Tecnológico de Monterrey

Closed-Loop BCI with Haptic Feedback and SINDy Algorithm for Attention Support in ADHD Students

Milton Osiel Candela Leal[1], Luis Antonio Marrufo Franco[2], Baudel Hiram Ruiz de la Fuente[3], César Francisco Cruz Gómez[4], Mauricio Adolfo Ramírez Moreno[5]
{[1]A01197730, [2]A01197689, [3]A00832005, [4]A00827233, [5]mauricio.ramirezm}@tec.mx
Instituto Tecnológico y de Estudios Superiores de Monterrey, campus Monterrey.
Nov 2024

Abstract - This project aims to develop a Brain-Computer Interface (BCI) system integrated with haptic feedback to enhance sustained and selective attention in students with ADHD. The system will use EEG signals and provide real-time feedback through vibrations to help users maintain focus during learning activities, potentially improving their academic performance. Students with ADHD often face challenges with sustained and selective attention, negatively impacting their academic performance. Current diagnostic tools like the Continuous Performance Test (CPT-II) help assess attention levels, but there is a lack of immediate feedback systems to assist users in maintaining focus during tasks. This project develops a Brain-Computer Interface (BCI) system using 4-channel Enophone EEG headphones to monitor brain activity and an Arduino-based haptic feedback module to deliver real-time vibrations when attention lapses are detected. Data will be collected through the CPT-II test and analyzed using machine learning algorithms such as the novel SINDy, designed to optimize focus at a closed-loop feedback based on EEG signals. The project leverages existing EEG and haptic feedback technologies, making it feasible within the planned timeline. Due to time and participant constraints, ADHD patients will not be involved in this phase, but the system will be tested with neurotypical subjects taking a lecture to validate its functionality. A functional BCI system with real-time haptic feedback for attention monitoring, along with a new EEG-based equation for attention measurement derived from spectral band analysis. This will be compared to the standard engagement index, and validation results will demonstrate its effectiveness in enhancing attention. The system has the potential to significantly enhance the learning experiences of students with ADHD, contributing to UN Sustainable Development Goals 3 (Health) and 4 (Education). The project could contribute to the development of cognitive training tools and assistive technologies aimed at improving attention for individuals with attention disorders.

***Index Terms* — EEG, brain-computer interface, attention, ADHD, education, biometrics, closed-loop algorithm, machine learning.**

I. INTRODUCTION

A. General Context

In a world filled with constant stimuli, attention is becoming an increasingly valuable resource for everyone, a resource that when not properly focused, can significantly reduce people's quality of life. Attention-related disorders are more common in children, with their prevalence decreasing among adolescents and adults. Among these, Attention Deficit Hyperactivity Disorder (ADHD) is the most common. ADHD is also associated with lower academic performance due to reading difficulties, resulting in lower grades and fewer opportunities for advanced education. In the workplace, ADHD patients often experience frequent job changes and reduced job stability. While various pharmacological treatments exist for this disorder, this project does not address the vast array of available treatments. Instead, it focuses on how ADHD can be diagnosed in conjunction with other methods currently in use [1].

There are two distinct types of attention: sustained attention and selective attention. As the names suggest, sustained attention is associated with a state of alertness or focus maintained over a period of time, while selective attention refers to the ability to respond to a relevant or discriminative stimulus. It is important to distinguish between these two types of attention before introducing the Conners Continuous Performance Test (CPT-II), which serves as the inspiration for the attention tests conducted in this project. The CPT-II presents users with a series of letters on a screen, requiring them to press the spacebar as quickly as possible—except when the letter X appears, which is presented randomly. The CPT-II allows for the evaluation of both types of attention and inhibitory function, as it activates these mechanisms when a stimulus to which no response should be given is presented. It is worth noting that this test can be administered alongside pharmacological treatment, showing higher performance when the treatment is effective. However, it should not be used in isolation to diagnose the disorder [1][2].

While the CPT-II serves as a useful indicator, the use of a Brain-Computer Interface (BCI) enables users to receive immediate feedback regarding their performance on the task at hand. By providing real-time feedback, this interface has the potential to improve task performance. During this project, the aim is to demonstrate higher performance in users employing a BCI while completing the CPT-II. Since this is a standardized test, it allows for easy comparison with results reported in the literature. This will help determine whether receiving instant feedback during a test is genuinely beneficial for users. [3]

B. Delimitation of the study

Given the limitations of time and difficulty in recruiting test subjects diagnosed with ADHD, no patients with the condition will be measured. As a result, we cannot precisely determine whether the feedback provided to the target user is appropriate, if it causes any discomfort, or if it fails to achieve the desired effect with ADHD patients.

Additionally, due to the spectrum of the disorder, the system would need to be tested on different individuals, such as those with hyperactivity, for whom the feedback stimulus might have a meaningful impact on the study's findings.

Similarly, it would be valuable to explore multiple types of feedback, such as visual or auditory, given that individuals respond differently to each stimulus. Comparing various feedback modalities would provide greater certainty about which is most effective in helping maintain attention during specific tasks.

Lastly, it is worth mentioning that, due to time and feasibility constraints, the EEG signal acquisition system will not be developed from scratch; instead, a commercial system will be utilized. This is worth emphasizing, as future projects under ISO 13485 standards will strive to uphold the highest standards of quality, safety, and regulatory compliance throughout every phase of medical device development, from conceptualization to large-scale production [4]. Additionally, for research purposes, we are limited to four available channels, with C3 and C4 being the most relevant in the EEG system used in the Neurofeedback device. However, successful implementations of BCI systems for attention measurement with a single channel have been reported [42].

C. Problem Statement

The prevalence of ADHD varies by age and other factors. Between 2020 and 2022, 8.6% of children aged 5 to 11 years and 14.3% of adolescents aged 12 to 17 years in the United States were diagnosed with ADHD [6]. Additionally, the disparity in prevalence between boys and girls highlights a significant inequality, with 13% of boys diagnosed compared to only 6% of girls [7].

Among college students, approximately 15.9% reported having ADHD in 2023 [8]. This disorder does not disappear in adulthood, though its symptoms may manifest differently [7]. It is important to note that students with ADHD often have shorter attention spans, with 40.7% maintaining focus for less than 20 minutes during distance learning [9], [10].

In light of this reality, technology offers innovative solutions to address these challenges. For instance, 68% of teachers in the U.S. have expressed the need for more technological educational resources to support students with special learning needs [11]. This highlights an opportunity to develop specific tools to assist students with ADHD.

D. Justification

In alignment with these identified needs, our proposed system is conceived as a user-assistive device designed to enhance focus during task execution. The system is particularly suited to supporting students with ADHD by improving their concentration during educational sessions. It integrates EEG technology with a real-time feedback mechanism, which detects lapses in attention and provides corrective feedback through vibrations—a non-invasive and empirically validated method.

Advanced technologies such as brain-computer interfaces (BCIs) that employ EEG signals to monitor neural activity have demonstrated efficacy in enhancing cognitive performance by delivering real-time feedback. This capability forms the cornerstone of our BCI system [12], [13], positioning it as a promising innovation to optimize focus and learning by offering precise, actionable insights into the user’s attentional state [14].

Beyond accurate attention measurement, there is a critical need for effective attention recovery methodologies. Such strategies are instrumental in enabling both male and female students to sustain focus on a given activity and reorient their attention to the original task when disrupted [15].

Empirical studies underscore the utility of haptic feedback in improving attention and cognitive task performance, supporting the integration of vibration stimuli into our system as a corrective mechanism. Furthermore, BCI-driven intervention strategies have shown substantial potential in benefiting individuals with ADHD, indicating that the proposed system may hold transformative applications for this population in future iterations [5].

Kosmyna and Maes have demonstrated that immediate feedback provided to users during tasks significantly enhances performance. Such feedback activates the brain's response mechanisms, enabling timely corrective actions that foster improved focus during academic activities. [4]

Although this project phase does not involve direct testing with ADHD patients, the proposed system offers significant potential for this demographic. The inability to sustain selective and prolonged attention remains one of the principal challenges for individuals with ADHD. The integration of BCIs with haptic feedback presents a compelling, accessible, and effective approach to support these individuals, offering a foundation for future advancements in this area.

E. Background

1) Attention: Attention, as an essential cognitive ability, allows us to filter out relevant stimuli while ignoring distractions, being key in learning, interaction and performance in various human activities. Among its various forms, sustained attention stands out for its importance in educational contexts, where the ability to maintain focus for prolonged periods is fundamental for the effective processing of information and the retention of knowledge [15].

There are two different types of attention, sustained and selective. Like the name suggests, sustained attention refers to the focus or concentration state during a period of time. On the other hand, selective attention refers to the capacity of answering to spontaneous stimuli that appear at any time and don´t have a defined time window. [2]

2) ADHD: ADHD is considered one of the most common neurological conditions being more prevalent in children than in adults. Additionally, ADHD is much more prevalent in males than in females, with ratios ranging from 3:1 to 16:1. This disparity is largely attributed to the likelihood that male patients present hyperactivity and behavioral issues (ADHD-HI), increasing their chances of being referred to a physician. In contrast, female patients are less likely to exhibit hyperactivity, with their symptoms more often manifesting as inattentiveness (ADHD-I). Females also tend to develop adaptive mechanisms to cope with their environment, reducing the likelihood of receiving a medical diagnosis. Moreover, adult patients with ADHD are more prone to substance abuse, depression, and eating disorders. [1]

In professional and educational settings, individuals with ADHD, regardless of its subtype, face challenges in organization, planning, and often make impulsive decisions. This leads to instability in both their professional and personal lives [1].

3) EEG & TMS: Dating back nearly 100 years, Electroencephalography (EEG) is defined as the non-invasive measurement of brain electric activity. By placing electrodes on the scalp to record voltage potentials, EGG has a diverse range of applications, its principal use being clinical diagnosis on brain disorders or diseases [43].

Transcranial Magnetic Stimulation (TMS) is a noninvasive technique used in the treatment field, mainly in psychiatric and neurological disorders. It consists in the stimulation of different brain areas, which helps with the modulation of the cortical excitability. The patient is seated with a coil positioned around the scalp which generates changing magnetic fields and cause a depolarization on the target region of the brain [41]. Gómez, L. and Vidal, B. showed in their study great results in children with ADHD when treated with TMS sessions during 5 consecutive days showing an increase in attentiveness during their school activities, and a decrease in general hyperactivity[42].

4) Neurofeedback: Developed in the 1960s by psychologists, they have proven their usefulness and therapeutic efficacy. Neurofeedback refers to the specific feedback focused on the activity from the nervous system by measuring electrical signals (EEG), and through that allowing the control and regulation of different processes. Technics relating to neurofeedback are used to treat diverse diseases such as ADHD, anxiety, compulsive behavior, addictions, epilepsy and more. [15]

F. Objectives

1) Main objective: Creation of a BCI system which optimizes sustained attention, focused on patients with ADHD while they perform e-learning activities, by using real-time measuring of EEG data and a personalized feedback aiming to improve their performance.

2) Secondary objectives:

- The construction of the BCI system integrating the *Enophones* to measure the EEG data, and a biofeedback loop which sends vibrations to the user.
- The design of the algorithm which interprets the EEG data to analyze and quantify the levels of attention during the e-learning activities, allowing an accurate follow up and evaluation of the cognitive performance.
- Validation of the BCI system by performing controlled tests with students, measuring their performance when doing e-learning activities.

G. Hypothesis

The students at the model (n=10) and index (n=10) groups, employing the neurofeedback tool, will have an increase in the EEG engagement index, in addition to an increase in performance at the after-test questionnaire and perceived engagement, with respect to the students at the control group (n=10).

However, it is expected that the students using the neurofeedback tool have more EEG fatigue index due to receiving haptic feedback during the lecture.

II. PROPOSAL

A. Methodology

1) Data collection: For the initial data collection, 20 subjects were recruited, all from *Tecnológico de Monterrey*, ranging from 18 to 23 years old, they received questionnaires regarding their demographic data and an informed consent of the ongoing project. The test used the *Enophones* system to record the data, while the CPT-II test, programmed in *PsychoPy*, was used. Each specific system will be thoroughly examined in the next sections. The test had a total duration of approximately 9 minutes, starting with 1 and a half minute of eyes open (EO) and followed by 1 minute of eyes closed (EC), then the user heard a sound to let them know the test had started.

When starting the test, the user was given a series of letters lasting a total of 0.2 seconds on screen, with 1.8 seconds of spacing before another character appeared on screen. The objective was for the user to press the X key as fast as they could each time they were presented with an X, the other stimuli had to be ignored by the user. A total of 200 different stimuli during the 7 minutes of testing were presented, distributing the X equally amongst the stimuli, having around 25% of target stimuli and 75% of no target stimuli.

2) Attention model: Attention was calculated via the participant's Reaction Time (RT) at each X stimuli during the CPT-II test. In which the minimum reaction time was 0.2 seconds and the maximum reaction time was 0.8 seconds. This according to Fig. 1, in which these cut-off thresholds were used in order to have a gaussian-like distribution of RT responses.

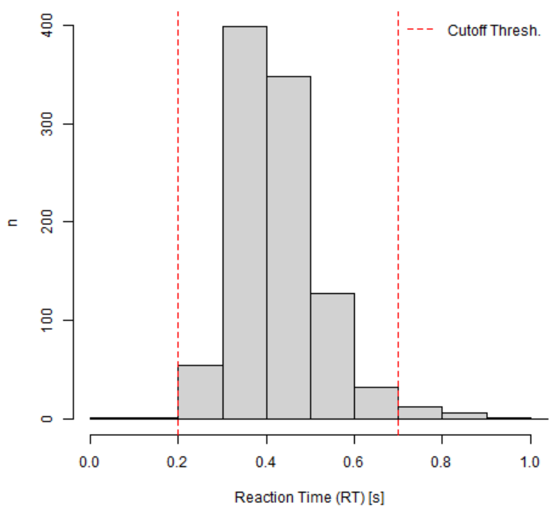

Fig. 1: Graph representing the Gaussian distribution of the different reaction times during the CPT-II test.

Therefore, min-max scaling was applied in order to normalize the metric to be between 0 and 1, in addition, due to attention score and RT holding an inversely proportional trend, the normalized score was a subtraction of 1. Finally, the score was multiplied by 100 in order to have a metric to be between 0 and 100, in which higher the score means higher the attention and lesser their RT, according to Equation 1.

$$Att(RT) = \left(1 - \frac{RT - RT_{min}}{RT_{max} - RT_{min}}\right) \cdot 100 \qquad [1]$$

The aforementioned attention score was used as a target feature, while EEG-derived features would be used as source features used to predict the attention score. Due to fitting a Machine Learning (ML) model, normalization is crucial, as model generalizability between subjects is desired. Hence, standard scaler was used in order to normalize the EEG source features based on a resting 30-second calibration period of Eyes Open (EO), in which the mean $\overline{x}$ and standard deviation σ of each participant would be taken at that stage, and used to obtain normalized X' source features from the non-normalized X source features, based on Equation 2.

$$X' = \frac{X - \overline{x}}{\sigma} \qquad [2]$$

3) Model performance: Model performance was measured via two regression metrics: Coefficient of determination and Mean Squared Error (MSE).

Coefficient of determination (R^2) is a widely used regression performance metric to measure how well the predictions of a model fit into the actual data [16]. The metric's domain is $0 \leq R^2 \leq 1$, where $R^2 = 1$ means perfect predictions, $R^2 = 0$ is the baseline model that predicts the mean $\overline{y}$, and $R^2 < 0$ means poor predictions; calculated as shown in Equation 3. Composed of both Sum of Squared estimate of Errors (SSE) and Sum of Squared Total (SST), Equation 4 and Equation 5 respectively [17].

When the error between predictions and the reference value is minimized $SSE \approx 0$, then $R^2 = 1$, which is concordant to the aforementioned, as the minimal error between samples would mean the predictive model is perfect, hence $R^2 = 1$.

$$R^2 = 1 - SSE/SST \qquad [3]$$

SSE, known as deviations between predicted and reference value, was calculated as shown in Equation 4. Where $\widehat{y}_i$ refers to the ith prediction and y_i to the reference value, summed across n testing samples.

$$SSR = \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2 \qquad [4]$$

SST, known as the total variation in the data, was calculated as shown in Equation 5. Where y_i refers to the i[th] sample and $\overline{y_i}$ to the target feature's mean, summed across n testing samples.

$$SST = \sum_{i=1}^{n} (y_i - \bar{y})^2 \quad [5]$$

MSE, which represents the average of squares of the differences between predicted values and observed values, calculated as shown in Equation 6, where the difference between the reference value y_i and the predicted value $\hat{y}_i$ is summed over n testing samples. MSE follows the L2-norm of normalization or the Euclidean norm, which measures the Euclidean distance between two points in a given vector space; this distance is significantly affected by outliers when compared to the L1-norm, which takes the absolute value of differences between two points [17].

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad [6]$$

4) Prototype built: The prototype used for the vibration module, in charge of receiving and sending data according to what is measured with the Enophones, was constructed taking into account various criteria; this is shown in Fig. 2. A compact system was needed to fit on the arm of the test subjects, in order to achieve this, the two main components were an Arduino Bluetooth Xiao nrf52840 and a mini disc vibration motor.

This arduino board had an inbuilt Bluetooth antenna with capabilities of Bluetooth 5.0, all while having dimensions of 21 x 17.8mm. This is why the board is widely used in applications regarding wearable devices. It has to also be taken into account that this board doesn´t have a long range of bluetooth, so the range in which it can be used is less than 2m.

The vibration motor module used when sending the vibrations to the user is a generic vibration module compatible with the Arduino ecosystem. This respective module was chosen as its small enough for the needed application (23x21x5mm), while also having an appropriate level of vibration.

To power the previous two components a 3 AAA battery holder was chosen. This is important, as the used board can only receive voltages in the range of 3.3 to 5V, when using this holder, the voltage in the system is of 4.5V, staying in the upper limit to avoid any problems with the whole system.

Finally, a 3D-printed case was designed to hold all the components, it had an assigned space for the vibration module and holes on each side of the case to allow the pass thru of a velcro band, which was used to hold the complete system on the arm of the user. The complete overview of the design will be approached on *Sect. II-E5* from this same main section. The next figure shows an example of how the system looked when attached to the arm of the user.

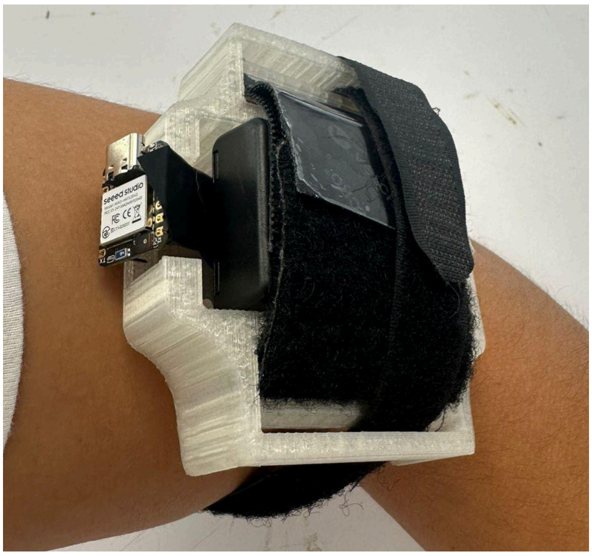

Fig. 2: Wireless system integrating the different components which performs the Feedback activities of the proposed system.

5) Prototype validation: The physical prototype of the system was subjected to a validation process to ensure that it complies with the established functional and structural requirements. The validation included technical integration tests between the Enophones, the Arduino Xiao nRF52840 and the vibration motor, ensuring that the haptic feedback was accurate and timely. In addition ergonomic aspects were evaluated, such as the adjustment of the device to the user's arm using velcro bands and comfort during prolonged use.

The system was tested in simulated scenarios to evaluate its performance under real operating conditions. The battery life, the stability of the Bluetooth connection and the response of the vibration module to different levels of attention detected were verified. It was detected that the system must be connected at a distance of no more than 3 meters, otherwise the connectivity failed.

At the same time, it was integrated with the compartment prototype, confirming that it adequately protects the internal components while maintaining a compact and lightweight design.

B. Methodological proposal to use: To validate the functionality and effectiveness of haptic feedback, we designed an experimental protocol focused on simulating real-world usage scenarios. The validation involved three experimental groups to compare the impact of our system:

- Control group: participants wore the device, but the neurofeedback system was disabled. This group served as the basis for comparison.
- MLR feedback group: participants wore the

device with the neurofeedback system active and used the MLR-derived attention index for real-time feedback.
- Literature index feedback group (Engagement Index): participants wore the device with neurofeedback active, but feedback was based on the standard engagement index widely used in the literature.

The experimental setup, implemented in PsychoPy, consisted of a 90-second eyes open (EO) calibration period followed by a simulated online lecture using a video of approximately 12 minutes about the specific topic of hurricanes (https://www.youtube.com/watch?v=NDm8RSJkMG4&t=5s) the topic was specifically chosen according to [4] a actuality subject and its status as common knowledge but this level of knowledge is not that very deep, because of this surface knowledge level about the topic the lecture was challenging for most participants. Following the session, participants completed a questionnaire assessing their knowledge retention from the conference and a self-assessment rating their perceived engagement during the activity, where participants' reported levels of engagement were rated on a scale of 1 to 5.

C. Techniques and technological tools used

1) Machine Learning: Multiple Linear Regression (MLR) is a statistical technique that uses source variables to predict a target variable, it models a linear relationship using coefficients β for each bandpower (δ, θ, α, β, γ), which would be applied for each sample [18]. A model using MLR was created as shown in Equation 7.

$$\widehat{Att}(PSD) = \beta_1\delta + \beta_2\theta + \beta_3\alpha + \beta_4\beta + \beta_5\gamma \quad [7]$$

In the equation, $\widehat{Att}$ is the predicted target variable, which would be compared to each real observation Att. Additionally, the β_0 coefficient constant term was ignored in order to increase R^2 and have a more explainable model, in which where all bandpowers are 0, the $\widehat{Att}$ would also drop to 0.

2) Closed-loop algorithm: In order to provide a constant haptic feedback to the user, a closed-loop algorithm is proposed. This is described in great detail in Fig. 3: It starts at the left-side with the desired attention level > 33, and depending on the predicted attention level by the ML model, it determines whether apply haptic feedback or not, but always use the standard processing pipeline on EEG electrodes in order to keep predicting the current attention level; hence, the algorithm's closed-loop fashion design.

This in turn provides a real-time neurofeedback, in which the predicted attention level by the ML regression model is used as a basis in order to determine whether the participant is having a low (A < 33), medium (33 < A < 66), or high (A > 66) attention level; this based on the proposed attention score previously defined at Sect. II-A2. In the case that the attention level is low, then a corresponding haptic feedback is applied to the user, this is modeled via an inverse linear relationship shown in Equation 8.

$$V(a) = -15a + 1024 \quad [8]$$

In which a is the level of predicted attention, and V the vibration analog response given to the vibration module. This was modeled based on the analog vibration module responses, in which a minimum vibration of 529 is barely felt, and 1024 is the maximum vibration possible by the device. Hence, Equation 8 serves as a digital to analog converter in order to provide a more precise response depending on how distracted the user is.

D. Infrastructure

For the development of the proposed system, various tools and resources were used to ensure its viability within a 10 week period. From the beginning, it was necessary to have a technological infrastructure that included two laptops, each one destined for specific functions within the experiments.

In the initial phase, the first laptop was in charge of presenting the Continuous Performance Test (CPT-II) and storing the reaction times, while the second processed in real time the data obtained from the EEG headphones (Enophones). In the final phase, the first device configured with PsychoPy broadcast the video along with its calibration period, while in the other laptop, the data from the Enophones was received and the feedback was transmitted to the vibration system, through an Arduino module connected by Bluetooth.

From the initial phase, the equipment was configured with the necessary libraries and software, such as Python, BrainFlow, PySerial, Scikit-learn and PsychoPy, ensuring fluid communication between the system components and the analysis of data in real time.

In later stages, SolidWorks design was required to model the device's casing, which was manufactured with a 3D printer in order to optimize the ergonomics of the system and guarantee its functionality as a portable prototype.

E. Resources used

1) Enophones: Focus headphones designed by ENO with noise-cancellation technology. They were connected to a laptop with Windows via Bluetooth; the Media Access Control (MAC) address of the device was used to acquire, process and clean its signal, based on *Brainflow's* (2.1.1) *Python* (3.8.5) library. Electroencephalographic (EEG) band powers from 4-channel gold-plated dry electrodes were extracted, following the 10-20 International System of Electrode Placement: A1, A2, C3, C4 as in Fig. 4, with a sampling frequency of 250 Hz.

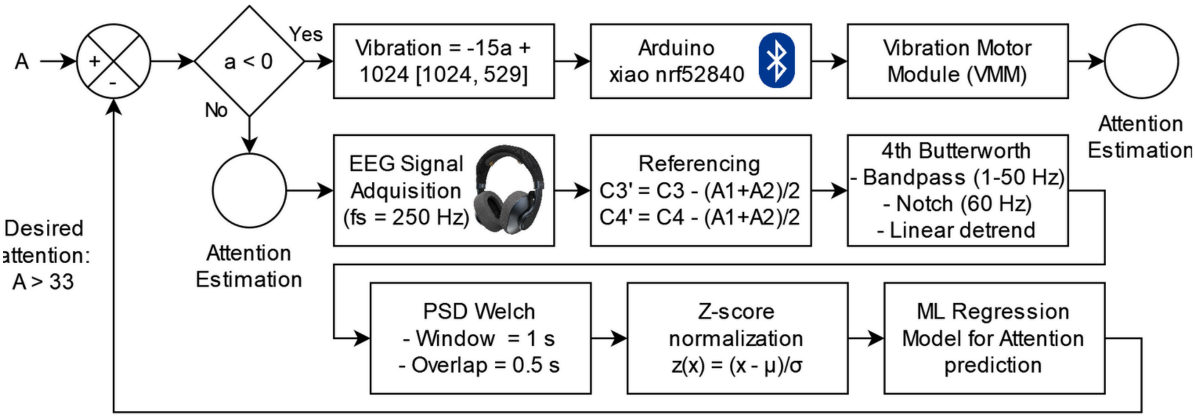

Fig. 3: Closed-loop algorithm employed in order to pre-process and process EEG signals, in addition to estimating the level of attention and sending a corresponding analog signal to the arduino controller. This in a loop fashion to have a constant monitoring of attention level and its corresponding haptic feedback response.

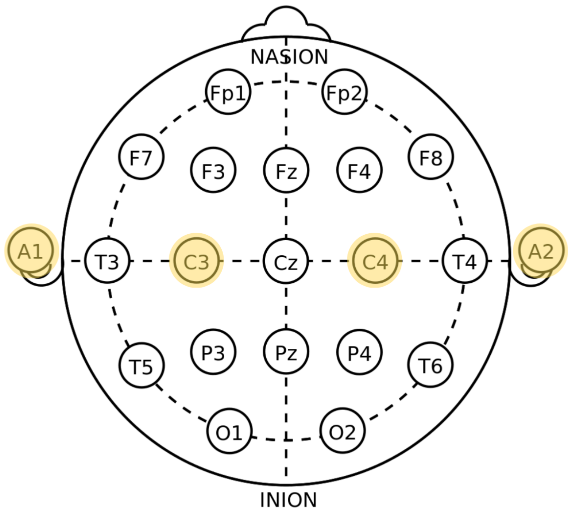

Fig. 4: 10-20 International System of Electrode Placement, in this case A1, A2, C3, C4 electrodes are used by the Enophones: 2 electrodes are in the earlobes (A) and 2 on the top of the central head (C).

The collected EEG signals are related to emotional states on different frequency band powers, so a band-pass filter was first applied to remove noise, then, the power of each signal was calculated using the Fast Fourier Transform (FTT). Lastly, a spectral analysis classified each signal using the following band power ranges: Delta (1–4 Hz); Theta (4–7 Hz); Alpha (8–12 Hz); Beta (13–29 Hz); and Gamma (30–50 Hz), via their power spectral density (PSD).

The electrodes located at the earlobes (A1, A2) are mostly used as reference electrodes [19], in which the mean of both electrodes represents the average reference voltage on which the other electrodes should be subtracted to. Instead of having an average reference at midline of the scalp (Cz), the Enophones are already measuring reference value using both sides of the head at the level of the ears [20]. Thus, as a pre-processing step, the re-references values of the electrodes located on the top of the central head (C3, C4) are calculated based on Equation 9. In which C3' and C4' are the re-referenced values.

$$C3' = C3 - (A1 + A2)/2 \qquad [9]$$
$$C4' = C4 - (A1 + A2)/2$$

2) Arduino Bluetooth: The board proposed to take the task of receiving/transmitting data wirelessly was the Seeed Studio XIAO nRF52840. Arduino/CircuitPython, a microcontroller with an integrated Bluetooth antenna; this is shown in Fig. 5. As discussed in the Prototype built section, this specific board was selected for its compact size and powerful hardware, which allowed us to complete the seeked task successfully.

This board has a pinout system similar to other Bluetooth boards, such as having 10 pins with capacity of being either analog or digital pins, and 2 different voltage outputs with a ground output. It is important to mention that the terminals to connect the battery system to this board are on the back, since the manufacturer had to do this in order to reduce the dimensions. This specific board needed to use the Bluefruit and Bleak libraries in order to be declared as a Bluetooth device and to receive the data thru Python. The pinout diagram of the board is shown in Fig. 6 [27].

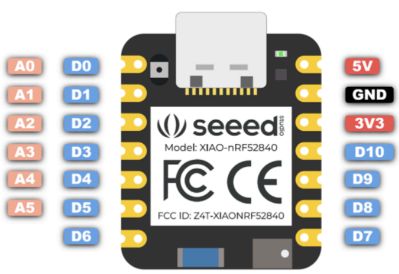

Fig. 5: Front pinout configuration of the Seeed Studio

XIAO nRF52840.

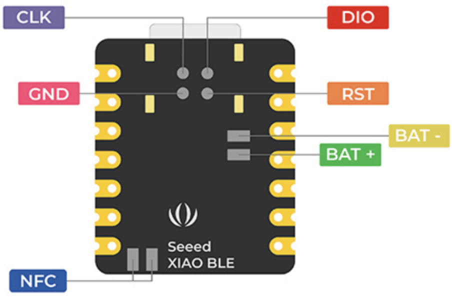

Fig. 6: Back pinout configuration of the Seeed Studio XIAO nRF52840.

3) Vibration module:

The mini vibration motor with disc, chosen for the task is controlled via PWM from an Arduino or another microcontroller, the 3-pin connector pinout is as it follows:

- VCC: 3.7 V to 5.3 V
- GND: 0 V Ground
- IN: Input (High is ON, Low is OFF) (connect to Arduino digital pin or another PWM output pin from the microcontroller)

This small vibration motor was the ideal transductor for the objective of the system, since it is small enough while providing an adequate level of vibration to the user; this is shown in Fig. 7. The motor also allowed us to regulate the level of vibration with an analog output, which then was regulated in order to provide the user with different levels of vibration depending on the concentration it showed while performing the e-learning activity. The next figure shows the used sensor.

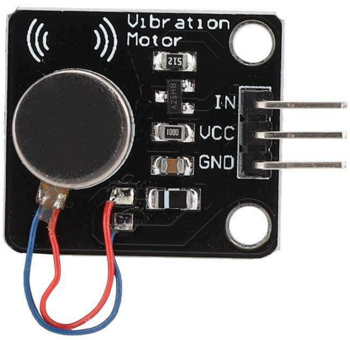

Fig. 7: Mini vibration disc sensor used for the vibration system.

4) Battery holder: To power the whole system a battery holder with capacity to hold 3 AAA batteries was chosen. Since the maximum voltage the Xiao board can receive via the battery terminals (BAT-, BAT+) is 5V, this battery holder allows us to supply the whole system with 4.5V; it is shown in Fig. 8. Even though the manufacturer suggests using a rechargeable lithium battery in case of wanting the direct voltage into the battery terminals, when approaching this way a new module to recharge the battery was needed, which meant a bigger case would be needed to hold the complete system. This approach was not taken into consideration because of dimension conflicts. Using the battery holder also allowed us to have an ON/OFF switch on the system, which was really useful when performing the tests. The next figure shows the battery holder used along with the dimensions.

Fig. 8: Battery holder used in the system along with the dimensions.

5) 3D-printed case for the vibration system: In order to hold all the components of the system, a CAD designed case was 3D printed; this is shown in Fig. 9. The idea of this case was for it to be robust enough to hold all the components in a sandwich-like configuration, meaning the vibration motor was the nearest component to the arm of the user, followed by the battery holder and the Xiao board on the next level. This configuration allowed us to reduce the dimensions of the system in order to make it an appropriate size for a prototype of a wearable device. Most of the space was taken away by the battery holder; this due to the nature of the AAA battery size.

The case also had a pass-thru configuration on each side for holding a velcro band, which was what allowed us to hold the system on the arm of the user.

Finally, a dedicated space to place the arduino was designed on one side of the system. This was important to monitor the state of the arduino-bluetooth connection, as the board had an LED which flashed in blue when waiting to receive the input, and stopped flashing when performing the task received. However due to space limitations, the top side of the arduino holder space was trimmed down to hold the arduino, as the designed space was too small in the end. The next figure shows the CAD simulation of the 3D-printed case.

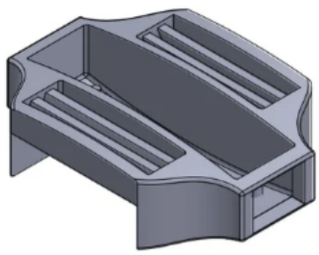

Fig. 9: CAD simulation for the 3D-printed case, where

the pass-thru configuration and dedicated space for the Arduino can be appreciated.

III. RESULTS

1) Attention model performance: At first, Sparse identification of nonlinear dynamics (SINDy), a data-driven algorithm that obtains the equation that models a response from data [21], was going to be used in order to obtain the attention model. However, it provided non-sparse and complex models with low R^2; thus, MLR model was fitted in order to obtain a relationship between the frequency bands and the attention score.

After fitting and simplifying the MLR model, the algebraic expression in Equation 10 was obtained, in which σ is a multiplication factor $\sigma = 80$.

$$Model(\theta,\ \alpha,\ \beta) = \sigma(-\ 3\theta + \alpha - \beta) \qquad [10]$$

On the other hand the engagement index, which is widely used in the literature [22], was calculated as shown in Equation 11.

$$Eng.\ Index(\theta,\ \alpha,\ \beta) = \beta/(\theta + \alpha) \qquad [11]$$

Based on the performance metrics described in Sec. II-A3, the MLR model and the engagement index were evaluated with respect to the true attention scores. The results are shown in Table I.

TABLE I

Regression model's performance on predicting attention

Model	R^2	MSE
MLR	**0.7253**	**1283.21**
Engagement Index	0.0930	18040.05

MLR then exhibits the most consistent results, with the highest R^2 (0.7253) and the lowest MSE (1283.21). In addition to explaining 72.53% of the attention score variance. In addition to the Table I results, a residual plot was also created in Fig. 10, in which the true responses are subtracted from the predicted responses. Hence, the nearer the residuals are to 0, the higher the accuracy of the model, due to it having an error of 0.

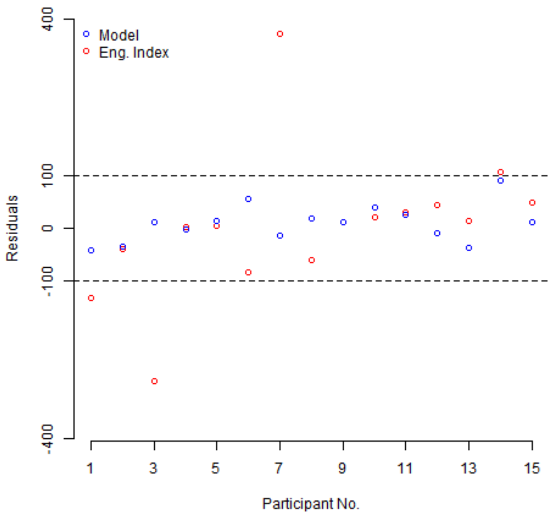

Fig. 10: Residuals graph of created ML model in Equation 10 and Engagement index in Equation 11.

At the residuals plot in Fig. 10, it is also observed that the MLR model exhibits the most consistent results. As all their residuals are between -100 and 100, in contrast to the Engagement Index, which generated 3 outliers from 15 participants' data: Around 120, 300, and 400. Model's consistency is key due to it being developed in a real-time setting, in which outliers could seriously affect the immersive experience the participant is experiencing. Thus, the MLR model was selected as the real-time model that was implemented in the neurofeedback tool

2) Neurofeedbacktool in EEG-derived indices: At the EEG literature, there are validated EEG-derived indices or frequency band ratios, which combine various frequency bands in order to determine an explainable behavior, thus presenting a more easy-to-understand performance metric related to the participant's cognitive state. The three used indices in this study are:

- *Excitement Index (β/α)*: Related to attention and engagement, the higher this index, the more alert and attentive the participant is, which in turn be related to excitement or increased amount of interest. A study [23] measured the efficiency of advertisements with individuals, in which ads that evoked higher beta/alpha ratio were more effective.
- *Mental Fatigue Index (α/θ)*: Related to mental weariness, a high alpha wave in relation to theta suggests relaxation or idling state of the brain. This is important at tasks that require sustained attention, which can thus indicate cognitive fatigue [24].
- *Engagement Index (β/(θ+α))*: Related to a balance of active cognitive processing in contrast to a more passive state. This index is particularly important in cognitive immersive scenarios. High index indicates robust

cognitive engagement or alertness at continuous mental effort activities [25].

Given the aforementioned, EEG-derived indices, a comparative barplot across groups was created and shown in Figure 11. In said barplot, each group's indices were averaged across subjects; hence, obtaining an average engagement, fatigue, and excitement for the control group with no neurofeedback, the experimental group with engagement index as neurofeedback, and the experimental group with MLR model as neurofeedback.

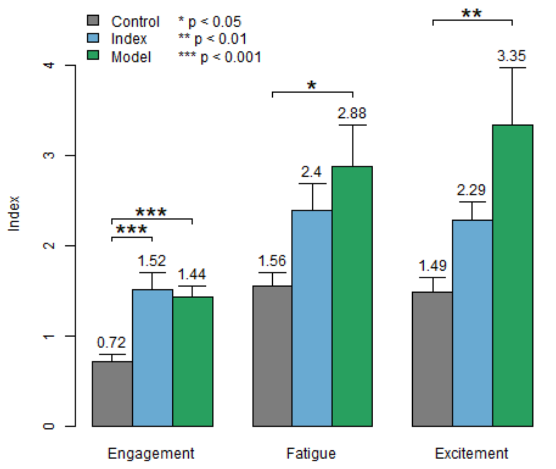

Fig. 11: Barplot of EEG-derived indices across groups, depending on whether neurofeedback was received and which model was used to do so.

At Fig. 11, a clear behavioral trend is exhibited, in which both neurofeedback groups had a significantly higher engagement than the control group with no neurofeedback ($p < 0.001$), in which the neurofeedback group had nearly two times more engagement than the control group. On the other hand, the participants at the neurofeedback groups exhibited a higher excitement index with respect to the control group, with the MLR model group having a strong statistical difference when compared to the control group ($p < 0.01$); being two times more excited. However, both neurofeedback groups also exhibited a higher fatigue index, in which the MLR model group had a small statistically significant difference when compared to the control group ($p < 0.05$); thus exhibiting twice as much fatigue than the control group.

Overall, disregarding the strong statistically significant difference between the control group and the neurofeedback groups at the engagement index, there seems to be a linear relationship across groups at the fatigue and excitement index: In which the control group exhibited the lowest index, followed by the index neurofeedback group, and finally the MLR model neurofeedback group with the highest index. Thus, suggesting that the model is so accurate in real-time that it is overwhelming the participants with its haptic feedback, thus increasing their fatigue and excitement levels to significant levels, in contrast to the index neurofeedback group. This trend is exhibited despite having similar results on their engagement index, perhaps due to the index neurofeedback group optimizing to that metric only.

In order to analyze the behavior of a participant while taking the lecture, the line plot at Fig. 12 was created, which shows the engagement index across time for a random subject at each group.

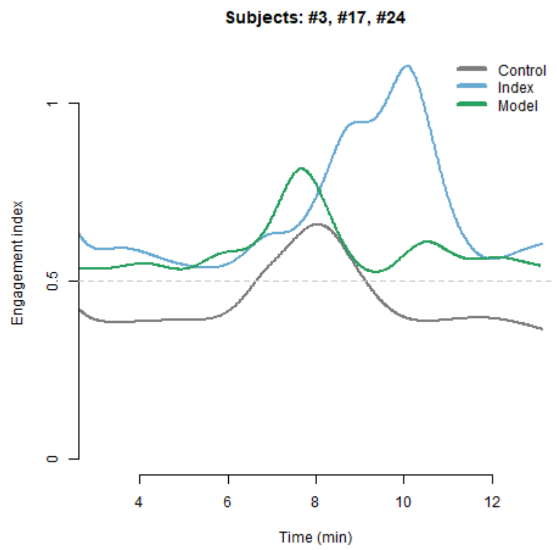

Fig. 12: Line plot of engagement index across the lecture from three random subjects that belong to each different group: Control with no neurofeedback, neurofeedback calculated based on the index, and neurofeedback calculated based on the model.

At Fig. 12, each subject exhibits an unique behavior, despite their similarities. The subject at the control group had a constant, near average (0.5), engagement index across the lecture, with a peak of engagement around the middle of the lecture (min. 8); while the subjects at the neurofeedback groups had varying amounts of engagement index across the lecture: The subject at the MLR model neurofeedback group had a peak at around min. 8 but also at min. 11, while the subject at the index neurofeedback group had a strong peak at around min. 9, further sustained through min. 11. This increases and sustained engagement significantly above the average might be due to the haptic feedback that is being applied by the neurofeedback system, thus penalizing the user when their engagement is low, with capabilities of not only having an engagement index above the average, but also at a constant rate; not going above the average at any time during the lecture.

3) Neurofeedbacktool in perceived engagement: As a part of our test for the lecture we included a question in which we asked the participants their perceived engagement during the duration of the lecture. The question had a score ranging from 1 to 5, with 1 being the lowest where they did not feel engaged during the lecture, and 5 being the highest where they felt a high level of engagement.

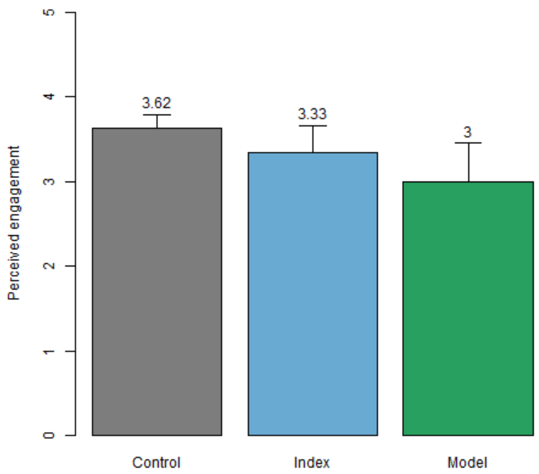

Fig. 13: Participants' average perceived engagement level after undertaking the 12-minute video.

At Fig. 13, shown in the graph above, the perceived index in each of our experimental groups, the highest self perceived engagement was from the control group, but the difference was not considerable enough to have conclusive results in this regard.

4) Neurofeedbacktool in students' performance: The results of the student's performance was measured by the score of a test about the lecture taken, each group was presented the same video and had the same exam as the other groups in order to standardize the difficulty of the exam to each group.

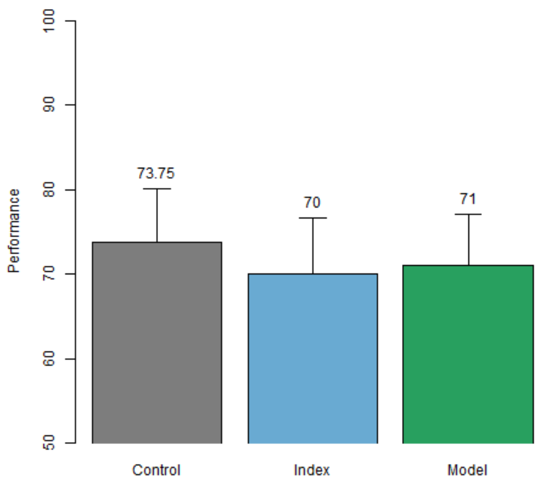

Fig. 14: Participants' average 10-question performance after undertaking the 12-minute video.

Fig. 14 shows us the average score on the test of each of our groups, the highest average score was achieved by the control group but the difference between the index group and model was not that meaningful in order to have a conclusive result on the functionality.

IV. DISCUSSION

The proposed system significantly contributes to improving sustained attention in clinical and educational settings in patients with ADHD through haptic feedback use. Likewise, our main approach focuses on the proposal of our own algorithm, in order to represent an advance and alternative to the Engagement Index, normally used in the literature since its introduction in 1995 [28].

Since the first proposed algorithm (SINDy) delivered non-dispersed and complex models with a low R^2, we chose to use MLR, which achieved a coefficient of determination of R^2 = 0.7253 and significantly lower mean square error of MSE = 1283.21 compared to the Engagement Index (R^2 = 0.0930; MSE = 18040.05). Furthermore, residual analysis showed consistently low error values close to zero, highlighting the model's reliability and applicability in dynamic settings [11].

The literature indicates that theta activity generally decreases during tasks requiring sustained attention, while it tends to increase in passive tasks and attention is multi-sensory divided, as low levels of theta correlate with increased cognitive control and reduced distractibility [29], [30]. This coincides with the observed improvement in engagement during neurofeedback testing. The MLR model took advantage of this decrease to provide corrective stimuli in real time.

On the other hand, the alpha band plays a crucial role in filtering out irrelevant stimuli and maintaining concentration. [30], [31], [32]. [33]. In tasks with rhythmic and well-calibrated haptic feedback, a moderate increase in alpha is expected, which facilitates a state of sustained focus [29], [34]. Thus, in our implication, we can observe that the engagement peaks recorded at minutes 8 and 11 (Fig. 12) imply an increase in alpha, emphasizing that the feedback is succeeding in maintaining states of concentration at key moments of the task.

Beta activity correlates strongly with task engagement, sustained attention, and cognitive processing. Increases in Beta are desired during tasks requiring vigilance and cognitive effort [4], [35], [36], [37]. Haptic feedback can enhance Beta power, reinforcing focus and task engagement. However, prolonged elevation in Beta might lead to cognitive fatigue, as noted in some studies [38] [39].

Regarding the results obtained in the performance and perceived commitment graphs require the need for a deeper analysis of the factors that may influence the experiences and performance of the participants.

While overall performance did not show significant negative interference with the use of the system, indicating that the feedback system does not hinder participants' ability to complete tasks. General performance showed no significant differences between the groups. The control group achieved a slightly higher average (73.75) compared to the index-based and model-based neurofeedback groups (70 and 71, respectively).

Conversely, subjective engagement perception presented an interesting paradox. Although objective metrics derived from EEG indices showed higher engagement in the neurofeedback groups, participants in the control group reported a higher subjective perception of engagement. This suggests that the experience of engagement does not always align with neurophysiological data, which may be influenced by factors such as mental fatigue, boredom, or users' cognitive expectations [37], [38], [39].

According to O'Hanlon, boredom arises when there is a conflict between habituation to repetitive stimuli and the sustained effort required to maintain an adequate level of arousal to perform a task [40]. This phenomenon, along with mental fatigue, could explain the observed results. Both states tend to emerge during prolonged tasks, affecting the subjective perception of performance and engagement, even when objective data reflects high levels of attention.

V. CONCLUSIONS

This project successfully combined EEG signals with a multiple linear regression (MLR) model, enabling real-time prediction and modulation of attention states. By outperforming traditional metrics, it paved the way for more personalized and adaptive educational tools.

The findings demonstrated that haptic stimuli can significantly influence attention states, though they also highlighted challenges such as the precise calibration required to avoid cognitive overload. These results underscore the inherent complexity in designing systems that balance technical effectiveness with user experience, particularly during extended or cognitively demanding tasks.

A key achievement was the system's ability to translate brain activity into effective feedback, validating the utility of specific EEG indices such as Theta, Alpha, and Beta bands. This approach not only advances the field of applied neurotechnology but also lays the groundwork for exploring applications in ADHD populations, a clinically and educationally relevant group not directly addressed in this study.

Overall, this work not only delivers a functional design that integrates advanced technology with neurocognitive principles but also establishes a framework for future research. Upcoming efforts should prioritize adaptive personalization, validation in clinical populations, and long-term impact assessment in educational and clinical environments. With these advancements, the system holds the potential to become an innovative and accessible tool to enhance educational quality and foster inclusion for populations with specific needs.

VI. REFERENCES

[1] O. C. Williams *et al.*, "Adult attention deficit hyperactivity disorder: a comprehensive review," *Annals of Medicine & Surgery*, vol. 85, no. 5, pp. 1802–1810, 2023, doi: 10.1097/ms9.0000000000000631.

[2] M. C. Etchepareborda, "Bases experimentales para la evaluación de la atención en el trastorno de déficit de atención con hiperactividad," *Revista de Neurología*, vol. 38, Suppl. 1, p. 137, 2004, doi: 10.33588/rn.38s1.2004042.

[3] NQA, "ISO 13485 Certification - Medical Devices Quality Management Systems," NQA. [Online]. Available:https://www.nqa.com/es-mx/certification/standards/iso-13485. [Accessed: Nov. 14, 2024].

[4] N. Kosmyna y P. Maes, "AttentivU: An EEG-Based Closed-Loop Biofeedback System for Real-Time Monitoring and Improvement of Engagement for Personalized Learning," *Sensors*, vol. 19, no. 23, p. 5200, 2019, doi: 10.3390/s19235200.

[5] X. Yang, D. Wang, and Y. Zhang, "An adaptive strategy for an immersive visuo-haptic attention training game," in *Haptics: Perception, Devices, Control, and Applications: 10th Int. Conf. EuroHaptics 2016, London, UK*, 2016, pp. 441–451, doi: 10.1007/978-3-319-42321-0_41.

[6] CDC, "Percentage of children in the U.S. who ever had attention deficit hyperactivity disorder in 2020-2022, by age and family income," Statista, 2024. [Online]. Available: https://www.statista.com/statistics/1458224/adha-among-us-kids-by-family-income-and-age/.

[7] Statista, "Attention deficit hyperactivity disorder (ADHD) in the U.S. - Statistics & facts," 2024. [Online]. Available: https://www-statista-com.us1.proxy.openathens.net/topics/5079/attention-deficit-hyperactivity-disorder-adhd-in-the-us/#topicOverview

[8] NCHA, "Percentage of U.S. college students that reported select disabilities or health conditions as of fall 2023," Statista, 2024. [Online]. Available: https://www.statista.com/statistics/827023/disabilities-among-us-college-students/.

[9] J. Gagliardi, "Percentage of children in Italy with different attention spans during COVID-19 distance learning by ADHD status as of 2020," Sage Journals (Journal of Attention Disorders), 2021. [Online]. Available: https://www.statista.com/statistics/1319107/children-with-and-without-adhd-having-different-attention-spans-during-elearning-italy/.

[10] V. Tessarollo, F. Scarpellini, I. Costantino, M. Cartabia, M. P. Canevini, and M. Bonati, "Distance Learning in Children with and without ADHD: A Case-control Study during the COVID-19 Pandemic," Journal of Attention Disorders, vol. 26, no. 6, pp. 902–914, 2022.

[11] Clever, "In which of the following areas, if any, would you like more edtech resources to support your teaching and district needs (choose all that apply)?" Statista, 2023. [Online]. Available: https://www.statista.com/statistics/1445771/k-12-teachers-opinions-on-what-areas-need-edtech-resources-us/.

[12] S. Khosravi, S. G. Bailey, H. Parvizi, and R. Ghannam, "Wearable sensors for learning enhancement in higher education," *Sensors*, vol. 22, no. 19, p. 7633, 2022, doi: 10.3390/s22197633.

[13] P. Kaushik, A. Moye, M. V. Vugt, and P. P. Roy, "Decoding the cognitive states of attention and distraction in a real-life setting using EEG," *Scientific Reports*, vol. 12, no. 1, p. 20649, 2022, doi: 10.1038/s41598-022-24417-w.

[14] M. Bustos-Lopez, N. Cruz-Ramirez, A. Guerra-Hernandez, L. N. Sánchez-Morales, N. A. Cruz-Ramos, and G. Alor-Hernandez, "Wearables for engagement detection in learning environments: A review," Biosensors, vol. 12, no. 7, p. 509, 2022, doi: 10.3390/bios12070509.

[15] H. S. Chiang, K. L. Hsiao, and L. C. Liu, "EEG-based detection model for evaluating and improving learning attention," *Journal of Medical and Biological Engineering*, vol. 38, pp. 847–856, 2018, doi: 10.1007/s40846-017-0344-z.

[16] A. G. P. Bruce Peter; Bruce, *Practical Statistics for Data Scientists*, 2nd Edition. O Reilly, 2020.

[17] M. O. Candela-Leal et al., "Multi-Output Sequential Deep Learning Model for Athlete Force Prediction on a Treadmill Using 3D Markers," Applied Sciences, vol. 12, no. 11. MDPI AG, p. 5424, May 27, 2022. doi: 10.3390/app12115424.

[18] A. J. Aguilar-Herrera et al., "Advanced Learner Assistance System's (ALAS) Recent Results," 2021 Machine Learning-Driven Digital Technologies for Educational Innovation Workshop. IEEE, pp. 1–7, Dec. 15, 2021. doi: 10.1109/ieeeconf53024.2021.9733770.

[19] A. A. Mendoza-Armenta et al., "Implementation of a Real-Time Brain-to-Brain Synchrony Estimation Algorithm for Neuroeducation Applications," Sensors, vol. 24, no. 6. MDPI AG, p. 1776, Mar. 09, 2024. doi: 10.3390/s24061776.

[20] A. P. Kulaichev, "Optimal choice of a reference electrode for EEG recording," Moscow University Biological Sciences Bulletin, vol. 71, no. 3. Allerton Press, pp. 145–150, Jul. 2016. doi: 10.3103/s0096392516030068.

[21] S. L. Brunton, J. L. Proctor, and J. N. Kutz, "Discovering governing equations from data by sparse identification of nonlinear dynamical systems," Proceedings of the National Academy of Sciences, vol. 113, no. 15. Proceedings of the National Academy of Sciences, pp. 3932–3937, Mar. 28, 2016. doi: 10.1073/pnas.1517384113.

[22] M. A. Blanco-Ríos et al., "Real-time EEG-based emotion recognition for neurohumanities: perspectives from principal component analysis and tree-based algorithms," Frontiers in Human Neuroscience, vol. 18. Frontiers Media SA, Mar. 13, 2024. doi: 10.3389/fnhum.2024.1319574.

[23] A. Kislov, A. Gorin, N. Konstantinovsky, V. Klyuchnikov, B. Bazanov, and V. Klucharev, "Central EEG Beta/Alpha Ratio Predicts the Population-Wide Efficiency of Advertisements," Brain Sciences, vol. 13, no. 1. MDPI AG, p. 57, Dec. 28, 2022. doi: 10.3390/brainsci13010057.

[24] M. A. Ramírez-Moreno et al., "Evaluation of a Fast Test Based on Biometric Signals to Assess Mental Fatigue at the Workplace—A Pilot Study," International Journal of Environmental Research and Public Health, vol. 18, no. 22. MDPI AG, p. 11891, Nov. 12, 2021. doi: 10.3390/ijerph182211891.

[25] L. E. Ismail and W. Karwowski, "Applications of EEG indices for the quantification of human cognitive performance: A systematic review and bibliometric analysis," PLOS ONE, vol. 15, no. 12. Public Library of Science (PLoS), p. e0242857, Dec. 04, 2020. doi: 10.1371/journal.pone.0242857.

[26] J. A. Carrobles, "Bio/Neurofeedback" Universidad Autónoma de Madrid, Clínica y Salud vol.27 no.3 Madrid nov. 2016. doi: 10.1016//j.clysa.2016.09.003.

[27] Seeed Studio. Getting Started with Seeed Studio XIAO nRF52840. Oct, 2024. https://wiki.seeedstudio.com/XIAO_BLE/

[28] A. T. Pope, E. H. Bogart, and D. S. Bartolome, "Biocybernetic system evaluates indices of operator engagement in automated task," *Biological Psychology*, vol. 40, no. 1-2, pp. 187-195, 1995.

[29] F. Shabani, S. Nisar, H. Philamore, and F. Matsuno, "Haptic vs. Visual Neurofeedback for Brain Training: A Proof-of-Concept Study," *IEEE Transactions on Haptics*, vol. 14, no. 2, pp. 297–302, Apr.–Jun. 2021. doi:10.1109/TOH.2021.3077492

[30] H. Alsuradi, W. Park, and M. Eid, "Midfrontal theta oscillation encodes haptic delay," *Scientific Reports*, vol. 11, Art. no. 17074, Aug. 2021. doi:10.1038/s41598-021-95631-1.

[31] H. Manjunatha et al., "Effect of Haptic Assistance Strategy on Mental Engagement in Fine Motor Tasks," *Journal of Medical Robotics Research*, vol. 5, no. 4, 2020. doi:10.1142/S2424905X20410044.

[32] H. Chaudhary and V. Goyal, "PERSONALU: An EEG-Based Closed-Loop Biofeedback System for Real-Time Monitoring and Improvement of Engagement for Personalized Learning," *International Journal of Innovations in Electronic and Electrical Engineering (IJIEEE)*, vol. 6, pp. 1–17, Jan.-Dec. 2020.

[33] C. Sas and R. Chopra, "MeditAid: An Adaptive Neurofeedback-Based Wearable System for Training Mindfulness State," *Personal and Ubiquitous Computing*, vol. 19, pp. 1169–1182, 2015, doi: 10.1007/s00779-015-0870-z.

[34] S. Zhang, D. Wang, N. Afzal, Y. Zhang and R. Wu, "Rhythmic Haptic Stimuli Improve Short-Term Attention," *IEEE Transactions on Haptics*, vol. 9, no. 3, pp. 437-442, July-Sept. 2016, doi: 10.1109/TOH.2016.2531662.

[35] S. Sudharsan, S. Siddharth, M. Uma and R. Kaviyaraj, "Learning Behavior Analysis for Personalized E-Learning using EEG Signals," *2024 International Conference on Advances in Computing, Communication and Applied*

Informatics (ACCAI), Chennai, India, 2024, pp. 1-9, doi: 10.1109/ACCAI61061.2024.10601997.
[36] I. A. Castiblanco Jimenez, J. S. Gomez Acevedo, E. C. Olivetti, F. Marcolin, L. Ulrich, S. Moos, and E. Vezzetti, "User Engagement Comparison between Advergames and Traditional Advertising Using EEG: Does the User's Engagement Influence Purchase Intention?" *Electronics*, vol. 12, no. 1, p. 122, 2023, doi: 10.3390/electronics12010122.
[37] P. Sena, M. d'Amore, M. A. Brandimonte, R. Squitieri, and A. Fiorentino, "Experimental Framework for Simulators to Study Driver Cognitive Distraction: Brake Reaction Time in Different Levels of Arousal," *Transportation Research Procedia*, vol. 14, pp. 4410-4419, 2016, doi: 10.1016/j.trpro.2016.05.363.
[38] G. Li, S. Huang, W. Xu, et al., "The Impact of Mental Fatigue on Brain Activity: A Comparative Study of Resting-State and Task-State EEG," *BMC Neuroscience*, vol. 21, p. 20, 2020, doi: 10.1186/s12868-020-00569-1.
[39] L. E. Ismail and W. Karwowski, "Applications of EEG Indices for the Quantification of Human Cognitive Performance: A Systematic Review and Bibliometric Analysis," *PLOS ONE*, vol. 15, no. 12, Dec. 2020, doi: 10.1371/journal.pone.0242857.
[40] J. F. O'Hanlon, "Boredom: Practical Consequences and a Theory," *Acta Psychologica*, vol. 49, no. 1, pp. 53-82, 1981, doi: 10.1016/0001-6918(81)90033-0.
[41] Sukhmanjeet Kaur Mann; Narpinder K. Malhi. StatPearls. Treasure Island (FL): StarPearl Publisher, 2024.
[42] C. Chen, J. Wang, and C. Yu, "Assessing the attention levels of students by using a novel attention aware system based on brainwave signals," *British Journal of Educational Technology*, vol. 48, no. 2, pp. 348–369, 2015, doi: 10.1111/bjet.12359.

VII. Appendix

i) CPT-II data collection questionnaire

Registro Achtung!

1.**Edad?**

A) 18-20
B) 21-23
C) 23-25
D) +26

2.Sexo

- Respuesta Abierta

3.**Carrera**

- Respuesta Abierta

4.**Carrera**

- Respuesta Abierta.

5.**Horas de sueño**

- Respuesta Abierta

6.**Del 1 al 10(el 1 siendo el más bajo y el 10 el más alto) en que nivel de cansancio te encuentras?**

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10

7. **¿Tomas regularmente café o alguna bebida energética?**

- Respuesta Abierta

8.**Padeces de algún padecimiento de neurodiversidad?**

- Respuesta Abierta

ii) Prototype validation lecture questionnaire

Examen Video Huracán Grupos

1.**¿Qué es un huracán según el video?(Respuesta Correcta B)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

2. **¿Cuál es la principal característica de un huracán?(Respuesta correcta B)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

3. **¿Qué condiciones son necesarias para la formación de un huracán?(Respuesta correcta C)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

4. **¿Cuál es una característica del "ojo" del huracán?(Respuesta correcta B)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

5 **¿Qué diferencia hay entre un huracán y un ciclón tropical en términos de ubicación geográfica?(Respuesta correcta A)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

6. **De las siguientes partes, ¿cuales forman parte de un huracán?(Respuesta correcta D)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

7. **¿De qué manera se calientan los océanos?(Respuesta correcta B)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

8. **¿Cuáles son efectos negativos de los huracanes?(Respuesta correcta D)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

9. **¿Qué fenómeno atmosférico es esencial para la formación de un huracán y por qué?(Respuesta correcta B)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

10. **¿ Cuales son efectos positivos de los huracanes?(Respuesta correcta A y C)**

A) Un fenómeno atmosférico de alta presión.
B) Un ciclón tropical con vientos fuertes.
C) Una tormenta de nieve intensa.
D) Un terremoto submarino.

11. **Que tan distraído te sentiste durante la realización de esta prueba?(5 siendo muy distraído y 1 siendo muy poco)**

- 1
- 2
- 3
- 4
- 5