Measuring and Decoding Emotion and Attention: An Experimental Model toward Evolving Innovative Adaptive Pedagogical Methods

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ABSTRACT

Adaptive pedagogy is a framework that systematically modifies instructional strategies, curricular content, and assessment methodologies in response to learners' diverse cognitive abilities, emotional and attention states, sociocultural contexts, and evolving educational needs to enhance learning efficacy and equity. The primary objective of this research was to illustrate an experimental model for measuring and deciphering learners' emotions and attention using brain waves through electroencephalogram (EEG) techniques and technologies such as the EMOTIV-EPOC-X Brainwear® headset hardware/software toward advancing novel adaptive pedagogical methods. The research design and methodology were specifically focused on the accuracy of these EEG measurements in assessing focus or consciousness and their accuracy in gauging some emotions, although with only limited reliability, through metrics such as excitement, engagement, and relaxation, as well as distinguishing electrical signals produced by facial expressions. The preliminary results of this research provided a robust experimental model for measuring and ultimately for training and testing learners in different environments for the purpose of obtaining accurate and consistent measurements for practical applications. The broader impact of the implemented experimental model will not only affect the field of adaptive pedagogy but also advance brain-computer interface theories and research in general.

Keywords: Adaptive Pedagogy, Emotion, Attention, EEG (Electroencephalography), BCI (Brain-Computer Interface)

Technical Definitions and Terminologies:

ADAPTIVE PEDAGOGY *- An instructional approach that dynamically adjusts teaching methods, content, and assessments based on learners' needs, including cognitive and emotional abilities, as well as contextual factors, in order to optimize educational outcomes.*
BCI *- Brain-Computer Interface. BCI functions by capturing brain signals produced by the central nervous system, subjecting them to analysis, and subsequently converting them into actionable commands, which are then transmitted to output devices for the execution of intended tasks.*
EEG *- An electroencephalogram (EEG) is a diagnostic procedure designed to gauge the electrical activity within the brain by employing minute metal discs (electrodes) affixed to the scalp. Brain cells communicate through electrical impulses, maintaining activity continuously, including during periods of sleep.*
EMOTIV-EPOC-X **14 Channel** ***Brainwear ® headset hardware/software*** *- A rotating headband suitable for placement either atop or at the back of the head, accompanied by specialized software tailored for contextualized neuroscience investigations and advanced applications in brain-computer interface (BCI) technology.*
EMOTIVE PRO SOFTWARE *- A software toolkit for professional brain research. Enabling to create neuroscience experiments and seamlessly capture EEG data from the EMOTIV headset. Allows conducting comprehensive customized brain research experiments, acquire and record raw EEG data, performance metrics, motion data, etc.*

1 Introduction and Concise Background

Adaptive pedagogy is a structured framework that continuously adjusts instructional strategies, curriculum content, and assessment methods to accommodate learners' diverse cognitive abilities, emotional and attentional states, sociocultural backgrounds, and evolving educational needs, with the goal of enhancing learning effectiveness and equity. Consequently, brain-computer interfaces (BCIs) relate to adaptive teaching and learning by enabling real-time monitoring of students' cognitive and emotional states, allowing for personalized and responsive educational experiences. By decoding attention levels and emotional engagement, BCIs can help educators adjust instructional methods, pace, and content delivery to optimize learning outcomes, enhance motivation, and reduce cognitive overload.

This experimental innovative research is inspired by the interest in being able to adequately measure emotions and attention to ultimately evolve innovative adaptive pedagogical methods.

The evolution of Brain-Computer Interfaces (BCI) has been tremendous in recent years and has thus impacted learners in various environments. For instance, Harvard Business Review article with the title of "*What brain-computer interfaces could mean for the future of work*" theorizes that drowsy driving can be mitigated and prevented with the help of brain-computer interface technology [9]. BCI technology has been around since the 1970s and recently has improved in accessibility and reliability [1,17,2]. These improvements have fluctuated in capacity within the academic and medical fields as prices and technology for BCIs have decreased. While BCIs can range in medical invasiveness (such as those inside and outside the scalp), the reliability for the *EMOTIV-EPOC-X* headset [EMOTIV-EPOC-X Brainwear ®,18], is that of a rather non-invasive external measurement outside the scalp [14,21,7,10,3,28]. Mak and Wolpaw published *Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects* with the goal of contextualizing research and advancements in the field to estimate how future progress will occur [16]. This particular research is vital insofar as it gives historical scope and a greater comprehension of what role BCIs have played, or have the capacity to play, in society and practical use. It begins by defining its terms, as it illustrates that BCIs link communication between brain signals and output to a digitally controlled interface. BCI advancement has origins in accessibility studies for restoring functionality to paralyzed or otherwise disabled individuals [16,6].

BCI technology typically measures muscular contractions, not brain signals, that allow for rather by brain signals, and allows for an increase in communication for those with severe motor disabilities, like those with Amyotrophic lateral sclerosis (ALS), spinal cord injury, and neuromuscular diseases [16]. The given article is thorough in that it covers topics of BCI signal types, the process of acquisition to BCI technologies, applications, and limitations.

While the *EMOTIV-EPOC-X* ® Headset can identify and provide different outlets, it primarily is driven by EEG waves to establish a connection with the BCI [8,30,11,12,1,13]. According to Mak and Wolpaw, "There are over 400 groups worldwide engaging in a wide spectrum of research and development programs, using a variety of brain signals, signal features, and analysis and translational algorithms" [16]. Given that this estimate is factual, this research is limited to the hardware provided and should only be understood to be a fraction of the potential practicality of this technology, especially given any hardware inconsistencies or difficulties in setup and use [20,24,15,27,26,19,22,31].

Moreover, the article "Brain-Computer Interfaces in Medicine" published by Shih, Krusienski, and Wolpaw [25] provides a new perspective on how humans use electrical frequencies in brain activity to influence or modify their environment. A new aspect of BCI applied science enables persons who cannot communicate or control their body parts to reconnect or operate assistive devices to walk or manipulate objects. This overview attempts to introduce BCI to the general medical community. Research into brain-computer interfaces is developing very rapidly, as indicated by the number of scholarly publications over the past decade. As an instance, the authors of the article have shown that frequencies recorded directly from the cortical surface can be translated by BCI to spell words accurately on a screen. To achieve the goal of BCI, the system consists of four sequential components: (1) signal acquisition, (2) feature extraction, (3) feature transformation, and (4) device output. Effective operational protocols make the BCI system adaptable and able to meet the specific requirements of varieties of users.

At present, research and study in the ultimate target group of impaired persons are largely limited to a few inadequate studies that are closely monitored by investigators [23]. Translating an exciting laboratory advance into clinical use, the BCI system that eventually improves the daily activities of handicapped users is just the beginning. It demonstrates that a selected BCI machine may be carried out in a shape appropriate for long-time period impartial domestic use, outline the proper consumer population and set up that they are able to utilize the BCI, reveal that they are able to set up BCI to help them in their local environments and also improve their lives. There are numerous headsets with scalp sensors available in the marketplace that may be used along with computers to create a device for controlling software applications. These and comparable headsets had been included in many industrial games, several of which declare to beautify consciousness and awareness through EEG-primarily based neurofeedback [25,5,4].

Studies in BCI and its improvement give outstanding encouragement to experts, scholars, and the general community. This inspiration could expedite the rapid growth of BCIs within a decade. They can also gradually be used regularly to update or repair beneficial characteristics for humans with serious disabilities with the aid of using neuromuscular and other related disorders. They could as well enhance recovery for humans with strokes, head trauma, and different diseases. Going forward, BCI will depend on progress in important areas such as the development of handy, accessible, and stable signal-acquisition hardware; validation and distribution of BCI; it also offers validated BCI reliability and value for many different user segments [25].

Concisely, the primary objective of this research is to illustrate an experimental model for measuring and deciphering emotion and attention using brain waves through EEG techniques and technologies, such as the EMOTIV-EPOC-X ® headset hardware and software, that contributes to innovative pedagogical methods. In addition to the standard brain wave signal collection, the measurements will be collected for excitement, engagement, and relaxation, as well as distinguishing electricity produced from facial expressions (future research phase). The results of this research may provide a pioneering experimental model for measuring, training, and testing users in varieties of environments with accuracy and consistency for practical applications. Ultimately, the implemented experimental model will significantly advance BCI theories and techniques, driving the evolution of innovative pedagogical methods to enhance learning.

1.1 Experimental Research Questions:

ERQ-1 *– Could an experimental model for measuring and deciphering emotion and attention using brain waves through EEG techniques and technologies, such as the EMOTIV-EPOC-X Brainwear ® headset hardware and software, be designed and validated for use in the brain-computer interface field in pedagogical methods?*
ERQ-2 *– Could a dynamic experimental model for measuring and deciphering emotion and attention be used ultimately for training and testing users in different environments for the purpose of accurate, and consistent measurements for practical applications?*
ERQ-3 *– Could an experimental model for measuring and deciphering emotion and attention produce statistically significant differences between meditation, action, and horror stimuli invoking scenarios using EMOTIV-EPOC-X Brainwear ® headset hardware and software?*

1.2 Alternative Hypotheses:

$\boldsymbol{H_a}$***-1*** *– An experimental model for measuring and deciphering emotion and attention produces a statistically significant difference between meditation and action stimuli invoking scenarios considering quantitative measurement [Theta 4-7 Hz] of relaxed brain wave.*
$\boldsymbol{H_a}$***-2*** *– An experimental model for measuring and deciphering emotion and attention produces a statistically significant difference between meditation and horror stimuli invoking scenarios considering quantitative measurement [Alpha 8-13 Hz] of excited brain wave.*
$\boldsymbol{H_a}$***-3*** *– An experimental model for measuring and deciphering emotion and attention produces a statistically significant difference between action and horror stimuli invoking scenarios considering quantitative measurement [Beta 14-30 Hz] of scared brain wave.*

2. Research Design Methods

2.1 Participants

Participants (*n=32*) of this research were volunteer students from several departments within the university. In this preliminary phase, the number of participants was intentionally kept at a level that allowed for a time-consuming procedure of setup of environment, testing, measuring, and collecting reliable data for analysis. The participants consisted of 24 males and 8 females with ages ranging from 19 to 37 years old.

2.2 Apparatus

An EEG system that is EMOTIV EPOC-X 14 Channel, capable of collecting various brain waves was used. A brief technical specification is presented below.

EMOTIV EPOC-X 14 Channel Brainwear ®
- *EEG sensors*
- *14 channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4*
- *2 references: CMS/DRL references at P3/P4; left/right mastoid process alternative*

EMOTIV Pro Software
The Emotiv Pro Software is used for conducting neuroscience research and education for EPOC X ® Flex, and Insight

2.3 Setting up EMOTIV EPOC-X Environment

In order to understand and break apart the components of research, the testing limitations, and the findings and results of the experiments, researchers must first establish the testing environment and software used to illustrate the brain waves measured. The *EMOTIV EPOC-X* ® headset can measure four brain waves. The frequency and brain states associated with the different brain waves reported by Abhang et al. and specifically, examples of each four brain wave characteristics (*Beta waves13-30 Hz, Gamma waves 12-16 Hz, Alpha Waves 8–12 Hz, Theta Waves 4–8 Hz, Delta Waves 0.5–4 Hz*) [1]. In Figure 1, these different brain waves are measured and displayed in two different ways in the software for the *EMOTIV EPOC-X*. They can be viewed in both a wavelength form and in a 3D brain visualization form. Figure 1 depicts a sample display of the wavelength form.

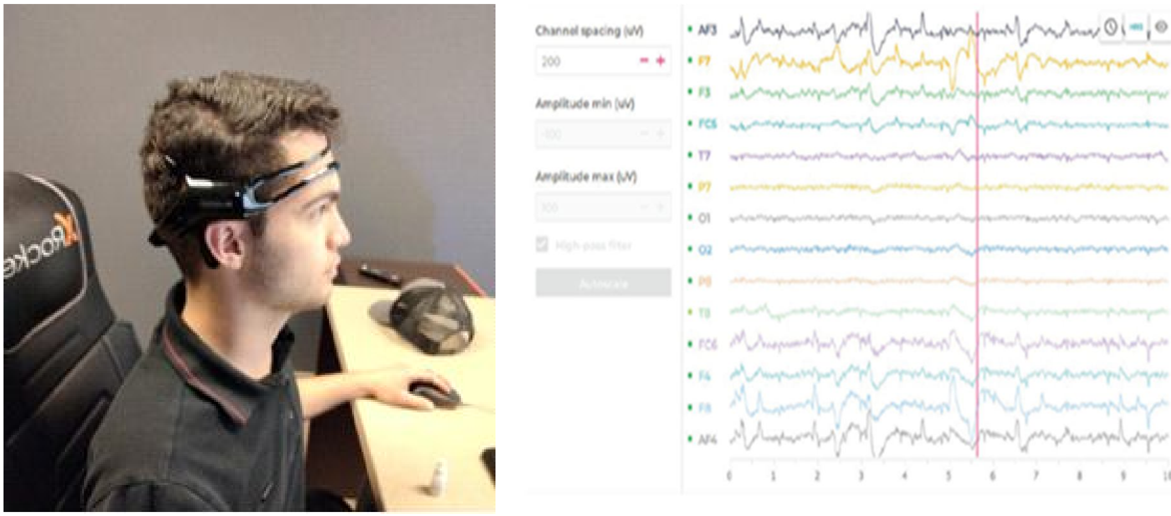
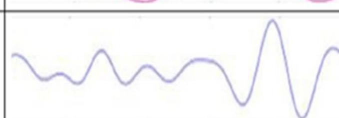
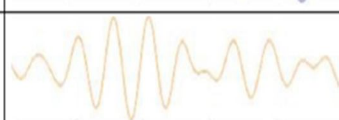
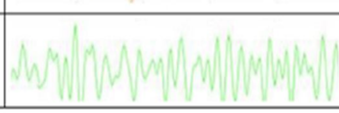


Figure 1. Sample display of the raw EEG Data wavelength from one of the participants (Left image) using *EMOTIV EPOC-X 14 Channel Brainwear and Insight ®* (Right image).

Moreover, Table 1 depicts slightly different brain waveforms classification (*Delta*, *Theta*, *Alpha*, and *Beta*) with their frequency, wave chart and color, and description/interpretation that is used in this research.

Waveform	Frequency	Wave Chart with Color	Description/Interpretation
Delta	0.5–4 Hz		Unconscious level wave Correlated with the deep stage of sleeping
Theta	4-7 Hz		Subconscious level wave Emotional experience, Sustained attention, Learning
Alpha	8-13 Hz		State of relaxation Focused state (excited brain), Recharging
Beta	14-30 Hz		Conscious mind Constant alert, Agitated, Problem-solving, Engaging

Note: For simplicity of design and composition, the Gamma waveform is not included in this table. Gamma waveform is a pattern of neural oscillation in humans with a frequency between 30 and 140 Hz that is associated with a higher level of focus and inspiration activities.

Table 1. Brain waveforms classification (*Delta, Theta, Alpha, and Beta*) showing waveform, frequency, wave chart with color, and description/interpretation.

There is a wide range of variation between the type of brain waves and the individual person or user who is emitting them. Individual brain waves are not emitted at the same time, and often take turns appearing in the brain (Figures 2 and 3 show samples using 3D Visualization by *EMOTIV EPOC-X* Lab Software). Each node on the scalp receives different characteristics that are then distinguished by the model, making much of the data produced extremely interpretable [1].

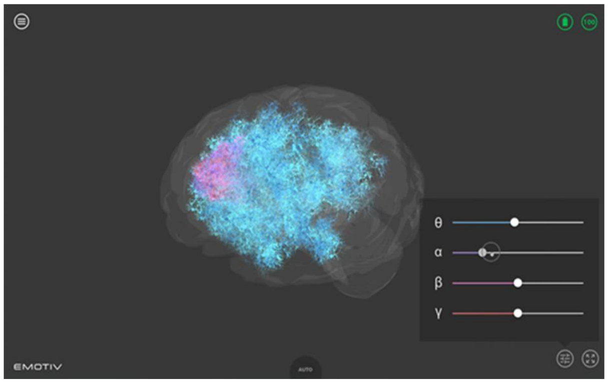


Figure 2. 3D Visualization of the Brain with each of the four brain waves present and adjustable.

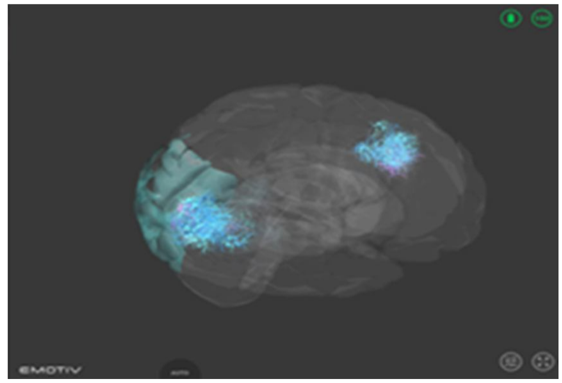


Figure 3. EMOTIV EPOC-X Brainwear Software allows for the mapping of different brain cortex areas, although the approximation of display for brainwave patterns is known to be inconsistent and individualized.

2.4 Testing and Tuning of EMOTIV EPOC-X Headset

In this phase of the testing with new users, an environment with music, photos, emotionally stimulating images, and guided meditations was set. During this process, experiments were conducted with different users to determine their mental activity and mental state at the time of testing. A video was used that provided the participants meditation scenario. The meditation evoked purple and blue theta and alpha waves, seemed to correlate to language processing and listening skills. The emotional wave detected was a red wave (*alpha*). Based on the prior practices, additional heterogeneous testing phases were implemented for tuning-up reasons [29]. Table 2 shows the testing and tuning phases, the approximate area of the brain affected, and the criteria for observation.

Testing and Tunning Phases	Area of the brain affected	Criteria for observation
Headset became connected and booted software	General testing: this didn't focus on any brain area	Initial hardware and software connection
EMOTIV EPOC-X Brainwear headset tested. EMOTIV headset was displayed on brain lab screens.	Auditory Cortex, the central part of the brain	Music/video games
Testing to try and measure memory with math	For memory, this triggered the back right of the brain.	Math problems (basic arithmetic)
Trying to test for emotion and relaxation	For relaxation, the prefrontal cortex is triggered	Meditation/ anxiety

Table 2. Listing of heterogeneous testing and tuning phases based on the prior researchers' experience for tunning-up the system and showing approximate area of the brain affected with criteria for observation.

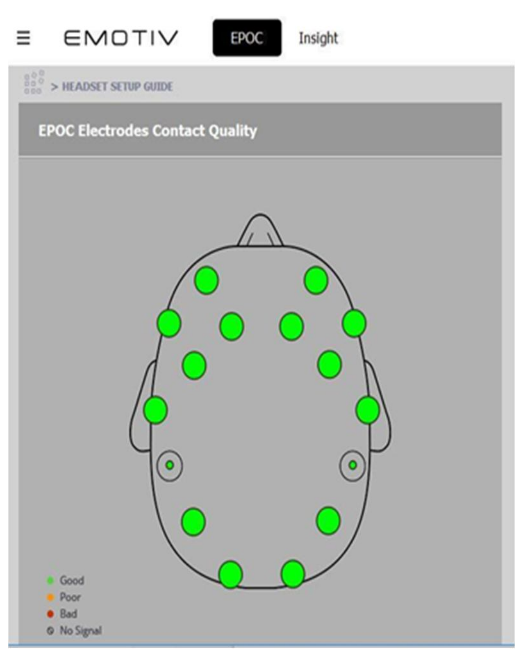


Figure 4. Connected points between EPOC-X nodes and participant's head scalp. When all individual nodes are turned green, the headset is properly set up to pick up and produce brain waves for each channel.

2.5 Procedures Including Data Collection

Participants were engaged in the experimental phases individually and were briefed regarding the purpose of the study and general data such as age and gender were collected at this time. Setting up, testing, and tunning of *EMOTIV EPOC-X 14 Channel Brainwear ®* was performed with alternative selected participants. In next phase, participants were assisted with the process of connecting the nodes to the scalp with the help of the saline solution that soaks the nodes on the EPOC headset. Just to reiterate, the process that an alternative participant was engaged in testing and tunning, the same process was conducted to ensure consistency. As seen in figure 4 (above), correct distribution and connection to the scalp must occur for a full and consistent connection. When the individual nodes are each turned green, the headset is properly set up for use. It is at this point that the participants collection of brain waves could begin producing output and the visualization could be seen. Pre-experiment questionnaires were administered to all participants prior to the experiment while post-experiment questionnaires were also given.

3 Preliminary Results and Analysis

In the next phase, three distinct experiments (scenarios) were designed and conducted with each participant watching a meditation video, watching an action-comedy movie, and watching a horror movie. Appropriate data were collected and displayed in 3D visualization format while the raw brain waves data were saved for analysis and interpretation. The preceding briefly describes three experiments.

3.1 Experiment I - Meditation Stimuli Invoking Scenario

Participants were introduced to a stimuli invoking scenario about meditation and how to relax their minds. Before listening to the narrator, they tried not to think or focus on anything, and let the brain blank. As a result, there was not much happening in the brain wave activity. When the participants closed their eyes and began a restful state, the alpha waves appeared progressively. As they thought about one happy thing that happened in their life, different shades of alpha and theta waves took place in most parts of the brain, including the parietal lobe and frontal lobe (Figure 5). This part is vital for sensory perception and integration. During the process when the participants felt peaceful and breathed slowly, the alpha went through each part of the brain continuously (Figure 6). However, for participants who were in a restful state, there were little to no signs of beta waves while more theta waves appeared as expected (Figure 7). In-depth description of qualitative and quantitative data analysis is covered in the next section.

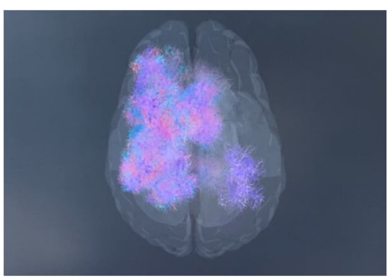


Figure 5. Alpha waves when participant thought about one happy thing in life

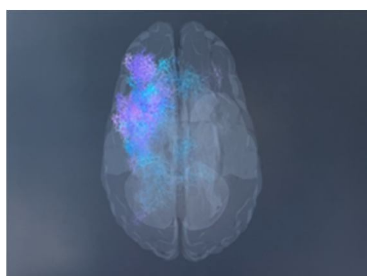


Figure 6. Brain waves when the participant closed their eyes and breathed peacefully

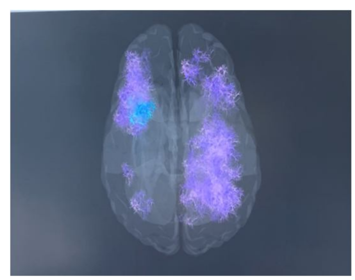


Figure 7. Brain waves when the participant was at ease and felt calm.

3.2 Experiment II – Action Stimuli Invoking Scenario

While participants watched the action stimuli invoking presentation, 3D brain visualization typically showed significantly more activity. Alpha waves, as well as blue theta, red beta frequencies appeared frequently. Alpha frequencies are associated with the state of relaxation and focused state, such as excited brain. Theta frequencies are associated with relaxed and creative states, also in memory recall, while beta frequencies are associated with active, task-oriented, busy, or anxious thinking (Figures 8 and 9). These frequencies were seen in more parts of the brain than in the last activity, including the left frontal lobe, and the temporal cortex. The frontal lobe is responsible for emotional regulation, planning, reasoning, and problem-solving. The temporal cortex is essential for processing sensory information, such as hearing, understanding language, and forming memories. The alpha waves frequencies appeared mostly when the participants were focusing on thrilling action scenes. In-depth description of qualitative and quantitative data analysis is covered in the next section.

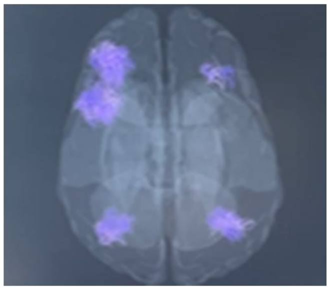


Figure 8. Brain waves when the participant watched a funny scene.

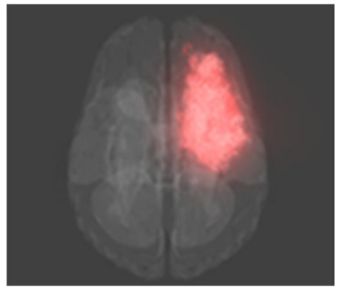


Figure 9. Brain waves when the participant watched a thrilling scene.

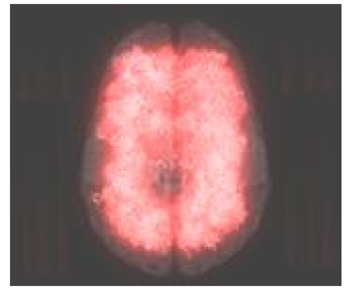


Figure 10. Gamma frequencies show in brain while participant watched a horror movie.

3.3 Experiment III – Horror Stimuli Invoking Scenario

The horror stimuli invoking scenario indicated much more brain activity than the action stimuli invoking scenario. The brain waves as shown in Figure 10 (above) while the participants experienced jump-scared scenes or saw a character being terminated in the movie. There were gamma, theta, and beta frequencies observed during the experiment. Overall, there was more brain activity when they were watching horror movies, and significantly more activity when something substantial happened. As shown in Figure 11, a significant increase in beta and gamma frequencies appeared and the frequencies lit up in most parts of the brain. Beta frequencies are associated with constant alert, agitated, problem-solving and basically engaging. In-depth description of qualitative and quantitative data analysis is covered in the next section.

3.4 Qualitative and Quantitative Data Analysis

Pre-experiment questionnaires were administered to all participants prior to the experiment. The post-experiment questionnaires were administered to participants using three experimental scenarios of mediation, action, and horror with emotional state of relaxed, excited, or scared. Qualitative and quantitative data were collected and analyzed based on the prior researchers' experience with these types of data using appropriate statistical procedures. Graphical visualization of collected subjective data using a standard questionnaire are depicted in Figure 11. Basically and intentionally, the post-experiment questions that were asked mirrored the objective data categories by EEG brain activities that were collected and visualized using the *EMOTIV EPOC-X* hardware/software of each experiment. The chart clearly demonstrates that participants merely rated higher scores for each scenario. That is a higher response to being relaxed (*Mean=6.38, SD=2.87*) in meditation scenario, higher response to excitement in action scenario (*Mean=5.1, SD=2.96*), and higher response to scaring stimuli in horror scenarios (*Mean=5.45, SD=2.07*).

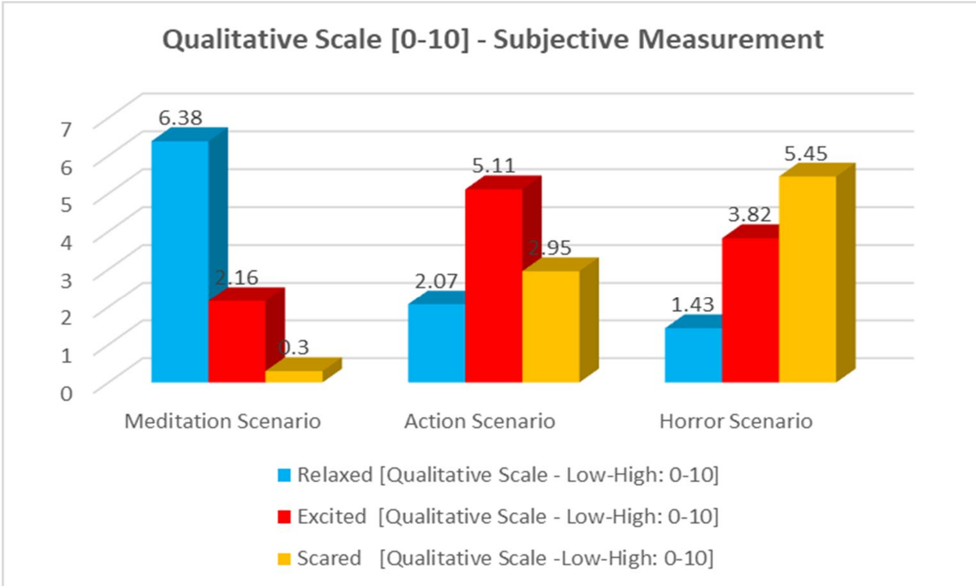


Figure 11. Depicted graphical visualization of collected subjective data using a simplified questionnaire. This graph directly correlated with the EEG data collected by EMOTIV- EPOC-X hardware/software

General data analysis of quantitative brain frequencies collected depicts that participant being relaxed (*Mean=7.82, SD=2.73*) in meditation scenario (baseline), higher response of excitement in action scenario (*Mean=5.76, SD=3.35*) in action stimuli scenario, and higher brain wave frequency (*Mean=5.07, SD=2.44*) related to scariness in horror invoking stimuli scenario (Figure 12).

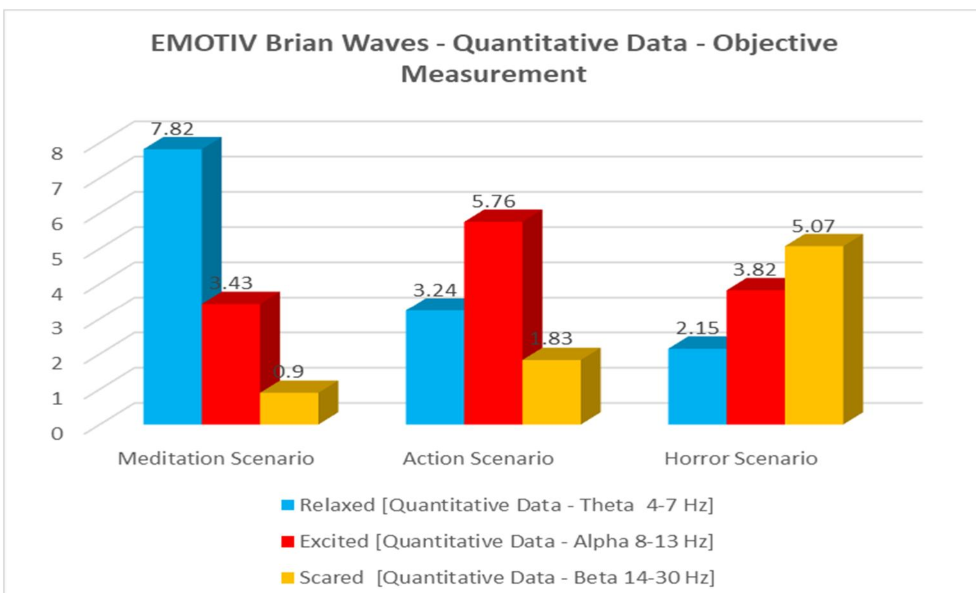


Figure 12. Computed the frequency of occurrence of various EMOTIV brain signals in Theta, Alpha, and Beta range for Meditation, Action Movie, and Horror Movie experiments are shown in this graph.

Further analysis of qualitative and quantitative measurements of emotion in the experimental model using *t-test* statistical procedures is shown in Table 3. Interpretations of all three alternative hypotheses are presented in detail below.

Experimental Model – Analysis of Qualitative and Quantitative Measurements of Emotion and Attention									
Qualitative Measurement (Subjective Rating Scale) [Low-High: 0-10]	**Meditation Baseline**		**Action Scenario**		**Horror Scenario**		**Analysis *t-test / p-value / df=62***		
	Mean	***SD***	***Mean***	***SD***	***Mean***	***SD***	***Meditation X Action***	***Meditation X Horror***	***Action X Horror***
Relaxed [Qualitative Scale - *Low-High: 0-10*]	6.38	2.87	2.07	1.02	1.43	1.60	*t=8.0046 p<0.0001***	*t=8.5218 p<0.0001***	*t=1.9080 p<0.0610 †*
Excited [Qualitative Scale - *Low-High: 0-10*]	2.16	1.31	5.11	2.96	3.82	1.56	*t=5.1554 p<0.0001***	*t=4.6097 p<0.0001***	*t=2.1810 p<0.0330**
Scared [Qualitative Scale - *Low-High: 0-10*]	0.3	0.02	2.95	1.84	5.45	2.07	*t= 8.1466 p<0.0001***	*t=14.0732 p<0.0001***	*t=5.1063 p<0.0001***
Quantitative Measurement (EMOTIV Brain Sys.)	**Meditation Baseline**		**Action Scenario**		**Horror Scenario**		**Analysis *t-test / p-value / df=62***		
	Mean	***SD***	***Mean***	***SD***	***Mean***	***SD***	***Meditation X Action***	***Meditation X Horror***	***Action X Horror***
Relaxed [Quantitative Data - *Theta 4-7 Hz*]	7.82	2.73	3.24	2.70	2.15	1.02	*t=10.8476p <0.0001***	*t=9.8074 p<0.0001***	*t=2.519 p<0.0143**
Excited [Quantitative Data - *Alpha 8-13 Hz*]	3.43	1.06	5.76	3.35	3.82	2.88	*t=4.4145 p<0.0001***	*t=0.9164 p<0.3630 †*	*t=5.0855 p<0.0001***
Scared [Quantitative Data - *Beta 14-30 Hz*]	0.9	0.4	1.83	1.20	5.07	2.44	*t=1.4812 p<0.1436 †*	*t=7.9851 p<0.0001***	*t=10.0269 p<0.0001***

Note: It must be noted that the state relaxation can span from Theta to Alpha wave level and state of excitement may also be covered by frequencies assigned to Alpha and Beta wave ranges. For computational reasons, three distinct wave ranges were used in this research (i.e., Theta, Alpha, and Beta).

* *Difference statistically significant*
** *Difference extremely statistically significant*
† *Difference not statistically significant*

Table 3. An experimental model for measuring and deciphering emotion and attention using brain waves by electroencephalogram (EEG) techniques and technologies such as EMOTIV-EPOC-X Brainwear ® headset hardware/software.

Alternative Hypothesis *Ha-1* stated that an experimental model for measuring and deciphering emotion and attention produces statistically significant difference between meditation and action stimuli invoking scenarios considering quantitative measurement [*Theta 4-7 Hz*] of relaxed brain wave. The *t-test* statistical analysis showed that both qualitative and quantitative data support statistically extreme significant between meditation and action stimuli invoking scenarios (Relaxed [*t=8.0046, p<0.0001***]; Excited [*t=5.1554, p<0.0001***]; Scared [*t= 8.1466, p<0.0001***]) and (Relaxed [*t=10.8476, p<0.0001***]; Excited [*t=4.4145, p<0.0001***]; Scared [*t= 1.4812, p<0.14636 † – insignificant in this category*]). Thus, Alternative Hypothesis *Ha-1* is accepted and asserting that this specific measurement technique can effectively show the present of emotion which in turn will be able to activate a BCI command.

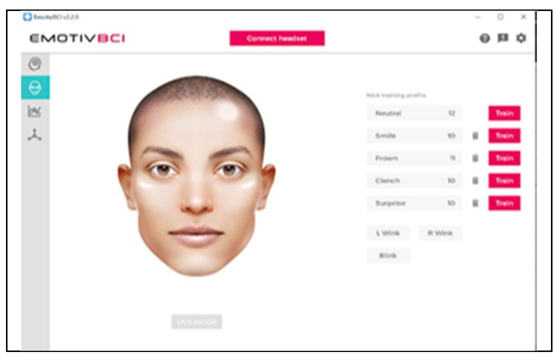
Alternative Hypothesis *Ha-2* – stated that experimental model for measuring and deciphering emotion and attention produces statistically significant difference between meditation and horror stimuli invoking scenarios considering quantitative measurement [*Alpha 8-13 Hz*] of excited brain wave. The *t-test* statistical analysis showed that both qualitative and quantitative data support statistically extreme significant between meditation and action stimuli invoking scenarios (Relaxed [*t=8.5218, p<0.0001***]; Excited [*t=4.0697, p<0.0001***]; Scared [*t= 14.0732, p<0.0001***]) and (Relaxed [*t=9.8074, p<0.0001***]; Excited [*t=0.9164, p<0.3630 † – insignificant in this category*]; Scared [*t=7.9851, p<0.14636, p<0.0001***]). Thus, Alternative Hypothesis *Ha-2* is accepted and asserting that this specific measurement technique can effectively show the present of emotion which in turn will be able to activate a BCI command.

Alternative Hypothesis *Ha-3* states that an experimental model for measuring and deciphering emotion and attention produces statistically significant difference between action and horror stimuli invoking scenarios considering quantitative measurement [*Beta 14-30 Hz*] of scared brain wave. The *t-test* statistical analysis showed that both qualitative and quantitative data support statistically extreme significant between action and horror stimuli invoking scenarios (Relaxed [*t=1.9080, p<0.0610 † – insignificant in this category*]; Excited [*t=2.1810, p<0.0330**]; Scared [*t= 5.10632, p<0.0001***]) and (Relaxed [*t=2.519, p<0.0143**]; Excited [*t=5.0855, p<0.0001***]; Scared [*t=10.0269,* *p<0.0001***]). Thus, Alternative Hypothesis *Ha-3* is accepted. Thus, Alternative Hypothesis *Ha-3* is accepted and asserting that this specific measurement technique can effectively show the present of emotion which in turn will be able to activate a BCI command. In addition to all three alternative hypotheses being accepted based on the data analysis of both qualitative and quantitative measurement, the responses to all research questions in this article are affirmative.

4 Conclusion and Discussion

The main objective of this research was to demonstrate an experimental model for measuring and deciphering emotion and attention using brain waves through EEG techniques and technologies, such as the EMOTIV-EPOC-X Brainwear ® headset hardware and software, to advance BCI technology and practice in creating novel pedagogical methods. After extensive initial testing and implementation of the system, three distinct simple experiments were set up and conducted. The preliminary results of this research offered a dynamic experimental model for measuring and ultimately for training and testing learners in different environments for the purpose of accurate, and consistent measurements for practical applications that could be incorporated in pedagogical methods. Clearly, the field of BCI theories and technologies will be broadly impacted by the implemented experimental model like this research. Furthermore, an interesting component of this research while collecting samples and data is the aspect of brain imaging itself. It can be rather intimate and vulnerable to display publicly the emotions and feelings being experienced inside the brain. If someone is laughing or embarrassed, it's visible on the 3D model of brainwaves. Expanding on the prior section, to get the headset to accurately read the data for facial expression research takes hours of training time. Thus, this phase will be included in future research activities. To show a preview, the following initial training profile is briefly described here (See Figure 13). For instance, for each participant, the neutral command took about 10 minutes for the first train. The smile and frown command took about 15 minutes to initially train. The clench and surprise commands both took around 18 minutes to initially train. The training sessions were repeated multiple times to increase their efficiency.

Figure 13. A screenshot of the training facial expression profile of *EMOTIV BCI* for further research activities.



Technology Usage Limitations: This research report is highly technical and deeply specialized in the BCI field, ultimately advancing an innovative method with pedagogical implications for learners. Furthermore, this report provides an experimental model for measuring and decoding emotion and attention in the specific field of BCI and the leading-edge research and technology surrounding it. To reiterate, using EEG in the research field of BCI is tremendously difficult and time-consuming. Brain signals are weak and difficult to interpret for different applications; thus, our research provides a novel model and approach that could be implemented with window-based computers, allowing more researchers to get involved in a variety of BCI applications. A new affordable visualization hardware and software to show brain waves and 3D images that work on a window-based computer system was used, thus allowing many more researchers to conduct research that would otherwise have been prevented by not having large-scale imaging systems (such as fMRI, which costs millions of dollars). However, the quality of brain images provided is not high, and developers are diligently working to improve it. The setup for the *EMOTIV EPOC-X* headset is a rather intensive one that requires a lot of adjusting, testing, and integration. Soaking the nodes beforehand and charging the headset to full capacity is important for getting a reliable connection. Moreover, factors such as head shape and participant patience are important hindrances that can affect the testing process. The time taken to adjust the headset correctly and make sure all nodes are at full capacity can be demotivating for those wanting to use the technology for any regular purpose. Frequently, this process requires a second person to help adjust and re-soak the nodes. This can be a limitation for those who want to quickly and efficiently use the headset in their research activities.

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