing with sound demonstrated significantly higher levels of blinking compared to the group playing without sound. However, even the group playing without sound showed a relatively high level of blinking. Notably, the group playing with sound exhibited greater dispersion of blinking values compared to the other two groups.

A test called t-student was used to compare three sets of data (normal hearing with sound, normal hearing without sound and impaired hearing) to see if there were any differences in attention, concentration and blinking. The results showed that there were no significant differences in attention and concentration levels between normal hearing with sound and impaired hearing individuals. However, the level of blinking was different.

The study also found that sound had an impact on attention and concentration levels in normal hearing individuals. The sound increased concentration levels but decreased attention levels, meaning that the focus was maintained. Interestingly, attention and concentration levels were similar between impaired hearing and normal hearing individuals when playing a game with sound. However, the level of blinking was different across all three groups.

It is worth noting that in normal hearing individuals without sound, the level of blinking was higher than in impaired hearing individuals.

This investigation focuses on the evaluation of the Mindwave Mindset device to determine the effect of sound on attention, concentration and eye-blinking levels in both normal hearing and impaired hearing individuals while playing a computer game. It proved the Mindwave Mindset capabilities regarding attention levels, concentration levels and eye-blinking analysis.

5.3 Study3: Does music help to be more attentive while performing a task? A brain activity analysis

The purpose of this study was to explore the impact of different types of music (heavy metal or relaxing) on the levels of attention and concentration of individuals with and without a mental workload task (playing a game) [96]. The study involved 5 participants (3 males—Ind1, Ind2 and Ind3, and 2 females—Ind4 and Ind5) from the college campus, with an average age of 19. The participants played the game "Despicable Me: Minion Rush2" and completed five tasks individually:

Task 1—playing the game without music.
Task 2—playing the game with heavy metal music.
Task 3—playing the game with relaxing music.
Task 4—listening to heavy metal music without playing the game.
Task 5—listening to relaxing music without playing the game

Each task lasted for 2 minutes. The results revealed that music had a varying impact on attention and concentration levels among the participants. A comprehensive statistical analysis was conducted to understand the relationship between these two parameters by task and by individual. The average attention and concentration levels for each task and each individual were computed, and the correlation coefficient between attention and concentration levels was determined. The study found that playing the game with relaxing music (Task 3) resulted in the highest levels of attention and concentration. Additionally, listening to relaxing music (Task 5) also showed a positive impact on attention levels. Conversely, heavy metal music (Tasks 2 and 4) had a negative impact on attention levels. The correlation coefficient analysis revealed that heavy metal music had a high correlation with attention and concentration levels in all individuals in Task 2. However, in Task 3, where individuals played the game with relaxing music, there was no significant correlation between these two parameters. The t-test analysis indicated that attention was statistically different among all individuals in Task 2, except for Ind2 and Ind5, who had statistically equal values on average. In terms of concentration, Ind1 and Ind2, as well as Ind4 and Ind5, had statistically equal values, while Ind3 showed different values compared to others. Overall, this study highlights the impact of different types of music on attention and concentration levels and shows the effectiveness of Mindwave Mindset in analyzing these parameters. This investigation focuses on the evaluation of the Mindwave Mindset device to investigate the effect of different types of music (heavy metal and relaxing music) on attention and concentration levels in individuals while playing a game. It proved the Mindwave Mindset capabilities regarding attention levels and concentration level analysis.

5.4 Study4 and Study5: Using brain computer interaction in programming problem solving and understand and characterize mental effort in a programming-oriented task

The primary objective of this study was to examine essential cognitive parameters, specifically attention and meditation, while students participated in a problem-solving oriented programming task [97, 98]. Furthermore, three EEG features were extracted, specifically the powers of Theta, Alpha and Beta bands, and the variability of energy within these bands was analyzed and compared with the device's parameters. The study also investigated the correlation between the duration of the experiment and the frequency bands. The study group consisted of 30 students, predominantly male

(98%), enrolled in the 2nd year of the Informatics Engineering degree. The participants, aged between 18 and 50 years, had an average age of 22.3 ± 5.7 years and had already developed some programming skills during the previous year. The students voluntarily participated in the study and were asked to play a classic Labyrinth-Angry Birds game, which consisted of 20 levels with increasing difficulty. The objective of the game was to join 2 objects using available blocks of code, and new elements were introduced at certain levels, changing the paradigm. The dataset acquisition was carried out in three steps. In the first and last steps, the mental workload of the participants was evaluated before and after playing the game for 3 minutes each. In the second step, the mental workload during the game was evaluated for a maximum of 10 minutes. **Figure 6** illustrates the protocol used in this study. The study's findings revealed that the frequency of Beta energy increased when the tasks required higher levels of reasoning and previous knowledge, as well as during a change in the game paradigm when participants faced difficulties or needed more time to complete tasks (attention). Conversely, a high level of energy in the Theta band was observed during states of drowsiness and deep relaxation (meditation). The time taken to solve a task was high, indicating a high energy load of the Beta bands, which corresponds to a higher cognitive load. The study provided evidence of a relationship between attention and meditation levels and the energy of various bands during cognitive demanding tasks. Furthermore, there was strong evidence of Theta activity during activities that require focused attention. An increase in EEG activity in the Theta band over the frontal midline regions of the scalp was observed when there was a demand for executive control, attention, and working memory. A deeper analysis using the t-test was conducted, revealing that in most levels where the bands presented statistically significant differences, the time spent was higher. An analysis of the Event-Related Desynchronization (ERD)/Event-Related Synchronization (ERS) complex was also conducted, and the results indicated that it reflects the activation or inhibition of brain activity during the game. The study concluded that there was a desynchronization with respect to the initial state at the levels with a paradigm change.

Figure 7 illustrates the ERD/ERS values considering the Theta band. The ERD value can be interpreted as a correlation of an activated cortical area with increased excitability—desynchronization. A desynchronized EEG indicates that a few neurons in the neuronal circuit work independently or desynchronized, representing a state of maximum agility and large capacity to store information. The study of the ERD/ERS complex yielded interesting results, indicating greater excitation of the neurons

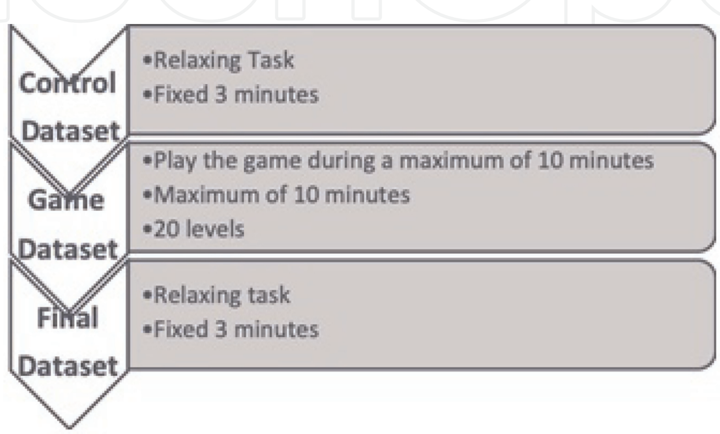

Figure 6.
The flow chart of the activity phases.

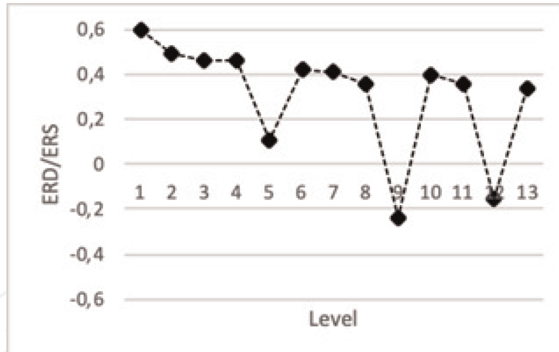

Figure 7.
ERD/ERS values considering Theta band.

during the more difficult levels or those that require more time to complete. This investigation focuses on the evaluation of the Mindwave Mindset device to analyze the effects of a programming problem-solving task on cognitive parameters such as attention and meditation, and the correlation with EEG features. It proved the Mindwave Mindset capabilities regarding attention levels, concentration levels and the ERD/ERS complex analysis.

5.5 Study6: An experimental study of typography using EEG signal parameters

The aim of this study was to examine the mental workload associated with three different typefaces and their impact on seven emotionally related words [99]. The importance of typeface in graphic design and its role in readability was considered, as certain fonts are more easily perceived and can lead to higher levels of understanding, attention, immersion, stress or fatigue. Despite increased knowledge about how readers interact with text, limited understanding exists about how the brain processes this information. EEG technology was used to investigate this, and the study aimed to assess mental fatigue, stress and immersion during a monotonous reading task with thirty participants (nine males and twenty-one females) aged 18 to 21. The experiment involved sequentially visualizing seven emotional words (Joy, Sadness, Love, Hate, Sympathy, Unrest and Calmness) in three different typefaces: Sans Serif (Open Sans), Serif (Old London) and Handwriting (Dancing Script). Each word was presented for 3 seconds, followed by a one-second pause, and the task lasted for a total of 83 seconds, **Figure 8**.

In the study, participants were shown words on a screen and asked to read them. The location and size of the words remained the same throughout the experiment. The EEG signal and signal associated with power bands were analyzed for each participant and divided into 21 segments of 3 seconds for each task (visualization and reading). The average of these segments for each group of words and typography was analyzed for Theta, Alpha, Beta, Fatigue, Immersion and Stress parameters. The study aimed to answer four questions regarding the effect of different words and typefaces on energy levels, Fatigue, Immersion and Stress.

- Q1—Different words written in the same typeface present different energy levels? In what waves?

- Q2—The same words written in different typefaces present different energy levels? In what waves?

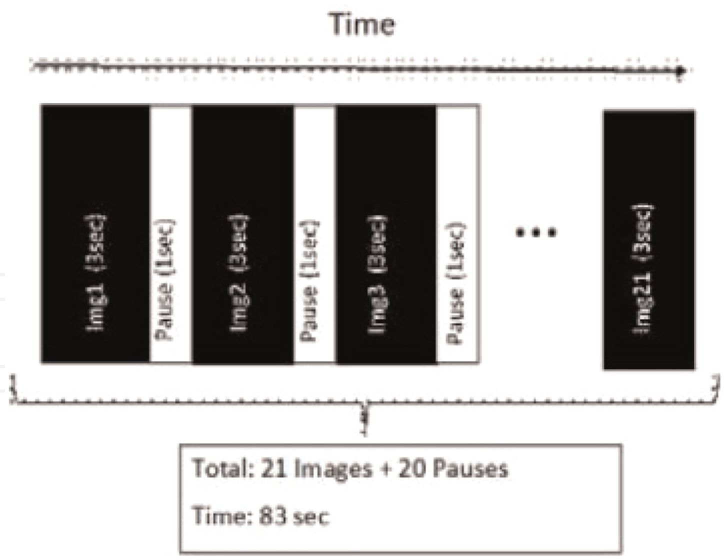

Figure 8.
The timing diagram of the experiment.

- Q3—Different words written in the same typeface present different levels of Fatigue, Immersion and Stress? In what typefaces (OS, OL and DS)?

- Q4—The same words written in different typefaces present different levels of Fatigue, Immersion and Stress? In what typefaces (OS, OL and DS)?

To answer the first question (Q1), energy levels were compared between words of the same typeface. No statistically significant differences were found in the Theta and Beta bands, but there were differences in the Alpha band, with "Calmness" showing the most significant energy differences. To answer the second question (Q2), energy levels in the Theta, Alpha and Beta bands were compared between the same words written in different typefaces. Overall, there were no statistically significant differences in energy levels, except for "Calmness" and "Sadness" in some cases. To answer the third question (Q3), levels of Fatigue, Immersion and Stress were compared between different words written in the same typeface. There were no significant differences in Immersion levels, but there were differences in Fatigue and Stress levels. "Calmness" showed the most significant differences in these parameters. To answer the fourth question (Q4), levels of Fatigue, Immersion and Stress were compared between the same words written in different typefaces. There were no statistically significant differences in Immersion levels, but some differences were found in Fatigue and Stress levels. Overall, there were no significant differences in wave energy and the parameters analyzed when words were grouped by typeface. However, significant differences were found when analyzing individual words and typefaces. The study highlights the importance of choosing the right typeface in communication projects to ensure readability and attention, and reduce Fatigue and Stress. Although the results were not conclusive, the study provides a foundation for future research in this area. This investigation focuses on the evaluation of the Mindwave Mindset device to assess mental workload (Fatigue, Stress and Immersion) while comparing three typefaces of letters and also their influence in seven words related with emotions. It proved the Mindwave Mindset capabilities regarding attention levels, concentration levels and the ERD/ERS complex analysis.

5.6 Study7: A study of color using Mindwave EEG sensor

The main goal of this study was to examine how color affects brain activity when analyzing complex figures made up of various color combinations of dots that form shapes [100]. Our objective was to understand the energy levels of Theta, Beta and Alpha waves in each figure and to analyze the levels of Fatigue, Immersion and Stress in order to determine how easily colors are perceived. We aimed to answer the following questions:

- Q1—What color combinations and levels result in faster response times?
- Q2—Which color combinations and levels lead to higher levels of Fatigue, Immersion and Stress?

The experiment involved sequentially displaying 15 images, each with a shape composed of dots of varying sizes, colors and distances from each other. Participants were required to select one of three answer options based on what they saw in each figure. Along with each level, participants were asked to identify the shape they could see, as shown in **Figure 9**. During the task, each figure was presented at the center of the screen with answer options, and participants were not restricted by any time limit to respond. They had to select the correct option and confirm their choice with a second click. A white screen appeared for 1 second after confirmation, and then, a new image appeared. After completing the experiment, participants were asked to classify the figures into three groups of difficulty levels (Low, Medium and High) based on the ease of identifying the shapes, **Figure 10**. The study included 28 participants (8 males and 20 females) aged 18–22 years, who were recruited to perform the task. The data was organized using three different clustering methods to determine if the parameters (Fatigue, Stress and Immersion) were discriminative. The three clustering methods were based on Error (average number of wrong answers for each figure obtained by all participants), Time (average time spent on each figure by all participants) and User Experience (UX) obtained through a survey of students to classify each image into three degrees of difficulty (Low, Medium and High). The clustering methods were compared using the parameters values for Stress, Fatigue and Immersion, and the UX method was found to be the most discriminative. The analysis focused on the UX clustering method, as it was the most effective for all parameters, **Figure 11**.

The three different forms of data clustering were considered to compare the parameter values:

- Stress, Eq. (1)
- Fatigue, Eq. (2)
- Immersion, Eq. (3)

The results of the cluster analysis showed that the figures in cluster C1 were the easiest to identify, with the lowest average response time, and correctly identified by all individuals. However, this cluster also had the highest levels of Fatigue, meaning that color combinations used in these images for long periods should be avoided as they cause tiredness. The average level of Immersion in this cluster was the highest,

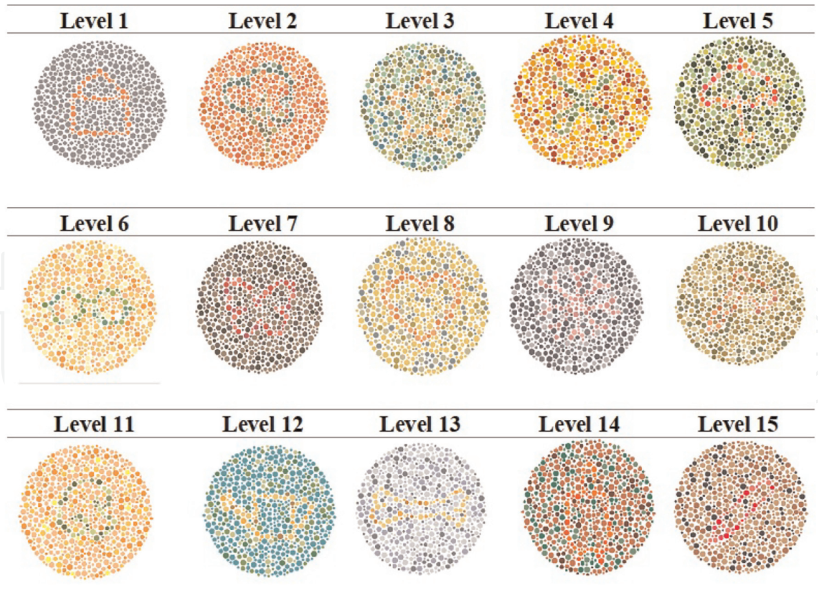

Figure 9.
Levels of the game.

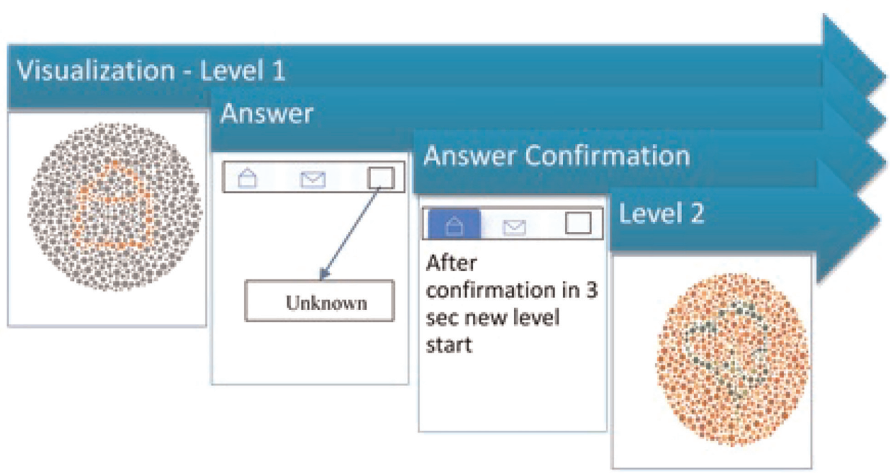

Figure 10.
Experimental design—protocol.

indicating a good Concentration level. In cluster C2, the average response times were higher than in the previous cluster, indicating that factors made the figures more difficult to identify. In this cluster, some images required more time to identify, even though they were correctly identified by all individuals. Some images had high levels of Fatigue due to vibrant and clear background and foreground colors, while others confused the users with the distribution of colors and size of dots in the image, contributing to higher levels of Fatigue, Immersion, and time to identify the picture. In cluster C3, response times were the highest, and there were more incorrectly identified images. The levels of Fatigue and Immersion varied and were intensified due to very vibrant, very light, or very dark color combinations between the foreground and background colors. While the research questions could not be answered clearly, the study confirmed that a good chromatic contrast is essential to minimize

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Error method		Time method		UX method	
C1_E:	L9, L14	**C1_T:**	L9, L14	**C1_UX:**	L1, L12
C2_E:	L2, L3, L10, L11, L13, L15	**C2_T:**	L2, L3, L4, L5, L6, L7, L8, L10, L11, L12, L3, L15	**C2_UX:**	L2, L3, L4, L5, L6, L8, L10, L11, L13
C3_E:	L1, L4, L5, L6, L7, L8, L12	**C3_T:**	L1	**C3_UX:**	L7, L9, L14, L15

Figure 11.
Clustering levels considering error, time and user experience methods

the levels of Fatigue and Stress. The level of Immersion can be caused by contrasts that are difficult to perceive or even absent.

This investigation focuses on the evaluation of the Mindwave Mindset device to investigate the effect of color on brain dynamics in the analysis of complex figures, including different color combinations of dots to obtain forms and consequently analyze the levels of Fatigue, Immersion and Stress in each one. It proved the Mindwave Mindset capabilities regarding Fatigue, Immersion and Stress levels and the ERD/ERS complex analysis.

5.7 Study8—A new methodology to learn loops: Validation through brain-computer interaction

The objective of the study was to evaluate the effectiveness of using a card-based methodology to teach for loops to students [101]. The study was carried out over a three-week period, with 18 students divided into two groups. One group was taught using traditional methods, while the other was taught using the card-based methodology. Two written tests were administered to both groups to assess their understanding of for loops, while a third test was conducted using a brain-computer interface (BCI) to measure brain activity. Test1 consisted of four questions, with two on simple loops and two on chained loops. Each question provided students with an output and four code options, and students had to select which of the four codes produced the output. Test2 consisted of seven questions, with two on simple loops and five on chained loops. In each question, a code was given, and students had to select which of the four output possibilities were generated by that piece of code. Test3 was a digital test that included questions similar to the ones in the paper-based tests, but students had BCIs, following a protocol described in **Figure 12**.

The study aimed to measure the effectiveness of the card-based methodology while also ensuring that students did not rely on guesswork to answer the questions. Brain activity in the Alpha band was analyzed to measure the ERD/ERS complex. The results of Test1 showed no significant difference in results among students taught with different methodologies. However, Test2 showed that the card methodology group had better results in some questions. The results obtained using BCI confirmed the results obtained in the paper-based tests. The students taught with both approaches had difficulties with simple decreasing loops and chained loops, but the card methodology showed better results in synchronization and required less attention and effort to comprehend the questions than the traditional method. The results indicated that for more difficult questions (decreasing simple loops and decreasing chained loops), there was a desynchronization (ERD) that was more accentuated in the traditional method. Alpha band activity was considered a correlation of

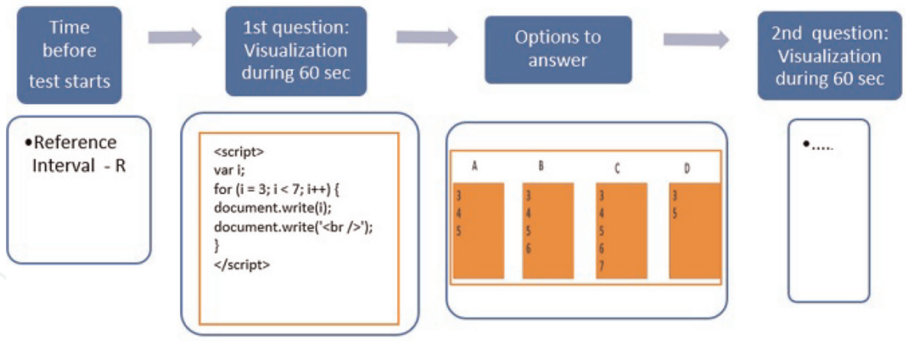

Figure 12.
The timing diagram of the experiment—protocol.

deactivated cortical networks, representing ERS, a synchronization state, and an activated state with enhanced processing of information, representing ERD, a desynchronization state. These findings suggest that the card methodology is effective in maximizing the comprehension of easier concepts, and the traditional method may be more suitable for more complex topics. This investigation focuses on the evaluation of the Mindwave Mindset device to measure the attention level, particularly in the Alpha band activity, of two different approaches to understand the repetitive structure "for." It proved the Mindwave Mindset capabilities regarding the analysis of the complex ERD/ERS on Alpha band.

6. Key findings and learning discussion suggestions

According to the results, there is a correlation between participants' self-reported subjective attention levels and the levels of attention that were tested objectively. What shows that the Mindwave device is feasible. The results also showed that the sound had an effect on attention and concentration levels. The sound increased concentration levels but decreased attention levels, meaning that the focus was maintained. The particular type of sound is also important to maintain the focus. According to the study's findings, Beta energy was more frequent when individuals encountered challenges or needed more time to finish tasks (attention), as well as when participants needed to use more reasoning and prior knowledge. On the other hand, it was found that when people were deeply relaxed and sleepy (meditation), there was a significant amount of energy in the Theta band. The length of time needed to complete a task suggested a high energy load on the Beta bands, which is consistent with a higher cognitive load. Interesting findings from the investigation of the ERD/ERS complex also showed that the neurons were more excited during the harder levels or those that took longer to finish. The research also emphasizes how crucial it is to select the proper typeface for projects in order to assure readability, facilitate communication and analyze crucial mental workload parameters (attention, Fatigue, Stress and Immersion). Certain color combinations made figures more difficult to interpret, requiring more time to identify or causing more levels of Fatigue, Stress or Immersion. These studies revealed information about the cognitive and neurological processes involved in several situations, using a brain-computer interfaces (BCIs) that can be transferred to educational settings to assess the achievement of many learning outcomes, including:

- Attention and focus: During learning exercises, BCIs may track a person's attention levels to determine how engaged and concentrated they are. This data can be used to evaluate the efficacy of educational materials or spot attention gaps that can impair learning.

- Mental workload: BCIs can calculate the cognitive load/stress that students are under while completing activities. By altering the degree of difficulty or adding more support when students are under a lot of mental workloads, this information can help instructional designers create the best possible lessons.

- Cognitive processing: BCIs can provide light on the brain activity underlying a variety of cognitive functions, including information retrieval, decision-making and problem-solving. Identification of efficient learning interventions and methods can be aided by monitoring these processes.

- Emotional states: BCIs are able to identify emotional states like stress, frustration or involvement during learning. Designing adaptive learning environments and treatments that encourage good emotional experiences and engagement can be informed by an understanding of learners' emotional reactions.

- Learning progress and performance: BCIs can monitor the brain activity patterns of students over time in order to evaluate their learning progress and predict performance results. This knowledge can help with adaptive feedback mechanisms and individualized learning strategies.

- Knowledge transfer and retention: By observing brain activity during the application of newly learned ideas or during memory recall activities, BCIs may measure the transmission and retention of information. This may be used to assess the success of learning initiatives and pinpoint areas for development.

The use of BCIs in evaluating these learning outcomes has great potential, but additional study and development are still required to improve the methodology and uses of BCIs in educational contexts.

7. Conclusions and future work

Brain-computer interfaces (BCIs) are increasingly being used across a variety of domains. In this context, our focus is on their potential use in the educational sphere, but implementing them in this context is a complex undertaking. It can also be intrusive to require students to participate in activities that involve BCIs. As a result, we conducted a series of preliminary studies using cost-effective BCI devices that measure aspects such as attention, concentration, stress or fatigue using EEG signals in a less invasive manner. With these studies, we were able to evaluate the effectiveness of these devices and determine the potential for measuring cognitive skills in educational settings. In this chapter, two different approaches were presented, namely using eSense's own parameters (a package from Mindwave itself) or manipulating the signal and doing a frequency analysis directly to the raw date. This work was able to access several parameters using a device with a reduced number of channels. The study analyzed individuals performing various tasks that required a certain cognitive load. The tasks included driving while operating other distractive tasks, playing computer games with and without sound, engaging in programming problem-solving tasks, comparing different typefaces or colors in complex figures, and testing the effectiveness of a new methodology in teaching for loops to students.

By evaluating parameters such as attention, concentration, fatigue, immersion and stress in these different tasks, the study can provide insights into how the brain responds to different types of cognitive load. It is interesting to note that the study analyzed not only traditional learning activities but also everyday activities such as driving, which can have implications for driver safety and the design of driving interfaces. Furthermore, the study's focus on testing the effectiveness of a new methodology in teaching for loops to students is particularly relevant, as it highlights the potential use of BCI in developing personalized learning approaches that cater to individual needs.

By using BCI to monitor students' cognitive states, educators can adapt their teaching methods to better suit students' needs and improve their learning outcomes. Overall, these preliminary studies will provide important insights into the potential use of BCI in learning contexts, such as understanding how students learn, the factors that affect their performance and engagement, and the development of personalized learning approaches that cater to individual needs. The results of these studies may also lead to the development of BCI-based tools and technologies that can be used in the classroom to enhance learning outcomes.

One key application of our research is the ability to assess whether students are attentive or distracted during learning activities, providing valuable insights into their cognitive states. This information can be useful for instructors to design alternative instructional materials that reduce cognitive load and improve learning outcomes. By minimizing cognitive load, learners can hold more relevant information in their memory, resulting in a more effective learning process. Furthermore, our study contributes to the development of new human-computer interaction (HCI) tools that can be tailored to individual cognitive and emotional states, making technology more user-friendly and accessible. Our research has potential applications in other domains such as neuroscience, psychology, neuromarketing, entertainment and education. For example, our findings can be used to create educational tools that cater to individual learning styles and cognitive abilities, leading to better academic outcomes. The data collected during driving tasks can be used to develop safer driving practices, while the data collected during computer game play can be used to design games that are more engaging and effective at promoting learning. The data collected during programming problem-solving activities can be used to develop better training programs for software developers, and the data collected during figure comparison tasks can be used to improve the design of complex figures for better comprehension. Overall, our work is a promising development in the field of BCIs, with vast potential applications. Continued research and development in this area can lead to revolutionary advancements in technology, changing the way we interact with it and our understanding of the human mind. We believe that our work represents a significant step in this direction, particularly in the field of human-computer interaction, with implications for many other areas. We consider that the outcome of the present work is encouraging and has the potential for educational applications in several directions. We believe that this work represents a set of promising developments that could be very relevant in the area of human-computer interaction and with applications to many other areas.

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