# Brain-EE: Brain Enjoyment Evaluation using Commercial EEG Headband

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## ABSTRACT

Previous studies that involve measuring EEG, or electroencephalograms, have mainly been experimentally-driven projects; for instance, EEG has long been used in research to help identify and elucidate our understanding of many neuroscientific, cognitive, and clinical issues (e.g., sleep, seizures, memory). However, advances in technology have made EEG more accessible to the population. This opens up lines for EEG to provide more information about brain activity in everyday life, rather than in a laboratory setting. To take advantage of the technological advances that have allowed for this, we introduce the Brain-EE system, a method for evaluating user engaged enjoyment that uses a commercially available EEG tool (Muse). During testing, fifteen participants engaged in two tasks (playing two different video games via tablet), and their EEG data were recorded. The Brain-EE system supported much of the previous literature on enjoyment; increases in frontal theta activity strongly and reliably predicted which game each individual participant preferred. We hope to develop the Brain-EE system further in order to contribute to a wide variety of applications (e.g., usability testing, clinical or experimental applications, evaluation methods, etc.).

## CCS Concepts

• **Human-centered computing~Interaction design theory, concepts and paradigms** • *Human-centered computing~User studies* • *Human-centered computing~HCI theory, concepts and models* • *Theory of computation~Active learning* • *Computing methodologies~Machine learning algorithms* • Mathematics of computing~Statistical paradigms

## Keywords

EEG; Headband; Enjoyment; Muse; Neurofeedback; BCI


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## 1. INTRODUCTION

Brain-Computer Interface (BCI) describes the neurofeedback interface that allows users to communicate and express their thoughts and feelings without talking or moving. Although BCI applications are still very limited, the focus of BCI has expanded over the recent years from helping diagnose mental disorders to enhance human life in different aspects. For instance, BCI can provide people with severe motor disabilities a new way to control augmentative technologies, and help others relief, relax and meditate. Since BCIs have access to the brain signals and can estimate the human emotions, the interaction between human and machine can be improved and adapting to the human preference [16].

In this paper, we present the Brain-EE system, which can predict engaged enjoyment when performing different tasks. We start this paper with a short background of EEG signals used in BCI systems (section 2). In section 3, we share related work of BCI systems designed for daily life use. A detailed description of the Brain-EE system is included in section 4. In section 5 and 6, we discuss our findings and outline future steps for the Brain-EE system.

## 2. BACKGROUND OF EEG

Electroencephalogram (EEG) is a measure of the electrical activity that typically occurs around the scalp as a result of brain activity (i.e., cortical activity). There are five EEG frequencies that are usually denoted in research: delta (1-4 Hz), theta (5-8 Hz), alpha (9-13 Hz), beta (12-30 Hz), and gamma (30-50Hz) [18]. EEG can typically be seen in neuroscientific research, where different activity patterns can reflect several types of phenomena. For example, EEG is one of the most common tools used in the study of sleep [2]. EEG studies often serve as important tools in memory research [6]. Many EEG studies are done in conjunction with other brain imaging techniques (like functional magnetic resonance imaging, or fMRI) to identify the presence of abnormal brain activity, such as with seizures or stroke [18] [19]. Some studies use EEG to measure mood states; for instance, it has been shown that increased cortical alpha and beta activity can reflect stress during activities [1] [12] [13]. Also, frontal alpha activity and increased theta correlations, but no change in frontal beta activity, has been connected to measuring engaged enjoyment during different types of activities [7] [9] [17].

Though EEG seems to have considerable versatility in helping people understand how their brain activity may correlate with certain states or activities, formal EEG methods in research laboratories can be expensive and difficult to set up. For example, formal EEG laboratories often use EEG caps that have many recording sites (i.e., electrodes) that require the placement of gel or paste on the scalp in order to ensure good connectivity for clean recordings. Researchers require advanced knowledge of statistical and practical techniques for running experimental studies. Data analysis may need complex methods and special computing requirements. These studies also often take a long amount of time as they move from early stages (preparation, IRB review) to later stages (data collection/screening/cleaning/analysis and formal write-up). Finally, as with any experimental study, applicability to everyday life is limited; the environment of the formal laboratory often does not reflect the environment in which people live their lives.

Lately, the consumer market has attempted to make use of the great advances discovered using EEG in the last couple of decades for a variety of uses. As such, EEG may be a useful tool for measuring several types of user states, and current experimentation and methodology are allowing for the expansion of EEG use outside of the laboratory and into everyday life.

# 3. LIFESTYLE EEG INSTRUMENTS AND APPLICATIONS

The advances of sensor technology have led new cost- and power-efficient devices to the market, making them available for a larger population of developers and researchers. Nowadays, many portable EEG devices are consumer-grade, low-cost devices that are targeted for lifestyle applications. These products also often rebrand EEG data with a simpler, easily-understood term: neurofeedback, or NFB.

There are many companies that produce these low-cost NFB devices. Vendors like InteraXon, NeuroSky, Emotiv, Melon, and Versus provide some of these off-the-shelf, inexpensive devices for consumers. The number of electrodes on these devices is limited (i.e., 2-14 electrodes) compared to the clinical grade devices (i.e., 16-32), their resolution is low, and the electrodes are usually focused on a specific portion of the brain; however, these devices are still appropriate for specific applications.

Many of these portable EEG devices are simple to set up; they connect via Bluetooth to a smartphone, a computer, or a microcontroller, where data can be analyzed directly. They use dry electrodes that do not require intensive preparation or clean-up, and these electrodes connect to the skin without the need for any gel or paste. These portable, cost-effective devices may also be used with related available EEG tools and open-source platforms (e.g., OpenEEG, BCI2000, OpenViBE, and MuLES). These changes have helped evolve EEG applications in both novel and established fields [3]. For example, [10] has designed a custom-made driver drowsiness detection system that uses an open-source hardware platform with dry electrodes to send drowsiness level to the driver's smartwatch, and alert him/her when it is unsafe to drive. As such, these changes allow vendors to provide research tools that make their devices applicable to newer, lesser explored methods [5].

One of these uses is detecting the psychological human state, including but not limited to: happiness, enjoyment, pain, or concentration. In [8], the Muse headband, from InteraXon, was used to detect cold-induced pain using self-calibrating protocols and various classification algorithms. Similarly, [11] has shown the possibility of using the Muse headband to measure concentration and relaxation.

Necomimi Brainwave Cat Ears, from NeuroSky, is a toy that uses EEG signals from the frontal lobe of the brain to present four mind states in real-time including: high relaxation, focus/relaxation, high focus, and high interest [15]. The pose of the friendly-looking ears on the headband changes according to the current state of mind. Also, [14] mimics the concept of "light bulb/idea" metaphor: mounted on the helmet is a light bulb that illuminates when the sensors detect an increase in thinking and focus.

Given that human emotions are traditionally qualitative and are very difficult to estimate, these devices can supplement other measures of emotions, like self-assessment (e.g., through Likert or dichotomous scales) or psychological examinations. In [4], researchers used activities that tested attention and executive functioning (i.e., the Stroop test [21] and the Towers of Hanoi [20]) as well as a questionnaire to assess the suitability of the NeuroSky headset for measuring meditation and attention levels. Further, in [17], game boredom and flow were estimated in personalized training using Support Vector Machine (SVM) analysis while playing different levels of Tetris games.

Based on this new line of research, we introduce an idea to use one such consumer-grade EEG device (Muse) to measure user enjoyment. Our system, the Brain-EE system, aims to measure engaged enjoyment in such a way that we can predict participant's preferences for activities based on their EEG data. In the next section, we explain the methods we used to evaluate user enjoyment.

# 4. SYSTEM DESCRIPTION

The Brain-EE system aims to measure participant enjoyment through EEG activity as it differs during two games. To measure EEG, Brain-EE uses the commercially available product, Muse. The two games that were played by the users, and for which users would rate their enjoyment, were Piano Tiles 2 and Soccer 2016. Both games were viewed and played in tablet platform. To create the user interface and to analyze the data, we used MATLAB. Figure 1 gives a general overview of the system setup. The following subsections go into greater detail about our methods.

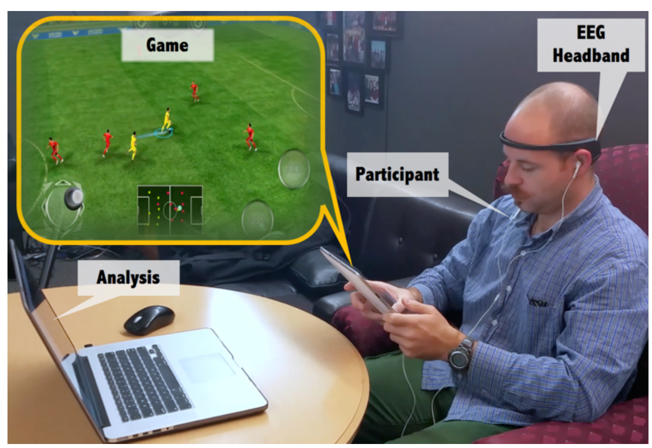


**Figure 1: System Overview**

## 4.1 Participants
Fifteen total healthy participants were used in this study. All were University of Texas at Arlington students (13 males, 2 female) aged 20-35.

## 4.2 Equipment and Software
### *4.2.1 Hardware*
The EEG device used in this experiment is the Muse headband from InteraXan. It is an off-the shelf, low-cost EEG headband, and it has been used in multiple studies [3, 5, 8, 11, 14]. It has seven EEG electrodes (4 Channels and 3 References) (please refer to Figure 2) and 3-axis accelerometer. The transmission frequency of the used EEG signals is 10 Hz, whereas the sample rate of the accelerometer is 50 Hz. All data are transmitted via Bluetooth to a laptop running Mac OS Yosemite 10.10.5. Also, for this study, Relax Melodies were used during baseline data collection ("Relax" phase), and the games used in testing ("Game 1" and "Game 2" phases) were run on Asus tablet running Android OS 4.0 .

### *4.2.2 Software*
For our experiment, we used two different games that were comparable in skill level (i.e., using a touchpad screen to complete the game) but were polarizing in likability; specifically, we used Soccer 2016 (less likability) and Piano Tiles 2 (more likability). With the Muse headband, InteraXon provides Muse SDK (i.e., Muse IO, MusePlayer, MuseLab). In our experiment, we take advantage of MuseIO, which connects with Muse via Bluetooth and acquires EEG data, accelerometer data, and other data (e.g., jaw clenches, eye blinks). The MuseIO streams these data back to a specific port on the PC in the form of OSC (open sound control) messages. To retrieve the data, we used MATLAB's Instrumentation Control Toolbox, which lets MATLAB connect directly to that specified port using a TCP/IP protocol. Once the data are received in MATLAB, our MATLAB GUI application filters, processes, and analyzes the data.

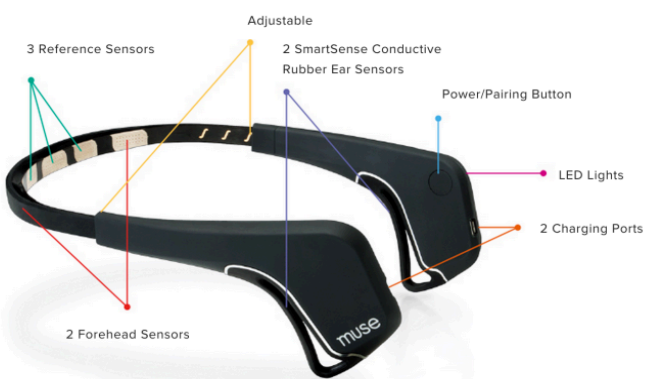


**Figure 2: Muse headband.**

## 4.3 Interactive User Interface
Our interface is user-friendly, clear, and easy to navigate. First, the GUI provides step-by-step instruction for proper completion of setup and data collection. Also, it plots real-time graphs for accelerometer data to check if data is fetched in real time, as well as the "is_good" signals provided by Muse that show whether the EEG sensors on the headband are well-connected to the participant's head. In our experiment, data were collected in intervals of 120 seconds, with each collection phase terminating automatically. Data are analyzed using an algorithm (discussed in detail Section 4.6), and the final result of the analysis is shown with a picture of the game that the participant is predicted to prefer.

## 4.4 Procedure
In our experiment, after giving consent to participate in the study, participants answered relevant demographic questions (e.g. age, gender). Then, participants were fitted with the Muse headset. Connectivity for all four channels (via "is_good" signals) was displayed; proper connectivity was checked before proceeding to the experimental phases. After proper connection with the Muse was ensured, the baseline phase ("Relax") was established. During this time, participants were asked to close their eyes and listen to calming white noise for 120 seconds, while their EEG data were recorded. After this, participants were asked to fill out a general mood survey. Next, the two active phases ("Game 1" and "Game 2") were established. During each of these phases, the participants were asked to play one of two games (Soccer 2016 or Piano Tiles 2) for 120 seconds, while their EEG data were recorded. After Game 1 and Game 2 phases, participants were asked to fill out general mood surveys and to rate the games. For a walkthrough of the protocol, as well as an example of the user interface, please refer to our video at https://youtu.be/brFZ93Omq5U.

## 4.5 Data Collection
The EEG signals are obtained from the four Muse input electrodes. Two input electrodes are located on the forehead, and one input electrode above each ear as shown in blue in Figure 3. Three reference electrodes are located in the middle between the two input electrodes on the forehead as shown in green in Figure 3. These EEG signals are represented as the absolute band power for the 5 standard frequencies commonly used in EEG applications (delta, theta, alpha, beta, and gamma). Due to the frequent disconnection of electrodes while moving the head, the EEG signals are filtered based on the "is_good" variable provided by the Muse. In case any electrode is not properly connected during the experiment, all the recorded data during the period of disconnection is omitted from analysis.

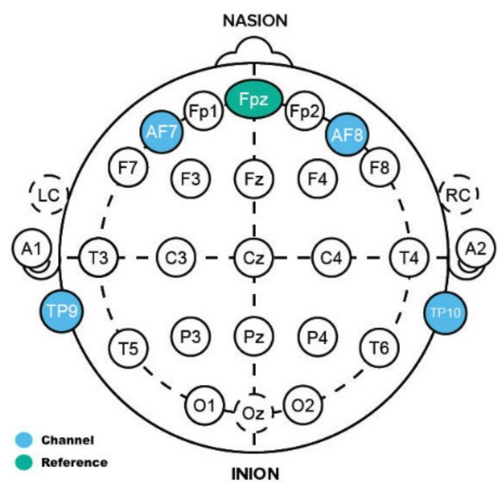


**Figure 3: Muse electrode locations by 10-20 International Standards.**

## 4.6 Classification Methods and Results

EEG data analyses, particularly those involved in experimental literature, often require elaborate filtering and preprocessing methods in order to make group comparisons (*t*-tests). However, brain activity and structures can vary drastically from person to person; this means that it can be hard to apply findings to the general populations [8]. Our goal is to apply a classification method that should work across these differences and for all healthy people. Therefore, we did not use the actual EEG data directly in our classification method. Instead, we used the *t*-test results.

For each frequency band (e.g., alpha) we used the average of the 4 channels. By doing that, we had five arrays of frequency bands data for each phase of the experiment (i.e., "Relax", "Game 1", and "Game 2"). During analysis, we filtered out data that reflected poor connectivity. Since this filtering process necessarily varied by individuals, there would sometimes be unequal amounts of data points for different phases of the experiment for different participants. To ensure that we had an equal amount of data points across phases and across participants, we omitted data based on the start and end times of each of the phases of experiments, and we ignored remainder data (for example, if the Relax phase had 800 data points, and Game 1 had 1000 data points, we would only use the first 800 data points of Game 1).

Then, we ran a *t*-test comparing Game 1 data and Relax phase data, as well as a *t*-test comparing Game 2 data and Relax phase data. By doing this, the data of each participant is simplified and summarized in *t*-test results that represent the changes in EEG between Relax vs. Game 1, as well as between Relax vs. Game 2 (one result each for delta, theta, alpha, beta, and gamma frequencies, for each of the two comparisons).

Finally, the results of the *t*-tests were used to train a linear regression to be able to predict which out of two options (Game 1 or Game 2) the participant engaged with more. After using the data of the first 10 participants to train the linear regression, the linear regression was run for the last 5 participants. Equation 1 is the result of the linear regression, and it evaluates both of the games based on the *t*-test results of all the frequency bands. The game that yields a higher $y$ value is the game that is predicted to be the game that the participant reports enjoying the most. When this equation was tested on the last 5 participants, it resulted in 100% accuracy in identifying which games they preferred.

$$y = -0.0651 - 0.0136\Delta + 0.0256\Theta - 0.0072\mathrm{A} + 0.0009\mathrm{B} - 0.0032\Gamma \quad (1)$$

## 4.7 Analysis of Results

In Section 2, we discussed that other studies have found that frontal alpha activity and increased theta correlations, but no change in frontal beta activity, has been connected to measuring engaged enjoyment during different types of activities [7] [9] [17]. We find that our results in this experiment partly agrees with these studies. Table 1 includes the coefficients of the linear regression equation, and their multiplication with the average of *t*-tests for each of the frequency bands for the training data that correspond to either enjoying or not enjoying the game. In the calculation of the coefficients of Equation 1, the $y$ in the linear regression is set to 1 for the games that participants enjoyed and to 0 for the games that the participants did not enjoy. With that in mind, we can see that in the highlighted section of Table 1, where coefficients are multiplied with the average *t*-test results of the participants, that theta is significantly higher for the game that they enjoyed, and in the algorithm, has a positive coefficient. This suggests that the increase in theta reflects more enjoyment. Contrastingly, alpha and delta are higher for the game that they enjoyed, but in the algorithm, they have negative coefficients. This contradictory result suggests that alpha and delta are less related with the prediction of enjoyment. Finally, though beta and gamma change very slightly, their coefficients seem to have little impact in predicting enjoyment. Despite the fact that these remarks may not apply to all participants, they hold potential for a significant influence on enjoyment research.

**Table 1: Summary of the *t*-test averages across all the frequency bands.**

| *t*-test of Frequency | Δ | Θ | Α | Β | Γ |
|---|---|---|---|---|---|
| Coeff.(C) | -0.0136 | 0.0256 | -0.0072 | 0.0009 | -0.0032 |
| Enjoy (E) | 34.49 | 60.97 | 29.33 | 64.01 | 23.01 |
| No Enjoy (NE) | 1.73 | 16.26 | 5.54 | 47.67 | 28.14 |
| C×E | -0.4691 | 1.5608 | -0.2112 | 0.0576 | -0.0736 |
| C×NE | -0.0235 | 0.4162 | -0.0399 | 0.0429 | -0.0900 |

"Coeff. (C)" represents the coefficients of the linear regression equation. "Enjoy (E)" represents the average of *t*-tests of the frequency bands corresponding to enjoying a game. "No Enjoy (NE)" represents the average of *t*-tests of the frequency bands corresponding to not enjoying a game. "C×E" and "C×NE" represent the simple multiplication of the coefficients and the corresponding *t*-test averages for enjoyment and no enjoyment, respectively.

# 5. DISCUSSION AND FUTURE WORK

Initial statistical analyses helped with the refinement of the Brain-EE system. First, group data for rest vs. active conditions matched what was expected: no changes in beta but increases in frontal alpha ($t(13774) = 27.22$, $p < .001$) and theta ($t(13774) = 62.69$, $p < .001$) activity, with theta being the best predictor of whether users reported liking vs. not liking a game ($\chi^2(3) = 4912.79$, $p < .001$, accounting for 67.8% of the variance). However, early variability of the results (especially with regarded to alpha and beta), as well as a desire to look for individual data differences rather than group differences, led to the development of the algorithm. This early variability in the EEG data might suggest differences in the magnitude of enjoyment. For instance, while one participant reported "yes" when asked if he liked the game, he rated the game a 6/10, which may suggest he did not *strongly* like the game. In the development stages of Brain-EE, the purpose of the study was to detect enjoyment, rather than to evaluate the participant's preference between two tasks. However, when the same method (equation 1) was used to detect enjoyment, the accuracy of the results hovered around 60%. One of the reason behind this low accuracy might be that participants sometimes have difficulties deciding whether they like a task or not, but it is easier for them to decide which of two tasks they prefer. Also, further testing can include analysis of questionnaire responses in conjunction with EEG data to see how user perceptions correlate with their brain activity. In particular, data can be grouped based on demographic information; for instance, further research can see how more experienced gamers might show a different trend in engagement and preference than less experienced gamers.

Future work includes expanding the usability of the Brain-EE system for other purposes. For example, the Brain-EE system can be utilized in usability testing to see how participants may be more engaged with different web designs, therapy games, movies, or advertisements. Finally, we plan to provide the data and the Brain-EE system as an open-source dataset to be used and evaluated by other researchers.

# 6. CONCLUSION

Currently, the Brain-EE system is able to measure EEG activity that reflects how much a user is engaged in a given task, which then allows for the comparison of which out of two given tasks are preferred by the user. The Brain-EE system supported much of the previous literature on enjoyment; increases in frontal theta activity strongly and reliably predicted which game each individual participant preferred. The Brain-EE system can be adapted to measure user engagement and enjoyment for other stimuli (e.g., usability testing for different products), or to measure other mood states (e.g., stress). It is the Brain-EE team's aim to refine our system with the hopes of increasing adaptability for a wide array of future uses, thereby giving more objective and concrete methods of measuring subjective phenomena.

# 7. ACKNOWLEDGMENTS

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