

Article

Development of RelaxQuest: A Serious EEG-Controlled Game Designed to Promote Relaxation and Self-Regulation with a Potential Focus on ADHD Intervention

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Abstract: This article presents the development of a serious game designed to help individuals improve their ability to relax and self-regulate, with a particular focus on children. Additionally, the game has the potential to become an effective tool for intervention in individuals with Attention Deficit Hyperactivity Disorder (ADHD) due to its integration of critical elements for measuring attention levels. These include omission errors, commission errors, response times, standard deviations of response times, and other relevant variables. The game allows control through electroencephalographic (EEG) signals, using alpha wave modulation and blinking as interaction methods. The amplification of alpha wave amplitude is associated with states of relaxation and mental tranquility, indicating that their modulation could potentially mitigate anxiety and enhance emotional self-regulation. The game's primary objective is to encourage participants to attain relaxing mental states by overcoming challenges as they progress. In order to achieve this, the game's development necessitated a comprehensive understanding of EEG signal processing, a crucial aspect meticulously explored in this article. In addition, this paper presents the results of alpha wave and flicker detection, along with a performance analysis that demonstrates satisfactory results. Subsequently, the game was assessed with children to evaluate its effectiveness, facilitating a comprehensive analysis of various performance parameters. The findings indicate that the game facilitates the gradual improvement of participants' skills with each iteration, notably enhancing their capacity to achieve a state of relaxation.

Keywords: serious game; brain-computer interface; relaxation; extended reality; brain signals processing; ADHD; self-regulation; healthcare



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1. Introduction

Relaxation involves maintaining a state of physical and mental inactivity, which is essential for rest, recovery, and emotional regulation. Furthermore, it contributes to mental clarity, facilitating a more efficient transition to a state of concentration. However, prolonged exposure to various stimuli and accumulated stress can hinder this ability to relax. Consequently, many adults and children face difficulties achieving a state of relaxation and may struggle to practice effective relaxation techniques, such as deep breathing and meditation. Furthermore, people with ADHD experience an aggravation of this issue, facing additional challenges in achieving a state of relaxation and concentration.

The two main characteristics of ADHD are impulsivity and inattention [1]. This disorder affects some children, and its symptoms can hinder their ability to concentrate and learn, impacting their development in school environments. These factors highlight the

need for timely detection of this priority issue to ensure that specialists provide appropriate support, enabling the child to perform at the same level as their peers. ADHD hampers children's ability to concentrate, as they are often easily distracted by external stimuli, resulting in short attention spans. Consequently, this can lead to various academic challenges, such as difficulties with listening and focusing during class and a lack of autonomy in completing tasks.

ADHD can persist and manifest throughout different stages of life, causing significant difficulties, such as in the university environment [2]. Rising expectations for self-regulation, organizational skills, time management, and sustained attention can further compound the inherent difficulties associated with the disorder. For some college students with ADHD, the difficulties can be so significant that discontinuing their college education may appear to be the only feasible option. Consequently, early treatment is crucial for significantly improving the prognosis and quality of life of individuals affected by the condition.

Researchers are exploring methods beyond traditional approaches to enhance relaxation skills and optimize ADHD treatment and detection. These new strategies aim to engage patients more naturally and effectively. Among the emerging alternatives are serious games for ADHD (SGADs), which have shown great potential as intervention tools [3–5]. These approaches support professionals in the early identification and treatment of the disorder while also facilitating the development of relaxation skills in patients. It is essential to highlight that these tools do not replace traditional methods; instead, they serve as valuable complements, offering a motivating and engaging way to involve patients and improve informed decision-making by specialists. Indeed, serious games provide substantial advantages for children, as play acts as a highly engaging and efficacious tool during this formative stage, effectively capturing their interest and fostering active participation.

Users can control relaxation games using various methods, including controllers, mice, keyboards, and motion capture systems. Developers choose these methods for their ease of use and efficient functionality. However, a growing trend is toward using Brain–Computer Interfaces (BCIs) in serious games [6–9]. User satisfaction is a significant aspect of system development, as various factors, including stability, speed, and response time, directly influence the overall user experience [10]. Therefore, conducting studies on implementing BCI systems is imperative to assess these critical aspects meticulously. By prioritizing these factors, developers can enhance user satisfaction and ensure that the resulting systems effectively address user needs and expectations.

BCI systems have successfully employed various EEG signals to control games [11], operate devices [12], detect pathologies [13], and develop rehabilitation procedures [14]. These signals include sensorimotor rhythms [15], event-related potentials [16,17], slow cortical potentials [18], and brain frequency bands such as delta, theta, alpha, beta, and gamma [19], selected based on the type of mental activity required to exert control. Researchers even successfully implemented system control by combining EEG signals. For example, Li et al. [20] controlled a 2-D cursor using motor imagery's Mu/Beta rhythms and the P300 potential.

Research suggests that developers can design games that allow participants to use their mental and emotional states to interact with the BCI game system [21,22]. For instance, relaxation and mental calmness are associated with alpha waves. The predominance of alpha waves during wakeful relaxation or meditative states, especially with closed eyes, highlights their potential importance in diagnosing and treating ADHD, particularly when combined with serious games.

Neurofeedback is a neurophysiological technique designed to teach users to self-regulate specific patterns of brain activity to improve specific cognitive abilities or alleviate clinical symptoms [23]. This process is based on neuroplasticity, the brain's inherent and continuous ability to reorganize its structure and function in response to learning and experience. Neuroplasticity drives a wide range of changes, from creating new neural connections to modifying specific brain areas, and is involved in motor skill acquisition,

strengthening cognitive functions, and recovery from injuries [24]. In this way, neurofeedback can influence various brain areas, enhancing specific skills by harnessing and guiding these natural mechanisms of brain reorganization. However, it is essential to note that the effectiveness of neurofeedback may vary depending on the type of disorder and the implementation of the training, and results may differ between individuals.

Alpha waves, with frequencies between 8 and 13 Hz [25], exhibit an increase in amplitude during states of relaxation. In contrast, their amplitude decreases under high concentration, stress, or when the individual is engaged in demanding cognitive tasks. In video game design, this knowledge can be incorporated by utilizing relaxation as a control element, evaluating the player's capacity to achieve that state, or encouraging them to relax with behavioral or therapeutic objectives.

The principal challenge in utilizing EEG signals stems from their stochastic nature, which can complicate extracting valuable information without proper processing. However, with a comprehensive understanding of EEG signals and the application of suitable algorithms, it is feasible to process and extract the desired information effectively.

This project focused on developing a serious game that promotes relaxation, which may serve as a valuable resource for diagnosing and treating ADHD. The game incorporates alpha signals to measure and evaluate the player's state of relaxation and uses them as a control element. Additionally, it detects voluntary blinking signals and integrates them as a control mechanism within the game.

Implementing processing algorithms encompassing data acquisition, noise removal, feature extraction, and classification was essential for the game's development. The virtual application features a simple and intuitive interface that allows the user to visualize the game and the real-time results of their EEG signals. Additionally, the physical elements of the application were built to synchronize with the virtual environment, providing the user with a more immersive experience that fosters greater engagement and a deeper connection with the game.

This research aims to design, develop, implement, and evaluate an EEG-controlled game that uses alpha wave feedback to promote relaxation and self-regulation. Additionally, it seeks to establish and monitor attention variables that could suggest its potential application in ADHD intervention. This game offers an interactive and engaging alternative to traditional therapeutic approaches while providing valuable real-time data for specialists.

2. Materials and Methods

2.1. Signal Processing Applied to the Classification of Relaxation State

The detection process consists of two main phases: the training phase and the real-time evaluation. During both phases, the system performs the following steps:

- Capture of signals from channels P7, O1, O2, and P8.
- EEG signal summation.
- Baseline correction.
- Signal segmentation.
- Noise reduction using wavelets.
- Filtering signals with a Butterworth filter (8–13 Hz).
- Application of the Fast Fourier Transform (FFT).
- Numerical integration using the trapezoidal rule.
- Thresholding.

Capture of signals from channels P7, O1, O2, and P8: The signals were captured using OpenBCI® equipment (Brooklyn, NY, USA). Specifically, the 8-channel Cyton® biosensor board was connected to the Ultracortex Mark IV® headset for signal acquisition. This headset features electrodes positioned according to the international 10–20 system, ensuring correct placement and accuracy in signal capture. The electrode placement includes positions Fp1, Fp2, C3, C4, P7, P8, O1, and O2, along with two additional electrodes on the ears. These extra electrodes provide a precise and stable signal reference, helping to

minimize interference and improve the quality of EEG signal capture. Only the signals from positions P7, O1, O2, and P8 were used to detect alpha waves.

EEG signal summation: Combining signals from the four electrodes involves summing the first samples from each electrode to generate the first data point. Similarly, the summation of the second samples from each electrode yields the second data point, and so forth. This process creates a unified vector that denotes the electrical activity of the various EEG signals. The mathematical expression for the total summation of all signals at a specific sample period k can be stated as follows:

$$S[k] = \sum_{i=0}^{M-1} s_i[k] \text{ where } k \text{ takes the values } 0, 1, 2, \dots, N-1. \quad (1)$$

The following are given:

- $S[k]$ represents the sum of all signals at the k sample.
- $s_i[k]$ denotes the value of the i -th signal at the k sample, for $i = 0, 1, 2$ and 3 .
- M is the total number of signals.
- N is the total number of samples.

As a result, the vector $\mathbf{S}$ is obtained, which is detailed below:

$$\mathbf{S} = \begin{bmatrix} S[0] \\ S[1] \\ S[2] \\ \vdots \\ S[k] \\ \vdots \end{bmatrix}_{k \rightarrow N-1} = \begin{bmatrix} s_0[0] + s_1[0] + s_2[0] + s_3[0] \\ s_0[1] + s_1[1] + s_2[1] + s_3[1] \\ s_0[2] + s_1[2] + s_2[2] + s_3[2] \\ \vdots \\ s_0[k] + s_1[k] + s_2[k] + s_3[k] \\ \vdots \end{bmatrix}_{k \rightarrow N-1} \quad (2)$$

Baseline correction: The baseline in an EEG signal refers to the reference level around which brain signals fluctuate. EEG signals often exhibit a baseline shift caused by various external factors, such as electrode fluctuations, direct current interference, or noise. This shift makes the signal move vertically, placing brain activity oscillations at a biased level instead of a neutral one. A baseline correction is implemented to rectify this issue and enhance data quality by eliminating the undesired shift from the signal.

Correcting the baseline of the EEG signal involves calculating the average over one second, corresponding to 250 samples. This average, denoted as $\bar{S}$, is obtained from the data interval $\mathbf{S}$:

$$\bar{S} = \frac{1}{250} \sum_{k=0}^{249} S[k] \quad (3)$$

Then, this value is subtracted from each sample in the interval to center the signal:

$$S'[k] = S[k] - \bar{S} \quad (4)$$

The corrected signal sample $S'[k]$ is obtained for $k = 0, 1, 2 \dots 249$. As a result, a new vector $\mathbf{S}'$ is generated, which includes the corrected signals and corresponds to the following:

$$\mathbf{S}' = \begin{bmatrix} S'[0] \\ S'[1] \\ S'[2] \\ \vdots \\ S'[249] \end{bmatrix} = \begin{bmatrix} S[0] - \bar{S} \\ S[1] - \bar{S} \\ S[2] - \bar{S} \\ \vdots \\ S[249] - \bar{S} \end{bmatrix} \quad (5)$$

The process repeats every second with a new set of samples, ensuring that each interval is free from biases and centered around zero.

Signal segmentation: Once the system accurately captures the signal, it is imperative to segment it into well-defined sample segments corresponding to specific time intervals.

This methodology enables the application of various processing algorithms to each packet, optimizing response time and facilitating real-time processing. Consequently, the signal $x[n]$ was divided into multiple segments or windows of size N . Each segment represents $x_k[n]$, where k indicates the segment number:

$$x_k[n] = x[n + kM], \quad \text{with } n = 0, 1, 2, \dots, N - 1 \quad (6)$$

- N is the size of each segment (window).
- M is the shift between windows, which can be equal to N (non-overlapping windows) or less (overlapping windows).

This project uses windows of 250 samples, equivalent to one second, with a shift of 25 samples, corresponding to 100 ms.

Noise reduction using wavelets: Implementing a noise reduction technique in this phase aims to attenuate unwanted noise in the EEG signal while preserving its original characteristics. The Discrete Wavelet Transform (DWT) decomposes the signal into different frequency components, allowing for the elimination or attenuation of undesired frequencies. The DWT of a signal $f(x)$ represents the sum of approximation and detail coefficients across various decomposition levels [26]:

$$f(x) = \frac{1}{\sqrt{N}} \left[T_\varphi(0,0) \varphi(x) + \sum_{j=0}^{J-1} \sum_{k=0}^{2^j-1} T_\psi(j,k) \psi_{j,k}(x) \right] \quad (7)$$

In this context, the terms are defined as follows:

$$T_\varphi(0,0) = \langle f(x), \varphi_{0,0}(x) \rangle = \langle f(x), \varphi(x) \rangle = \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x) \varphi^*(x) \quad (8)$$

$$T_\psi(j,k) = \langle f(x), \psi_{j,k}(x) \rangle = \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x) \psi_{j,k}^*(x) \quad (9)$$

N is a power of 2 (for example, $N = 2^j$), where $j = 0, 1, \dots, J-1$ and $k = 0, 1, \dots, 2^j - 1$. The scaling function is $\varphi(x)$, and $\psi_{j,k}(x)$ represents the mother wavelet. The equations $T_\varphi(0,0)$ and $T_\psi(j,k)$ represent the transformation coefficients, known as approximation and detail coefficients.

In the signal processing, the Daubechies wavelet of order four was used, and a level 2 decomposition was performed, applying a soft threshold to the obtained coefficients. For the reduction, only the detail coefficients from both decomposition levels were considered, generally represented as $cD_{i,k}$, where i indicates the decomposition level and k represents the multiple coefficients within each level. A threshold was applied for each set of coefficients at every level, which required estimating the noise for each decomposition level:

$$R_i = \frac{\text{Median}(cD_{i,k})}{0.6745} \quad (10)$$

Subsequently, the threshold λ_i was calculated using the following formula:

$$\lambda_i = R_i \cdot \sqrt{2 \cdot \log(N)} \quad (11)$$

Then, soft thresholding was applied to the coefficients $cD_{i,k}$, obtaining the new coefficients $cD_{i,k}^{\text{soft}}$:

$$cD_{i,k}^{\text{soft}} = \begin{cases} 0 & \text{if } |cD_{i,k}| \leq \lambda_i \\ cD_{i,k} - \lambda_i & \text{if } cD_{i,k} > \lambda_i \\ cD_{i,k} + \lambda_i & \text{if } cD_{i,k} < -\lambda_i \end{cases} \quad (12)$$

After attenuating the detail coefficients, the signal is reconstructed using the Inverse Discrete Wavelet Transform (IDWT). This process combines the approximation coefficients $cA_{2,k}$, with the attenuated detail coefficients $cD_{1,k}^{\text{soft}}$ and $cD_{2,k}^{\text{soft}}$ to produce the smoothed signal:

$$\tilde{S} = \text{IDWT}\left(cA_{2,k}, cD_{1,k}^{\text{soft}}, cD_{2,k}^{\text{soft}}\right) \quad (13)$$

The symbol $\tilde{S}$ represents the reconstructed signal, improved by the noise reduction process.

Filtering signals with a Butterworth filter (8–13 Hz): A 6th-order bandpass Butterworth filter with a cutoff range of 8 to 13 Hz was used for EEG signal filtering. The general equation that describes the amplitude response of a Butterworth filter is as follows [27]:

$$|H(jw)| = \frac{K}{\left[1 + \left(\frac{s}{w_1}\right)^{2n}\right]^{1/2}} \quad (14)$$

In this context, n represents the filter order as a positive integer, w_1 denotes the filter's -3 dB cutoff frequency, and K indicates the filter's gain.

Application of the Fast Fourier Transform (FFT): The Fast Fourier Transform (FFT) is a highly efficient algorithm used to compute the Discrete Fourier Transform (DFT) and its inverse. The DFT is essential for converting signals from the time domain to the frequency domain, enabling the analysis of frequency components within a signal. The following formula represents this transformation:

$$X(m) = \sum_{n=0}^{N-1} x[n]e^{-j\frac{2\pi mn}{N}}, \quad m = 0, \dots, N-1 \quad (15)$$

- $X(m)$ is the complex value representing the frequency component of the transformed signal.
- $x[n]$ is the value of the signal in the time domain at sample n .
- N is the total number of samples in the signal.
- m is the index of the frequency component.
- j is the imaginary unit.

In the DFT, N terms must be calculated for each value of m that can range from 0 to $N-1$. Therefore, the total number of operations grows proportionally to N^2 , resulting in a complexity of $O(N^2)$. FFT optimizes the calculation of the DFT by dividing the problem into smaller subproblems and combining the results, reducing the operations from $O(N^2)$ to $O(N \log N)$.

Fast Fourier Transform (FFT) can provide frequency information without a temporal reference, concealing frequency changes over time. To address this limitation, the signal was segmented, and the FFT was applied to each segment. This approach enabled the extraction of the frequency spectrum associated with each time interval. Specifically, the FFT was utilized to obtain the frequency spectrum for each segment:

$$X_k(m) = \text{FFT}(x_k[n]) = \sum_{n=0}^{N-1} x_k[n]e^{-j\frac{2\pi mn}{N}} \quad (16)$$

- $x_k[n]$ represents a specific segment of the original signal.
- $X_k(m)$ is the result of the FFT applied to segment k , which takes values corresponding to the different segments, specifically $k = 0, 1, 2, \dots, K-1$, where K represents the total number of segments analyzed.

The matrix $\mathbf{X}$ resulting from applying the FFT to the segments of the signal is organized as follows:

$$\mathbf{X} = \begin{bmatrix} X_0(0) & X_0(1) & X_0(2) & \cdots & X_0(N-1) \\ X_1(0) & X_1(1) & X_1(2) & \cdots & X_1(N-1) \\ X_2(0) & X_2(1) & X_2(2) & \cdots & X_2(N-1) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{K-1}(0) & X_{K-1}(1) & X_{K-1}(2) & \cdots & X_{K-1}(N-1) \end{bmatrix} \quad (17)$$

K is an integer indicating how many segments (or windows) have been created from the signal $x[n]$.

Numerical integration using the trapezoidal rule: The chosen measurement method for obtaining a characteristic value that distinguishes between relaxed and active states was approximating the area under the spectrum curve in the 8 to 13 Hz range using the trapezoidal rule:

$$A \approx \frac{h}{2} \left(f(x_0) + 2 \sum_{i=1}^{n-1} f(x_i) + f(x_n) \right) \quad (18)$$

- A is the sum that approximates the area under the curve in the interval $[a, b]$ using a series of discrete points $x_0, x_1, \dots, x_n$.
- h is the step size or distance between two consecutive points on the x-axis, represented as $h = \frac{b-a}{n}$, where a is the lower limit of the interval, b is the upper limit of the interval, and n is the number of subintervals.

Thresholding: In this phase, thresholds were established for state classification and calculated during the training stage. In this stage, various approximations of the area under the curve of the spectrum were obtained, and the mean was calculated from these values. Once the areas $A_1, A_2, \dots, A_n$, from the n samples were obtained, the mean μ was calculated:

$$\mu = \frac{1}{n} \sum_{i=0}^{n-1} A_i \quad (19)$$

Next, the standard deviation σ of the area under the curve approximations was calculated:

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=0}^{n-1} (A_i - \mu)^2} \quad (20)$$

Three levels are defined based on the following thresholds:

- Level 0 (active state): $X < \mu - \sigma$
- Level 1 (relaxed state 1): $\mu - \sigma \leq X \leq \mu + \sigma$
- Level 2 (relaxed state 2): $\mu + \sigma < X < \mu + 2\sigma$

2.2. Signal Processing Applied to Blink Classification

The system detected voluntary blink signals and used them as a control mechanism, integrating them as a selection tool within the game. The system implemented the following algorithms for its detection:

- Capture of signals from channels Fp1 and Fp2.
- EEG signal summation
- Baseline correction.
- Signal segmentation.
- Filtering signals with a Butterworth filter (4–20 Hz)
- Application of the Fast Fourier Transform (FFT).
- Numerical integration using the trapezoidal rule.
- Thresholding.

The algorithms are explained in Section 2.1, and the procedure, as can be seen, is similar to that used for alpha wave detection. However, some key differences exist. In this case, noise reduction using wavelets was not applied, and a 4 to 20 Hz filter was utilized. Additionally, thresholding classifies the signals into two states:

- Null state (no blinking): $X < \mu - \sigma$ or $X > \mu + \sigma$
- Active state (blinking): $\mu - \sigma \leq X \leq \mu + \sigma$.

2.3. Training Phase

Prior to initiating the detection process, it is crucial to establish an individualized threshold that enables the precise identification of the targeted brain signals. This threshold must be precisely calibrated for each participant. Accordingly, each subject undergoes an

initial training phase, during which targeted activities are conducted to capture the relevant brain signals.

In alpha waves, participants are instructed to alternate between closing their eyes for 10 s and keeping them open for 10 s, repeating this cycle five times. This method is employed to ascertain the threshold associated with the state of relaxation.

Similarly, participants in blink detection training are instructed to follow a specific protocol that involves blinking every second for 10 s, alternating with 10 s of open eyes, and repeating this cycle five times. This approach effectively establishes the threshold associated with blink activity.

The calibration process ensures the personalization and optimization of the detection system, allowing for greater accuracy in identifying the relevant brain signals for each individual.

2.4. Execution of the Virtual Game RelaxQuest

The virtual game RelaxQuest was entirely developed using the Python[®] programming language, version 3.13.0. It is designed to promote and maintain a state of relaxation in its participants. In RelaxQuest, users control a vehicle along a predefined route and can choose from various paths or actions. The player's decisions significantly influence the outcome, as each choice can lead to either a positive or negative result. For example, selecting the wrong path may prevent the user from reaching the intended goal. Additionally, all game elements are accompanied by sound, enabling players to identify which component is selected even with their eyes closed. Figure 1 presents the comprehensive game map, illustrating the routes and constituent elements.

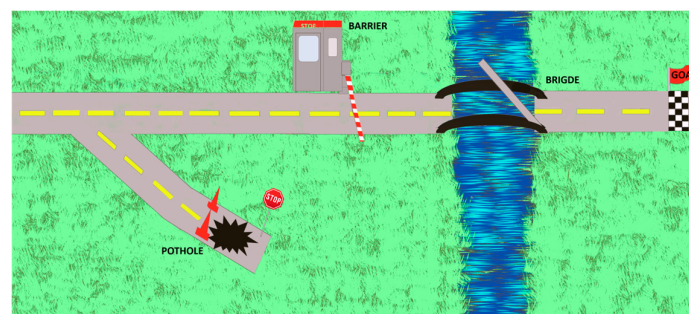


Figure 1. Virtual map of RelaxQuest.

It is essential to highlight that the game, with its wide variety of actions and routes, is a flexible model that can be expanded in scope and functionality. Its complexity and features can be adjusted and modified to meet the specific needs of specialists.

The game begins on the left side of the map, with a car parked in front of a single road. This initial state, called phase 1, is illustrated in Figure 2.

In this initial phase, two bars appear at the top: CAR and TIME. The CAR bar only increases when the BCI system detects a rise in the patient's alpha waves. Specifically, when these waves exceed a certain threshold, the bar accumulates points, which increase faster as the alpha waves surpass successive thresholds. As the CAR bar increases, the car moves forward progressively. Meanwhile, the TIME bar gradually decreases automatically, indicating the time limit assigned to complete the phase to the player. The game will end if the player fails to meet the objective within the established time.

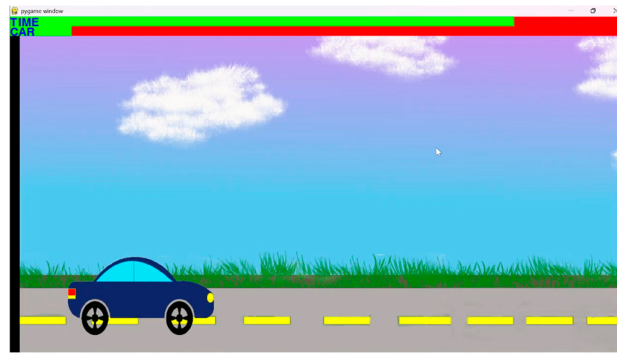


Figure 2. Initial phase of the application.

After the previous phase, the player enters phase 2, which differs significantly by presenting only a TIME bar. In this phase, the player chooses between two possible paths. The system detects the user's blink, allowing the player to toggle between the two available routes. The game visually highlights the selected option and decides once the time is up. Figure 3 shows phase 2 of the virtual application.

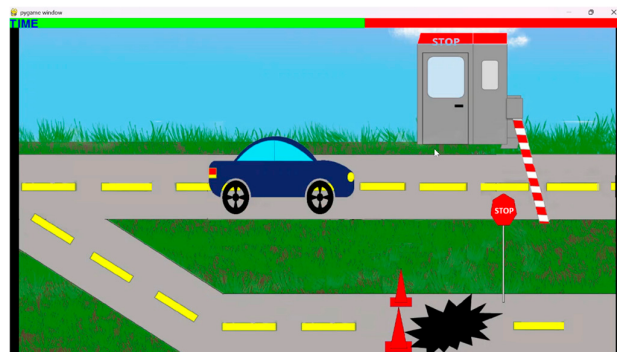


Figure 3. Second phase of the application.

In the third phase, the system presents three bars. The CAR and TIME bars function in the same manner as described in phase 1. The third bar, known as the BARRIER, is designed to rise and clear the path for the vehicle. If the car reaches the barrier without being raised, the vehicle cannot progress, and the phase remains incomplete. To complete this phase, the user must first select the barrier by blinking and fill its indicator by increasing the alpha waves. Once the barrier indicator is complete, it will rise. The user must then select the vehicle and continue the relaxation process to enhance the alpha waves, allowing the car to move forward and complete the phase. Figure 4 shows phase 3.

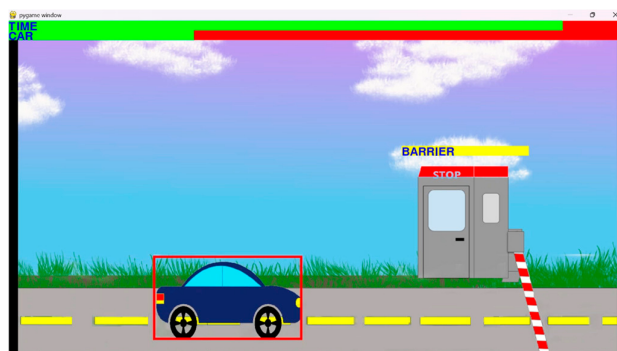


Figure 4. Third phase: activation of the barrier and car progress. Red frame indicates the selected option.

In phase 4, three bars are presented: CAR, TIME, and a new one called BRIDGE. As in the previous phase, the user must perform a specific action before time runs out. If

the user initiates the car's movement and encounters the raised bridge, the car cannot continue its path. To resolve this situation, the first step is to select the BRIDGE bar by blinking. Subsequently, the user must close their eyes to increase the alpha waves and fill the BRIDGE bar. Once this bar is complete, the bridge will lower. Then, the user must select the CAR bar by blinking and increasing the alpha waves to allow the car to continue on its path and complete the journey. Figure 5 illustrates phase 4.

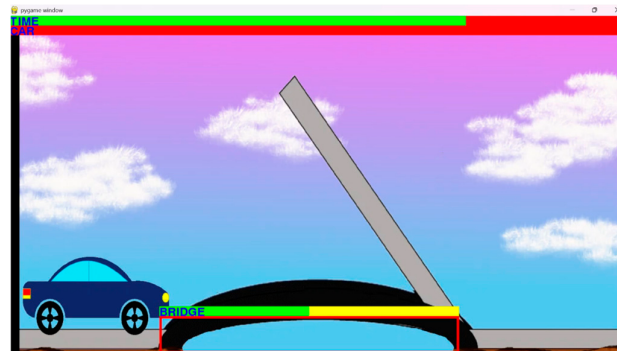


Figure 5. Fourth phase: bridge activation and car advancement.

In the final phase, the player faces a straight path and manages two bars: CAR and TIME. The goal is to move the vehicle toward the finish line, as shown in Figure 6. After completing this step, the game ends, and a congratulatory screen displays the time taken to complete each phase and the total time for the entire session. This feature enables the player to evaluate their performance and identify areas for enhancement in future attempts.



Figure 6. Fifth phase: car advancement toward the final goal.

The game will systematically record the duration of each stage, the levels of alpha wave amplitude achieved, and the frequency of blinks. These automatically generated data can serve as performance indicators for specialists in the field to analyze.

2.5. Interactive Physical Development

An interactive physical version of the game RelaxQuest was developed and designed to replicate the actions and movements of the virtual application. This model includes a vehicle that follows the programmed routes in the virtual environment, along with a barrier and a bridge that operates in synchronization. Servomotors activate the barrier and bridge, while stepper motors control the car's movement, allowing it to reach the desired positions along the X and Y axes. All control is managed through the Arduino Uno board® (Turin, Italy). This integration allows the user to control objects mentally in real time and offers an immersive experience in the game. This increases user motivation, generating more remarkable dedication and interest in repetition, which promotes a more significant development of self-regulation skills. Figure 7 illustrates the interactive physical development of the game.



Figure 7. Interactive physical model of the RelaxQuest game.

2.6. Subjects

During the validation process for alpha wave detection, tests were conducted with three healthy subjects: one child and two adults, identified as Subject 1, Subject 2, and Subject 3, respectively. The average age of the participants was 18 ± 7.81 years.

The blink detection performance was evaluated using three healthy adult participants with an average age of 27.33 ± 6.85 years.

The evaluation of the game RelaxQuest included six healthy children, each completing three tests, with an average age of 8.67 ± 1.49 .

3. Results

3.1. Signal Processing

This section explains the results of the different signal processing stages, including channel summation, noise removal, feature extraction, and classification.

In the detection of alpha waves, the sum of the channels located in the occipital region (P7, O1, O2, P8) was performed, as they exhibit similar and synchronized behavior in response to visual stimuli, especially when opening and closing the eyes, which generates a clear and consistent variation across all channels. Similarly, for blink detection, the frontal channels (Fp1 and Fp2) were summed, as they respond consistently and synchronously to these events, producing an evident variation in the signal. Since these channels respond together, amplifying or reducing the signal synchronized, their summation is viable and appropriate.

Next, the results of baseline removal in the signal are presented, achieved by subtracting the mean. Figure 8 illustrates this process, comparing the original summed signal with the baseline-corrected signal.

As seen in Figure 8a, the signal offsets from the origin of the Y-axis. After applying baseline correction, the signal adjusts towards the origin of the Y-axis without altering the original signal variation.

The elimination of baseline noise in the EEG signal is achieved by applying the average subtraction technique, an essential method due to the significant deviation of the original signal from the Y-axis origin. Estimating baseline noise is performed by averaging the signal over one-second intervals. Subsequently, this average is subtracted from the original signal, effectively mitigating noise while retaining the variations pertinent to the analysis. This procedure is iteratively executed every second with a new set of samples, ensuring each interval is free from bias and centered around zero, as explained in Section 2.1.

Figure 8 illustrates the effectiveness of the method. Figure 8a shows the original signal with noise, while Figure 8b presents the processed signal. The implemented algorithm effectively removes the noise without compromising the critical information for this study.

The signal shown in Figure 8 corresponds to the sum of the electrodes P7, O1, O2, and P8. Similarly, the same procedure was applied to the sum of the electrodes Fp1 and Fp2 to analyze blinking.

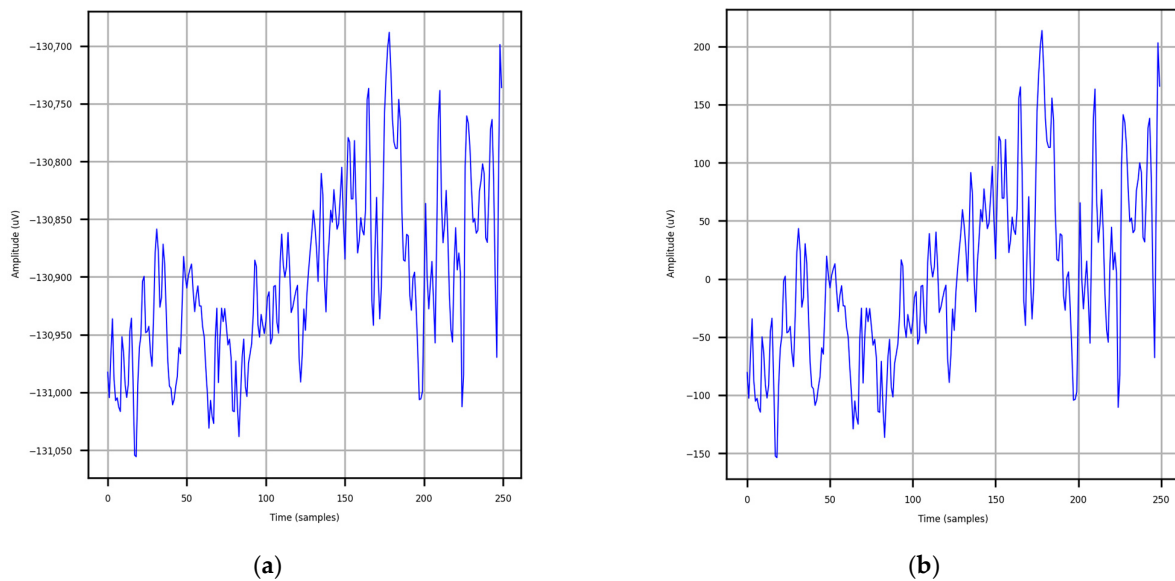


Figure 8. Raw EEG signal (a) and baseline-corrected signal (b).

The summation of signals from multiple electrodes increases baseline noise. However, the proposed method effectively eliminates this noise. Moreover, the baseline average is recalculated every second, enabling the process to adapt to interference from factors such as power grid fluctuations, electrode movements, and other influences. This ensures that the subtracted baseline remains accurate, preserving the integrity of the data.

Afterwards, noise reduction is applied using wavelets. In Figure 9, Figure 9a shows the signal without the baseline, while Figure 9b presents the signal with noise reduction.

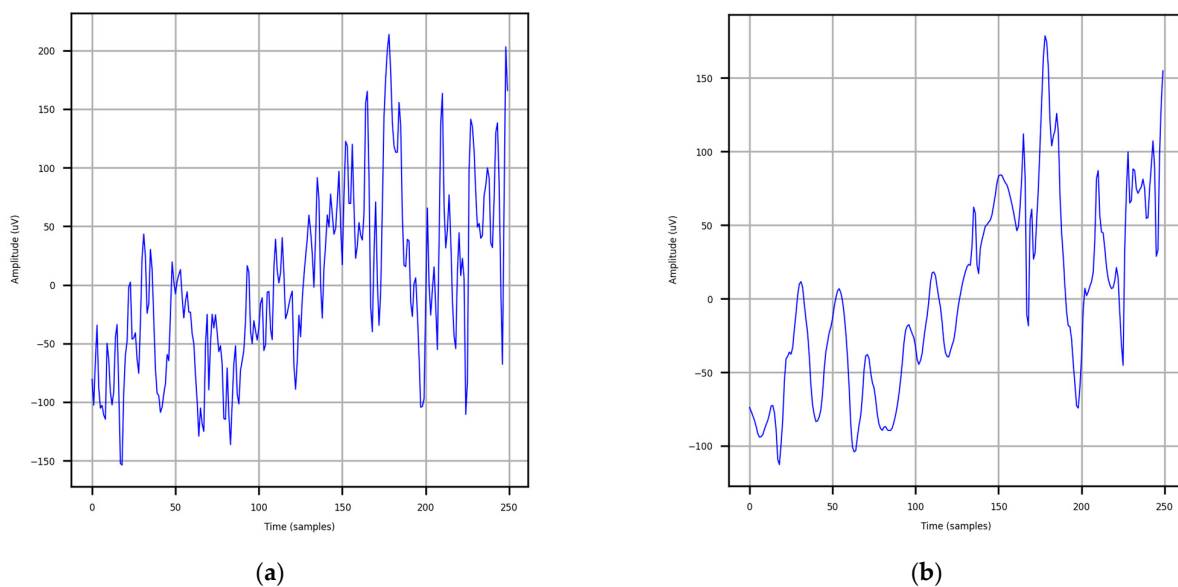


Figure 9. EEG signal without baseline (a) and with noise reduction using wavelets (b).

In this figure, the attenuation of the higher frequencies is observed, allowing for greater clarity in the variation in the EEG signal without significantly modifying the signal without baseline. This study uses DWT exclusively for noise reduction, focusing on higher frequencies. This process improves the signal quality by preserving relevant

information and generating a clearer signal, which enables accurate monitoring of changes. Figure 9 compares the signal without noise reduction (Figure 9a) and the attenuated signal (Figure 9b), highlighting the improvement achieved. It is essential to emphasize that the noise reduction implemented through the DWT, primarily focused on higher-frequency components, does not necessarily enhance the detection of alpha wave amplitudes and blinking in this study. This is because the detection process relies on lower-frequency signals. The main objective of reducing noise in higher frequencies was to generate a real-time visual signal during the experiments, allowing continuous observation and providing an additional analytical tool for specialists.

Next, a Butterworth bandpass filter with 8 to 13 Hz cutoff frequencies is applied, resulting in the signal shown in Figure 10.

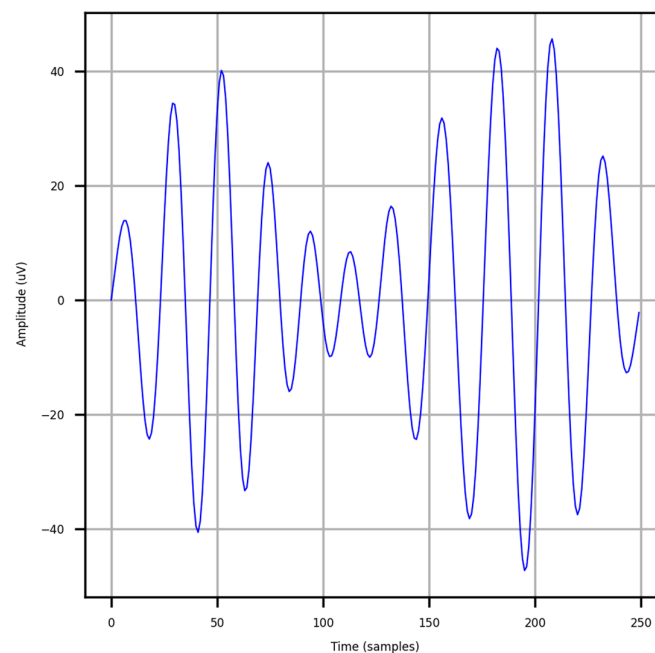


Figure 10. Signal filtered in the 8 to 13 Hz range using a Butterworth filter.

This signal only includes frequencies related to alpha waves, which are the main focus of this study. In this study, a Butterworth filter is utilized to analyze specific frequency ranges that highlight the relevant features for detection. A filter between 8 and 13 Hz is employed to identify relaxation, emphasizing variations in alpha waves. A filter between 4 and 20 Hz is applied for blink detection, revealing a clear signal increase during blinking events. By filtering the signal within these designated ranges, most unwanted signals are eliminated, allowing for a focused analysis of the signals of interest. After filtering, the signal was divided into one-second time windows, and the FFT was used to obtain the frequency response for each segment, as shown in Figure 11.

As observed, the frequency spectrum from 8 to 13 Hz is obtained and generated for each 1-s segment with a 100 ms step in the signal. This study applies the FFT to obtain the signal's spectrum, highlighting relevant features and facilitating the identification of the signal of interest. The FFT provides precise information about the amplitude at specific frequencies, which, when combined with techniques such as numerical integration using the trapezoidal rule, enhances the identification of amplitude variations, thereby improving the accuracy of detecting the desired signal.

The area under the curve was approximated using the trapezoidal method for these frequency representations, and the resulting data were used to define the thresholds during training. Subsequently, the data were categorized into three levels in the classification phase: 0, 1, and 2. Level 0 indicates that the user is in an active state with their eyes open; level 1 reflects an increase in alpha waves associated with inactivity and closed eyes; and

level 2 indicates an additional increase in alpha waves related to a higher level of relaxation. On the other hand, in the case of blinking, the same process was carried out, obtaining the thresholds and classifying only two states: an active state and a null state.

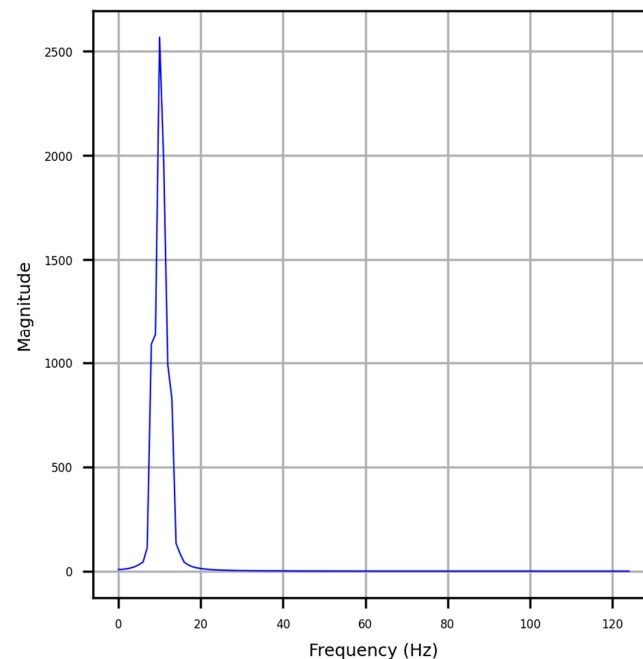


Figure 11. Frequency spectrum from 8 to 13 Hz.

3.2. Alpha Wave Detection Efficiency

The effectiveness of the alpha wave detection system was assessed through tests conducted with three participants: one child and two adults, identified as Subjects 1, 2, and 3, respectively, with an average age of 18 ± 7.81 years. Before the experiment, informed consent was obtained from the participants or their legal guardians, as appropriate. The tests involved alternating periods of 10 s with eyes closed and 10 s with eyes open, repeated three consecutive times, resulting in 60 s per test. Detection occurred every 100 ms during the experiment, yielding 600 detections per test. Each participant completed three tests, resulting in 1800 detections per participant. The results were compared with the actual state of the participants during the tests, and the system's performance was evaluated based on the number of correct detections, as detailed in Table 1.

Table 1. Alpha wave detection performance.

Subject	Detection Efficiency (%)			Subject Average (%)
	T1	T2	T3	
1	76	80	85	80
2	94	92	90	92
3	88	77	83	83
Overall Average of Participants				85

Subject 1 showed a minimum value during Test 1, achieving a performance of 76%, while Subject 2 recorded the maximum value during Test 1, reaching a performance of 94%. Overall, Subject 2 demonstrated high levels of relaxation.

The results demonstrate an average detection rate of 85%, reflecting a satisfactory identification of alpha waves and meeting the essential criteria for implementation in the serious game detailed in this article.

3.3. Voluntary Blink Detection Efficiency

Blink detection performance was evaluated, focusing primarily on detecting voluntary blinks. Figure 12 shows a blink in the 4–20 Hz filtered EEG signal.

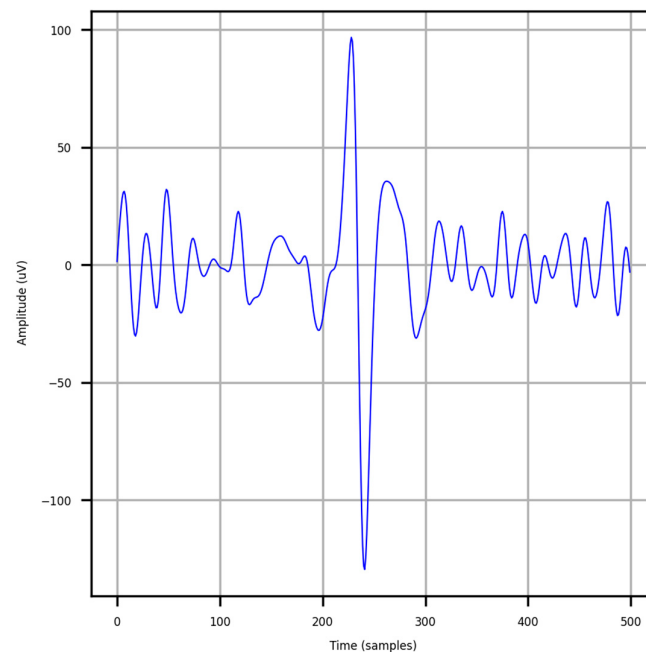


Figure 12. Visualization of blinking in 4–20 Hz filtered EEG signal.

The graph's peak corresponding to the blink clearly indicates the moment when the event occurred. Tests were conducted with three subjects to ensure the detection system functioned properly.

The participants were healthy adults with an average age of 27.33 ± 6.85 years. Before beginning the experimentation, informed consent was obtained from each participant. Participants were instructed to perform continuous, voluntary blinks for 10 s, followed by a 10-s period during which they were required to refrain from blinking voluntarily, allowing only involuntary blinks. Subsequently, they were directed to alternate between keeping their eyes open for 3 s and closing them for another 3 s, for 15 s. This sequence, lasting 35 s, was repeated in three cycles, resulting in a total test duration of 105 s.

Each participant completed three tests, a cumulative duration of 315 s. During the tests, blinks were only to be detected during the voluntary blinking period; any detection during the resting period or the 3-s intervals of closing/opening the eyes was considered an error. Based on this protocol, performance data were calculated and are presented in Table 2.

Table 2. Performance of voluntary blink detection.

Subject	Voluntary Blink Detection Efficiency (%)			Subject Average
	T1	T2	T3	
1	84	97	86	89
2	70	81	95	82
3	76	87	78	80
Overall Average of Participant				84

In test T1, Subject 2 showed the lowest performance, with a value of 70%, while Subject 1 achieved the highest performance, reaching a value of 97% in Test 2. The overall detection average was 84%, indicating effective recognition of voluntary blinks and fulfilling the requirements for implementation in the serious game.

3.4. RelaxQuest Evaluation

In the development of the tests, six children participated with an average age of 8.67 ± 1.49 years. Before starting this study, informed consent was obtained from the children's tutors.

Participants were briefed on the game rules while actively playing. They also received careful guidance on controlling the game elements until they reached the goal. Subsequently, three tests were administered, instructing each participant to complete the game as quickly as possible. Figure 13 shows the child's participation in the serious game using the EEG equipment.



Figure 13. Child's participation in the serious game using the EEG equipment.

Multiple parameters were collected during these tests, including the completion time for each phase, the overall duration to complete the game, the time spent in relaxation states in levels 1 and 2, and other pertinent characteristics. Table 3 presents the results detailing the completion times for each phase.

Table 3. Game time results.

Subject	Test	Phase 1 (s)	Phase 2 (s)	Phase 3 (s)	Phase 4 (s)	Phase 5 (s)	Total (s)
S1	T1	9.89	7	21.10	18.62	7.74	64.35
S1	T2	12.39	7	16.28	18.44	17.66	71.77
S1	T3	10.11	7	21.04	14.68	9.38	62.21
S1	Average	10.8 ± 1.13	7 ± 0	19.47 ± 2.26	17.25 ± 1.82	11.59 ± 4.34	66.11 ± 4.10
S2	T1	6.40	7	30.93	23.09	4.73	72.15
S2	T2	5.46	7	18.54	20.82	6.97	58.79
S2	T3	4.42	7	13.47	17.00	4.01	45.90
S2	Average	5.43 ± 0.81	7 ± 0	20.98 ± 7.33	20.30 ± 2.51	5.24 ± 1.26	58.95 ± 10.72
S3	T1	4.00	7	19.00	23.60	7.37	60.97
S3	T2	6.02	7	22.04	21.39	6.86	63.31
S3	T3	5.36	7	17.2	15.54	4.7	49.8
S3	Average	5.13 ± 0.84	7 ± 0	19.41 ± 2.00	20.18 ± 3.4	6.31 ± 1.16	58.03 ± 5.90
S4	T1	5.48	7	16.22	21.69	11.05	61.44
S4	T2	3.9	7	11.9	17.01	3.51	43.32
S4	T3	3.43	7	13.81	14.34	3.90	42.48
S4	Average	4.27 ± 0.88	7 ± 0	13.98 ± 1.77	17.68 ± 3.04	6.15 ± 3.47	49.08 ± 8.75
S5	T1	4.19	7	18.33	12.64	18.6	60.76
S5	T2	7.32	7	21.38	22.48	3.79	61.97
S5	T3	6.62	7	20.37	16.84	4.89	55.72
S5	Average	6.04 ± 1.34	7 ± 0	20.03 ± 1.27	17.32 ± 4.03	9.09 ± 6.74	59.48 ± 2.71
S6	T1	7.12	7	30.52	21.65	6.31	72.6
S6	T2	10.51	7	13.79	17.07	6.81	55.18
S6	T3	3.38	7	11.14	15.08	6.37	42.97
S6	Average	7 ± 2.91	7 ± 0	18.48 ± 8.58	17.93 ± 2.75	6.5 ± 0.22	56.92 ± 12.16
Overall Average		6.44 ± 2.6	7 ± 0	18.73 ± 5.35	18.44 ± 3.27	7.48 ± 4.24	58.09 ± 9.55

The game results exhibited variability influenced by several factors, with each individual's ability to relax as a primary determinant. Subject 6 recorded the longest average completion time in Test 1, at 72.6 s, while Subject 4 achieved the shortest average time in Test 3, at 42.48 s. In phase two, the game sets a fixed time of 7 s, as players only need to wait after making the path selection.

In summary, several participants exhibited notable improvements in their scores, resulting in a decrease in the time required to complete the game as they progressed through the trials. This progression is clearly evidenced in Table 3, which shows longer completion times in trial one and significantly reduced times in trial three.

The data presented in Table 4 outline the durations during which participants sustained active and relaxed states across levels 1 and 2.

Table 4. Times in active and relaxed states.

Subject	Test	Active State (s)	Relaxed State (s)		Total Test (s)
			Level 1	Level 2	
S1	T1	37.95	26.4	0	64.35
S1	T2	46.56	22.47	2.74	71.77
S1	T3	37.17	23.23	1.81	62.21
S1	Average	40.56 ± 4.25	24.03 ± 1.70	1.52 ± 1.14	66.11 ± 4.10
S2	T1	39.02	28.74	4.39	72.15
S2	T2	31.46	23.24	4.09	58.79
S2	T3	17.1	24.91	3.89	45.90
S2	Average	29.19 ± 9.09	25.63 ± 2.30	4.12 ± 0.21	58.95 ± 10.72
S3	T1	23.35	35.35	2.27	60.97
S3	T2	22.19	39.57	1.55	63.31
S3	T3	18.66	29.9	1.24	49.8
S3	Average	21.40 ± 1.99	34.94 ± 3.96	1.69 ± 0.43	58.03 ± 5.90
S4	T1	31.02	29.66	0.76	61.44
S4	T2	15.92	26.16	1.24	43.32
S4	T3	13.49	26.39	2.6	42.48
S4	Average	20.14 ± 7.75	27.4 ± 1.6	1.53 ± 0.78	49.08 ± 8.75
S5	T1	34.86	25.01	0.89	60.76
S5	T2	34.47	26.99	0.51	61.97
S5	T3	26.72	28.56	0.44	55.72
S5	Average	32.02 ± 3.75	26.85 ± 1.45	0.61 ± 0.2	59.48 ± 2.7
S6	T1	44.39	24.53	3.68	72.6
S6	T2	28.78	21.79	4.61	55.18
S6	T3	22.46	17.38	3.13	42.97
S6	Average	31.88 ± 9.22	21.23 ± 2.95	3.8 ± 0.61	56.92 ± 12.16
Overall Average		29.2 ± 9.58	26.68 ± 4.89	2.21 ± 1.44	58.09 ± 9.55

In the preceding graph, it is evident that certain subjects exhibited prolonged periods in the active state during specific tests. For instance, Subject 1 in Test 2 displayed an extended duration in this state, indicating inferior game performance. Conversely, there were instances where subjects demonstrated shorter periods in the active state, as evidenced by Subject 4 in Test 3, suggesting better game performance and a greater capacity for relaxation.

4. Discussion

The development of serious games has gained considerable importance, especially in their application for intervention in various pathologies, such as depression [28], autism [29], and dementia [30], as well as in physical rehabilitation processes [31]. However, researchers have highlighted their implementation in treating ADHD. Several games have been developed to target this condition [32–34], with some incorporating EEG signals as a crucial element for measurement and control [35–38]. In particular, frequency bands, including delta, theta, alpha, and beta, are employed in studies due to their significant relationship with various mental states and cognitive functions [19].

Hyperactivity is one of the main characteristics of ADHD, making it difficult for people with this condition to relax and maintain calm compared to those without it. This challenge is reflected in their alpha waves, which tend to have lower amplitude, indicating difficulties in achieving relaxation and tranquility. The game RelaxQuest aims to teach participants

how to regulate their relaxation, serving as a complementary intervention to facilitate the achievement and maintenance of this state. Additionally, the game allows for capturing, measuring, and analyzing the obtained data, which may contribute to a more accurate diagnosis and more effective monitoring of the participant's progress.

The advancement of players within RelaxQuest relies on inducing relaxation by increasing alpha wave activity and promoting states of inactivity, which are more pronounced when players close their eyes. This approach allows the brain to reduce its engagement with visual stimuli, thereby decreasing activity in the areas involved in visual information processing. This method was chosen for its ability to rapidly elevate alpha wave activity, making it particularly effective for tasks that require prompt responses.

The game is capable of identifying three distinct states: an active state (N0), a level 1 relaxation state (N1), and a deeper relaxation state (N2). The player's progress within the game depends on their ability to reach the relaxation state, which allows them to activate critical elements such as the car, the barrier, and the bridge. Furthermore, progress in the game occurs faster when the N2 state is detected than the N1 state. For instance, the vehicle moves more quickly, and barriers or bridges are activated more swiftly, suggesting that achieving a deeper state of relaxation facilitates the game's completion in less time.

All generated data are systematically collected, monitored, and recorded for subsequent analysis and evaluation, as described in Sections 3 and 3.4, supported by Tables 3 and 4. For example, Table 3 shows the participants' completion times for each phase. Shorter times indicate a remarkable ability to achieve relaxation and solve game challenges more efficiently and quickly. This is evidenced in the case of Subject 4 during Test 3, who completed the game in a significantly shorter time, with only 42.48 s. This result indicates that the subject relaxed effectively between phases and maintained less active states, as shown in Table 4, where a low value in N0 is observed of 13.49 s.

In contrast, difficulty in quickly and profoundly reaching relaxation states may indicate a lower capacity for self-control, often associated with the predominance of emotions such as anxiety and stress or behaviors like hyperactivity. This difficulty in relaxing is evident in the results obtained, where the most relevant indicators are prolonged times to complete the game's stages or the inability to finish them. An example of this is presented in Table 3, where Subject 6, during Test 1, completed the game in 72.6 s, significantly longer than another test. This extended time is partly attributed to the fact that the participant spent a considerable amount of time in the active state (N0), as shown in Table 4, which indicates they remained in this state for 44.39 s, hindering their progress in the game.

The analysis of measurable data can assist specialists in making more precise diagnoses. Furthermore, the game offers participants an opportunity to enhance their relaxation techniques, as repetition can facilitate an increase in alpha wave activity, thereby optimizing their performance within the game.

In Sections 3 and 3.3, this study demonstrated efficient detection of signals associated with voluntary blinking, allowing differentiation from involuntary blinking and the act of opening and closing the eyes non-immediately. Although blinks are often considered artifacts that should be eliminated to avoid interference in measurements, these signals were effectively utilized as an additional control mechanism within the context of this game. In particular, voluntary blinking was implemented as a selection tool within the game system, optimizing user interaction and enhancing system functionality.

Numerous applications and games have utilized alpha waves as tools for control and monitoring in the context of relaxation, effectively enhancing mental well-being [39]. This project introduces an innovation by integrating alpha waves and blinking as immediate control methods within a game designed for potential intervention in ADHD. This approach is grounded, in part, in the characteristics of the utilized EEG signals and the applied processing algorithms, which facilitate efficient and rapid detection. These control elements may encourage future developers to implement similar techniques in designing other games requiring quick responses based on brain signals, whether for entertainment, diagnostic, or therapeutic purposes. This technology could also find applications in trend-

ing research fields, such as the development of soft exoskeletons [40], where its integration with human–machine interfaces [41] aims to enhance therapeutic interventions and support daily living assistance.

Detecting and classifying ADHD requires specific instruments that measure attention levels. Roh and Lee [42] identify four critical variables for this measurement in their study. The first, omission error, captures instances where individuals fail to respond to expected stimuli, reflecting attention problems. The second, commission error, evaluates impulsivity-related errors, such as responses to irrelevant stimuli. The third variable, response time, measures how quickly the child responds to a stimulus. Finally, the standard deviation of response time indicates the consistency of responses; a high deviation reveals difficulties in maintaining stable and organized responses.

The elements mentioned above have been incorporated into RelaxQuest. Omission error is the lack of action to move the car, barrier, or bridge within the game. On the other hand, commission error (impulsivity) is evaluated by counting additional blinks used to select the correct option and eye openings or closings before reaching the desired objective. Errors such as choosing an incorrect path or failing to activate necessary elements to advance are also recorded. Response time is when the participant remains active (N0) without relaxing to progress to the following states (N1 and N2). Additionally, the times spent in states N1 and N2 are measured, along with the time required to complete each phase and the game. These data reflect the participant's ability to follow instructions and maintain a calm and inactive state, both essential for achieving the objectives. The standard deviation is recorded in the stored results after multiple trials, allowing analysis of variations in the time needed to complete each phase, the entire game, and the time spent in states N0, N1, and N2. This analysis facilitates the evaluation of response consistency. For these reasons, RelaxQuest has the potential to be an effective support tool for ADHD intervention.

5. Conclusions

The development of RelaxQuest represents a significant advancement in the creation of tools to promote relaxation and self-regulation. The integration of EEG control within the game and its focus on teaching relaxation skills offers an innovative approach to digital and immersive interventions. Furthermore, the game is a training platform and tool for data capture and analysis, enabling more accurate diagnostics.

RelaxQuest provides a tailored approach that adapts to the specific needs of specialists, allowing for difficulty adjustments based on user progress. This platform enhances therapeutic intervention by integrating EEG signals with real-time virtual and physical applications focused on mental regulation. This innovative combination significantly improves user engagement and encourages a more significant commitment to therapeutic exercises.

The results showed that participants could complete the game, indicating adequate control of their relaxation states and effectively detecting their voluntary blinking. Additionally, the game can provide relevant characteristic values that include essential metrics for measuring attention levels, such as omission errors, commission errors, response time, and response time deviation. These elements are crucial and could serve as potential support in the intervention for individuals with ADHD.

One of the main limitations of this study is the absence of clinical validation of the game as a therapeutic tool for ADHD treatment. Achieving such validation would require a more significant number of trials involving specialists, which exceeds the resources and scope of this work. However, it is identified as a promising area for future research, potentially yielding significant and valuable outcomes.

This study's main contribution was developing an EEG-based interactive game to measure attention metrics and promote self-regulation and relaxation. The project included creating the software, control devices, underlying algorithms, and physical integration, all developed by a multidisciplinary team. This innovation opens new opportunities for future research and broadens the potential applications of interactive tools in therapeutic and educational contexts.

In future work, the goal is to collaborate with specialists in the field, such as psychologists, psychiatrists, occupational therapists, and neurologists, to establish a study group that will conduct the necessary tests with this game and analyze its impact on the intervention of people with ADHD.

Author Contributions: A.F.P.V., J.-A.C. and F.D.J.S.-V. participated in the conceptualization of the project, the processing of EEG signals, the methodological development, and the overall supervision of the project; J.Y.R.-M. and G.O.-T. contributed to the generation and classification of critical values through statistical processes and data cleansing, as well as in the analysis of the results; C.A.C.M. and I.d.I.T.A. developed the application software, implemented the communication protocols between the processing algorithms, the video game, and the interactive physical development system, and conducted the corresponding tests of the study. All authors have read and agreed to the published version of the manuscript.

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