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# Low-Cost Assessment of User eXperience Through EEG Signals

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**ABSTRACT** EEG signals are an important tool for monitoring the brain activity of a person, but equipment, expertise and infrastructure are required. EEG technologies are generally expensive, thus few people are normally able to use them. However, some low-cost technologies are now available. One of these is OPENBCI, but it seems that it is yet to be widely employed in Human-Computer Interaction. In this study, we used OPENBCI technology to capture EEG signals linked to brain activity in ten subjects as they interacted with two video games: Candy Crush and Geometry Dash. The experiment aimed to capture the signals while the players interacted with the video games in several situations. The results show differences due to the absence/presence of sound; players appear to be more relaxed without sound. In addition, consistent analysis of the EEG data, meCue 2.0 and SAM data showed high consistency. The evidence demonstrates that interesting results are able to be gathered based on low-cost EEG (standard) signal-based technologies.

**INDEX TERMS** User eXperience, player eXperience, EEG signals, video games, low-cost technologies.

## I. INTRODUCTION

Human-Computer Interaction (HCI) is a research area related to the design and use of technology and computers by people. Preece *et al.* [1] define HCI as pertaining to *designing* a *computer system* that *supports people so that they can carry out their activities productively and safely*. As HCI primarily focuses on people, evaluating the user experience is a basic concern. User eXperience (UX) is defined by ISO 9241-210 [2] as *the perception and responses of a person resulting from the anticipated use of a product, system or service*.

UX does not have one single definition. The Nielsen Norman Group [3] consider UX as "*Senses, feelings, emotional response, assessment and satisfaction of the user and of the interaction with the provider*". Meanwhile, Hassenzahl [4] relates UX to how *people perceive interactive products, taking into account two dimensions: (1) pragmatic quality is related to how the user manages to perceive the product in performing a specific task to achieve its objective; (2) hedonic quality is related to the psychological needs and emotional experience*.

UX is concerned with the emotional and affective aspect in entertainment media such as the video game. The term Player eXperience (PX) thus duly emerged. The experience of playing video games is multifaceted, depending on the game type, as well as the amount of experience the players have and the skills they possess. As González *et al.* [5] indicate, video games can be considered a *special* interactive system, the objective of which is *to make the player feel good when playing*. PX may thus be considered as a particular case of UX, but with very specific dimensions. It involves UX characteristics with player dimensions using a broad set of attributes and properties to measure the experience of players when playing a video game. In the literature, we find several definitions related with PX in games. In 2011, Gerling *et al.* [6] defined the term PX as follows: "*in video games, [PX] describes the individual perception on the interaction process between player and game*". Lazzaro [7] meanwhile mentions that the two definitions are not the same. This is because UX is related to the experience of use, and PX is the experience of play.

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Evaluating PX is challenging because we have to consider its specific aspects. Therefore, HCI and video game researchers are starting to learn from each other. This article discusses the evaluation of the user experience in interactive entertainment systems, such as video games.

Video games are able to induce emotions in the player. For example, learning in video games can be difficult, as they require significant effort from players to achieve the set goal. This can turn into a challenge, as can learning to play the game itself. In contrast, the game may be quickly abandoned because trying to advance may be a frustrating experience.

In the video game field, different types of players are found. Some players are more skilled or have more experience than others so that the skill levels of some players are not suitable for the difficulty level of a certain game. One of the aspects that affects UX is the level of challenge. In addition, the attention span of a player can affect his/her level of immersion [8].

Video games themselves have different forms of interaction: traditional forms such as the mouse, keyboard, or joystick, as well as non-traditional ones such as the touch screen. The type of interaction can therefore affect user experience in interacting with a video game. A number of studies have sought to evaluate user experience through proposed qualitative methods (direct observation, interviews, surveys and focus group) [9], [10] and quantitative methods [11]. Different methods are used in different stages of development of a product, reflecting the importance of evaluating before, during and after use of the product. Some authors focus on evaluating emotions. SAM (Self-Assessment-Manikin) was created to assess the affective states [12], and PrEmo [13] is an instrument specifically designed to measure emotions. PrEmo uses pictograms that represent 14 emotional states. Applying these questionnaires to the user, the emotional state upon interacting with a product must be determined, even if the user experiences a number of emotional states within a short period of time during the interaction. Other questionnaires have been created to assess UX, such as the UEQ (User Experience Questionnaire) [14] composed of 26 items grouped into the following six scales: attractiveness, perspicuity, efficiency, dependability, stimulation and novelty.

Use of these techniques/methods can result in the player becoming distracted while interacting with the system. In addition, the questions must be asked at specific moments [15]. With other methods such as recording or direct observation, it is not possible to identify when there is frustration or confusion in users. Moreover, a questionnaire can be delivered to players directly after playing, but the full experience is not contained in their memory. Questionnaires provide a way of obtaining quantitative insights into player feelings and attitudes, but they lack the depth of objectivity of metrical measures. Another type of evaluation, heuristic, carried out by a group of specialists, does not evaluate the end user and experts only intuit about the use of the technologies and the possible impacts they might have on users.

As a result, the questionnaires and techniques that exist to evaluate aspects of UX are behavioural, and in other words not as objective as they might be. The responses and physical reactions identified in the users are very subjective, and very often fail to detail any relevant aspects that can affect user experience. Today, physiological responses [16] are being implemented to evaluate such UX aspects as emotions and perceptions. Technologies for measuring physiological signals can aid in the evaluation of UX, identifying small variations that cannot be perceived directly.

Techniques and methodologies enable affective data to be gathered without asking users what they have experienced and how they feel. Studies have been carried out on measuring affective perception using physiological methods that feed from body responses including body temperature, pupillary response, galvanic skin response (GSR), electromyography (EMG), plethysmograph (blood pressure and volume), and electroencephalogram (EEG). Currently, there is a growing interest in studying and decoding states from physiological responses, not only in evaluating UX of video games but also applied to industry and health. Today, researchers working in the field of neuroscience have used the electroencephalogram (EEG) technique using BCI (Brain-Computer Interface) technology, based on monitoring, analysing and decoding signals captured from a subject. These EEG signals are obtained through electrodes placed on the head of a subject. The signals are captured during a stimulus or other type of mental/motor activity, the objective of which is to find a correlation between the action executed by the subject and the brain response generated.

BCI was developed in response to the need to understand the behaviour of human beings when presented with technology such as a video game and enables analysis of neuron physiology through the study of neuronal waves. It is thereby possible to capture the EEG signals of a person's brain activity [17]. EEG activity comprises a variety of waves identified by frequency, localization or amplitude. EEG signals are directly related with the functional activity of the brain, and the process of decoding and classification is related with the associated type of action. Therefore, the aim of the studies in this article is to decode the EEG signals associated with UX while a subject is interacting with a video game.

The development of this technology brings about new problems. New technology can often mean high costs, and fewer people being able to access it. Additionally, it is necessary to learn which signal types to use. EEG devices measure brain activity through one or more electrodes placed on the scalp. However, processing techniques must be applied to determine the relevance of the information, and without extensive medical expertise. In addition, it is time-consuming, requiring approximately one hour in some cases [18]. The captured EEG amplitude values are very small and noise may occur in the signal due to sudden movements or artefacts [19]. Capturing EEG signals requires patient preparation, which involves applying conductive gel to the scalp to improve electrical conductivity [20]. Dry electrode technology is used as a novel mechanical design to achieve improved connection with the skin without the use of conductive gels. However, the type of dry comb electrode used in OPENBCI [21] that can penetrate the hair and make direct contact with the scalp may cause the patient to experience an unpleasant pain.

One of the main problems when using EEG technologies in HCI research is their high cost. It is expected that their costs will decrease, and no technologies will become available. However, for now, the low-cost technologies are also providing relevant results.

This work presents a study of UX through EEG signals using OPENBCI, an open-source approach based on a low cost hardware device.

The main objective of this study is therefore formulated through the following research question: Is a low-cost open source EEG device capable of collecting information to help evaluate UX?

## II. BACKGROUND

Today, with the growth of technology, different ways of interacting with video games have been implemented. The games have been implemented in a number of areas, with specific purposes. They have thus captured the imagination of researchers studying cognitive and emotional processes through brain activity that occurs while playing.

There is stronger interest in the HCI line from researchers evaluating UX through physiological responses. As a consequence, EEG signals have become a field capable of adding new dimensions in the field of HCI.

Today, researchers aim to evaluate emotions through psychophysiological responses using several means with the support of technology. One research group [22] conducted a study of pupillary response using eye tracking to sense changes in arousal while gaze analysis revealed the focal attention of the user during moments of increased arousal. Arousal detection has thus been used to identify frustration. These authors focused on frustration-induced arousal, using common causes of frustration during user interaction, comparing pupillary responses between frustrating tasks and normal tasks. The authors discuss how arousal sensing opens up research avenues for usability and accessibility testing. Other authors [23] meanwhile explore the relationship between eye movements and the pupillary response from formative user experience.

Elsewhere, researchers [24] observe that responses obtained through the physiological responses of a subject are usually involuntary, and as such may be more objective. In using sensors to capture physiological signals, the responses captured are uncontaminated by the verbal response of the participant. These measures are more sensitive when capturing responses in real time, within which context an evaluator cannot manage to identify every detail while observing the subject at play.

A number of studies have been conducted [25]–[28] in which electrodes were used to capture the brain activity responses of a subject. Physiological sensors can be used to take account of changes in the body of a subject in HCI [29]. These include recording EEG signals to analyse brain activity responses upon interacting with a multimedia system [26], [27].

According to some research [30], the predominant waves for measuring cognitive load in frequency analysis are the Theta and Alpha waves. Changes in these two wave types are related to cognitive performance [31]. For example, when the eyes are open, a suppression of Alpha activity occurs, indicating alert attention. There are certain EEG parameters that are widely used for measuring mental workload. A low amplitude of the Alpha wave is assumed to represent the attribution of attention more than a high Alpha amplitude. A high Theta amplitude represents an increase in the load of a task: the smaller the amplitude, the lower the load.

In 2015, a group of researchers analysed video game effects using brain waves [32]. They sought to analyse brain wave Alpha-Beta signals during the playing of a game, with the aim of analysing the effect of stress during play. Applying an analysis of Power Spectral Density (PSD) per histogram on the Fp1 channel for each type of wave, they identified that, as the player begins playing, Alpha waves in this region decrease, while Beta waves in the Fp2 increase. The same authors concluded that more subjects experienced more high frequency Beta waves, which indicate that a person is in a state of stress, while before playing the subject is in a state of relaxation.

Research presented by [33] evaluated UX using EEG measurement techniques. The authors applied an experimental study with eight participants (four men and four women) between the ages of 20 and 40. Each evaluation was applied individually, in which each participant was shown five videos in order to induce different emotional states, e.g., disgust, serenity, or enjoyment. Some of the videos were shown with and without audio.

EEG is related to the cognitive and emotional states that may be captured from a subject. Work carried out by [34] proposed to capture brain activity signals using the EEG technique to evaluate user experience upon interacting with a system. To evaluate UX, they proposed three methods: mental load, attention and error recognition. Their experiment consisted of evaluating the user in the course of interacting, but they selected two interaction types – **indirect**, using the keyboard, and **direct**, using Touch. To measure UX, an analysis of EEG signals was carried out for the Delta, Alpha, Theta, and Beta wave types. Analysis of the EEG signals was performed at a spectral and temporal level. The authors employed 32 electrodes using the EEGLab library: AF3, AFz, AF4, F7, F3, Fz, F4, F8, FC3, FCz,FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P7, P3, Pz, P4, P8, PO7, POz, PO8, O1, Oz, and O2. Other authors [35] carried out a study of EEG signals while interacting with video games. The authors performed an analysis of the signals in the frequency domain, where they observed changes in the Theta (4-8 Hz) and Alpha (8-13 Hz) wave types. They further observed that the Theta waves increased in the frontal lobe, while in the parietal lobe the Alpha waves decreased. Authors have used the NASA-TLX questionnaire to validate the workload induced.

For this study, 128 channels were used, recording a subject for 3 minutes as they played. To perform a spectral analysis, they also used the Welch method of spectral density estimation. In 2019, a group of researchers [36] used two types of waves (Alpha and Beta) to identify mood: when the Alpha wave is in a low state, it indicates stress, high means reluctant, and optimal indicates relaxed. A low Beta wave means lack of attention, high indicates anxiety, and optimal, focused. The experiment consisted in the user playing a video game called DX-Ball while the signals were captured using the Neurosky Mindwave Mobile 2 system as BCI. The system features two electrodes, one located in the frontal lobe (FP1) and the other in the temporal lobe (T3).

In 2015, researchers examined surprise effects in a serious game using EEG Signals [37], where players were exposed to surprising situations. Authors used Neurosky's Mindwave Mobile to capture the brain activity.

There are video games whose purpose is entertainment, while others are more educational and are called serious games. Affective studies evaluate the player's emotion [38] and cognition using psychophysiological methodology. Therefore, techniques of affective computing have received much attention in video games, both in entertainment and serious games [39], where those studies supported subjective methods to validate the consistency using questionnaires, such as: Self-Assessment Manikin (SAM) [40], Game Engagement Questionnaire [41], and others.

In addition, some researchers have worked with commercial video games to analyse the effects of video games with a brain-computer interface. Carrera *et al.* [42] used five-channel EMOTIV and participants played the video game Call of Duty, which aimed to provide an early insight into how playing a video game with an EEG-based BCI would impact a participant's mood as compared with a traditional video gaming setup. Commercial video games have been used to analyse emotions, including Little Big Planet2 [43], Counter Strike [32], DX-Ball [36] and Quaker3 Arena [44].

## III. VIDEO GAMES, EMOTIONS AND GENDER

Researchers are interested in studying how video games impact the emotional experiences of players. Emotions are feelings that are experienced over a short time and can change rapidly [45]. Emotions are associated with activation of certain regions in the brain. When a player is gaming, he/she can experience various emotional responses if the game becomes too boring or too exciting. Entertainment is commonly related to games. A study made by Salminen *et al.* [46] showed that games with different characteristics (i.e., Tetris, Super Monkey Ball 2, Monkey Bowling 2 and James Bond 007: NightFire) presented different emotional responses. A study presented by Porter and Goolkasian [47] used two types of video games, Mortal Kombat and Tetris, to determine the effect on stress. Authors found that the players presented higher positive emotions ratings while fighting, while the puzzle game (Tetris) players presented a stress response. Therefore, the video games include attributes, such as: type of interaction, storytelling, colours, mechanics, sounds, and other elements that can influence the emotional state. A study presented in 2000 by Wolfson and Case [48] measured the impact of emotions when changing the colour and sounds of the video game. A study was designed by researchers [49] to analyse how the physiological effects of colour in EEG signals can influence perception and attention. Various colours showed effects on the mean power of Alpha band, Theta and on the total power in the Theta-Beta EEG bandwidth.

In addition, video games do not have the same emotional effects on people. Researchers have examined the role of gender in video games. Studies have shown that men and women prefer different types of gaming experiences [50]. Another study presented by Desai *et al.* [51] examined the effects of player gender. Authors found differences both by gender and by gaming experience.

Therefore, video games have effects on emotions of players, which can be influenced by elements of video games including type of interaction, storytelling, and colours, among others. However, they may affect females and males differently.

## IV. METHODOLOGY

The brain activity of five male and five female subjects was recorded and analysed for each experiment. The mean age was 20 years old and none of the subjects suffered any discomfort or pain during the recordings. All experiments were conducted in a quiet room and with the subject seated playing a video game. In our study, the OPENBCI EEG device used was configured using the Cyton board (+reference, +ground) and eight channels (Fp1, Fp2, T5, T6, T3, T4, O1 and O2), using as reference and ground those located in positions A2 and A1, respectively. A sampling frequency of 250 Hz was used to capture the EEG signals. Recordings were composed of four tasks: 90 s eyes closed, 180 s playing a video game, 90 s eyes closed and 60 s answering two questionnaires: meCUE 2.0 [52] and SAM [53]. Both are considered as qualitative assessment instruments, a common practice to allow the players or participants to self-assess their emotions and perceptions. Figure 1 shows the flowchart of the experiment protocol, where 153,600 data points per channel were captured for each subject in 10 minutes.

The meCUE 2.0 questionnaire is based on the component of the user experience model (CUE-Model). The SAM (Self-Assessment-Manikin) questionnaire was created to assess the emotional states of participants and is made up of three pictographic scales, each with five humanoid drawings, which represent each of the three dimensions of emotion:

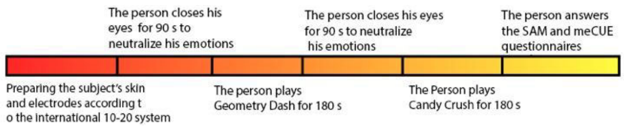



**FIGURE 1.** **Flowchart of experiment protocol.**

Valence (Pleasant-unpleasant), Arousal (Relaxed-active) and Dominance (Dominant-dominated). Two case studies were applied in this experiment: (1) a video game featuring direct interaction, called Geometry Dash[1] [2]; (2) a video game featuring indirect interaction, called Candy Crush[2]. Figure 2 shows the methodology of the experiment.

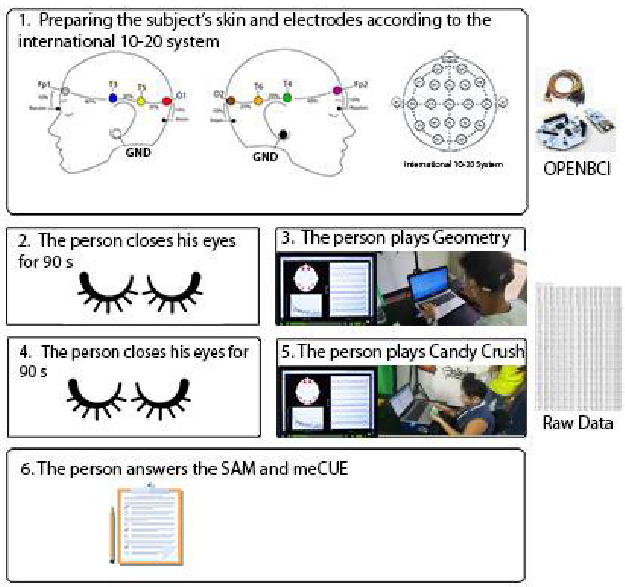



**FIGURE 2.** **Methodology of the experiment.**

The raw data were captured using Processing (Java). In addition, the raw data recorded were processed offline using signal processing techniques developed by MATLAB. As seen in Figure 2, two PCs were used: one for capturing EEG signals and the other by the player.

The procedure carried out for this study is shown in Figure 3, in which a set of steps is followed in order to analyse the EEG signals. In data analysis, the PSD (Power Spectral Density) was calculated, taking the highest amplitude value (peak). The PSD was obtained by applying FFT (Fast Fourier Transform) to the power of the square to the signal. PSD was applied for each electrode [32], [54], [55] to determine differences between the type of wave for each electrode.

In the **Signal capture** stage, the skin of the subject was carefully cleaned at the positions determined for the wet electrodes, and the electrodes were placed on the skin of the scalp. In the **pre-processing** stage, the signals collected were then divided into segments and processed off-line using MATLAB, the EEGLab library. According to the work presented by [70], a high-pass filter using fourth-order Butterworth filter was applied to remove frequencies below 0.2 Hz, and a notch filter was used to remove power line noise. The signals were segmented and grouped by gender. The method used were proposed by [32]. In the **Feature extraction**stage, FFT (Fast Fourier Transform) was applied, where the average of the first two thousand samples and the last two thousand samples is calculated for each segment for each subject, thereby revealing the differences between the initial and final reaction of each segment with the aim of reducing the dimensionality of the sample to 384,000 data points. Having separated the data by channel, gender and segment, the signal in the frequency domain was transformed by applying FFT to analyse the data. In the last stage, **Data analysis**, the MATLAB EEGLab library was used, obtaining a representation of the signal by wave type. The EEG signals vary in frequency and amplitude. There are five basic EEG frequency patterns: Delta (0-4 Hz), Theta (4-7 Hz), Alpha (8-13 Hz), Beta (13-35 Hz) and Gamma (35 Hz and higher) [56]. According to the studies presented in the background, the wave types analysed were Theta (4-7 Hz), Alpha (8-13 Hz), and Beta (13-35 Hz) [56].

[1]https://geometrydash.io/

[2]https://play.google.com/store/apps/details?id=com.king.candycrushsaga&hl=en

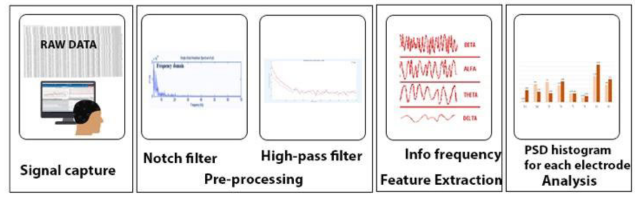



**FIGURE 3.** **Procedure for EEG signal processing.**

### A. PARTICIPANTS

Ten subjects were selected (five male and five female), aged between 18-23 years, with an average female age of 19 and male age of 21 (mean=20, SD=1.8). Each subject provided their signed, informed consent to participate in the study, at which point the conditions and protocol of the experiment regarding publication of the data were explained. In turn, the procedures followed met the human experimentation ethical standards according to the Helsinki declaration. All participants had some prior experience with video games.

### B. INSTRUMENTS

The OPENBCI device was used to measure the electrical activity of the brain using electrodes placed on the skin of the scalp. According to previous studies [57], EEG signal quality is excellent using wet electrodes with an appropriate preparation of the skin and the use of a conductive gel, aimed at reducing skin-sensor interface impedance [58]. The type of electrode used, therefore, was Gold Cup, applying conductive gel to the scalp of the subject. When too much gel is applied, however, it excessively presses on the scalp. In the skin preparation, the subject must wash his or her hair with coconut soap, with the aim of establishing a better contact area between skin and electrode and to reduce the impedance (between 10 kOhm to 5 kOhm).

Two types of video games were selected. The first, Geometry Dash, whose interaction is through a computer and keyboard, can be said to involve direct interaction. Geometry Dash is a video game created in 2013 by the Swede, Robert Topala. In synopsis, the focus of the game is the completion of various levels. Stars, coins, power fragments, diamonds and keys may be earned in the course of the game. The second game, Candy Crush, which makes use of a smartphone, involves indirect interaction. The mechanics of Candy Crush involve gathering three of the same kind of candy to build up a score.

Questionnaires were also used for evaluating each participant. The questionnaires were meCUE 2.0 [52] and SAM [12]. The meCUE 2.0 questionnaire is based on the component of the user experience model (CUE-Model). This questionnaire has five modules: Perception of the quality of the instrument (Module I), Perception of non-instrumental qualities (Module II), Emotions of the user (Module III), Consequences of use (Module IV) and Global assessment (Module V). The meCue 2.0 questionnaire is a scale that relates its variables bi-directionally, and allows an accepted analysis of user experience for desktop applications, web applications, video games and other types of interactive systems. For this study, modules II and III were used. The questionnaire features a Likert scale of 1 (strongly disagree) to 7 (strongly agree).

The SAM (Self-Assessment-Manikin) questionnaire was created in 1985 by P.J. Lang [53]. It assesses the emotional states of participants and is made up of three pictographic scales, each with five humanoid drawings, which represent each of the three dimensions of emotion: Valence (Pleasant-unpleasant), Arousal (Relaxed-active) and Dominance (Dominant-dominated). The questionnaire utilizes a Likert scale from 1 to 9, where 9 is the best score and 1 the lowest.

### *C. PROCEDURE*

The subjects were first asked to close their eyes for 90 s. They then followed the two phases proposed for data capture. In the first phase, the subject interacts with the first video game for 90 s, without sound, followed by another 90 s, this time with sound, repeating this same process with the second video game (see Figure 4).

The second phase makes use of the two qualitative assessment instruments - meCUE2.0 and SAM. It is possible to capture 153,600 data points per channel for each subject. For the eight channels used, a total of 1,228,000 data points were captured per subject. With 10 subjects participating, therefore, 12,288,000 data were collected.

Once the signals were segmented, the results were grouped by gender, since we sought to show differences by gender.

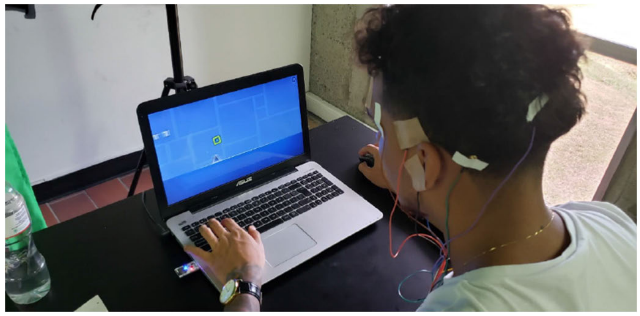


**FIGURE 4.** Interaction with the video game. The participant is wearing an EEG cap.

An algorithm was implemented in MATLAB to calculate the average of the first two thousand samples and the last two thousand samples of each segment, for each subject, thereby revealing the differences between the initial and final reaction of each segment with the aim of reducing the dimensionality of the sample to 384,000 data points.

## V. RESULTS

Tables 1 and 2 show the results obtained for the two video games, separated by gender and channel. To identify the behaviour of the signals, maximum values were taken for the Alpha, Beta and Theta wave types for each channel. In turn, they were subdivided into segments according to the activity, as follows: Candy Crush with sound, Candy Crush without sound, Geometry Dash with sound, Geometry Dash without sound. Each segment was divided into an initial and final phase for each activity type.

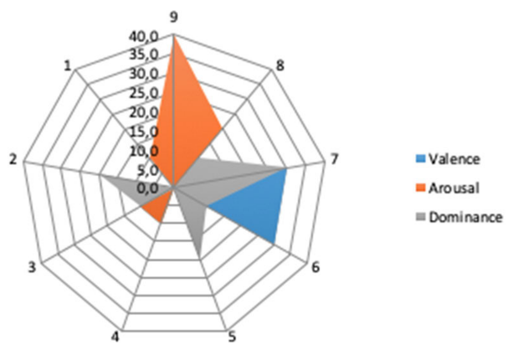



**FIGURE 5.** Results of the SAM questionnaire for the geometry dash video game, determining valence, arousal and dominance.

Data were also collected from the SAM and meCue2.0 questionnaires. Figures 5 and 6 show the results obtained using the SAM questionnaire with the Geometry Dash game. In the Geometry Dash video game, the following results were obtained for the female gender: Valence: 40% (9), 40% (6) and 20% (7); Arousal 40% (9), 20 (8) and 20% (6); Dominance 20% (8), 20% (7), 20% (6), 20% (2) and 20% (1). Meanwhile, the results for males were as follows. Valence 40% (9), 40% (7) and 20% (6); Arousal 40% (9), 20% (8),

**TABLE 1. PSD histogram from male subjects.**

| Candy Crush | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Beginning of experiment | | | | | | | Finishing of experiment | | | | | | |
| | PSD - with sound | | | PSD - no sound | | | | PSD – with sound | | | PSD - no sound | | |
| Channel | Alpha | Beta | Theta | Alpha | Beta | Theta | Channel | Alpha | Beta | Theta | Alpha | Beta | Theta |
| Fp1 | 2.663 | 1.359 | 9.027 | 4.729 | 0.095 | 8.835 | Fp1 | 8.673 | 3.915 | 18.31 | 9.139 | 0.7611 | 11.13 |
| Fp2 | 2.325 | 3.356 | 10.85 | 7.91 | 1.973 | 8.061 | Fp2 | 4.526 | 2.144 | 16.88 | 2.075 | 1.968 | 10.06 |
| T3 | 1.972 | 2.224 | 12.55 | 3.6 | 2.716 | 17.45 | T3 | 2.591 | 2.638 | 8.38 | 5.692 | 2.956 | 7.563 |
| T4 | 4.629 | 6.625 | 0.4493 | 1.427 | 3.635 | 1.64 | T4 | 0.6566 | 3.071 | 3.436 | 2.21 | 6.227 | 6.229 |
| T5 | 1.902 | 3.338 | 2.272 | 9.043 | 1.405 | 2.32 | T5 | 2.439 | 1.764 | 2.33 | 0.8115 | 0.06122 | 4.112 |
| T6 | 1.355 | 0.5974 | 3.997 | 6.783 | 1.458 | 3.978 | T6 | 0.09667 | 2.063 | 4.427 | 1.98 | 3.802 | 1.668 |
| O1 | 8.374 | 5.215 | 3.92 | 12.74 | 2.322 | 4.328 | O1 | 7.571 | 5.121 | 6.093 | 7.397 | 4.877 | 3.354 |
| O2 | 5.11 | 3.619 | 5.554 | 10.47 | 3.42 | 10.34 | O2 | 7.064 | 5.586 | 7.297 | 7.482 | 3.262 | 5.385 |
| Geometry Dash | | | | | | | | | | | | | |
| Beginning of experiment | | | | | | | Finishing of experiment | | | | | | |
| | PSD - with sound | | | PSD – no sound | | | | PSD – with sound | | | PSD - no sound | | |
| Channel | Alpha | Beta | Theta | Alpha | Beta | Theta | Channel | Alpha | Beta | Theta | Alpha | Beta | Theta |
| Fp1 | 4.8 | 0.3069 | 9.856 | 4.343 | 2.152 | 9.198 | Fp1 | 3.258 | 3.403 | 7.377 | 1.298 | 0.5797 | 11.61 |
| Fp2 | 4.992 | 5.903 | 10.33 | 7.091 | 3.628 | 8.792 | Fp2 | 0.4556 | 4.12 | 5.948 | 6.932 | 0.3151 | 10.41 |
| T3 | 0.3385 | 2.635 | 2.697 | 3.915 | 1.996 | 7.982 | T3 | 0.009 | 0.4098 | 2.765 | 1.589 | 0.3195 | 8.067 |
| T4 | 2.829 | 4.347 | 3.845 | 1.305 | 5.684 | 0.6745 | T4 | 1.878 | 4.228 | 5.937 | 2.041 | 0.3602 | 3.88 |
| T5 | 1.989 | 2.874 | 0.2742 | 8.49 | 2.25 | 3.535 | T5 | 2.355 | 2.337 | 0.66357 | 4.52 | 0.8703 | 5.22 |
| T6 | 4.682 | 2.271 | 0.4054 | 6.275 | 1.306 | 4.355 | T6 | 4.949 | 1.976 | 0.532 | 0.1323 | 0.667 | 1.635 |
| O1 | 4.508 | 0.2488 | 6.731 | 9.711 | 3.575 | 7.801 | O1 | 3.31 | 0.1053 | 9.318 | 5.904 | 0.3796 | 6.813 |
| O2 | 3.838 | 4.825 | 5.12 | 10.29 | 0.8722 | 6.699 | O2 | 3.525 | 5.469 | 7.073 | 6.688 | 4.747 | 9.556 |

20% (4) and 20% (1); Dominance 20% (9), 40% (7), 40% (5) and 20% (2).

Figure 6 shows the results obtained with the Candy Crush video game, where 40% (9) of the participants rated the valence at 9, 40% at 7, 10% at 6 and 10% at 5. Valence scored 9 for 40% of men and 20% women, and Arousal for 40% (9) of men and 20% (8) of women.

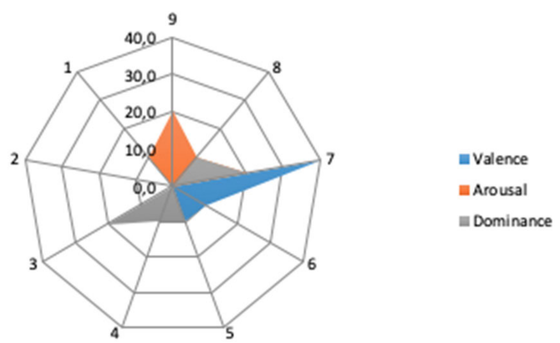



**FIGURE 6. Results of the SAM questionnaire for the candy crush video game determining valence, arousal and dominance.**

The results obtained in the meCUE2.0 questionnaire from module III, which correspond to assessing player emotions for both video games, are shown in Figure 7. It is observed that women (Figure 7a) have an average of 4.23 positive emotions and men (Figure 7b) presented an average of 5.08 positive emotions.

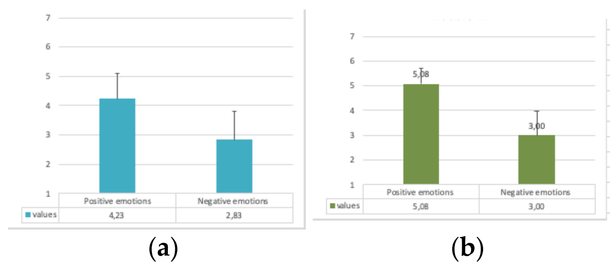



**FIGURE 7. Results of the meCue2.0 questionnaire for both video games.**

## VI. DATA ANALYSIS

The analysis of the captured data was carried out according to three aspects: by gender, by presence/absence of sound, and by interaction type (direct or indirect). One Spectral Density (PSD) analysis per histogram was applied for each electrode position for Alpha and Beta waves.

### A. GENDER

Differences were compared between gender (male and female). In Figure 8, the results of the Alpha waves are observed. It is observed that men have greater amplitude in the Fp1, T4, O1 and O2 channels. Meanwhile, the most active electrodes in women are Fp2 and T3. FP1 is related to attention, organization of responses and is more related to visual working memory [59], while Fp2 is more related to

**TABLE 2.** PSD histogram from female subjects.

| Candy Crush | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Beginning of experiment | | | | | | | End of experiment | | | | | |
| | PSD - with sound | | | PSD - no sound | | | | PSD - with sound | | | PSD – no sound | | |
| Channel | Alpha | Beta | Theta | Alpha | Beta | Theta | Canal | Alpha | Beta | Theta | Alpha | Beta | Theta |
| Fp1 | 0.3147 | 0.593 | 5.08 | 2.518 | 2.152 | 5.347 | Fp1 | 3.42 | 2.181 | 12.81 | 6.388 | 4.639 | 15.79 |
| Fp2 | 4.03 | 1.57 | 10.12 | 4.46 | 1.8 | 10.24 | Fp2 | 5.338 | 2.033 | 16.99 | 8.005 | 4.089 | 19.17 |
| T3 | 4.5 | 1.3 | 9.3 | 3.6 | 2.3 | 13.6 | T3 | 2.989 | 2.963 | 10.24 | 5.457 | 4.623 | 11.43 |
| T4 | 3.735 | 3.385 | 2.012 | 2.195 | 4.947 | 0.715 | T4 | 4.124 | 2.454 | 1.576 | 0.7317 | 0.9973 | 2.974 |
| T5 | 1.919 | 0.9115 | 1.94 | 2.658 | 3.686 | 2.715 | T5 | 2.972 | 2.094 | 8.664 | 7.237 | 5.178 | 13.19 |
| T6 | 0.9784 | 0.8683 | 5.777 | 4.514 | 2.518 | 10.33 | T6 | 1.874 | 2.334 | 3.083 | 2.259 | 0.635 | 3.719 |
| O1 | 5.794 | 3.539 | 5.327 | 5.722 | 0.4797 | 6.131 | O1 | 5 | 4.357 | 12.48 | 6.725 | 4.988 | 5.838 |
| O2 | 3.865 | 3.935 | 8.398 | 6.924 | 1.057 | 7.365 | O2 | 3.744 | 5.088 | 6.429 | 9.041 | 5.966 | 9.287 |
| Geometry Dash | | | | | | | | | | | | | |
| | Beginning of experiment | | | | | | | End of experiment | | | | | |
| | PSD - with sound | | | PSD – no sound | | | | PSD - with sound | | | PSD – no sound | | |
| Channel | Alpha | Beta | Theta | Alpha | Beta | Theta | Canal | Alpha | Beta | Theta | Alpha | Beta | Theta |
| Fp1 | 2.3 | 3.199 | 6.711 | 7.53 | 1.694 | 12.16 | Fp1 | 0.316 | 4.42 | 9.482 | 1.043 | 2.006 | 12.72 |
| Fp2 | 2.14 | 0.5506 | 11.76 | 7.469 | 4.718 | 15.4 | Fp2 | 4.33 | 3.052 | 13.47 | 3.931 | 1.066 | 14.69 |
| T3 | 2.594 | 2.275 | 9.631 | 2.018 | 0.042 | 9.509 | T3 | 1.144 | 0.5243 | 13.77 | 2.1 | 1.388 | 15.2 |
| T4 | 4.509 | 2.264 | 0.6592 | 0.1828 | 3.306 | 2.582 | T4 | 4.558 | 4.733 | 0.076 | 4.692 | 3.325 | 0.413 |
| T5 | 1.702 | 0.1743 | 6.463 | 3.122 | 1.194 | 6.433 | T5 | 0.4582 | 0.4673 | 4.324 | 3.604 | 0.1138 | 3.453 |
| T6 | 0.1545 | 0.6355 | 9.504 | 4.307 | 0.3702 | 11.07 | T6 | 2.048 | 0.08577 | 4.134 | 0.3492 | 1.561 | 4.94 |
| O1 | 3.809 | 3.115 | 5.034 | 8.567 | 5.434 | 8.204 | O1 | 0.7528 | 2.548 | 3.275 | 3.643 | 4.724 | 7.979 |
| O2 | 4.471 | 3.479 | 10.82 | 8.455 | 2.405 | 10.41 | O2 | 3.313 | 2.548 | 6.737 | 5.254 | 6.28 | 7.519 |

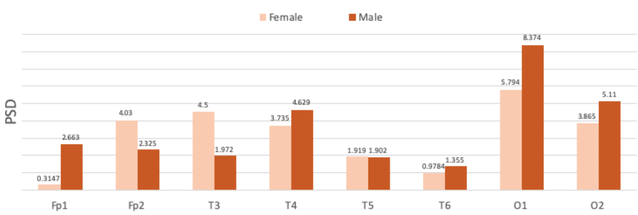



**FIGURE 8.** Alpha waves for females and males playing the candy crush video game.

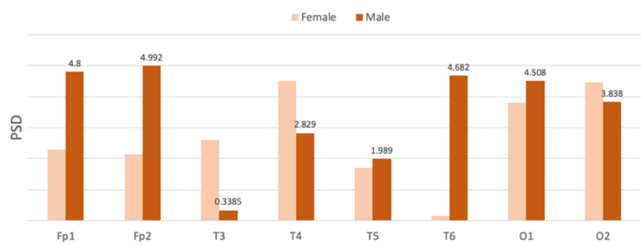



**FIGURE 9.** Alpha waves for females and males playing the geometry dash video game.

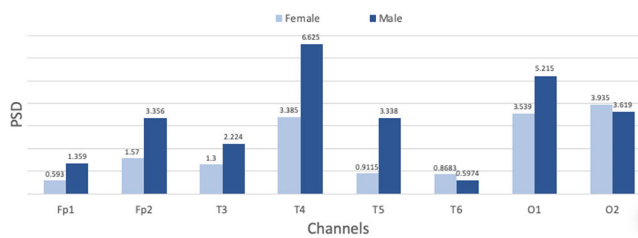



**FIGURE 10.** Beta waves for females and males playing the candy crush video game.

emotions. As seen in Figure 8, women had greater amplitude of Fp2. Channels O1 and O2 are related to visual stimuli. T5 and T6 are related to certain memory functions. Therefore, for the Alpha waves, the most active areas are the frontal and occipital regions.

In Figure 9, the results obtained for the Geometry Dash video game are observed: the Fp1, Fp2, T5, T6 and O1 channels are activated more in men, and the T3, T4 and O2 in women. In men, the active Fp1 and Fp2 electrodes relate to the frontal lobe and are associated with emotions [60]. The hemispheric valence theory [61] argues that positive emotions occur in the left frontal cortex, while negative emotions occur in the right frontal cortex. This could be observed in areas Fp1 (left frontal cortex) and Fp2 (right frontal cortex), where Fp2 was activated more than Fp1 in women, while in men Fp1 was activated more than Fp2.

Figure 10 shows that the Beta waves with the greatest amplitude during Candy Crush video gameplay in men are obtained in the Fp1, Fp2, T3, T4, T5 and O1 channels, and channels T6 and O2 in women.

Beta waves relate to relaxation and originate in the occipital lobe, which indicates that functioning accelerates when attentive to visual stimuli or movement, as occurred with Candy Crush, where in men the occipital region was activated on both sides of the brain: O1 (left Lobule) and O2 (right Lobule).

Similarly, with Geometry Dash (Figure 9), most electrodes with the greatest amplitude are from the male gender.

The greatest amplitude in the female gender is observed for Fp1 and O1. It is important to mention that Beta waves have a frequency range of 13-30 Hz. This type of wave is activated in mental activities, so it is usually associated with active things, attention and active focus, or for the resolution of specific problems. Some studies have found that Beta waves better describe arousal/alert status [62]. Therefore, a decrease could indicate a reduction in concentration.

### *B. ABSENCE/PRESENCE OF SOUND*

Data analysis was performed for both video games without/with sound regardless of gender. The results obtained from the Alpha and Beta waves are shown in Figures 11-14. Amplitude was observed to decrease when there is a change from no sound to sound for Alpha waves (Figure 11-12). Studies have used Alpha waves to measure stress levels with acoustic stimuli [63].

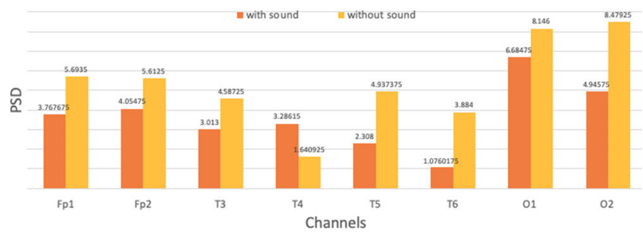



**FIGURE 11.** **Alpha waves for the candy crush video game with/without sound.**

It has further been reported that the amplitude of the Alpha wave is reduced and the wave fluctuations increase significantly in the face of an unpleasant sound, which can influence the emotion of a subject [64]. Figure 11 shows that major changes occur with sound and without sound for O1 and O2 (left and right Occipital channels) and that Geometry Dash elicits a higher activation than Candy Crush. For both games, T3 was greater without sound, and T4 was greater with sound. The temporal lobe is related to the recognition of auditory stimulation, perception and memory.

For the Beta waves (Figure 13-14), there is an increase in changing from no sound to sound for electrodes O1-02, T3-T4 and T5-T6 for both games. With the Candy Crush game, O1 and O2 are activated more compared to Geometry Dash.

What was observed in the interaction by auditory perception, that both Alpha and Beta waves increase, is a response to stress [65]. Therefore, it can be concluded that people became more stressed in the presence of sound.

### *C. TYPE OF INTERACTION (KEYBOARD vs TOUCH)*

The results obtained from the Alpha and Beta channels to evaluate the interaction are shown in Figures 15 and 16.

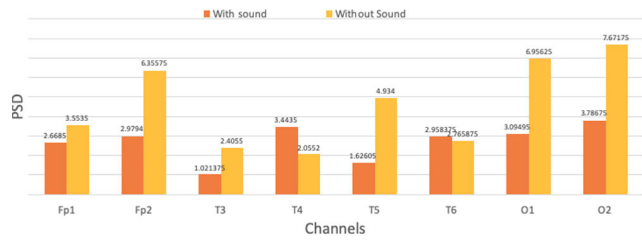



**FIGURE 12.** **Alpha waves for the geometry dash video game with/without sound.**

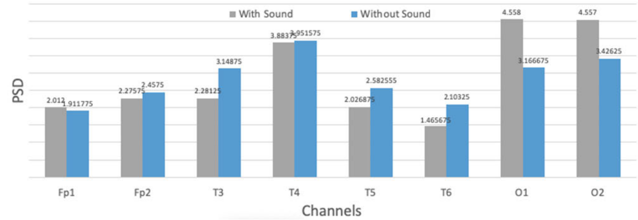



**FIGURE 13.** **Beta waves for the candy crush video game with/without sound.**

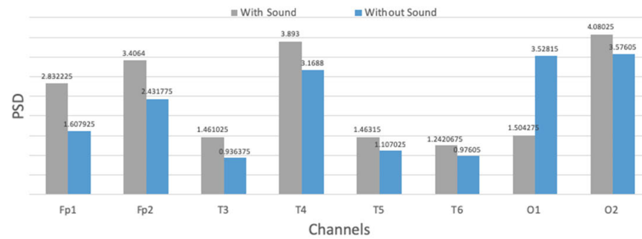



**FIGURE 14.** **Beta waves for the geometry dash video game with/without sound.**

The results are obtained by averaging the genres and segments with/without sound. It is observed in Figure 14 that Alpha waves showed greater activation for a type of direct interaction - using the mobile device - while the amplitude is smaller with the computer.

The most active region with direct interaction was the occipital (O1 and O2). Furthermore, Alpha waves were observed to decrease in an indirect interaction. Some studies [66], [67] have mentioned that this decrease may be related to the increased demand for attention and cognitive load, i.e., the type of interaction can affect the emotional state of a subject, since an increase in cognitive load indicates that their attention span is overloaded, and could produce a negative emotional state.

The Beta waves increase with direct interaction for electrodes T3, T4, T5, T6, O1 and O2. However, for Fp1 and Fp2, indirect interaction is greater.

For the beta waves, the frontal and central areas of the brain predominate. The Beta wave is associated with increasing arousal and activity [68]. In 2009, Dooley [69] indicated that this type of wave represents cognitive awareness, activity, busy state or anxious thinking.

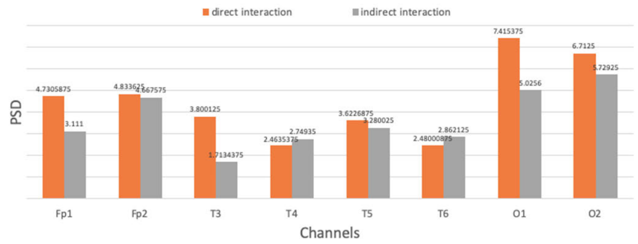



**FIGURE 15.** **Alpha waves from candy crush (direct interaction) and Geometry Dash (indirect interaction).**

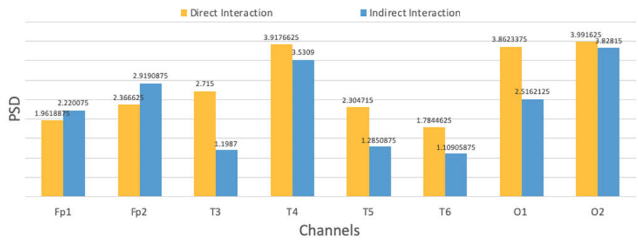



**FIGURE 16.** **Beta waves from candy crush (direct interaction) and geometry dash (indirect interaction).**

Alpha waves are also observed to decrease when subjects must perform an indirect interaction. Samples were taken when subjects closed their eyes for 90 s. Observation was thus made when they moved from a state of relaxation to interacting with a video game. In the data obtained, Fp1 positions decreased for the Alpha wave type upon starting play, while Fp2 in Beta increases, indicating that the person is in a state of stress upon starting play.

In the meCue 2.0 questionnaire results in module III, corresponding to emotions, the men had a higher positive emotional state (5.08) than the women (4.23). In the negative emotional state, there was little difference between the two. It could therefore be determined that direct interaction activates more cognition than indirect interaction, while indirect interaction causes more effort to be required to perform the task.

In the SAM questionnaire for the Geometry Dash game, a valence mean of 7.83 for women and 7.4 for men was obtained, along with arousal of 6.67 for women and 7 for men and dominance of 5.83 for women and 5.2 for men. Relating the results obtained in the EEG signals, the Alpha and Beta waves present gender differences. A study carried out to analyse valence, arousal and dominance in the EEG signals during gameplay [70] found some correlations between the Alpha and Beta waves.

Using Candy Crush, the valence mean is 8.1 in women, and 7 in men; arousal is 6.33 in women and 5.6 in men; dominance is 3.6 in women and 5.4 in men. Women thus had higher percentages in valence and arousal, and men in dominance. The arousal is related to the activation of emotion, and valence is the motivational component of emotion (pleasure vs. displeasure). Dominance, meanwhile, is related to the degree of control the person perceives over their emotional response, in which men obtained higher scores.

It is also worth noting that another aspect related to UX is visual perception. One of the aspects related to visual perception in a video game is colour. A study carried out mentions that there may be an influence of colour on emotions [71]. Therefore, colour can be a stimulating signal for a subject. A group of researchers in 2018 [72] performed an EEG analysis on the visual response to colour variation. They identified that the FP1 electrode presented changes in response to varying colours.

The O1 electrode that is located high in the visual cortex in the occipital region, and both O1 (left) and O2 (right), are responsible for colour processing [73]. However, this analysis should be carried out in a more detailed and controlled manner, since both video games were similar in colour.

## VII. BCI TECHNOLOGIES

There are a number of BCI systems that can support the recognition of emotions in computer games. Literature was reviewed to evaluate the emotions, and researchers have used some BCI devices such as EMOTIV, EPOC+, MindWave Mobile, USBamp, *and* InterAxon Muse, among others [74]. These devices use the standard EEG technique, which consists of capturing signals of brain activity by means of dry electrodes. However, wet electrodes provide much better quality of recorded signals compared with dry electrodes [58].

EPOC+ is developed by Epoch. This device has 14 channels + 2 references at the mastoids. EPOC+ does not generally offer access to the data. However, access to the data can be acquired with a monthly subscription, which can end up being more expensive in the long run. Given this, using EPOC requires internet connectivity. The MindWave Mobile headset is a low cost device, but only provides two electrodes (A1 and T4). The information is very limited, and it is used more to measure the level of attention. USBamp is a biosignal amplifier of medical grade. Therefore, medical grade device signals are very close to EEG readings. OPENBCI is an open source DIY hardware and software device which can be analysed with respect to 4 (Ganglio board) to 16 channels (Cyton board + Daisy module). In addition, data can be read with Processing (JAVA), MATLAB, Python, or OpenVIBE, among others. The electrode connection of the OpenBCI can include a 3D-printed headset (Ultra-cortez Mark IV) or any traditional gold cup electrode system. Therefore, the device is very modular, and it is possible to fix and replace parts that fail.

## VIII. CONCLUSION

The analysis carried out in the frequency domain by means of EEG signals shows that there are differences between women and men in their interaction with video games.

These differences were further emphasized by the results from the instruments used, the exception being the SAM test results with Candy Crush, where differences were minimal. A high consistency was thus found between the EEG data and the data produced by meCue 2.0 and SAM.

Differences in EEG signals were also evident in the type of interaction, with sound and without sound, with the game without sound being more relaxing, as observed in the Alpha waves, and more stressful with sound, with an increase in the Beta waves.

Differences in interaction type are also observed, in which direct interaction turns out to be less stressful for the subjects, whereas indirect interaction activates more logical processes in users. The OpenBCI system provides economical and non-invasive EEG capture, making the technology easily accessible, and its documentation is extensive and complete, facilitating its use. One of the limitations that arose when collecting data is that when using Bluetooth for the connection of the OpenBCI programmable dongle, some data are lost during capture.

Due to the significant presence of Theta waves in the EEG signals, a more robust pre-processing of the signal (or the use of a more precise hardware) is recommended in future work to eliminate noise signals that can affect the final result of the investigation. Alpha and Beta waves are characteristics that contribute to the analysis of user experience. Inconsistencies were also evident between the results obtained through the questionnaires and the neuronal signals obtained by EEG. This is because the questionnaires have subjective components, while the EEG analysis is objective.

Results showed that the use of low cost technology was nevertheless able to produce results similar to those obtained using more expensive techniques. As such, a low cost technology may offer an alternative for evaluating UX. Additionally, when using high-cost commercial devices, access to the monitoring data must be paid for through service plans, depending on the number of users to be monitored.

Future work would include applying other analysis techniques that allow relevant information to be gathered in order to evaluate user experience.

## REFERENCES


[1] J. Preece, Y. Rogers, H. Sharp, D. Benyon, S. Holland, and T. Carey, *Human-Computer Interaction: Concepts And Design*. Wokingham, U.K.: Addison- Wesley, 1994, pp. 3–23.

[2] *Ergonomics of Human-System Interaction—Part 210: Human-Centred Design for Interactive Systems*, Standard ISO 9241-210:2019, 2019. Accessed: Sep. 20, 2019. [Online]. Available: https://www.iso.org/standard/77520.html

[3] J. Norman, *User Experience-Our Definition*. Nielsen Norman Group Ed., 2003. Accessed: Sep. 20, 2019. [Online]. Available: https://www.nngroup.com/articles/definition-user-experience/

[4] M. Hassenzahl, "The thing and I: Understanding the relationship between user and product," in *Funology: From Usability to Enjoyment*, M. Blythe, C. Overbeeke, A. F. Monk, and P. C. Wright, Eds. Dordrecht, The Netherlands: Kluwer, 2003, pp. 31–42.

[5] J. L. G. Sánchez, N. P. Zea, and F. L. Gutiérrez, "Playability: How to identify the player experience in a video game," in *Human-Computer Interaction—INTERACT* (Lecture Notes in Computer Science), vol. 5726, T. Gross, Ed. Berlin, Germany: Springer, 2009.

[6] K. M. Gerling, M. Klauser, and J. Niesenhaus, "Measuring the impact of game controllers on player experience in FPS games," in *Proc. 15th Int. Acad. Mindtrek Conf. Envisioning Future Media Environ. (MindTreck)*, New York, NY, USA, 2011, pp. 83–86.

[7] N. Lazzaro, "The four fun keys," in *Game Usability: Advancing the Player Experience*, K. Isbister and N. Schaffer, Eds. Burlington, VT, USA: Elsevier, 2008, pp. 315–344.

[8] N. A. Imran, A. Jaron, A. Aishat, A. Josh, A. Josh, and C. Paul, "Attention, time perception and immersion in games," in *Proc. ACM CHI EA*, New York, NY, USA, 2013, pp. 1089–1094.

[9] A. P. O. S. Vermeeren, E. L.-C. Law, V. Roto, M. Obrist, J. Hoonhout, and K. Väänänen-Vainio-Mattila, "User experience evaluation methods: Current state and development needs," in *Proc. 6th Nordic Conf. Hum.-Comput. Interact., Extending Boundaries (NordiCHI)*. Association for Computing Machinery: New York, NY, USA, 2010, pp. 521–530, doi: 10.1145/1868914.1868973.

[10] J. Takatalo, J. Häkkinen, J. Kaistinen, and G. Nyman, "Measuring user experience in digital gaming: Theoretical and methodological issues," *Proc. SPIE*, vol. 6494, Jan. 2007, Art. no. 649402.

[11] B. Fehnert and A. Kosagowsky, "Measuring user experience: Complementing qualitative and quantitative assessment," in *Proc. 10th Int. Conf. Hum. Comput. Interact. Mobile Devices Services (MobileHCI)*, New York, NY, USA, 2008, pp. 383–386, doi: 10.1145/1409240.1409294.

[12] P. J. Lang, "The cognitive psychophysiology of emotion: Fear and anxiety," in *Anxiety Anxiety Disorder*, A. Tuma and J. Maser, Eds. Mahwah, NJ, USA: Lawrence Erlbaum, 1985, pp. 131–170.

[13] P. M. A. Desmet, R. Porcelijn, and M. B. Van Dijk, "Emotional design; application of a research-based design approach," *J. Knowl., Technol. Policy*, vol. 20, no. 3, pp. 141–155, 2007.

[14] *User Experience Questionnaire*. Accessed: Jan. 2020. [Online]. Available: https://www.ueq-online.org/

[15] J. Joe, S. Chaudhuri, T. Le, H. Thompson, and G. Demiris, "The use of think-aloud and instant data analysis in evaluation research: Exemplar and lessons learned," *J. Biomed. Informat.*, vol. 56, pp. 284–291, Aug. 2015.

[16] R. L. Mandryk, K. M. Inkpen, and T. W. Calvert, "Using psychophysiological techniques to measure user experience with entertainment technologies," *Behav. Inf. Technol.*, vol. 25, no. 2, pp. 141–158, Mar. 2006, doi: 10.1080/01449290500331156.

[17] R. A. Ramadan and A. V. Vasilakos, "Brain computer interface: Control signals review," *Neurocomputing*, vol. 223, pp. 26–44, Feb. 2017.

[18] R. Lloyd, R. Goulding, P. Filan, and G. Boylan, "Overcoming the practical challenges of electroencephalography for very preterm infants in the neonatal intensive care unit," *Acta Paediatrica*, vol. 104, no. 2, pp. 152–157, Feb. 2015.

[19] E. Walls-Esquivel, M. F. Vecchierini, C. Héberlé, and F. Wallois, "Electroencephalography (EEG) recording techniques and artefact detection in early premature babies," *Neurophysiologie Clinique/Clin. Neurophysiol.*, vol. 37, no. 5, pp. 299–309, Oct. 2007.

[20] H. A. Miller and D. C. Harrison, *Biomedical Electrode Technology*. New York, NY, USA: Academic, 1974.

[21] *OpenBCI*. Accessed: Jan. 2020. [Online]. Available: http://openbci.com/

[22] O. Matthews, A. Davies, M. Vigo, and S. Harper, "Unobtrusive arousal detection on the Web using pupillary response," *Int. J. Hum.-Comput. Stud.*, vol. 136, Apr. 2020, Art. no. 102361, doi: 10.1016/j.ijhcs.2019.09.003.

[23] J. Strohl, J. Luchman, J. Khun, E. Pierce, and K. Andrews, "Exploring the relationship between eye movements and pupillary response from formative user experience research," in *Universal Access in Human-Computer Interaction. Methods, Techniques, and Best Practices* (Lecture Notes in Computer Science), vol. 9737, M. Antona and C. Stephanidis, Eds. Cham, Switzerland: Springer, 2016.

[24] J. M. Kivikangas, G. Chanel, B. Cowley, I. Ekman, M. Salminen, S. Järvelä, and N. Ravaja, "A review of the use of psychophysiological methods in game research," *J. Gaming Virtual Worlds*, vol. 3, no. 3, pp. 181–199, Sep. 2011.

[25] F. Paas and P. Ayres, "Cognitive load theory: A broader view on the role of memory in learning and education," *Educ. Psychol. Rev.*, vol. 26, no. 2, pp. 191–195, Jun. 2014.

[26] J. Frey, M. Hachet, and F. Lotte, "Recent advances in EEG-based neuroergonomics for human-computer interaction," in *Proc. Int. Neuroergonomics Conf.*, H. Ayaz and F. Dehais, Eds., 2016, p. 275.

[27] K. Jyotish and J. Kumar, "Affective modelling of users in HCI using EEG," in *Proc. 7th Int. Conf. Intell. Hum. Comput. Interact. (IHCI)*, vol. 84, 2016, pp. 107–114.

[28] X. Shan, E.-H. Yang, J. Zhou, and V. W. C. Chang, "Neural-signal electroencephalogram (EEG) methods to improve human-building interaction under different indoor air quality," *Energy Buildings*, vol. 197, pp. 188–195, Aug. 2019.

[29] S. H. Fairclough, "Fundamentals of physiological computing," *Interacting Comput.*, vol. 21, nos. 1–2, pp. 133–145, Jan. 2009, doi: 10.1016/j.intcom.2008.10.011.

[30] D. Waard. (1996). The measurement of drivers' mental workload (Doctoral thesis). Doctor Philosophy Univ., Groningen, The Netherlands. Accessed: Jan. 2020. [Online]. Available: http://www.rug.nl/research/portal/files/13410300/09_thesis.pdf

[31] A. Gevins, "Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style," *Cerebral Cortex*, vol. 10, no. 9, pp. 829–839, Sep. 2000, doi: 10.1093/cercor/10.9.829.

[32] M. Mustafa, R. A. Mustafar, R. Samad, N. R. H. Abdullah, and N. Sulaiman, "Observation of the effects of playing games with the human brain waves," *Jurnal Teknologi*, vol. 77, no. 7, pp. 61–65, Nov. 2015.

[33] M. Van Camp, M. De Boeck, S. Verwulgen, and G. De Bruyne, "EEG technology for UX evaluation: A multisensory perspective," in *Advances in Neuroergonomics and Cognitive Engineering*, vol. 775, H. Ayaz and L. Mazur, Eds. Cham, Switzerland: Springer, 2019.

[34] J. Frey, M. Daniel, J. Castet, M. Hachet, and F. Lotte, "Framework for electroencephalography-based evaluation of user experience," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, May 2016, pp. 2283–2294.

[35] C. Sheikholeslami, H. Yuan, E. J. He, X. Bai, L. Yang, and B. He, "A high resolution EEG study of dynamic brain activity during video game play," in *Proc. 29th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2007, pp. 2489–2491, doi: 10.1109/IEMBS.2007.4352833.

[36] S. Z. Diya, R. A. Prorna, I. I. Rahman, A. B. Islam, and M. N. Islam, "Applying brain-computer interface technology for evaluation of user experience in playing games," in *Proc. Int. Conf. Electr., Comput. Commun. Eng. (ECCE)*, Cox'sBazar, Bangladesh, Feb. 2019, pp. 1–6, doi: 10.1109/ECACE.2019.8679203.

[37] K. Georgiadis, H. Oostendorp, and J. van der Pal, "EEG assessment of surprise effects in serious games," in *Proc. Revised Sel. Papers 4th Int. Conf. Games Learn. Alliance (GALA)*, vol. 9599. Berlin, Germany: Springer-Verlag, 2015, pp. 517–529, doi: 10.1007/978-3-319-40216-1_56.

[38] G. N. Yannakakis, K. Karpouzis, A. Paiva, and E. Hudlicka, "Emotion in games," in *Affective Computing and Intelligent Interaction* (Lecture Notes in Computer Science), vol. 6975, S. D'Mello, A. Graesser, B. Schuller, and J. C. Martin, Eds. Berlin, Germany: Springer, 2015.

[39] K. Georgiadis, H. van Oostendorp, and J. van der Pal, "EEG assessment of surprise effects in serious games," in *Games and Learning Alliance* (Lecture Notes in Computer Science), vol. 9599, A. De Gloria and R. Veltkamp, Eds. Cham, Switzerland: Springer, 2016.

[40] M. Granato, D. Gadia, D. Maggiorini, and L. Ripamonti, "An empirical study of players' emotions in VR racing games based on a dataset of physiological data," *Multimedia Tools Appl.*, 2020, doi: 10.1007/s11042-019-08585-y.

[41] J. H. Brockmyer, C. M. Fox, K. A. Curtiss, E. McBroom, K. M. Burkhart, and J. N. Pidruzny, "The development of the game engagement questionnaire: A measure of engagement in video game-playing," *J. Experim. Social Psychol.*, vol. 45, no. 4, pp. 624–634, Jul. 2009.

[42] F. J. Carrera Arias, L. Boucher, and J. L. Tartar, "The effects of videogaming with a brain–computer interface on mood and physiological arousal," *Games Health J.*, vol. 8, no. 5, pp. 366–369, Oct. 2019, doi: 10.1089/g4h.2018.0133.

[43] Y. Y. Ng, C. W. Khong, and R. J. Nathan, "Evaluating affective user-centered design of video games using qualitative methods," *Int. J. Comput. Games Technol.*, vol. 2018, pp. 1–13, Jun. 2018.

[44] A. G. Bakaoukas, F. Coada, and F. Liarokapis, "Examining brain activity while playing computer games," *J. Multimodal User Interfaces*, vol. 10, no. 1, pp. 13–29, Mar. 2016, doi: 10.1007/s12193-015-0205-4.

[45] S. P. Robbins, *Organizational Behavior*. Upper Saddle River, NJ, USA: Prentice-Hall, 2008.

[46] N. Ravaja, M. Salminen, J. Holopainen, T. Saari, J. Laarni, and A. Järvinen, "Emotional response patterns and sense of presence during video games: Potential criterion variables for game design," in *Proc. 3rd Nordic Conf. Hum.-Comput. Interact. (NordiCHI)*. Association for Computing Machinery: New York, NY, USA, 2004, pp. 339–347, doi: 10.1145/1028014.1028068.

[47] A. M. Porter and P. Goolkasian, "Video games and stress: How stress appraisals and game content affect cardiovascular and emotion outcomes," *Frontiers Psychol.*, vol. 10, p. 967, May 2019.

[48] S. Wolfson and G. Case, "The effects of sound and colour on responses to a computer game," *Interacting Comput.*, vol. 13, no. 2, pp. 183–192, Dec. 2000.

[49] A. Yoto, T. Katsuura, K. Iwanaga, and Y. Shimomura, "Effects of object color stimuli on human brain activities in perception and attention referred to EEG alpha band response," *J. Physiol. Anthropol.*, vol. 26, no. 3, pp. 373–379, 2007.

[50] T. Hartmann and C. Klimmt, "Gender and computer games: Exploring Females' dislikes," *J. Comput.-Mediated Commun.*, vol. 11, no. 4, pp. 910–931, Jul. 2006.

[51] N. Desai, R. Zhao, and D. Szafron, "Effects of gender on perception and interpretation of video game character behavior and emotion," *IEEE Trans. Comput. Intell. AI Games*, vol. 9, no. 4, pp. 333–341, Dec. 2017, doi: 10.1109/TCIAIG.2016.2570006.

[52] M. Minge, M. Thüring, I. Wagner, and C. V. Kuhr, "The meCUE questionnaire: A modular tool for measuring user experience," in *Advances in Ergonomics Modeling, Usability & Special Populations*, M. Soares, C. Falcão, and T. Z. Ahram, Eds. Cham, Switzerland: Springer, 2016, pp. 115–128.

[53] P. J. Lang, "The cognitive psychophysiology of emotion: Fear and anxiety," in *Anxiety Anxiety Disorder*, A. Tuma and J. Maser, Eds. Mahwah, NJ, USA: Lawrence Erlbaum, 1985, pp. 131–170.

[54] O. Dressler, G. Schneider, G. Stockmanns, and E. F. Kochs, "Awareness and the EEG power spectrum: Analysis of frequencies," *Brit. J. Anaesthesia*, vol. 93, no. 6, pp. 806–809, Dec. 2004, doi: 10.1093/bja/aeh270.

[55] W. B. Ng, A. Saidatul, Y. F. Chong, and Z. Ibrahim, "PSD-based features extraction for EEG signal during typing task," in *Proc. Conf., Mater. Sci. Eng.*, vol. 557, 2019, Art. no. 012032.

[56] M. G. Frank, "Brain rhythms," in *Encyclopedia of Neuroscience*. Berlin, Germany: Springer, 2008.

[57] L.-D. Liao, I.-J. Wang, S.-F. Chen, J.-Y. Chang, and C.-T. Lin, "Design, fabrication and experimental validation of a novel dry-contact sensor for measuring electroencephalography signals without skin preparation," *Sensors*, vol. 11, no. 6, pp. 5819–5834, May 2011, doi: 10.3390/s110605819.

[58] H. A. Miller and D. C. Harrison, *Biomedical Electrode Technology*. New York, NY, USA: Academic, 1974.

[59] J. S. Kumar and P. Bhuvaneswari, "Analysis of electroencephalography (EEG) signals and its categorization—A study," *Procedia Eng.*, vol. 38, pp. 2525–2536, Jan. 2012.

[60] M. Roohi-Azizi, L. Azimi, S. Heysieattalab, and M. Aamidfar, "Changes of the brain's bioelectrical activity in cognition, consciousness, and some mental disorders," *Med. J. Islam Repub Iran*, vol. 31, no. 1, p. 53, 2017, doi: 10.14196/mjiri.31.53.

[61] G. Pfurtscheller and F. H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: Basic principles," *Clin. Neurophysiol.*, vol. 110, no. 11, pp. 1842–1857, Nov. 1999.

[62] S. K. L. Lal and A. Craig, "A critical review of the psychophysiology of driver fatigue," *Biol. Psychol.*, vol. 55, no. 3, pp. 173–194, Feb. 2001, doi: 10.1016/S0301-0511(00)00085-5.

[63] S. Nishifuji, M. Sato, D. Maino, and S. Tanaka, "Effect of acoustic stimuli and mental task on alpha, beta and gamma rhythms in brain wave," in *Proc. SICE Annu. Conf.*, Taipei, Taiwan, Aug. 2010, pp. 1548–1554.

[64] S. Nishifuji and I. Miyahara, "Destabilization of alpha wave during and after listening to unpleasant and pleasant acoustic stimuli," in *Proc. SICE Annu. Conf.*, Aug. 2008, pp. 2732–2737.

[65] M. Murugappan, M. Rizon, M. Nagarajan, R. Yaacob, S. Hazry, and D. Zunaidi, "Lifting scheme for human emotion recognition using EEG," in *Proc. 4th Kuala Lumpur Int. Conf. Biomed. Eng.* Berlin, Germany: Springer, 2008.

[66] W. Klimesch, H. Schimke, and G. Pfurtscheller, "Alpha frequency, cognitive load and memory performance," *Brain Topogr.*, vol. 5, no. 3, pp. 241–251, Mar. 1993.

[67] M. Osaka, "Peak alpha frequency of EEG during a mental task: Task difficulty and hemispheric differences," *Psychophysiology*, vol. 21, no. 1, pp. 101–105, Jan. 1984.

[68] T. Nykopp, "Statistical modelling issues for the adaptive brain interface," M.S. thesis, Helsinki Univ. Technol., Espoo, Finland, 2001.

[69] C. Dooley, "The impact of meditative practices on physiology and neurology: A review of the literature," *Scientia Discipulorum*, vol. 4, no. 1, pp. 35–59, 2009.

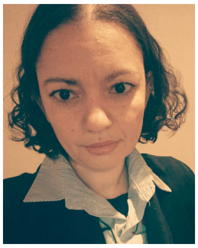
[70] B. Reuderink, C. Mühl, and M. Poel, "Valence, arousal and dominance in the EEG during game play," *Int. J. Auton. Adapt. Commun. Syst.*, vol. 6, pp. 45–62, Dec. 2013, doi: 10.1504/IJAACS.2013.050691.

[71] B. S. M. Peláez, G. G. Paula, and M. A. Becerra, "Emociones cromáticas: Análisis de la percepción de color basado en emociones y su relación con el consumo de moda," *Anagramas - Rumbos y sentidos de la comunicación*, vol. 14, no. 28, pp. 83–96, Jan. 2016.

[72] G. V. Tcheslavski, M. Vasefi, and F. F. Gonen, "Response of a human visual system to continuous color variation: An EEG-based approach," *Biomed. Signal Process. Control*, vol. 43, pp. 130–137, May 2018, doi: 10.1016/j.bspc.2018.03.001.

[73] D. H. Hubel, *Eye, Brain, and Vision*. New York, NY, USA: Henry Holt and Company, 1995.

[74] P. Sawangjai, S. Hompoonsup, P. Leelaarporn, S. Kongwudhikunakorn, and T. Wilaiprasitporn, "Consumer grade EEG measuring sensors as research tools: A review," *IEEE Sensors J.*, vol. 20, no. 8, pp. 3996–4024, Apr. 2020, doi: 10.1109/JSEN.2019.2962874.



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