POLITECNICO DI TORINO

Master's Degree in Biomedical Engineering

Comparison of Amplitude-Time rewards and Sham-Control in EEG-neurofeedback

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Abstract

The search for non-invasive and interactive therapeutic approaches has increased in the last decades, and Neurofeedback (NF) has been explored in the context of brain disorders or enhancement of cognitive performance, both in research and clinical settings. The NF technique aims to train self-regulation of brain activity in real-time (RT), and it is primarily utilized in research with functional magnetic resonance imaging (fMRI) or electroencephalography (EEG). The training undergone with NF is based on associative learning, which offers a non-pharmacological and non-invasive treatment. Different levels of reinforcement can be used in the approach, and even though the underlying NF mechanisms remain to be fully elucidated, studies have shown effectiveness in improving the relief of symptoms. Despite promising results, several limitations exist, including emotional and cognitive confounds, and the fact that about one-third of the population is not able to learn self-regulation of brain activity. Furthermore, the indexes utilized for learning outcome are not fully defined nor standardized and focus on the amplitude of the brain activity of interest, in detriment of time-bound information. Least but not last, only recently have sham and control groups been included regularly in study protocols.

This project aims at studying the efficacy of an EEG-based NF-training protocol that includes reward for both amplitude (continuous feedback) and duration (discrete feedback) of the brain activity of interest. The protocol is embedded in a game-based learning approach, and the NF training group is compared to a control-sham group, and simultaneously, attention, motivation, memory, and mood are assessed. The brain activity of interest was defined as the power of the upper alpha (UA) band, with the aim to increase its amplitude and reward when the goal is achieved for longer periods. This choice binds to the existing know-how at the laboratory where the project was developed. The final goal would be to have a protocol design with proven efficacy that could be adapted to clinical settings in migraine patients.

Twenty-two female participants were enrolled in the study, meeting inclusion criteria of no known neurological disorders and no use of psychotropic medication, and were divided in two groups, the real NFT and the SHAM group. The protocol consisted in 4 training sessions to be performed in consecutive days at approximately the same time of the day. Each session lasted about 2 hours and comprehend questionnaires and cognitive tests, a pre-baseline recording for calibration, the real NF training, and the post-training baseline calculation.

Subsequently, the neurofeedback signal was calculated offline from channel Cz, with the EEG data pre-processed using Matlab toolbox EEGLAB, and then divided into 30 epochs. Time-frequency (TF) decomposition was performed using wavelet transforms and timing information was tagged, to see when each participant achieved the goal of maintaining the NF signal above a predefined threshold. The information was subsequently analysed for the identification of training effects, both within and between sessions, for each of type of reinforcement feedback, and for each group.

Finally, we aim at classifying between groups (NF and SHAM) and at identifying the features that better disentangle NF learners from non-learners.

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ADHD	Attention-Deficit/Hyperactivity Disorder
BF	BioFeedback
BCI	Brain Computer Interface
EC	Eyes Closed
ECG	ElectroCardioGraphy
EEG	ElectroEncephaloGraphy
EMG	ElectroMyoGraphy
EO	Eyes Open
FKS	Flow Kurz Scala
fMRI	functional Magnetic Resonance Imaging
IAB	Individual Alpha Band
IAF	Individual Alpha Frequency
ISR	Institute for Systems and Robotics
IST	Instituto Superior Técnico
LA	Lower Alpha
LaSEEB	Evolutionary Systems and Biomedical Engineering Lab
NF	NeuroFeedback
NFT	NeuroFeedback Training
QCM	Questionnaire of Current Motivation
SMR	SensoriMotor Rhythm
UA	Upper Alpha
VR	Virtual Reality

1. INTRODUCTION

1.1 Context

Over the past few years, it has become increasingly important to seek non-invasive methods that can be used in clinical settings for future sickness treatment with the goal of minimising or getting rid of possible disease-related symptoms, since they are pain-free and have less side-effects than invasive techniques and pharmacological treatments. Several studies have been conducted to investigate the biofeedback (BF) methods in different fields, such as treatments for psychiatric disorders (Schoenberg & David, 2014), rehabilitation (Giggins et al., 2013), and emotion regulation and cognitive enhancements (Lorenzetti et al., 2018; Loriette et al., 2021). Among others, the BF can be applied using electromyography (EMG), blood-volume pulse and peripheral skin temperature; other techniques have differentiated themselves by focusing on signals derived from brain activity, like electroencephalography (EEG) (Stokes & Lappin, 2010), electrocorticogram, magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI). These last techniques used to regulate brain activity are referred to as neurofeedback (NF).

NF has gained popularity in clinical and academic settings for its ability to normalise or reverse abnormal brain activity patterns in a range of neurological and neuropsychiatric disorders (Pineda et al., 2012) and it works by training the brain to respond in a pre-defined manner (increase or decrease of activity) to specific stimuli and stressors (Lorenzetti et al., 2018). This technique is applied with real-time (RT) brain recordings, irrespective of brain imaging method, to extract features of interest (Kopel et al., 2017), which are used as associative feedback representation with different sensory modalities, such as visual, auditory, or tactile stimuli (Enriquez-Geppert et al., 2017), or using a game-based approach with screen-based display or virtual reality (VR) (Mohammadi et al., 2018; Rubio-Tamayo et al., 2017). Behavioural neuroscience posits that associative learning is at the base of self-regulation of brain activity in NF training (Angelakis et al., 2007). According to research, the feedback task could benefit from the addition of a game-based learning approach with different levels of reinforcement, both positive and negative (Klöbl et al., 2020; Reinschluessel & Mandryk, 2016). The most recent studies are focusing on the use of this approach, as the results from EEG-based training of healthy volunteers are promising.

1.2 Motivation

Even though NF training (NFT) studies have produced encouraging results, there are still some limitations that should be taken into account. These include the lack of a control condition or control group in the majority of reported studies, the failure to consider attention and motivation as factors that affect learning capacity, as well as other psychological factors (Sitaram et al., 2016). Hence, ongoing efforts are made to improve the design of rewards and feedback given to the participant in order to improve the NFT outcome. In addition, it is still not standardized how to evaluate the learning, the best way to classify the subjects who are able to self-regulate and the predictors of this outcome. The latter is a big limitation, since it is proved that about one third of the population is not able to learn self-regulation (Sitaram et al., 2016), so knowing in advance who will benefit from NFT would be very useful.

The current thesis attempts to address these limitations by utilising a sham group (a sort of control group) (Ros et al., 2020) and by examining the impact of adding reinforcement levels on EEG-based NFT (Klöbl et al., 2020), which are aspects not enough researched. In this study, the game-based learning approach is used to increase the engagement in the training for the participants, and a new approach of evaluating the learning has been studied. In fact, up to now, most experiments have focused on the participant's ability to modulate his or her brain activity by increasing or decreasing the amplitude of the waves of the desired feature, without considering the time spent above a certain defined threshold for that same feature. Indeed, it has been thought that there may be people who, despite not being able to increase the relative amplitude of a certain brain wave very much, can learn to maintain this amplitude at a fairly high value (above threshold) for increasing times during NFT sessions (Dempster & Vernon, 2009). Another innovation implemented in this study is the attempt to classify participants into learners or non-learners, considering both the standard and the new features, through the application of automatic classification techniques for EEG signals as reported in the literature.

This research is part of a project whose ultimate goal is the optimisation and design of an efficient protocol for the treatment of migraine in adult women, which represents one of the most common and debilitating illnesses (Reddy et al., n.d.; Viana et al., 2020). The focus of the study are adult women since they are more likely than men to experience migraines of higher intensity and length, especially during menstruation, with menstrual migraine believed to be a prevalent subtype (Dib, 2008). Moreover, it is often recognised that women are more likely to get migraines throughout puberty and perimenopause, the latter of which is associated with the body's natural transition to menopause (between 25 and 55 years old) (Anne Sahithi et al., 2020). Migraine is a neurological disorder that causes a very strong headache, and that can be categorized in two forms: without aura, the most common (about 80% of all cases); with aura, which is a condition caused by neural dysfunction (Zivoder et al., 2018). It should be noted that using VR goggles to improve NFT is not the first choice for migraine patients, as they frequently experience increased pain or discomfort when pressure is applied to the head for extended periods of time. It is important to find the optimal protocol for the treatment before applying it to the migraine patients in a clinical environment.

For the presented reasons, the participants recruited for this thesis were only healthy women between the age of 18 and 35 years, the technique chosen was the EEG with the visual sensory modality for the NF without the use of VR goggles, but with a game-based approach to increase interest in the training. The presence of a control group, in this case Sham, has the advantage of offering a more rigorous comparison with the NFT group in order to evaluate behavioural changes and/or changes in the EEG activity data.

1.3 Thesis Outline

The thesis is divided into five chapters. This first chapter consists in a general background about EEG and NF, with a literature review and state-of-the-art about the techniques currently used in NFT. In the second chapter, the techniques used in the thesis are explained in full, including the description of the participants, the questionnaires submitted, the training protocol used and the methods to analyse the data. The chapter three illustrates the obtained results, which are discussed in chapter four, where a comparison with the literature is done. The final chapter five explains the principal conclusions, the limitations found in the research and the possible future development and application.

1.4 Electroencephalography

EEG is the physiological method of choice to record the electrical activity generated by the brain via electrodes placed on the scalp surface (Olejniczak, 2006). The first EEG recording on a human was made in 1924 by neuropsychiatrist Hans Berger at the University of Jena in Germany. Using the term "electroencephalogram," he employed EEG to graphically portray the electrical signals generated in a patient’s brain (Yasin et al., 2023). This technique records the brain’s electrical activity, measuring the voltage difference between the electrodes placed on the scalp and a reference electrode (Olejniczak, 2006). It has a good temporal resolution but, due to the volume conduction effect and the distance between the electrodes, it has a poor spatial resolution. EEG can also be used with other imaging techniques, like fMRI and computed tomography (CT) to compensate for its inherent limitations (Niedermeyer, 2011).

1.4.1 Neurophysiological Basis

The EEG signal results from populations of cortical neurons’ synchronized synaptic activity; when postsynaptic neurons are stimulated a negative extracellular voltage is generated, creating a dipole. These neurons are primarily cortical pyramidal cells, which have their apical dendrites uniquely aligned parallel to one another and perpendicular to the cortical surface. These neurons generate both intra- and extracellular currents when they are stimulated. Local field potentials and local magnetic fields are produced simultaneously by magnetic field lines that are formed around the neuronal membrane, whose permeability can change in response to a stimulus (Lopes Da Silva, 2013). Consequently, the cell might encounter an influx of positively charged ions such as sodium (Na+), which would depolarize the membrane and cause an action potential. On the other hand, inhibitory mechanisms may lead to an increase in the membrane's permeability to ions that are negatively charged, such as potassium (K+) or chloride (Cl-), which causes the cell to become hyperpolarized and inhibits the generation of action potentials (Olejniczak, 2006). Ion channels facilitate the passage of these ions across the membrane, allowing certain ions to pass in the direction of their concentration gradient. K+ is more concentrated inside the cells, although Na+ and Cl-are more concentrated outside of them. In order to produce these electrical currents a neuronal activity is needed, which can be an action potential or a synaptic activity. Although action potentials have a considerable amplitude intracellularly, they have a much lesser amplitude outside of cells. The second type, the synaptic activity, enables chemical communication between neurons and their dendrites. Neurotransmitters released by pre-synaptic neurons interact with receptors on post-synaptic neurons to produce excitatory (EPSPs) or inhibitory (IPSPs) post-synaptic potentials that travel down the post-synaptic membrane. Synaptic currents lasts longer than those generated by action potentials and as a result, synaptic activity is the factor primarily responsible for the EEG signal’s contribution. The measured voltages are indicated in millivolts (mV) when measured at the surface of the brain (between 1 and 2 mV), or in microvolts (μV) when recorded in the scalp (near to 100 μV) (Malmivuo & Plonsey, 1995). The noise from the ground electrode can be eliminated by choosing a reference electrode from the recorded EEG channels to serve as the "baseline" for all other channels, which will substitute the ground electrode (Yao et al., 2005), the reference is explained in detail in section 1.4.4.

In conclusion, EEG is primarily caused by the spatiotemporal average of postsynaptic potentials that emerge in the cortical pyramidal cells (Figure 1.1). The spatial scales include single neurons(A), small networks of a few hundred neurons(B), and vast networks of millions of neurons in various brain regions(C).

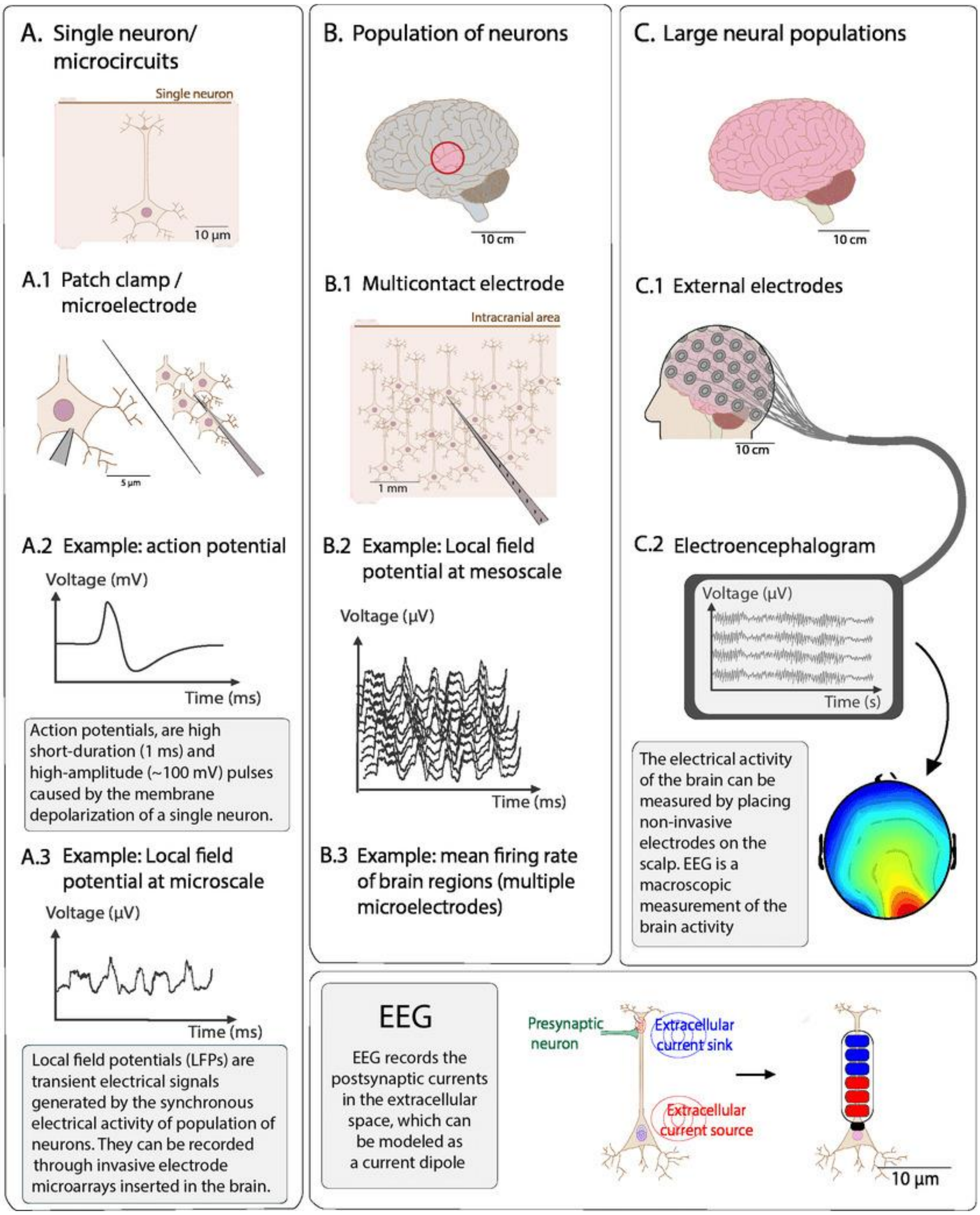

Figure 1-1 Electrophysiology of neural activity and EEG at different scales. (A) Microscopic scale. (B) Mesoscopic scale. (C) Macroscopic scale. (Glomb et al., 1234)

1.4.2 EEG signal propagation and measurements

The EEG signal is transmitted throughout the brain through volume conduction. Considering the fundamentals of electrical charge: similar charges repel one another whereas opposing charges attract one another, when this process concerns a pool of ions, the phenomenon is called volume conduction and cause a charge "wave" to propagate through the extracellular area. Since the brain is not a homogeneous volume, the currents find some obstacles like the myelin-coated nerve tracts through which ions cannot flow or different densities of tissue that may impede the flow (Jackson & Bolger, 2014). The signal has to travel from the brain to the external electrode in order to be measured through four main layers: dura layers, skull layers, scalp and electrode gel. These forms a series of conductive volumes separated by insulating layers, they work as capacitors and the charge is conducted until it reaches the electrode. This process takes some time to settle, for this reason it's necessary to wait a few minutes before beginning the recordings (Jackson & Bolger, 2014, p. 4). These conduction processes lead to a phenomenon called spatial smearing, which is a diffusion of the signal of the dipoles present in the brain, where the measured signal is the sum of several dipoles that are within a certain range (Yasin et al., 2023). EEG can measure both tangential and radial dipoles, since it can detect them when the source and the sink are not equally spaced from the electrode (Ahlfors et al., 2010). Beside limited spatial resolution, one of the principal limitations relates to the strength of the source needed for the signal to reach the electrode, since the produced electric field drops off quickly, and the noise corrupts the signal. For this reason, the electrode gel and an amplifier are necessary to face these limitations. The first one is highly conductive and is used to create a conductive channel from the scalp to the electrode. The noises that corrupt the signal can be caused by internal or external sources, the amplifier should be placed as close as possible to the electrode in order to have a high signal-to-noise ratio (SNR), which is the measure for the quality of the signal. The internal noise can be handled by controlling environmental factors and with post-processing methods (Jackson & Bolger, 2014).

1.4.3 Brain Waves

The amplitudes and frequencies of the electrical brain activity, or brain waves, can be used to identify the patterns of neuronal activity. The scalp EEG signal fluctuates primarily in the frequency range of up to 50 Hz, and the recorded EEG wave's features are greatly influenced by the person's mental state such as wakefulness, different sleep stages or mental disorders, and they are typically irregular and lack of a precise pattern. High levels of consciousness are indicated by an increase in the EEG rhythm, whereas slow waves are indicative of lower levels of brain activity (Roohi-Azizi et al., 2017)

Based on their frequency, brain waves can be divided into 4 major types (Figure 1.2) (Niedermeyer, 2010):

- Delta waves (0.5-4 Hz): There are two cellular sources of delta activities, one in the thalamus and the other in the cortex. These slow oscillations are recorded during deep sleep or extremely low brain activity, like in anesthetized animals or humans (Amzica & Lopes Da Silva, 2010).
- Theta waves (4-7 Hz): They are recorded during stages 2 and 3 of slow wave sleep, and they originate in the human hippocampus. These waves play a role in attention, sensorimotor integration, memory processes, and spatial navigation. A larger activity was recorded during rapid eye movement (REM) sleep (Amzica & Lopes Da Silva, 2010; Bódizs et al., 2001).

Alpha waves (8-13 Hz): the occipital cortex produce the majority of the signal in these frequencies during consciousness, but it can be recorded also from the somatosensory cortex (mu rhythm) and the temporal cortex (tau rhythm). The wave rhythms generated by the occipital cortex are better identified during reduced visual attention and in a state of muscular relaxation (Amzica & Lopes Da Silva, 2010), occurring often during peaceful, relaxed wakefulness or a rested state and with a tendency to vanish during sleep (Iaizzo, 2020). Alpha amplitude can be diminished or inhibited by concentration and mental effort (Shaw, 1996), whereas lack of attention or closed eyes both raise it (Nunez et al., 2001), and its phase predicts cortical excitability and affects perception of visual inputs (Thut et al., 2012). Moreover, it is diminished in amplitude or entirely suppressed by eye opening, which is a phenomenon known as alpha desynchronization. Alpha band can be divided in two sub-bands, based on the cognitive process that generates them: Lower alpha (LA) band and Upper alpha (UA) band. LA is divided in two other sub-bands, lower-1 (LA1) and lower-2 (LA2), its width is about 3.5-4 Hz and the desynchronization occurs in the range of 6-10 Hz, it is probably associated with attention (Klimesch, 1999). UA band is thought to be caused by memory processes and processing semantic information. Its width is smaller than LA band, in fact it comprises only 1-1.5 Hz and in this case the desynchronization occurs around 10-12 Hz (Klimesch, 1999). Since there is a large variability in this band, due to different factors like age and brain volume, Klimesch proposed to use an Individual Alpha Band (IAB) instead of a well-defined band. This is based on the definition of Individual Alpha Frequency (IAF), which is the frequency presenting maximum power. The IAB can be defined in different manners, but in this project, we will use the definition IAB = [IAF-2Hz, IAF+2Hz].

- Beta waves (14-30 Hz): beta rhythmic activity is associated to the motor cortex's neurons generating commands. These waves are fast oscillations with a low amplitude, and they are recorded during alert wakefulness and motor activity. Beta I (14–20 Hz) and beta II (20–30 Hz) are the two subclasses that make up the beta band. The first appears concurrently with alpha waves and is similarly influenced by mental activity, while the second only appears during periods of great mental effort and tension.
- Gamma (30–80 Hz) and High gamma (80–150 Hz): these high frequencies waves are rarely seen in scalp EEG, but they can be detected via intracranial recordings. They are associated with memory, attention, and problem-solving tasks.

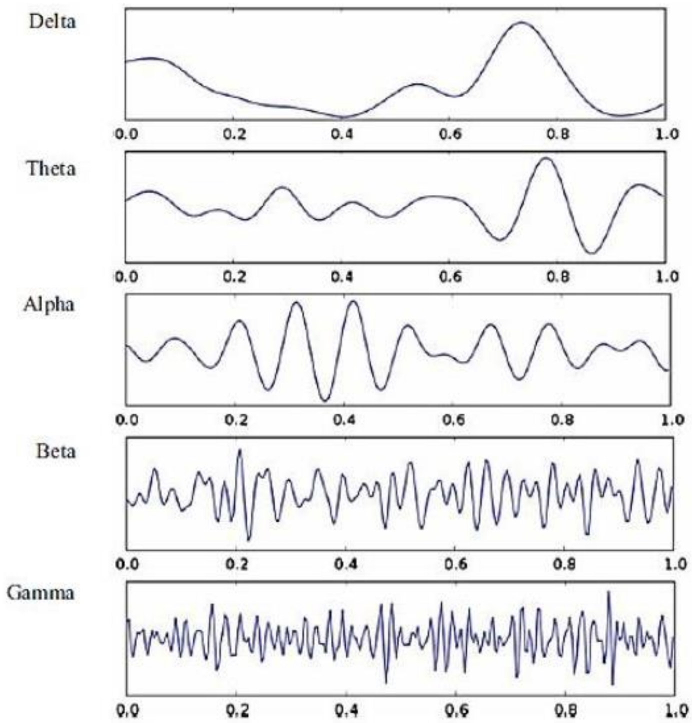

Figure 1-2 Typical brain waves in different frequencies (Jasek et al., 2018)

1.4.4 Electrode placement

A set of electrodes must be positioned on the scalp in order to record EEG signals. There are various possible placements, but the standard ones are the most used because considering the same relative position enables repeatability through different studies (Jurcak et al., 2007). The most common placement is the 10-20 International System, which considers the head size and shape by the identification of specific anatomical landmarks: nasion (Nz), placed on the nose bridge; inion (Iz), the prominence at the base of the occipital bone; and the left (LPA) and right preauricular points (RPA), an anterior root of the tragus's centre of peak region (Jurcak et al., 2007). The next step is to position adjacent electrodes at conventional measurement distances of either 10% or 20% of the length of the lines connecting Nz, Iz, LPA and RPA, with a total of 21 electrodes (Figure 1.3). To identify the position of a certain electrode, two coordinates are used: a letter, which refers to the anterior/posterior position on the head, and a number, which gives information about the media/lateral position (odd numbers = left hemisphere; even numbers = right hemisphere). The midline electrodes are identified by the letter "z," which stands for "zero," and the numbers rise as one moves away from the midline (Fisch, 2010).

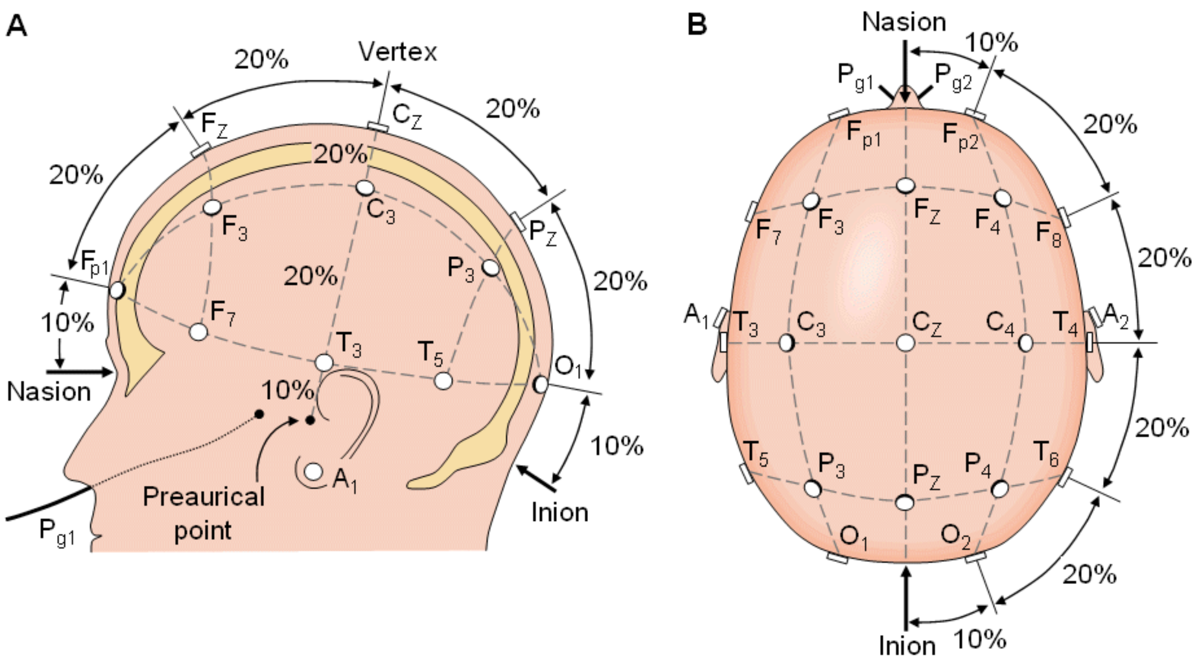

Figure 1-3 The international 10-20 system seen from (A) left and (B) above the head. A = Ear lobe, C = central, Pg = nasopharyngeal, P = parietal, F = frontal, Fp = frontal polar, O = occipital **(Malmivuo & Plonsey, 1995)**

The letters correspond to frontal polar (Fp), frontal (F), central (C), parietal (P) and occipital (O) areas of the head, where the C location is placed over the central sulcus.

Each electrode's signal is determined by the difference in electric potentials between that electrode's location and that of another electrode known as the reference, which includes electrodes like FCz, Oz, Cz, connected ears, and the nose. Post-acquisition re-referencing procedures use references such as the mean mastoids, the average, or the reference electrode standardization method (Lei & Liao, 2017), among others. Over the years, more extensive variants of this system were studied, like the 10/10 or 10/5 systems, which allow a higher density of electrodes and a better spatial resolution (Jurcak et al., 2007). The 10-10 system adds extra electrodes to have a more in-depth EEG and consists in about 70 channels, which fills in the gap of the 10-20 system. This system was then expanded by completing the spaces between the points to form the 10–5 system, where the points are separated by 5%, permitting the use of numerous electrodes, ranging from approximately 140 to over 300 electrode sites (Oostenveld & Praamstra, 2001).

Electrode caps are currently used in research settings because they are simpler to use and come with pre-marked holes for inserting each electrode in accordance with the intended system. In addition to having pre-positioned electrodes, these caps have the added benefit of being available in multiple sizes to suit individuals with varying head shapes, which makes it easier to install the electrodes correctly (Casson et al., 2018).

Reference Electrode

The reference electrode used to record the EEG is typically affixed to the mastoid (bones behind the ears), FCz or Cz electrodes, single or attached earlobes, or the tip of the nose; nonetheless, using a single channel as an in-line reference is advised. The reference channel is typically not displayed in the EEG data since recording it would entail recording variations of zero volts. Also, it is important to place the reference, while recording EEG data, far from the region of interest, otherwise the information about brain activity in that area might be lost during NFT, since the signal from the reference channel is subtracted from the other channels.

There are different ways to re-reference the channels, for example the reference electrode could be an offline reference used after recording to recalculate the voltage of the channels. After that, the voltage at these channels indicates the difference to this new reference. This technique is useful when the data from the online reference channel contains important information, and recovery of the online reference channel is possible.

Other possible techniques include: (i) the average of the mastoids electrodes (M1 and M2 / TP9 and TP10), which is commonly employed when the target signal is situated in the middle or in the midline of the scalp; (ii) the average of all channels and subtracting that value from the value of each channel, so that each contributes equally to the new reference, to apply this method it is necessary to have electrodes equally spaced (about 64 channels) to avoid problems due to the different density of channels on the scalp; (iii) the reference electrode standardization technique (REST), which translate a reference point at infinity from a channel on the scalp or an average utilised as a reference (Yao et al., 2005).

1.4.5 Typical artifacts of EEG recordings

The signal quality is degraded by the EEG recording environment and subject-related electrical activities, these interferences are known as artifacts. The frequency or time domain of the EEG can be contaminated by artifacts that come from the subject's own physiologic processes and movement as well as external sources including equipment, equipment noise, and the movement of electrodes and wires. External artifacts can be avoided with a proper insulation of the cables, whereas internal and physiological artifacts represent still a challenge for the researchers (Kaya, 2022; Tatum et al., 2011). The most common artifacts are (Dworetzky et al., 2011) described here and some examples are depicted in the Figure 1.4:

- Eye movements: blinking or eye rolling may cause interference, due to the movement of the dipole that is formed between the cornea and the retinal surface, which is more negatively charged than the cornea, introducing slow waves and larger voltage potentials, especially in the frontal regions, although they may expand to the central and temporal regions as well. While lateral motions mostly influence the electrodes F7 and F8, vertical movements are most noticeable in Fp1 and Fp2. The Eyes Closed (EC) condition also results in the appearance of these artifacts.
- Electromyographic: they have higher frequencies, in general, then the signals generated in the brain and measurable on the scalp. They are mostly caused by the muscular activity of the head, face and neck and appear in frontal and temporal lobes, even if they can be observed also in other regions.
- Glossokinetic: this term refers to the tongue movement. The tongue, similarly to the eyes, acts as a dipole and produces a potential between the frontal and occipital areas, although it isn’t as strong as the one brought on by eye movements. While speaking or eating, certain involuntary tongue motions can produce waves in the delta range with superimposed muscular artifacts, while horizontal tongue movements can induce unilateral artifacts in the EEG.
- Electrocardiographic: this is the artifact caused by the cardiac activity, its presence depends on the montage and on the size of the patient. It is a periodic signal, and it has a sharp shape. The “cardiac-cerebral relationship” can be recognized and understood using the presence of this artifact.
- Sweat: the noise introduced by the scalp perspiration is due to the formation of erroneous electrical connections between electrodes. It appears as undulating waves with low-amplitude and low-frequency (about 0.5 Hz) and this kind of artifact is seen

in more than one channel or over the entire head. By raising the low-frequency filter or keeping the scalp dry, it can be reduced.

- Patient movement: it can cause the movement of the electrodes and introduce an artifact in the recordings, they can be characterized by different frequencies or amplitudes. They can be caused by the patient's tremors or breathing, and they can be associated with simultaneous body movement to be easily recognized.

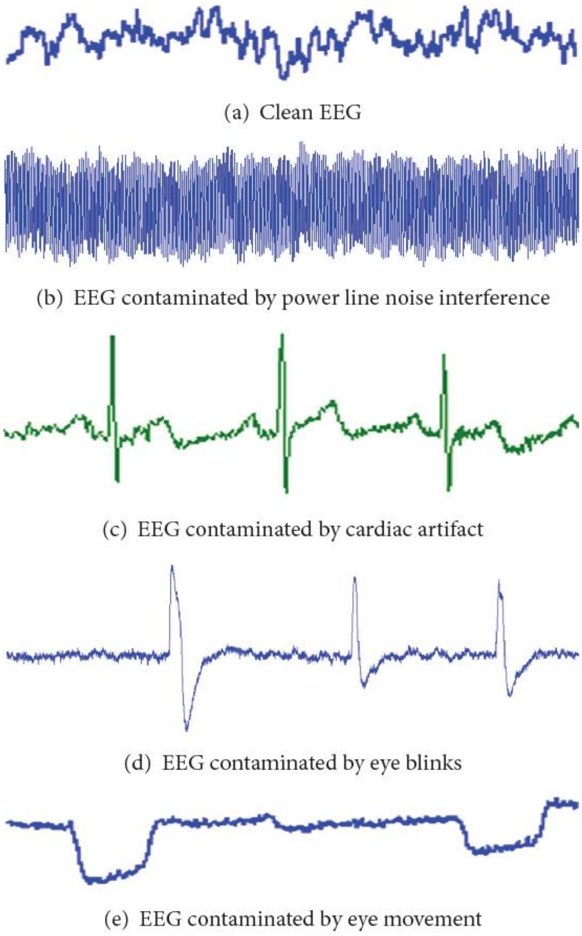

Figure 1-4 Common EEG artifacts waveforms (Kareem Abdullah et al., 2014)

Non-physiologic artifacts have a wider range of characteristics, making it more difficult to identify them. Instances of such artifacts include (Dworetzky et al., 2011):

- Electrode and lead: this artifact can be produced by inadequate electrode-scalp contact, which results in sudden positive discharges and frequently delayed, low-amplitude activity that is typically localized to a single electrode. These types of artifacts can be recognized by the unique form, positive charge, and apparent superimposition on normal activity. High impedance electrodes can deceitfully cause low or high EEG amplitudes and loss of low-frequency components.

- Instrumental: these artifacts are caused by issues with the EEG equipment.
- Environmental: they are caused by electrical interference of the AC power supply; in Europe it is at 50 Hz.

1.5 Neurofeedback

Neurofeedback (NF) is a technique that involves giving people a feedback loop that mimics their own brain activity, in this way some people can learn to intentionally regulate it, increasing or reducing specific patterns, depending on the request (Biswas & Ray, 2017). Participants can assess their progress during the process and become conscious of the fluctuations in their brain activity in real-time (RT), allowing them to adjust and reach better performances (Marzbani et al., 2016).

NF has a lot of potential in fields like rehabilitation and cognitive enhancement thanks to its non-invasive manner of reprogramming the brain's electrical neural circuits with little to no side-effects (Niv, 2013a; Ros et al., 2014). Moreover, since it doesn't require the addition of pharmaceutical substances, electromagnetic activity, or electrical stimulation, it can be done without requiring reliance on outside sources.

The feedback can be provided to the subject in two main sensory modalities, visual or auditory. The first one is visible feedback on the screen, such as images, videos or games; the second modalities can be obtained with the use of music or sounds, these two modalities can be used separately or combined together (Enriquez-Geppert, Huster, Herrmann, et al., 2017).

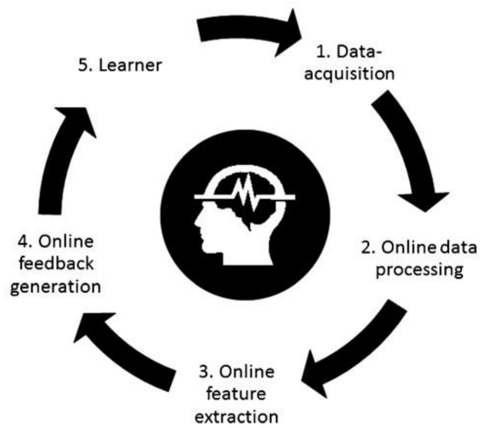

Figure 1-5 The five most crucial processing steps of a neurofeedback system included in the pipeline. (Enriquez-Geppert et al., 2019)

The five main steps of the NF pipeline are typically as follows: first, the EEG is acquired; second, the raw data are pre-processed online; third, the feedback feature (power frequency band or ratios for EEG) is chosen; fourth, this feature is converted into a stimulus (visual, auditory, mixed, etc.) for the study participant in RT; and, as a final step, the participant can learn how to regulate his own brain activity (Enriquez-Geppert et al., 2019). The main steps are presented in the Figure 1.5, and they are fully explained in section 1.4.3.

1.5.1 Neurofeedback Mechanisms

The brain mechanisms behind NF remain unclear to this day, and the research lacks consensus and a theoretical foundation for them. Through the past years, many studies focused on explaining the concepts of NF (Niv, 2013b) and the first important factor identified is the neuroplasticity, the brain's ability to adapt to both internal and external stimuli. It is possible that neurofeedback is having an impact via strengthening synapses through repetitive firing, which may result in an increment of the signal transmission between two neurons when they are stimulated synchronously (Justyna Ksiazek-Winiarek et al., 2015), and affect brain rhythms. Since the neuroplasticity requires some time, the NF protocols consist usually in many sessions of training, as will be explained in detail later, and in the initial training phase, the feedback signal fluctuates unconditionally until a threshold (the reward threshold) is achieved, and the participant receives the feedback. As a result, the brain can learn how to create this kind of neuronal state and replicate the signal after a few sessions (Ros et al., 2014), so control-theoretic closed-loop models could serve as the foundation for NF learning (Sitaram et al., 2016).

One of the most problematic things about neurofeedback is that the induction of brain processes targeted during neurofeedback training may not be the cause of the behavioural changes seen in traditional neurofeedback investigations, since many other factors can have an impact. Some of them were studied by Shibata et al. (2018), to assess in which case they could somehow explain the results of the NF training. These factors were for example the placebo effect, giving to the participant an explicit strategy (which led to no learning at all), physiological artifacts or the neuronal plasticity coming from a non-target area (Shibata et al., 2018). They found that the last one is very unlikely to influence the results, whereas the others may have an impact in the conventional protocols of NF. These are things to consider when designing a NF training.

Notably, the targeted self-regulation with NF is linked to three core neurocognitive networks (Niv, 2013b; Sitaram et al., 2016):

- Default-mode network (DMN): a widely recognised neural structure that functions as an integrated system to regulate self-related cognitive activity. It is enhanced via consistent meditation practise and can effectively alleviate many symptoms;
- Central Executive Network (CEN): in charge of executive and cognitive processes like organising, making decisions, and managing working memory and attention;
- Salience Network (SN): a brain network that aids in the recognition and guidance of both internal and external stimuli.

It should be noted that any change made to any one of these networks could disrupt the others, causing oscillations in frequencies at the target characteristics or frequency ranges of NF protocols, such as alpha and theta, thus training demonstrates a general improvement in symptoms and reinforces such characteristics (Menon, 2019; Niv, 2013b).

In order to evaluate the data, direct research efforts, and create and/or enhance protocols, investigators in clinical and research settings should have a thorough understanding of the mechanisms underlying NF, which has not yet been fully achieved (Davelaar, n.d.). Also, it's still unknown how training may affect hormonal systems and, consequently, symptoms of specific diseases (e.g., migraine) (Razoki, 2018).

1.5.2 Neurofeedback Types

The NF can be produced with different approaches: neuroimaging recordings (e.g. functional NIRS, fMRI, PET), electrical recordings (e.g. EEG, electrocorticogram, local field potential, spikes), magnetic recordings (e.g. MEG), and brain stimulations, divided in repetitive transcranial magnetic stimulation, transcranial direct current stimulation and deep brain stimulation (Lee et al., 2023). In the present study, it was chosen to use the EEG, since it is the simpler to implement, it is a non-invasive technology, and the signals' frequency analysis allows for an efficient classification, which makes it possible to assess brain activity at different frequencies both when performing a task and when at rest. For all these presented reasons the EEG is also the most used NF type (Arpaia et al., 2020).

The number of features linked to the self-regulation of brain activity varies throughout research, and in the present thesis the features of interest come from the information obtained with the electrodes.

These three illustrated techniques all have advantages and disadvantages. The EEG and MEG have a higher temporal resolution than fMRI, reaching the order of milliseconds. This important characteristic makes possible to work with the NF signal in RT, which cannot be done with the fMRI-NFT due to the hemodynamic response that delay the feedback. On the other hand, fMRI has the advantage of offering a high spatial resolution compared to the other two and allows monitoring of the entire brain (Emmert et al., 2017; Hirano & Tamura, 2021).

As mentioned, the EEG-NFT is the most used NF technique and can be further classified into different types of NF. The most used of them is the frequency/power training in both practice and research, which consists in regulating specific brain waves' frequencies (e.g., alpha rhythm) in targeted areas (e.g., temporal lobe) or modifying their amplitude (Lee et al., 2023). Some of the others NF types are: Low Energy NF System (LENS), which helps participants' brain waves to be regulated when they are relaxed and still with their eyes closed (EC), by applying a mild electromagnetic signal as a stimulus to the scalp (Ochs, 2013); Live Z-Score NF (LZT), which uses a continuous systematic database to compare brain electrical activity parameters and give the users continual feedback on their performance (Thatcher, 2013); Slow Cortical Potential (SCP), which has an effect on the slow cortical potential by improving their direction, positive or negative, to control specific event-related potentials (ERPs) and it may enhance SCP's ability to self-regulate cortical excitability (Strehl, 2009); NF that uses the electromagnetic stimulation to increase or inhibiting a certain brain activity, in an effort to return brain activity to normal, much like what happens during meditation sessions, an example is the study on a depression treatment using the ROSHI Neurodynamic Activator™Instruments (Pasadena, USA) by Hammond (2000).

1.5.3 Optimal Protocols for Neurofeedback

A fundamental step in a NF training is how to design the optimal protocol to reach the wanted goal, such as relaxation or focus, and to do that the correct frequency band to use should be determined (Israsena et al., 2021). The different bands are related to specific brain activities, when the feature of interest is the high-frequency components, the beta and gamma bands are the one studied; on the other hand, when low-frequency components are desired, the alpha and theta bands are investigated.

As introduced at the beginning of the section 1.4, the design of an optimal protocol needs to comprehend five steps, the first one (**Data acquisition**) is linked to the section 1.4.2 where the different techniques to acquire data are presented.

Data Pre-Processing

The pre-processing step is very important to be able to interpret and extract information from the EEG signals, since there are many artefacts that can quickly taint EEG data, as explained in section 1.3.5. These artefacts frequently result in waveforms that accurately replicate cerebral potentials and typically influence the entire EEG frequency spectrum, including the frequencies that are the subject of NF training (Tatum et al., 2011). Finding and eliminating these artefacts is crucial to prevent patients from erroneous modulation learning of their activity instead of the appropriate brain activity. This is especially true for patient populations with significant motor agitation or uncontrollably moving parts of their bodies(Chaumon et al., 2015; Enriquez-Geppert, Huster, Herrmann, et al., 2017). There are different ways to reject artifacts, some of the most used techniques are (Dworetzky et al., 2011; Kim, 2018): a band pass filter to keep the wanted frequencies and remove the others (e.g., remove the power supply artifact at 50 Hz); manual rejection of part of signals clearly corrupted by external components; reject automatically values exceeding a set threshold; cleaning techniques able to recognize non-brain activity and remove it; automated methods of component decomposition to remove the unwanted artifact. The last one can be done with principal component analysis (PCA) or independent component analysis (ICA), among others. In the presented thesis the ICA technique was chosen. The ICA works by recognizing the independent components in an EEG signal, which can be broken down into separate, linear combinations of its original components. The identified components coming from artifacts can be subtracted from the original signal, however, this technique is difficult to use in RT because of its computational time, but it is very useful with the recorded signals. In general, the artifact rejection is complex to perform online during the NF training, and to minimize their influence the subjects are asked to refrain from making sudden movements or blinking, and the EEG features selected are the ones less contaminated by artifacts.

Feature Selection and Extraction

In a NF experiment, the features chosen and retrieved from brain activity typically correspond to the oscillatory brain activity that is intended to be modulated, to evaluate the effectiveness of the protocol used and thus verify the achievement of the goal, such as the increasing of a specific band linked to a specific cognitive function (Enriquez-Geppert, Huster, Herrmann, et al., 2017; Marzbani et al., 2016). Each brain lobe is dedicated to a specific function, furthermore the same lobe in two different hemispheres may have very different functions; for this reason, the feature of interest is usually extracted from one or more channels combined at the lobe under examination. This feature is used as feedback parameter, which is often the power during the training compared to the baseline power acquired before NF, and that can correspond, for example, to part of or the whole frequency band power or to ratios of power between different frequency bands (Huster et al., 2014).

Feedback Generation

The fourth step is the generation of a sensory stimulus from the selected feature. When designing the protocol of a NF training, the choice of the best feedback is critical, as it is the way the participant will be able to see the variations of the own brain activity and can therefore influence learning, which is the final goal of the protocol (Huster et al., 2014). Through the years, many studies have tried to find the best solution, first by comparing visible feedback with audible ones, which although less used remains interesting (Bucho at al., 2018), and then by testing different visual sensory modality, that remains the most common method. Usually, these studies include linear changes in the visual properties of objects displayed on a screen, for example in the studies by Bucho et al. (2018) and Nan et al., (2012) the size and colour of the object changed according to brain activity, the size represented the amplitude of a feature whereas the colour corresponded to a goal achievements; in the researches conducted by Escolano et al., (2011, 2013, 2014) and Zoefel et al., (2011) only colour was used and the saturation changed based on the average amplitude of the UA; other studies considered the speed of an object in movement (Israsena et al., 2021; Jirayucharoensak et al., 2019; Reinschluessel & Mandryk, 2016); or dimmering a picture to make it harder to watch (Pérez-Elvira et al., 2021), among other things. Regarding studies with auditory feedback stimuli, an example is the study conducted by Stokes & Lappin (2010) where it was used as feedback a "beep" heard by the participant; in another research by Ghaziri et al., (2013), the sound was heard only when a defined threshold was reached and exceeded. Another possible auditory feedback could be to increase the volume of the sound or its frequency following the amplitude of the feature (Fernández et al., 2016; Lecomte & Juhel, 2011; Bucho et al., 2018). In the current literature, the results of the studies that used multimodal feedback were almost the same obtained with visual-only feedback, and there is only one study where better results were obtained with only auditory modality (Fernández et al., 2016). According to the authors, this result is related to operant conditioning's strong correlation among reinforcement and learning, which increases the efficacy of learning. They explained the results with the fact that, in the experiment, the auditory stimulus was simpler than the visual one, which was harder to process.

It should be noted that in this study the population was composed of children with learning disabilities, so this can be relevant for certain clinical populations but not in general.

Learner

The last step consists in recognizing if a participant can be considered a learner or a non-learner, which means to understand if it is able to self-regulate the brain activity with mental strategies (Enriquez-Geppert, Huster, Herrmann, et al., 2017). This is one of the biggest problems of NF training, since about one third of the population is not able to do it and there aren't clear ways to identify them a priori, as well as there aren't standard methods to define the learners. In the following section this topic is treated in detail.

When designing a protocol for NFT, two things that need to be defined in detail are the duration and the frequency of the sessions, because learning is associated to mechanisms like the formation of long-term memory, so the time has an important role in it. It is recommended to have multiple training sessions with nights of rest in between in order to solidify the training memory because sleep plays a crucial role in the learning process (Gaume et al., 2016). In literature, experiments ranging from a single training session (Reinschluessel & Mandryk, 2016) to more than 40 sessions (Ghaziri et al., 2013) can be found.

Considering the cited studies that used visual sensory modality with different protocols of NFT, it can be deduced that it is more convenient to have more than one session to allow the participants to have time to learn the self-regulation of brain activity, and it's better if the sessions are in the same week (Bussalb et al., 2019). Anyway, these factors should be adapted to each specific protocol, if the overtraining is reached or the participant is experiencing tiredness then the number of sessions should be reduced (Dekker et al., 2014; Matthews, 2008).

1.5.4 Reward and Punishment system

Reward and punishments are reinforcements techniques used in the NFT session to reinforce desired responses. The participant is awarded for any event or stimulus that follows a desired answer, and they are punished (e.g., red flag) if the required response was not received. The first is given to encourage that particular response to happen again under the same circumstances, while the punishment aims to prevent the occurrence of an undesirable reaction. The term reinforcement comprehends both of the event, positive or negative, after the response to the stimulus, either by making the response more or less likely to happen again, respectively (Sherlin et al., 2011; Strehl, 2014).

This system aims to increase the motivation of the participant to successfully complete the NFT session, based on the assumptions that the NFT can modulate the dopaminergic midbrain activity which is linked to the levels of motivation, as well as decision-making and reinforcement learning (Hellrung et al., 2022). An increasing amount of research has shown that using games to create more engaging learning strategies is possible and very effective too, people can therefore improve their motivation and, consequently, how they view the reward they receive (Gaume et al., 2016).

The way this reinforcement is given depends on the protocol used. In the presented thesis a reward is given after a certain threshold for the feature of interest has been reached, whereas the punishment is given when falling below the threshold again. The choice of this value is very critical, since there is correlation between the optimal reward threshold and the effectiveness of the NFT: if the difficulty level is too high, participants may become frustrated; if the difficulty level is too low, they may lose interest in the work (Enriquez-Geppert, Huster, Herrmann, et al., 2017; Vernon et al., 2009). Even if most of the studies base the threshold value on the participant's resting activity to have a tailored value, there are also some works where the threshold was a fixed value for all the subjects. A review of the different thresholds used in literature is presented.

One example is the study conducted by Van Boxtel et al., (2012), they didn't fix a specific threshold but gave continuous feedback, which consisted in participant's favourite music, by decreasing the volume of the music if the alpha rhythm was low, and by making the music more pleasant when alpha values were high. Nan et al., (2012) proposed a study with an adaptive threshold that was updated after every session, depending on the performance. In case the preceding session's percentage of time spent above the threshold was greater than 60%, a certain amount was added to the threshold. On the other hand, it was lowered if it was less than 40%. Diaz Hernandez et al. (2016) tried to use as individual threshold the percentage of time needed to produce microstate D, which was the feature considered, to receive feedback for at least 50% of the trial duration. Individual thresholds were established by Vernon et al., (2009) using the average amplitude measured at rest with the eyes open (EO) before each training session.

In addition to the threshold, another important factor is defining which kind of reinforcement is the optimal one. Furthermore, the types of punishments could be implemented by eliminating the desired attribute (such as an object in motion that stops). There are four different types of reinforcement found in literature:

i) One-property, wherein a linear increase of a particular attribute is applied. This is used in many studies, like the ones conducted by Escolano et al., (2011, 2013, 2014) or the research by Fernández et al., (2016b), who used both auditory and visual feedback defined by the decrease in the Theta/Alpha ratio. Other examples of this type of reinforcement are the studies by Israsena et al., (2021) and Jirayucharoensak et al., (2019) who used visual feedback and a game-based approach.
ii) Two-property, for situations where two characteristics are altered at the same time. This is the method used in the study by Ide-Walters & Thompson (2021), they used a bar to give feedback for alpha band features, which was meant to be enhanced, and another bar for the EMG activity, which had to stay low to reduce movement artifacts, the colours of the bars also changed from green to red in bad conditions. Another example is the experiment by Ghaziri et al. (2013) where an audiovisual feedback loop with two columns was used, one representing the EEG activity at channel F4 (visual feedback) and the other showing the EEG activity at channel P4 (audio feedback).
iii) In series, used when two different forms of reinforcement are applied consecutively. Two studies with this method were found in literature, the one from Reinschluessel & Mandryk (2016) and the one from Nan et al. (2012), in which a sphere's colour changed when UA value exceeded the threshold, and more slices were added when the first goal was reached for more than two second consecutively. The second goal can be obtained only after reaching the first one. Another example is the study led by Dempster & Vernon (2009), in this work the information about alpha activity were given with a moving bar, and the information about the time spent above threshold was given by changing the colour of that bar.
iv) Discrete, in which, based on the participant's performance, more specific feedback is given during or at the conclusion of the trials. In the study by Klöbl et al. (2020) this technique is applied, and the additional intermittent feedback consisted in a yellow smile as positive reward or a grey smiley as punishment for bad performances.

1.5.5 Neurofeedback learning evaluation

According to the underlying principles of reinforcement learning and operant conditioning (Sitaram et al., 2016,Domjan, 2004), it is hypothesized that participants can exert control over their brain activity when they are provided feedback or contingent rewards that elicit the desired brain responses during the study.

As already mentioned, standard metrics to evaluate the learning are not consensual and standardized across the scientific and clinical field. Yet, several options exist, among them two major frameworks (Dempster & Vernon, 2009):

- **intra-session,** which can be derived from the average results of the assessments conducted at the beginning and conclusion of each training session, or from the comparison of variations within each session to a baseline measurement.
- **inter-session,** that evaluates the learning over time, considering the variation through all the sessions (e.g., slope of the regression line) or also comparing the first and the last session. This is thought to be the best one to define the ability of a person to learn with the NFT.

Combining the two methods may also lead to a better comprehension of how effective learning processes are (Zuberer et al., 2015).

Learning curves can be utilised to examine these learning metrics and visualise the process by which each participant learns to control their own neural activity based on the chosen feature (Cowley et al., 2016; Enriquez-Geppert, Huster, Herrmann, et al., 2017). There are other techniques to evaluate the learning, such as counting how many times the participant has reached a certain goal. The chosen method depends on the focus of the study. In the context of this thesis the variations over time are important, so the first kind of evaluation is used.

The efficacy of the NFT is also seen in the long period, it was effective if the changes are maintained over time, for weeks or even months, which is referred to as transfer learning of NFT (Sitaram et al., 2016).

Learning curve

The learning curve represents graphically the variations of the feature of interest to analyse it. It displays the learning process on the Y-axis and the evolution of the feature's control over each session and in relation to all sessions on the X-axis (Ribeiro Ribas et al., 2016). This can be done for each participant individually or as a group analysis involving all participants. The learning curves have a stagnation point, where the rate of learning decreases or stops, and they tend to a plateau value, which can be explained by the intrinsic aspects of the NFT, such as the number and the length of the sessions, and by the possible feelings of fatigue or loss of motivation experienced by the participant (Wang et al., 2022). Nonetheless, certain studies showed that individuals usually regain their ability to learn after the period of stagnation, a phenomenon referred to as the relearning effect (Fielenbach et al., 2019; Wang et al., 2022).

Through the years, learning metrics have been employed in several studies to gauge the success of the research, both between and within sessions. For example, to confirm that lowering the theta/beta ratio will speed up processing, Keune et al., (2019) accessed that ratio. It was not successful learning over the course of the two-week training period, however there was a brief drop-in theta activity that was noted within sessions.

Other examples, include the study by Dessy et al., (2020), who used both learning metrics and found an increment in the UA amplitude comparing the last and the first session, and the study by Chen & Lin (2020) that also have investigated both metrics, finding a variation between the pre- and the post-training conditions. Least but not last, the study conducted by Wang et al., (2022), which aimed to downregulate the alpha band, evaluated the immediate impact of the NFT in raising working memory and attention levels using the intra-session metric and the long-term effect with the inter-session metrics. Also, another study found significant results only with the intra-session metrics, which is the one conducted by Nawaz et al., (2022).

1.5.6 Factors Affecting Learning Ability

As pointed out by Wan et al. (2014), recognising the elements that influence learning capacity is just as crucial as establishing the pertinent methods/indices to assess learning ability.

The participant's success may be influenced by their mood or other psychological traits. It has been suggested that a variety of factors, such as motivation, commitment, perceived difficulty of the training, and the variety of tactics used, are related to training outcomes (Huster et al., 2014; Kleih & Kubler, 2013).

One of the factors that can affect the learning outcomes is the **Reinforcement**, which was explained in detail in section 1.5.4. In this section two other factors are detailed, the mental strategies and the Intrinsic characteristics.

Mental Strategies

Although it was suggested that mental strategies can affect the learning, there are few studies that tried to assess the hypothesis that using these strategies or providing them beforehand to the participants can influence the results (Enriquez-Geppert, Huster, & Herrmann, 2017; Huster et al., 2014). Further consideration should be given to how individuals can effectively learn to take control of their own brain activity, given the relatively high percentage of non-learners (Kober et al., 2015). Two ways were tried out, some researchers gave suggestions about the strategy to begin with, others merely give participants general instructions to try whatever helps them to self-regulate their brain activity. In the study by Chikhi et al. (2023), they compared two groups of people, the first group was given a list of strategies to try during the NFT, the second received no instruction on how to modulate the brain activity, but they were asked to report the strategy used at the end of the training. They found out that giving the list of mental strategies didn't help the participants to increase the UA activity, however it was revealed that cognitive effort and recalling memories were useful strategies in the learners. Nan et al. in 2012 conducted a study where they assessed that participants able to reach the NFT goal had specific mental strategies, such as positive thought (e.g., thinking about family), whereas participants who used neutral strategies had limited success. It is interesting to note that those who used as strategy negative thoughts had the opposite effect, with worse performance. Another example is the research led by Zoefel et al. (2011), in which it was found that the majority of subjects actually used mental strategies, in particular thinking and evoking their emotions.

Intrinsic characteristics

It should be kept in mind that learning-related elements are frequently unconnected to psychological causes or aspects of the training design, sometimes the intrinsic factors of the individual can have a big impact on the learning ability. Alkoby et al., in 2018, conducted a study on the predictors for a successful learning, which are found to be correlated with the inter-individual differences. Enriquez-Geppert, Huster, & Herrmann, (2017) discovered, for instance, that learning ability was also predicted by the volume and concentration of specific neuroanatomical regions rather than by motivation or commitment. Another possible factor is the intelligence of the person, since participants with higher intelligence are reported to having better performances, this is probably caused by a good understanding of the task provided and the best ways to enhance the feature of interest (Jausovec, 2011; Keizer et al., 2010). According to Nawaz et al. (2023), the working memory is another intrinsic characteristic that influence the learning, in fact the subjects with higher memory tend to reach better results with NFT. Another aspect that was taken into consideration was the participant's self-confidence in his ability to achieve the goal, where high values are associated with more engagement in the training, and so, better performances (Schönenberg et al., 2021).

1.5.7 Identification of Non-Learners

As discussed previously, no clear criteria have been established to identify a learner (able to self-regulate) from a non-learner (not able to self-regulate) (Wan et al., 2014). This section will provide an explanation of the non-learner identification criteria used in various NF research studies and according to different training aspects. These metrics, used to establish a metric of learning outcome, are divided into the classical measures, which are focused on the features regarding the amplitude, and the newest, and less studied, features regarding the modulation over time. Since terminology used in literature can change, in this section, "learner," "responder," and "performer" are interchangeable.

Standard learning metrics

The standard learning metrics have so far focused on the use of features regarding the increment or decrement of, mostly, frequency band power ratio on one or more channels. Most of the protocols found in literature studied alpha, theta and beta frequency bands or a combination of them (Hammond, 2007; Marzbani et al., 2016).

There are in the literature several studies that used Beta protocols, which is intended to enhance thalamic inhibitory function, such as the one conducted by Razoki, in 2018. Other studies focused on the sub-band of beta from 13 to 15 Hz, known as sensorymotor rhythm (SMR) for protocols related to anxiety (Nan et al., 2019) or the one from Weber et al. (2011) in which the performers were identified as the participants whose mean percentage of EEG amplitude increased during the training, when compared to the baseline, and tends to increase across the sessions. Other research used the Beta/Theta power ratio, considering again only the amplitude in this frequency band, which is the commonly used protocol for ADHD conditions (Janssen et al., 2020; Lee et al., 2022).

Nevertheless, many studies were conducted using Alpha protocols in order to reduce pain or stress (Lee et al., 2022; Marzbani et al., 2016) or to enhance cognitive performances, especially when they focused on UA frequency (Escolano et al., 2014; Zoefel et al., 2011). In a study led by Escolano et al. in 2011, non-responders were defined as those whose average UA power in the final trial of the previous session did not differ statistically from UA in the "pre-active assessment block" of the first session, leading to the elimination of three out of nine participants. Dekker et al. in 2014 determined that alpha band responders were those people for whom the alpha power showed a positive difference between training sessions 1 and 15 (the last session), which were 13 out of 18 participants (about 72%). Another example of identification consists in calculating the total alpha durations of the three sessions at the beginning of the experiment and then defining responders the participants with the total alpha duration of the twelfth and last session higher than that value (with a 95% confidence interval) (Hsueh et al., 2016).

There are also studies about the Theta/Alpha power ratio, they had different goals like enhance the Theta and inhibit Alpha, to increase creativity, or reduce this ratio to improve the learning (Fernández et al., 2016; Gruzelier, 2009).

In the present thesis the UA band is the choice for the feedback generation, but also the total Alpha and Theta band are considered in the analysis.

Time percentage

Very few studies have been conducted about the relevance of the time spent above the threshold, after it was reached, as a potential metric to help identify learners and non-learners. Despite this gap in the literature, it was suggested that this could be an important aspect to consider in order to evaluate the ability of a participant to learn the self-regulation, since they could obtain good results in amplitude and percentage of time, or only in one of them (Enriquez-Geppert, Huster, Herrmann, et al., 2017).

Some years ago, Hardt & Kamiya, in 1976, published a study about the percent time index and they opened a debate on its usefulness as an evaluation index. They noted that most of the effective research on alpha neurofeedback made use of the feedback signal's continuous characteristics. According to them, this wouldn’t be an efficient way to assess the learning, since this is a binary metric (above threshold/below threshold) and it isn’t sensitive to the small variations of brain activity, this could lead to a discourage for the learners when the changes are brief. This study was then discussed by Lansky et al. (1979), who suggested that the percent-time measures enable more accurate and natural alpha spindle recognition, which is a unique characteristic of the alpha rhythm, even though they are unable to record minute variations in the feedback signal. Additionally, they asserted that threshold-based methods provide more accurate spindle frequency tracking. One of the most important and recent study about this topic was conducted by Dempster & Vernon in 2009, they proposed three metrics to evaluate the EEG activity after NFT, the standard (values of amplitude/power), the percent of time above the threshold, and a third measure intended to combine the other two, the integrated alpha. These metrics have been calculated with four methods: within session, across the sessions, within session compared to a resting baseline and across sessions compared to a resting baseline. The researchers assessed that the percent time can provide useful information, for instance a participant may have learned to maintain alpha activity consistently above a pre-set threshold for the majority of the training session to enhance alpha amplitude in the desired direction, rather than to the short but high fluctuations that would be detected by measuring changes in amplitude. In fact, this index would bear greater significance than the other one in the event of a marginal increase just above the threshold ($0.1\mu V$), provided that such elevation remains constant over progressively extended periods (Dempster & Vernon, 2009). It can thus be concluded that both metrics are important and should be kept separate, as they encapsulate distinct yet complementary information regarding variations in brain activity and learning with NFT. Nevertheless, it remains important to conduct further studies on the use of time as an index, as currently, no studies validate its consistency. In this thesis, this aspect has been taken into consideration, utilizing the percent time as an index to explore whether this factor indeed holds significance in the identification of learners. This index is of further relevance considering that the NFT protocol applied in this thesis rewards positively for the time spent above a pre-defined threshold.

1.5.8 Classifiers for EEG in Neurofeedback

Over the years, numerous studies have aimed to discover the optimal approach for classifying EEG signals using machine learning. The investigated methods can be categorized into two main groups: supervised and unsupervised classifiers. The former necessitate a labelled training set to learn during the training process how to appropriately interpret features and allocate data to the correct class. The latter, on the other hand, are utilized when data assigned to a specific class are absent, autonomously determining how to distinguish features and thus, into which and how many classes to divide the data (Hosseini et al., 2020). In this study, a labelled training set is not available, leading to the choice of unsupervised learning. Consequently, this section provides a general overview solely focusing on this type of methods.

Unsupervised classification

The unsupervised learning algorithms infer result patterns without reference by using only input datasets; this eliminates the requirement for outside supervision and allows the machine to learn from the data on its own. This technique includes the clustering algorithms, like k-means, hierarchical clustering, and self-organizing map (SOM), which are used to compare the input data, find the ones that have similarities and categorize them in relation to the presence or absence of those similarities (Luján et al., 2021).

The k-mean method (Figure 1.6 – A) separates information into k distinct groups that do not overlap, where items are grouped into these clusters based on their proximity to the centre of each cluster, and by employing these K clusters, K-means aims to reduce the total sum of squared distances/errors (Sinaga & Yang, 2020). One of the advantages of K-means is its straightforward implementation and high computational speed, especially when K is relatively small. However, K-means has several disadvantages, including its sensitivity to initial conditions impacting final outputs, susceptibility to scaling differences, a correlation between the order of data and the resulting outputs, and the choice of the number of clusters must be done a priori (Hosseini et al., 2020). In a very recent study by Eroğlu et al. (2023), the authors applied the k-Means clustering to the calculated Z-scores derived from QEEG data obtained from children with dyslexia, identifying three different clusters, before and after a neurofeedback training protocol, the Auto Train Brain, to assess the efficacy of this treatment.

Hierarchical clustering is a method used in data analysis to organize similar data points into nested groups or clusters. It builds a hierarchical structure where each data point starts in its cluster and as the algorithm progresses, it combines clusters based on their similarity until all points are in a single cluster or in separate clusters. This process forms a tree-like structure (dendrogram) illustrating the relationships between the data points(Murtagh & Contreras, 2011). This technique was used by Liu et al. in 2020, in this study an average-linkage hierarchical clustering method was utilized to group the fMRI data collected during the training sessions, creating complete brain networks, including the lower alpha network to which the lower alpha band is affiliated. At the group level, the clustering analysis revealed that the feedback training didn't impact the quantity of networks across the entire brain. However, it did modify the arrangement and functional connections within the lower alpha network.

The self-organizing map (SOM, Figure 1.6 - B) is a type of artificial neural network used for clustering and visualization of high-dimensional data in lower dimensions, typically in a 2D or 3D map. It involves a competitive learning process where neurons or nodes in the map self-organize to represent different features or patterns present in the input data. SOMs arrange similar input data points closer to each other on the map, preserving the topological properties of the data while reducing dimensionality (Vesanto & Alhoniemi, 2000). An example of this technique applied is the study by Chenane et al. (2019) to categorize five distinct brain activities observed across ten subjects' recordings for BCI applications.

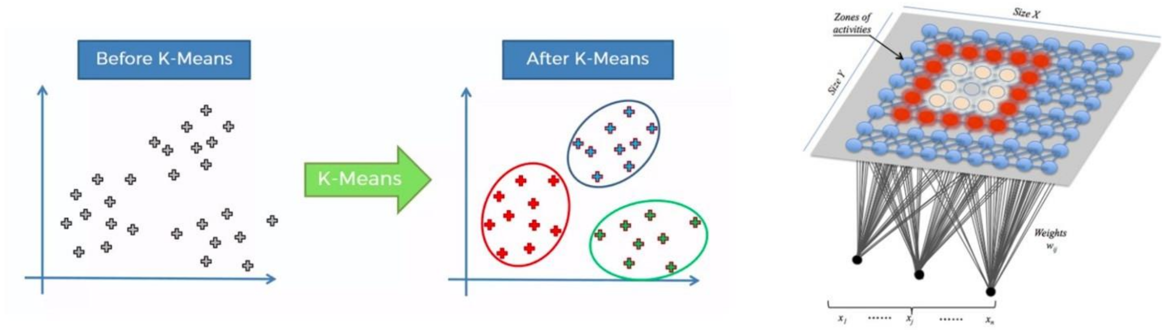

Figure 1-6 On the left, general K-means classification (A) (Hosseini et al., 2020). On the right, a general SOM net architecture (B). (Chenane et al., 2019)

1.6 Neurofeedback applications

Through the years, NF efficacy has been tested and developed for many purposes, and its application can be divided into three main fields. The first is the clinical context due to its potential in reducing or removing symptoms of different diseases; the second is the cognitive performance enhancement, in both healthy and diseased subjects; the third possible application is as a tool to investigate the connections between fluctuations in behaviour and cognition (Enriquez-Geppert, Huster, & Herrmann, 2017; Huster et al., 2014; Parsons & Faubert, 2021).

Many studies have been conducted in both fields, for example the studies from Israsena et al. (2021) and Lecomte & Juhel (2011) tried to enhance the cognitive functions in healthy participants with a game-based NFT. In other studies, aimed at enhancing the cognitive performances, the participants were all young adults (Escolano et al., 2011; Bucho et al., 2018; Zoefel et al., 2011). For example, in the study by Zoefel et al. (2011), the group of participants included two groups of subjects, the real NF and the control group; the cognitive performance was assessed with the mental rotation test and UA increment was significant in the real NFT group. This was done also in patients with different cognitive disfunctions, like the study by Jirayucharoensak et al. (2019) where researchers applied the NFT technique to amnestic mild cognitive impairment patients. The most investigated cognitive function is memory, which was proven to have a positive relationship with alpha frequency (higher alpha, better memory) (Klimesch et al., 1993). After that, it was shown that theta and alpha had opposite and distinct response, UA band is connected to long-term information (semantic memory), while theta synchronization is linked to performance of episodic memory (Klimesch et al., 1994). For instance, the recent study led by Hsueh et al. (2016) focused on the effect on working and episodic memory when alpha band is trained; the evaluation was done with two tasks:

backward digit span; operation span. The training group showed progressive changes in mean relative amplitude (RA) and total alpha duration over the course of sessions, indicating that the alpha rhythm was successfully trained.

A wide range of clinical objectives have been achieved through the use of NFT research, including, for example, enhancing the cognitive function of individuals suffering from type 3 traumatic brain injury and offering an alternative to traditional rehabilitation through the use of an NF protocol in conjunction with VR, in the recent study conducted by Arroyo-Ferrer et al. (2021). Clinical trials for major depressive illness and even stroke survivors have been pursued in a similar manner (Escolano et al., 2013; Kober et al., 2015). Some applications sought to improve the behaviour of children diagnosed with autism spectrum disorders (Pineda et al., 2008), reduce impulsivity in substance abusers to increase programme retention (Scott et al., 2005), and control pain experienced by patients with chronic spinal cord injury, where NFT was done using brain computer interface (BCI) (Al-Taleb et al., 2019). It is noted that one of the main clinical applications of NFT is the treatment of patients suffering from ADHD, like the study by Deiber et al. (2021), in which the NF was applied to metrics based on event related potentials (ERPs, a brain response generated by an event), which are known to be correlated with attention and inhibitory processes in ADHD patients. The results showed an improvement on the continuous performance task, and they are promising for treating patients suffering from this disease. Other studies obtained similar promising results, such as the one from Cabaleiro et al., (2021) and Subandriyo et al. (2021).

The third application is represented primarily by the NF used with BCI, that connect brain and computers in an open-loop application where the feature extracted from brain activity are recognized by a computer and translated into commands; it is a very important application to enhance the quality of life of disabled people (Enriquez-Geppert, Huster, & Herrmann, 2017; Ros et al., 2014).

1.6.1 Neurofeedback for Migraine

A very interesting clinical application of NFT is its used for a treatment of migraine patients. In the book published in 2007, Evans reported a previous study by Anderson (1989) in which they used a protocol of 30-minute audiovisual training sessions to reduce the duration of migraines from a pre-treatment of approximately six hours to a post-treatment of about 35 minutes, with 49 of the 50 migraine headaches having their severity reduced and 36 having them stopped. The brain activity was modulated through light and sound pulses at specific frequencies, this environment sometimes helps the NF process. Participants showed a preference for alpha frequency and bright lights (Evans, 2007).

Another more recent study involved 37 patients suffering from migraine with 1 to 20 episodes per month, it combined three different types of BF: EEG, passive infrared hemoencephalography and themal (Stokes & Lappin, 2010). When compared to thermal-only therapies, the patients' migraine frequency decreased significantly, and the effects were longer lasting than with the typical medication. The NFT sessions were 30 and each consisted of 30 minutes training, participants were instructed to watch a video game and received as auditory reward a "beep" every time they achieved the goal (increase the band between 8-18 Hz and reducing the rest). The study's results show that 26 out of 37 patients experienced at least a 50% decrease in headache frequency, which remained stable for an average of 14.5 months after the medications were discontinued, and that the patients were able to learn to control their susceptibility to migraine episodes (Stokes & Lappin, 2010).

In 2011 another study was proposed by Jonathan Walker, he examined the effectiveness of NFT in lowering the frequency of migraine attacks in 71 patients with recurrent migraines. The NFT consisted in 24 sessions lasting 30 minutes each using QEEG procedure, and 46 patients participated, whereas the others remained with medication only. The reward was given in association to an increment of 10 Hz rhythm or a decrement of activity in the frequencies from 21 Hz to 30 Hz. The NFT was very effective, in fact in more than 50% of subjects the migraine episodes were eliminated, and in 40% of patients they were reduced in frequency of more than 50% (Walker, 2011).

More recently, research led by Martic-Biocina et al. (2017) reported positive results from combining BF treatments with the aim of reducing migraine symptoms. A migraine sufferer aged 25 years was assessed and chosen to get 25 treatments of combination BF, and the protocols were determined individually. In addition to a reduction in migraine pain, this study demonstrated a steady decrease in the frequency of migraine occurrences (Martic-Biocina et al., 2017).

1.7 Objectives

The aim of this thesis is to investigate the impact of incorporating a new form of reinforcement, in addition to the standard amplitude-based reinforcement in the NFT protocol targeting the UA frequency band power (Zoefel et al., 2011) in healthy subjects. Participants receive rewards each time they stay above the threshold for a specific duration of time, aiming to provide insight into the duration they maintain a high value. The selected participants were healthy adult women without known diseases, since it's important to assess the efficacy of this reinforcement before applying it to clinical patients, specifically to migraine patients who represent the final target of the project.

These participants were divided in two groups, the real NFT and the control group, or sham condition, where the feedback presented was obtained from other participants' sessions and it didn't have any correlation with the real brain activity of the sham subject. This was done to investigate the possible effect of placebo condition and assess the real efficacy of NFT.

The motivation, the stress, and the anxiety levels, among others, were characteristics evaluated before performing the task, as well as two cognitive tests to see their attention and their working memory.

Another objective was to discover an optimal pre-processing pipeline enabling the utilization of the entire acquired signals, eliminating the necessity to exclude data segments affected by noise or artifacts.

The method used for NFT included visual feedback with positive reward when the power of the selected frequency band was above the threshold and a positive punishment when it fell below it, in addition to it a new level of reinforcement about time was added, as already mentioned. The features of interest for the analysis were the relative amplitude of UA (RAUA), considering its power, and the percentage of time spent above the threshold, they were both evaluated within sessions and across sessions. It was our intention to experiment the latter as an index to identify the learners and the non-learners, combined with the classical learning metrics, which is the slope of the RAUA.

The last objective of the study was to start to investigate on a way to automatically classify the participants in the two groups by using a machine learning algorithm, this is an intriguing field, albeit one that requires further studies and research.

2. METHODOLOGY

The characteristics of the experiment will be described in detail in this chapter, starting with a description of the participants involved and their mental state evaluations, moving to the description of the setup and the protocol followed in the study. Then it will be described how the data have been processed, a discussion of the training evaluation metrics, and finally the statistical analysis used to determine the significance of the findings.

2.1 Participants

The recruitment was focused on a female population between 18 and 35 years old, fifteen girls with age between 22 and 34 years old participated to the study voluntarily and unpaid. They were randomly assigned to the real NFT or to the Sham group, used as control group. In addition to that, the data acquired previously by Ana Rita Santos Lopes in her thesis (Rita et al., 2023) were used, eight female participants aged between 22 and 29 years old divided equally in the two group. The complete dataset consists in twenty-two subjects since one participant only completed three sessions out of four and was excluded from the results.

Prior to the study's start, a document of informed consent was given to each participant, with the detailed explanation of the goal of the project and the protocol followed as well as the possible side effects and the exclusion criteria. These criteria included age (underage and adults over 35 years old were excluded), serious medical conditions such as neurological, psychiatric disorders, heart disease, abnormal cortical activity detected by EEG, significant skull/brain damage and consumption of prescribed psychoactive drugs that could significantly alter brain function and state of consciousness. After reading the terms of the training they would participate in, each subject voluntarily agreed to participate and signed the informed consent form, knowing that the information would be published anonymously. The study was approved by the Ethics Committee of CHULN (North Lisbon University Hospital Center) and CAML (Lisbon Academic Medical Center) in July of 2022.

Before beginning the study's preparation, the participants completed a questionnaire, including question about demographic information (Table 1), asking about their (1) age, (2) gender, (3) dominant hand and (4) level of education. Between the two groups, the age was not significantly different (Mann-Whitney U test: $p = 0.456$). Another optional section of the questionnaire asked questions about the menstrual cycle for future analysis since the long-term objective of the research is to find a NF treatment for females migraineurs.

Participants were also subjected to four further questionnaires concerning mental health, the Current Motivation, the HADS, the STAI Y-1 and STAI Y-2, to evaluate the motivation, the state of depression and anxiety of each participant that could influence the results of the experiment. They were also asked to take two cognitive tests to assess working memory with the Digit Span, and the ability to keep a high concentration level with the CPT-X. These questionnaires and tests will all be described in detail later.

Table 1 – Demographic distribution of two groups

Group	Sham	NFT
Age (years; mean ± SD)	24.41 ± 2.27	25.48 ± 3.94
Gender (F/M)	11/0	11/0
Dominant hand (R/L)	10/1	10/1
Level of Education	9 Degree 2 Master's Degree	7 Degree 3 Master's degree 1 Secondary education

At the end of each session of the experiment, one last questionnaire was submitted to evaluate the learning motivation, performance, and positive affect, this is the Flow Experience Measurement which was originally called "Flow Kurz Skala" (Vollmeyer & Rheinberg, 2006). This survey evaluates six variables, including the balance between challenge and skill of the participant, combining of awareness and action, unambiguous feedback, focusing on the current task, change over time, and fluency of action (Vollmeyer & Rheinberg, 2006). FKS is divided into ten questions for flow and three for worry, the participant has to answer about how they felt during the experiment in a scale from 1 (not at all) to 7 (very much). The score is calculated separately for flow and worry by summing the items in the two groups (Elbe et al., 2010).

2.2 Mental Health Evaluation

In the following chapter the questionnaires used to assess the mental state of the participants will be described, as excessively high values of anxiety or depression would have led to exclusion from the study.

2.2.1 HADS

The Hospital Anxiety and Depression Scale is a questionnaire developed to find out the level of anxiety and depression by asking a total of fourteen questions divided equally between the two pathologies, each answer has a point that goes from 0 (lowest level) to 3 (highest level) (Zigmond & Snaith, 1983). The scores are calculated separately by summing the score of each question and are presented in the Table 2.

Table 2 – HADS scores

SCORE	GRAVITY
0-7	Non-cases
8-10	Mild
11-14	Moderate
15-21	Severe

This questionnaire was submitted one time before the beginning of the first session to exclude from the rest of the experiment those whose levels are considered abnormally high, which means a score above 15 in one of the two pathologies. The participants are asked to respond to these questions while considering how they have been feeling during the week.

2.2.2 STAI Y-1 & STAI Y-2

The State Trait Anxiety Inventory are two self-assessments questionnaires divided into two forms, the STAI Y-1 is used to assess the state of anxiety of the subject in that specific day, while STAI Y-2 evaluates the trait type of anxiety over time. Both consists in 20 statements regarding feelings about tension, nervousness, worry and apprehension, the patient can indicate on a four-point rating scale the frequency of the symptoms in the trait Y-2 and the level of agreement in the state Y-1, where 1 is the lowest level and 4 is the highest, the total score goes from 20 to 80.

The participants are asked to fill the state questionnaire at the beginning of each session of the experiment to see how it influence the results and the trait one only during the first session to assess the mental state of the subject (Spielberger et al., 1971).

2.2.3 Current Motivation

The last questionnaire that the participants were asked to fill is the Questionnaire for Current Motivation (Vollmeyer & Rheinberg, 2006) for all sessions, immediately following the researcher's description of the task and soon before it began. By evaluating four distinct factors—interest, challenge, anxiety, and the likelihood of success—over the course of several sessions, QCM is used to analyse the participants' motivation between learning about the task to be completed and the precise start of the training by indicating the level of agreement to some statements. It is known that these factors can change over time and a high motivation and challenge combined with a low degree of anxiety and thoughts of failure lead to positive results during the experience.

2.3 Cognitive Tests

Performance tests that measured working memory (Forward and Backward Digit Span) (Woods et al., 2011) and attention (Continuous Performance Task: CPT-X) as well as vigilance and the capacity to maintain attention for an extended period were also given to participants before the study began (beginning of the first session) and at the conclusion of the last session. The Presentation-Neurobehavioral Systems software (Neurobehavioral Systems, Inc.) was used to administer the questions.

2.3.1 Digit Span

The Digit Span test is used to assess the memory of the participant by presenting sets of numbers of increasing size that the subject has to memorise and rewrite. It is divided into two parts, the first part is forward, so the order in which the numbers must be written down is the same with which they are presented. In the second part the order is inverted, so the numbers must be written down backward (Woods et al., 2011). Additionally, it is important to note that the forward digit span is intended to measure verbal working memory and attention, whereas the reverse span evaluates cognitive control and executive function.

2.3.2 CPT-X

In the Continuous Performance Task X, participants see a list of letters and click on each one using the mouse, except for the target letter X, for which they should take no action. A total of 500 milliseconds of the test are divided into two blocks, each of which contains 50 trials. In one block, the target letter ("X") appears 20% of the time, whereas in the other block (CPT-X), it does so 80% of the time (Conners, 1992).

2.4 Experimental Setup & Signal Acquisition

The software used to perform the experiment were the OpenViBE 3.3.0 software (OpenViBE | Software for BCI and Real Time Neurosciences; Renard et al., 2010) and Unity® 2020.3.18f1 software platform (Unity | Engine Para 3D, 2D, VR and AR) to acquire and process the EEG in real-time for the generation of the NF signal. Unity is a platform fully integrated for the development of games and it can be connected to OpenViBE which is used to collect brain activity using electrodes.

The data were acquired in The Evolutionary Systems and Biomedical Engineering Lab's (LaSEEB) NeuroLab, a research facility of the Institute for Systems and Robotics (ISR) at Instituto Superior Técnico (IST) in Lisbon.

The condition of the room was under control and kept always the same for all sessions, only half of the lights were on, and the windows were covered, the door was shut the entire time to minimize the noise from outside. The participants were told to remain as still and silent as possible during the training in order to reduce the number of artefacts, they were sitting on a comfortable chair in front of a computer monitor with the game running while wearing headphones, the only sounds they heard during the training were the "beeps" at the start and conclusion of trials and pauses. The researcher sat next to the participant without interfering, it was there to provide technical support and make sure the experiment went smoothly.

The data were collected using a 32-channel electrode cap and the LiveAmp EEG amplifier (LiveAmp Series | Brain Products GmbH > Solutions) at a sampling frequency of 500 Hz with the international 10-20 system (Fp1, Fz, F3, F7, FT9, FC5, FC1, C3, T7, FCz, CP5, CP1, Pz, P3, P7, O1, Oz, O2, P4, P8, TP10, CP6, CP2, Cz, C4, T8, FT10, FC6, FC2, F4, F8 and Fp2) (Figure 2.1), this active electrodes are integrated with a built-in pre-amplifiers and coloured indicators that change colour according to the impedance value: red indicates an impedance of more than 500 kΩ, green indicates a good value under 15 Ω, the orange is in between.

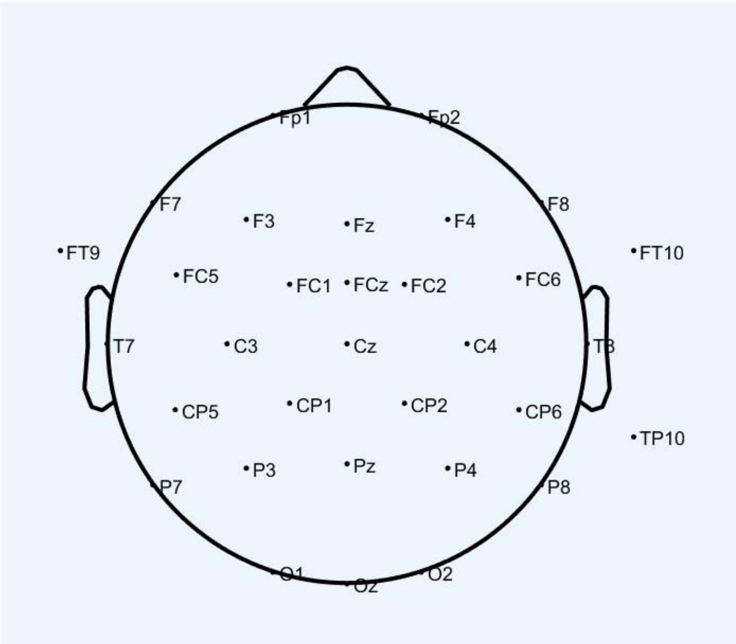

Figure 2-1 Channel locations representation from EEGLAB

The ground electrode was put on the forehead as usual, whereas the reference electrode was positioned on the left mastoid, specifically on the TP9 channel to avoid the removal of useful signal in the alpha band. In order to lower scalp impedance below 10 k**Ω**, a conductive paste (SuperVisc, EasyCap, Germany) was placed through the electrode aperture using a blunt needle after the skin had been cleaned locally by wiping the electrode sites with a cotton swab dipped in alcohol.

2.5 Protocol Design

The enhancement of the relative amplitude of the UA (RAUA) value for the electrode situated at Cz was the feature of the NFT protocol selected for this study. It has been extensively researched how to use the RAUA feature to do certain exercises that are meant to improve the regulation of mental and cognitive skills, such working memory. In addition, both a reward and a penalty are utilised when the feature time exceeds the threshold. Thus, the amplitude of the RAUA and the period while that amplitude is above a predetermined threshold are the two parameters that are examined in the current study.

For this investigation, we employed a protocol with experience timings designed in the dissertation by Teresa Bucho (2018) and afterwards by Ana Rita Santos Lopez (Rita et al., 2023) in order to provide a method of further comparison, with the difference of the group compared. As she investigated the differences between the auditory or visual modality of the feedback protocol, in this study the two groups were the real NFT, where the participants received their NF in real-time, and the Sham or Control group, in which they saw another participant's gaming session and received no feedback regarding their own brain activity, without being aware of it.

The pre-baseline phase of the NFT technique lasts for four minutes and is used for calibration. During this time, the participant was told to remain calm and quiet. The IAF and the UA band, which were taken from this calibration phase, were applied to all four NFT sessions. The NFT period was then split into 5 sets of 3 blocks, each block consisting of two one-minute trials. A minimum of 37 minutes were allotted for training, with breaks of 15 seconds set up between blocks and 10 seconds between trials. A post-baseline period that mirrored the pre-baseline period was recorded at the conclusion. The complete training programme included four NF sessions, which were scheduled to take place over the course of four days and at similar times from the pre-baseline to the post-baseline. The complete protocol followed is showed in the Figure 2.2.

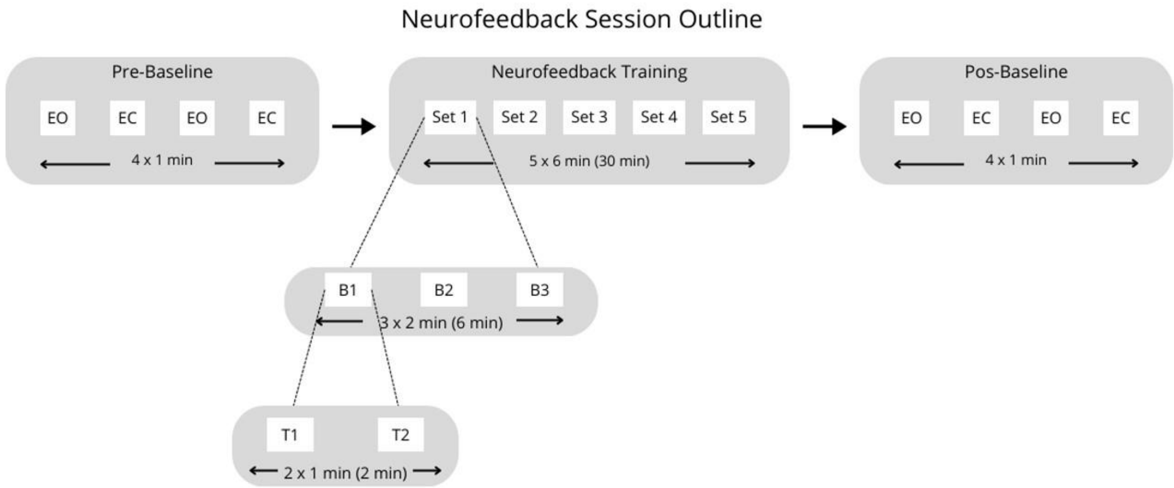

Figure 2-2 NFT session's temporal description. The pause was 10 s long in between trials, 15 s long in between blocks and at least 15 s long in between sets. EO = Eyes Open; EC = Eyes Closed.

2.5.1 Calibration

After the questionnaires and the tests, the participants were positioned in front of a screen to begin the NF session. The impedance of the electrodes was corrected to reach values below 10 kOhm. The calibration phase consisted of a four-minute presentation of a black image with a white cross in the middle (Figure 2.3-B), during which the participant had to alternate between eyes closed (EC) and eyes open (EO) for one minute, with the transition between these periods being indicated by a "beep". The EEG data was captured in both the .ov and .gdf file formats (Figure 2.3-A).

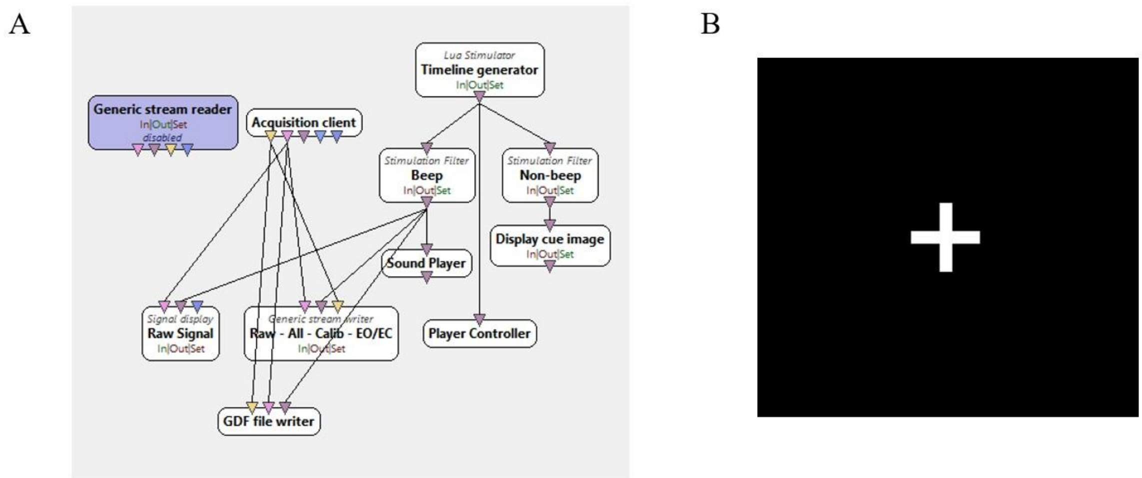

Figure 2-3 (A) Scheme of the calibration phase on OpenViBE and (B) image presented to the participant during this phase.

As proven in literature (Klimesch, 1999), alpha frequency varies greatly between individuals, for this reason it is necessary to adapt the frequency limitations of theta and alpha bands for each participant. It is suggested to use as reference point the IAF to measure the IAB to define these limits.

The measurement consisted in the estimation of the power spectral density (PSD) using the Welch method (Welch, 1967), which was executed through a built-in Matlab (R2016b, MathWorks) function, the PSD of the EO and EC conditions are presented overlaid in the Figure 2.4. The fast Fourier transform (FFT) is calculated for each of the overlapping windows that the signal is divided into using this method. Next, by averaging the FFT of these windows, the PSD estimate is calculated. It is necessary to provide the number of discrete Fourier transform (DFT) points (N), which influences the spectrum's frequency resolution and was chosen equal to the size of the window, as well as the window's length (5 seconds) and overlap percentage (10%), which affect the spectrum's smoothness and noisiness. The Savitzky-Golay filter was used on the spectra to remove oscillations. The IAF is defined as the peak frequency of the EC spectra and the lower and upper bounds of the IAB were established by the lower transition frequency (LTF) and higher transition frequency (HTF), respectively obtained following the study by Kober et al. (2015), in which LTF=IAF-2Hz and HTF=IAF+2Hz. The frequency range between IAF and HTF is then identified as the UA band. Each participant's IAB was measured using the Pre-Baseline signal (Figure 2.4), and the same measurement was repeated after the NF-training in case we want to check variations on IAB later. The baseline values for the NF were estimated in the first session and remains the same, while in the following sessions the individual's performance was taken into account to modify only the game's threshold value (detailed in section 2.5.3).

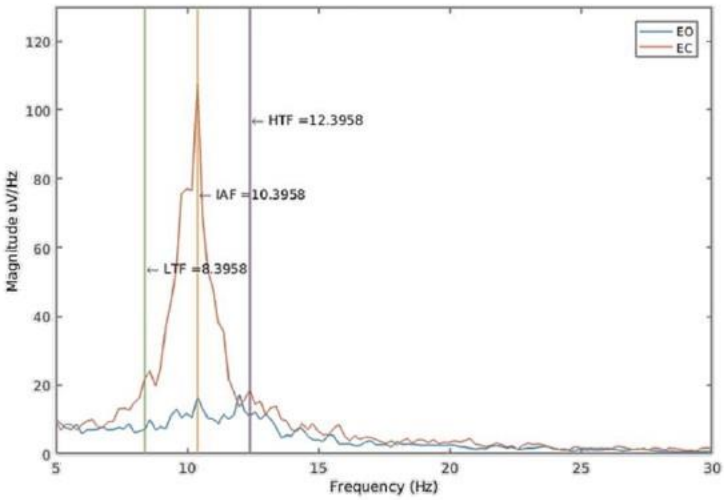

Figure 2-4 EEG spectrum of participant NFT1, session 2 for LTF, IAF and HTF. UA is obtained by the interval between IAF and HTF.

2.5.2 Feedback Parameter

The feedback parameter for the NFT group was the RAUA which comprehends the frequency between IAF and HTF, as explained before. The relationship between the analysed EEG measurement and a predetermined threshold value determines the thesis's objective. Every time the RAUA is higher than the cutoff, the goal is deemed accomplished because improving the UA band is the primary objective.

As shown in Equation 1, the relative amplitude (RA) is calculated by dividing the intended frequency band to analyse by the total range of EEG amplitude (4 Hz to 30 Hz).

$$RA = \frac{Band\ Amplitude}{Fullband\ Amplitude} \qquad \textit{Equation 1}$$

This will be done for each band of interest by replacing the numerator with the desired frequencies, in Equation 2 is represented the RAUA, where the Δf represents the resolution of the frequency and *X(k)* is the amplitude spectrum at frequency *k*.

The individuals in the Sham group did not get information from their own brain activity, instead they received as feedback a signal from a member in the training group.

$$RAUA = \frac{\dfrac{\sum_{k=\frac{IAF}{\Delta f}}^{\frac{HTF}{\Delta f}} X(k)}{HTF-IAF}}{\dfrac{\sum_{k=\frac{4}{\Delta f}}^{\frac{30}{\Delta f}} X(k)}{30-4}} \qquad \textit{Equation 2}$$

2.5.3 Online Processing & Feature Extraction

Data feature calculation is a crucial step in the capture of the EEG signal that helps determine the RAUA's degree of self-regulation and the complete pipeline for the online processing followed is presented in the Figure 2.5, on the left the processing of the signal and the phase after the RAUA is obtained, on the right the generation of the stimuli and the markers.

The signal recorded at Cz was epoched using a two-second data window that moved every 125 milliseconds (“Time based epoching” block) and then the FFT (“Spectral Analysis” block) was used to determine the spectrum amplitude for each incoming window. A spectral analysis is performed over the entire window, from which the bins corresponding to the UA frequency band and a band between 4 Hz and 30 Hz were selected, to minimise the effect of eye-related artefacts. These bins were both found in the “Frequency Band Selector” boxes and averaged across all contained frequencies (“Spectrum Average” block).

The “Epoch average” block represents a moving average used to smooth out excessive signal fluctuations by calculating the mean of the last ten collected epochs and the so processed signals are then used for the calculation of the RAUA at location Cz (“Simple DSP” block). Once the feature of interest is obtained, the value must be sent through the Lab Streaming Layer (“LSL Export” block) system to the Unity software platform, where the game was implemented. This value is updated every 125 milliseconds and the visual feedback showed to the user is based on it.

Beyond the feedback parameter, the LSL system also allows the streaming of stimuli and markers, which were used to establish the trial and interval times, generated with the “Lua Stimulator” block on OpenViBE that interprets a written manual in the programming language LUA.

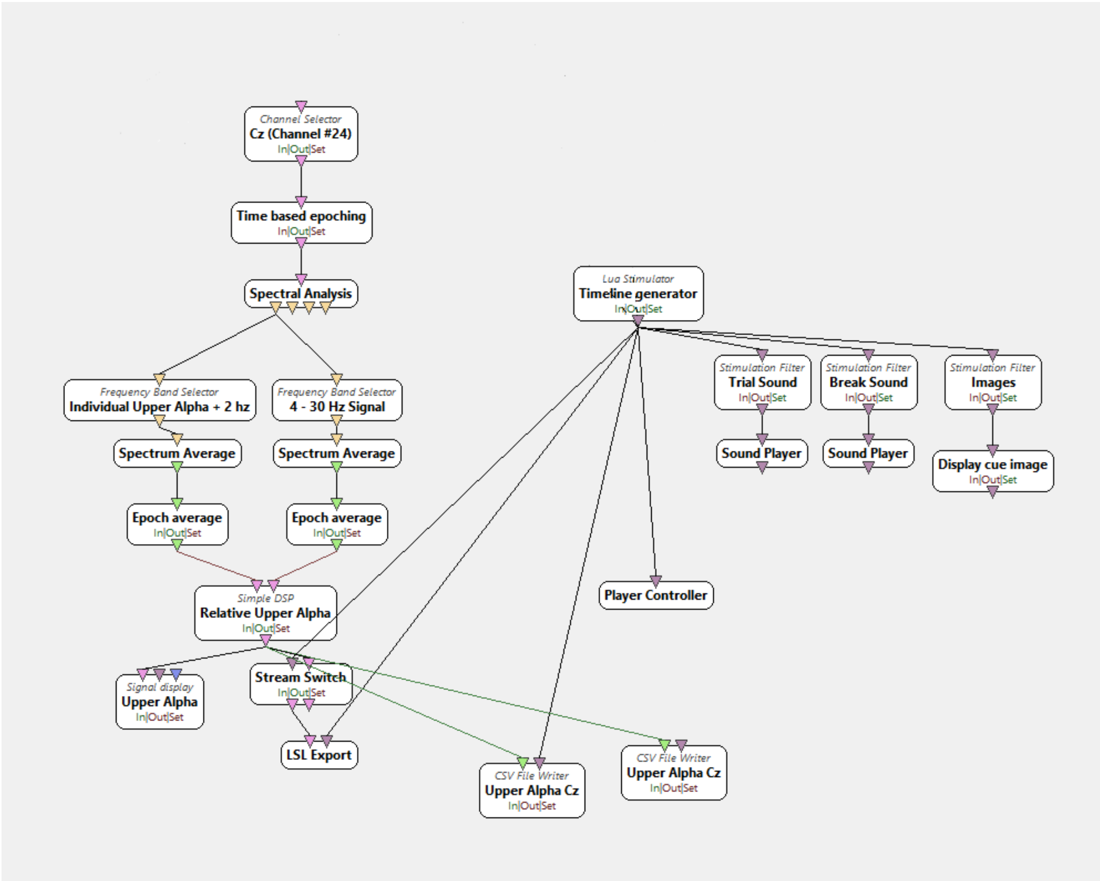

Figure 2-5 OpenViBE schematic pipeline for online processing and RAUA estimation and LSL system to forward the data to Unity platform (on the left). OpenViBE schematic for the “Timeline Gerator” for the stimuli and the markers (on the right).

2.5.4 Reward Threshold

Determining the values for which a reward is given is crucial, in this case the RAUA, this will presumably change throughout the NF sessions. To define the threshold, the maximum and the minimum are determined during session one, by using the EO and EC pre-baseline recording. By importing the .ov file created during the calibration period and solely using the data from channel 24, which corresponds to Cz, these values were acquired using OpenViBE. The calculated RAUA during the calibration phase was saved on a file .csv, this was then opened on MATLAB to obtain the percentiles, the minimum, and the maximum of the EO condition.

The percentiles saved goes from the 40th to the 90th with steps of 5, whereas the minimum corresponds to the 1st percentile and the maximum to the 99th percentile + 20% of the EO periods, to keep the maximum zoom from being saturated. In fact these two values are used to fix the zoom in the game, the first is the totally blurred image and the second the maximum zoom in. The defined threshold value, the maximum and the minimum are set in the game in Unity through the menu display before the beginning of the sessions (Figure 2.6).

Figure 2-6 Menu presented on Unity before starting the NF training to define min, max and current threshold to use ("Set Values" botton).

The 60th percentile of the RAUA just calculated was the threshold set in the first session; however, in subsequent sessions, the threshold had to be modified based on the participant's performance in the preceding session. This is adjusted accordingly to the percentage of time spent above it, if during the session it exceeded the 60% of total time, considering only the time during the trials, in the following session the threshold is increased of five percentiles. Conversely, if the participant's percentage of time above the established threshold fell below 40%, the new threshold is reduced by five percentiles; in case the percentage of time is between

40% and 60%, the threshold value stayed the same from the previous session. The percentage of time is calculated through the software Excel with the file saved in .csv format.

2.5.5 Feedback Display

As already mentioned, the visual feedback depends on the RAUA and the minimum and maximum values, and when the scenario was designed, it was important to remember that the objective was to assess the duration and amplitude above the predetermined threshold.

Two different scenarios were created and used alternately during the sessions to prevent the participant from becoming bored and instead feel more engaged to the game, since the kind of scenario is something to assess whether it could have an impact on the game's focus and, consequently, success. One of the two consisted in an image of a tropical environment (Figure 2.7) with vivid colours with images of birds appearing, whereas the other scenario was one with more soft colours, a picture of a diver underwater with images of fishes appearing (Figure 2.8). They were alternately shown as first scenario to the participants to have a more statistically independent result, so if the first one was the diver, in the next session the participant used the tropical, and so on. The scenario was chosen in the menu (Figure 2.6) through the buttons “Start NF diver” or “Start NF tropical”, anyway it is important to remember that the game's objectives remain the same in both, which is to evaluate the amplitude and the time over the threshold.

The amplitude is the feature that defines the degree of blurring and zooming of the image. If the RAUA value received from OpenViBE is between the minimum and half of the threshold, the image is shown as completely blurred, as the RAUA exceeds that value the dimmer is only partial and the image gets clearer. Once the threshold is reached the image is completely visible and the zoom starts accordingly to the amplitude, as it gets higher the zoom increases until the defined maximum value of RAUA is reached, which corresponds to the maximum possible zoom. These two effects correspond to a continuous type of reinforcement.

The time is evaluated once the threshold is reached, giving feedback to the participant by visually presenting objects on the screen every 2.5 seconds spent above the threshold. All of the acquired items disappeared, and a dimmer returned to the visual feedback (positive punishment) when the RAUA dropped back below the threshold, and it starts again when the threshold is reached again. This reinforcement is of a discrete type.

It’s important to keep in mind that the positive rewards are different for amplitude and time, the first is provided by removing the blurring and zooming in closer, the second correspond to the appearance of a fish or an exotic animal, like parrots or monkeys. In addition, this study included penalties that occurred when the RAUA fell below the threshold, which included the loss of both rewards—the zoom and the game objects—as well as the appearance of blur.

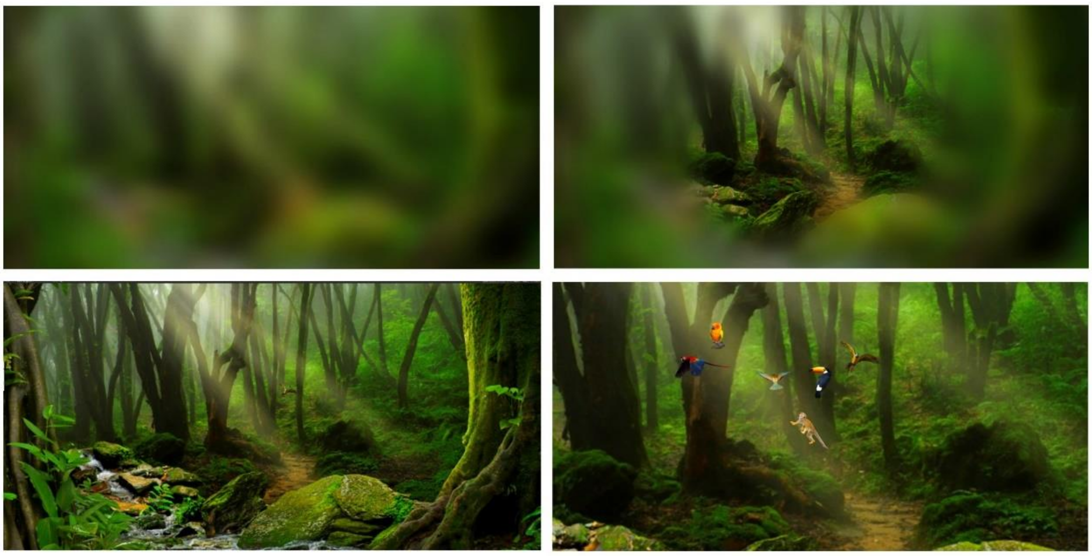

Figure 2-7 Visual feedback when playing the tropical forest scenario. (Upper left) Completely blurred image when the RAUA is lower than half of the threshold. (Upper right) Displayed when the RAUA is between half of the threshold and the set threshold. (Bottom left) Image shown after remaining above the threshold for 2.5 seconds. (Bottom right) Maximum zoom reachable at the maximum amplitude.

Figure 2-8 Visual feedback when playing the diver scenario. (Upper left) Completely blurred image when the RAUA is lower than half of the threshold. (Upper right) Displayed when the RAUA is between half of the threshold and the set threshold. (Bottom left) Image shown after remaining above the threshold for 2.5 seconds. (Bottom right) Maximum zoom reachable at the maximum amplitude.

2.6 Data Analysis

The technique of analysing the EEG data offline is described in depth in this section. The built-in functions of MATLAB (R2022b and R2023a, MathWorks) and its toolbox EEGLAB 2022/2023 were utilised to outline the preprocessing, processing, and feature estimates.

2.6.1 Pre-processing

As already mentioned before, to be able to study the EEG signal it is mandatory to pre-process the raw data since it may contain artifacts coming from the subject itself, like muscle activity, eye movements or breathing, but also from the electronic system, caused by the power supply, or the electrodes, for example their impedance or the placement. This step is necessary to minimize the noise caused by these artifacts, since it cannot be removed completely, to read the signal properly and be able to evaluate the brain activity of interest, without the interference of other signals.

Many pre-processing techniques can be used to remove these unwanted artefacts from the EEG data; in the current thesis, the strategies employed are the following.

First, the signal was filtered with:

- A high-pass filter with a cutoff frequency of 1 Hz, this is useful to remove the DC component of any voltage or the low frequency artifacts like the one induced by breathing;
- A low-pass filter with a cutoff frequency of 40 Hz, to block the higher frequencies noises like the one induced by the power line.

These filters were used with a Hamming window type.

The next step was to identify and remove the bad channels manually, checking through the EEGLAB display the PSD and removing the channels that behaved very differently from the others. In addition, an automatic check on the channels was also made using two functions built-in EEGLAB, *clean_flatlines()*, which removed the channels with too many zero values consecutively, and *clean_channels()*, this is an automatic artefact rejection which controls that there are no channels in the data that record nothing but noise for long stretches of time.

At this point, the independent component analysis (ICA) was performed to remove the artefacts coming from muscle movements, eye blinks or heartbeat, that were recognized with a confidence of 85% or more, which was the used threshold for rejection (Figure 2.9).

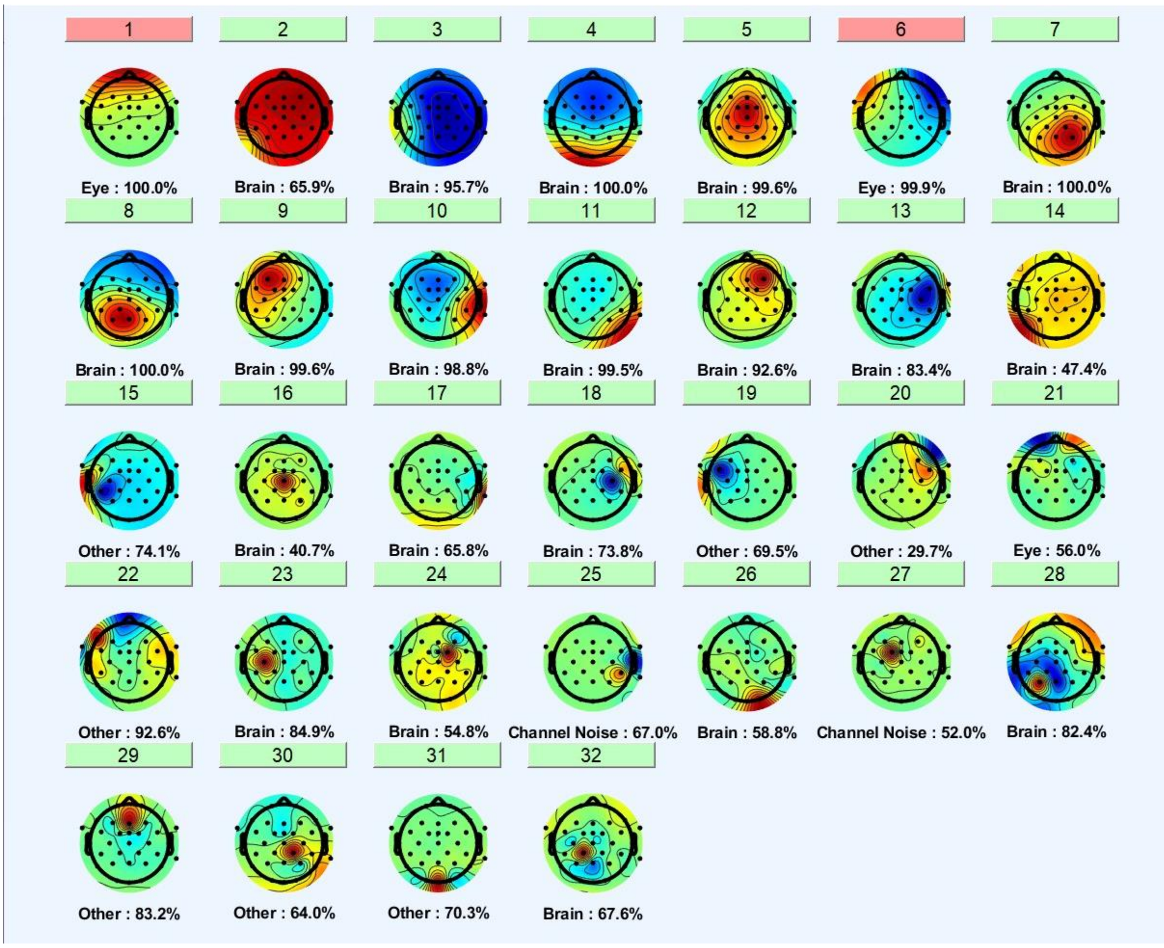

Figure 2-9 Example of ICA with the rejection of the unwanted components recognized with a confidence of 85% or more. The ones labelled in red are the rejected components recognized as eye blinking.

After removing all the bad channels and artefact components, the signal was cleaned with an additional function, the *clean_asr()* with a deviation cutoff of 10, since the default value was too aggressive, and the risk was to remove too much cerebral signal. This is an EEGLAB function useful to reduce the noise which still corrupts the data.

The removed channels were then interpolated by using a spherical interpolation and the channel TP9 was retrieved to be used as reference, at this point the total number of channels were 33. Subsequently the re-referencing was performed using the average value of all channels with the TP9, this step is important to avoid the bias deriving from having the reference on one side of the head.

The last part was dividing the pre-processed data in epochs, each one lasted 60 seconds and the intervals were not considered, so the total number is 30. They were organized into five sets of six epochs each for further analysis.

2.6.2 Processing

As additional control, all the sessions underwent visual inspection, since the session 3 from subject 21 (SHAM10) had technical issues, this will not be considered for the following part. Also, in session 3 of SHAM5 the last 7 epochs had recording problems, but most of the data are present so it was used with a specific control on it.

Before performing the time-frequency (TF) decomposition, it was necessary to define the number of time points to use (set at 120, equally distant) and the number of frequencies to consider in the whole band, from 4 to 30 Hz (set at 150, equally distant). Then the TF was performed using the wavelet transforms method with the function from EEGLAB *pop_newtimef()* for each channel, which saves the time points, the frequencies and the TF data, and allow the representation of the event-related spectral perturbation (ERSP) (Figure 2.10).

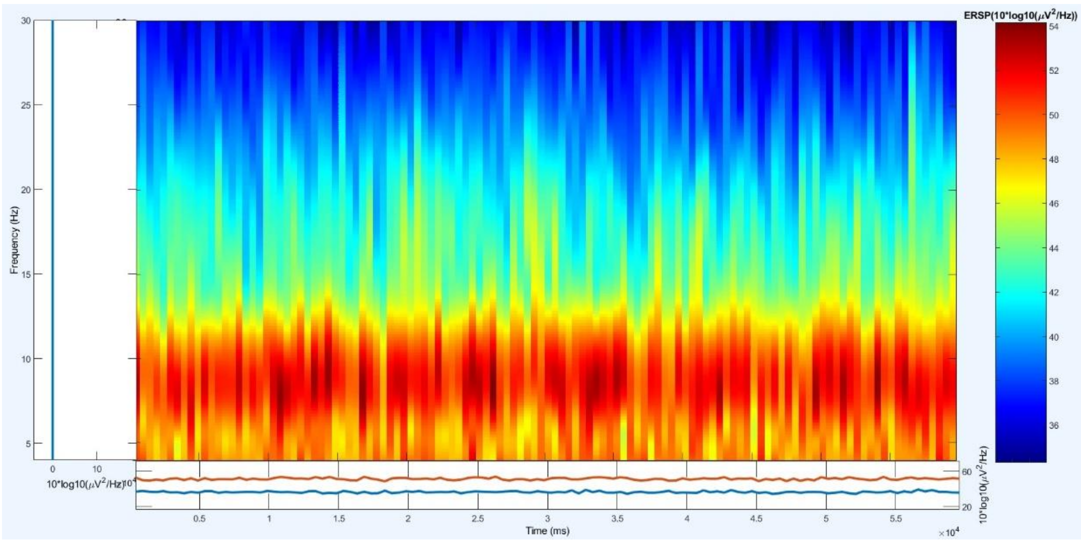

Figure 2-10 ERSP plot obtained from the function pop_newtimef() which represents how much a signal's power at various frequencies changes in proportion to a particular time point. The frequencies are between 4 and 30 Hz, the time is one epoch long (60 seconds) and the values are in a logarithmic scale. This representation is from NFT7, session 1.

It was chosen to use the wavelet in order to maintain the information about the time, instead of the previously used pwelch function which consider only the frequency domain. The power was then obtained taking the absolute value of the square of the TF values just calculated and then normalized with the total average power, considering each channel in the 4 Hz to 30 Hz, to visualize its behaviour in the whole band of frequencies considered and through all the epochs.

After considering each epoch, the data were divided in five sets of six epochs, and the relative amplitude of each one of the four bands of frequencies was calculated, by doing the ratio between the average power in the considered band and the mean of the power in the full band, and then performing the moving average, which reduces the effect of outlier values. At this point, what is significant for this study was the channel Cz, which was used to calculate the average value of each set in all the frequencies and to do the plot of the trend through the session.

Subsequently, the NFT and the SHAM participants' values were divided, and the mean with the standard deviation value per set were calculated and plotted for both groups.

2.6.3 Standard Training Effect Measures

As done in the previous studies by Lopes et al., (2023) and Bucho, (2018), at first standard learning metrics were used to present an in-depth analysis of the training parameter, RAUA, inside a single session or between different sessions. The indexes considered were three intra-sessions:

- IntraA1, which calculate the average of the first set for each session (i) and the mean difference between the means of each set (j), and then averaging throughout sessions (Equation 3).

$$IntraA1 = \frac{\sum_{i=1}^{nsess}\sum_{j=2}^{nset}\left(\overline{set_j} - \overline{set_1}\right)_i}{nsess*(nset-1)} \qquad \textit{Equation 3}$$

- IntraA2 to consider the variations in the feedback parameter within sessions, the difference between the first and last sets' means of each session and the first set's mean is calculated and then these differences are then averaged across sessions (Equation 4).

$$IntraA2 = \frac{\sum_{i=1}^{nsess}\left(\frac{\overline{set_5} - \overline{set_1}}{\overline{set_1}}\right)_i}{nsess} \qquad \textit{Equation 4}$$

- IntraS, which correspond to the linear regression's slope (m_i) that matches the learning parameter's evolution along the means of each session's five sets (Equation 5).

$$IntraS = \frac{\sum_{i=1}^{nsess} m_i}{nsess} \qquad \textit{Equation 5}$$

The standard path to define if a participant was a learner or not, was to consider as the most important index the IntraS. This was used by defining as non-learners those who had negative values (downward slope) in two or more sessions or those with negative values for the average of the slopes of all sessions. These measures were used to compare the outcomes of the NFT group with the sham group, as well as to assess how effective the NFT was.

Identification of Non-Learners

As already discussed in section 1.5.7, there are no precise standards to identify if a subject is able to learn self-regulation. The problem of finding the best way to evaluate the NF learning was studied by Dempster & Vernon (2009), they concluded that using the intra-session features is more significant than considering the inter-session trend. The initial choice of using the IntraS was made following these conclusions, whereas in this study, a different way of proceeding was tried out, explained in detail in the following section.

2.6.4 Training Effect Time Measure

The usage of percent time as an evaluation metric was introduced in section 1.5.7. In this study, it was chosen to consider this index combined with the standard one to identify the learners.

The percentage of time has been calculated for each session, considering the specific threshold, which varies across the sessions. Two different methods were used:

i) Percent time for each epoch, this technique required to calculate how much time the participant spent above the set threshold each minute (epoch) of the training. This approach was considered to obtain an overview of the intra-session trend of the feature to be able to note if there was a significant increment from the beginning to the end of the NFT;
ii) Percent time for each session, this method considered the time spent above the threshold during the whole session, taking into account only the training (no pause). This approach was used to see how the participant performed across the sessions, indeed, if the subject is able to learn this value should increase from the first to the last session.

The RAUA values compared to the threshold are those obtained online, ensuring that the time considered is indeed what the participant received as feedback. Following the procedures outlined in the online processing section, the data underwent analysis using 2-second windows every 125 milliseconds. Consequently, each epoch contained approximately 480 aggregated values, representing the mean value over the 2-second interval. The values obtained were 30x4 for the first approach (one per epoch, each session) and 4 with the second method (one per session). These were graphically depicted using a MATLAB plot, and the slope of their progression was calculated, both within each session and across multiple sessions.

A positive slope of the line in both scenarios suggests that the subject was able to modulate their brain activity correctly. Therefore, they could potentially be considered a learner in this context, whereas a negative slope suggested the opposite effect and may identify a non-learner. However, other factors need to be considered when evaluating this parameter, such as potential participant fatigue towards the end of the experiment or varying motivation levels on different days due to external factors (e.g., tiredness, stress or anxiety). Additionally, another factor to consider is that the utilized online RAUA is processed approximately to reduce computational costs and minimize feedback delay, consequently, its values might differ from those derived offline after a thorough signal pre-processing to ensure cleanliness.

The hypothesis suggested was that there could be a participant able to self-regulate only one of the two features (amplitude/time), if that happens it is equally important to be able to recognize it as a learner. For this reason, the metrics were combined, considering features such as the slope of RAUA, the slope of time per session, the slope of time between sessions, and the total time spent above the threshold in each session; a learner was identified when at least two out of the first three features showed positive values.

2.6.5 Statistical Tests

Statistical analyses were conducted on the acquired data to verify if there were any statistically significant differences between pre- and post-training conditions and between the two considered groups, in order to have a mathematical description of these data, which is more specific than a qualitative description. The statistical tests were conducted using JASP software (Version 0.18.1) [Computer software]. Specifically, between the groups, the non-parametric Mann-Whitney U test was performed for two independent groups, and this was conducted for the HADS and STAI Y-2 (trait) questionnaires. The Mann-Whitney test is the non-parametric version of the Student's t-test for independent samples (Whitley & Ball, 2002). Regarding the cognitive tests, the effect of NFT was evaluated by comparing pre- and post-training conditions using the non-parametric Wilcoxon signed-rank test, it was conducted for the two groups separately (within group). This test is the non-parametric version of the Student's t-test for paired samples, where the nulla hypothesis is that there is no difference between samples (Corder & Foreman, 2011). Additionally, the Friedman test was used to have a statistical description of the development of RAUA and percent time above the threshold across the session within groups, considering only the identified learners participants. Non-parametric tests were chosen due to the non-normal distribution of the data, given the limited subject database available.

2.6.6 Classification with Machine Learning

Classification using unsupervised machine learning techniques is still relatively new in the domain of EEG-applied NF, nevertheless, it holds significant potential, particularly considering that the optimal features for identifying learners have not yet been clearly defined.

Consequently, arbitrarily assigning subjects to a class is challenging, making it difficult to establish comprehensive training sets. Furthermore, due to the time requiring nature of NFT, there are very few studies with a sufficiently large dataset to efficiently train the algorithm.

In this study, this approach was investigated, and to address the limited dataset issue, each session was individually considered, resulting in 87 input data sets; the real NFT group were then individually examined, comprising a total of 44 sessions. Two of the most studied methods were tested: K-means and self-organizing map (SOM).

In both techniques different groups of features were tried out, the choice was made to consider the two slopes within the session of RAUA and percent time. In addition to that, it was added the slope of the percent time across the sessions, which was the same in all four sessions, and the total time percentage of each specific session. It was then obtained two matrices: all subjects (87x4) and NFT group (44x4). The second was the one used to train the network, since the effect on the control group is not clearly understood.

In the K-means approach, it was defined the number of cluster equal to two, and the algorithm was performed with all the different combinations of features. The number of clusters must be chosen a priori in this technique, in this context it was defined as two because the classes to identify were learner or non-learner.

Regarding the SOM network, various training iterations were tested, from 500 to 5000 and they were eventually settled at 1000 iterations due to the limited dataset to prevent overfitting. Different topologies and number of neurons were also explored, since the number of neurons corresponds to the number of clusters created by the algorithm, at first only 2 neurons were used to obtain a binary classification. Anyway, with this approach the algorithm wasn't optimized ultimately finding the best configuration with an equal number of neurons per row and column. Some examples are depicted in the Figure 2.11.

The best topology resulted the 2x2 neurons (Figure 2.11, left), the results are reported only for the network obtained with this topology.

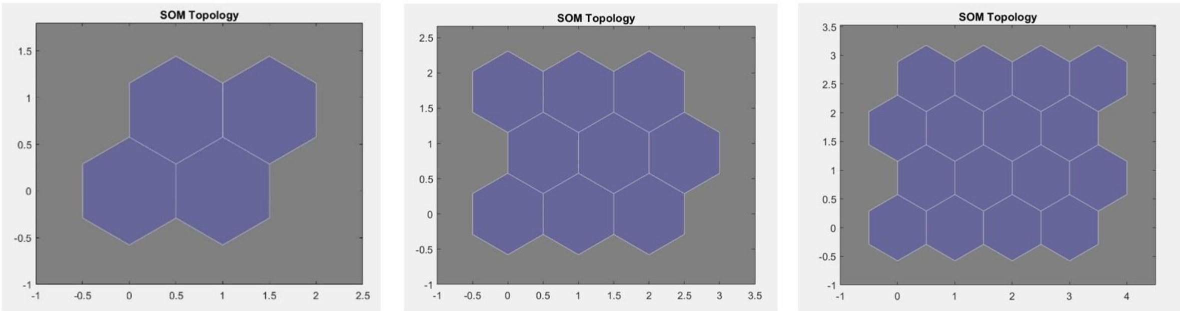

Figure 2-11 Different SOM topologies. On the left configuration with 2x2 neurons; in the middle configuration with 3x3 neurons; on the right configuration with 4x4 neurons.

3. RESULTS

The next chapter showcases the outcome derived from participants' responses to questionnaires, cognitive tests, and EEG data analysis conducted within each group.

3.1 Self-assessment Questionnaires

In this section, the results from the questionnaires of self-assessment are presented.

3.1.1 HADS

Based on the analysis of the questionnaire findings, it appears that participants from both groups exhibit higher levels of anxiety compared to depression, as it can be seen in the boxplots depicted in the Figure 3.1. Only five out of twenty-two individuals reported anxiety values within the normal range (below or equal to 8), while other five subjects presented borderline values (between 8 and 10). All the remaining participants showed abnormal anxiety levels (above 10). The results indicate that most of the participants exhibited values within the range considered typical for depression symptoms (scoring below 8), there were only two subjects with higher values, one in the NFT group (equal to 11) and one in the SHAM group (equal to 8) (Bjelland et al., 2002). All the scores are reported in detail in Annex A, there is no significant statistical difference between the values of the two groups (Mann-Whitney U test: Anxiety p = 0.409; Depression p = 0.408).

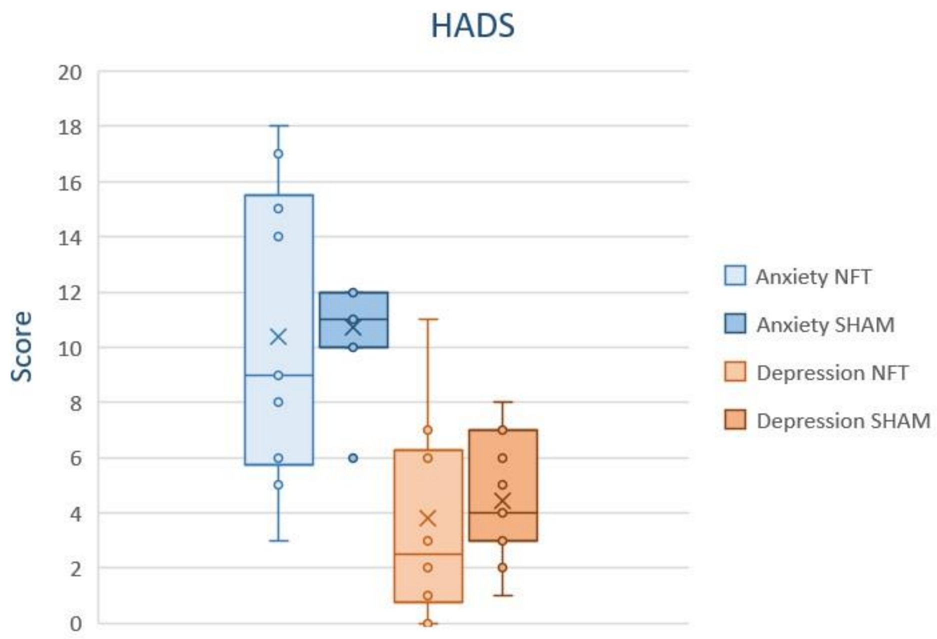

Figure 3-1 Scores of HADS questionnaire from all subjects (0=normal value; 21=abnormal value)

3.1.2 STAI Y-1 & STAI Y-2

As explained before, the STAI questionnaires are divided in two, the Y-2 (trait) and the Y-1 (state). The first was filled once in the first session, while the latter was presented to participants every session. The results are reported in the Figure 3.2

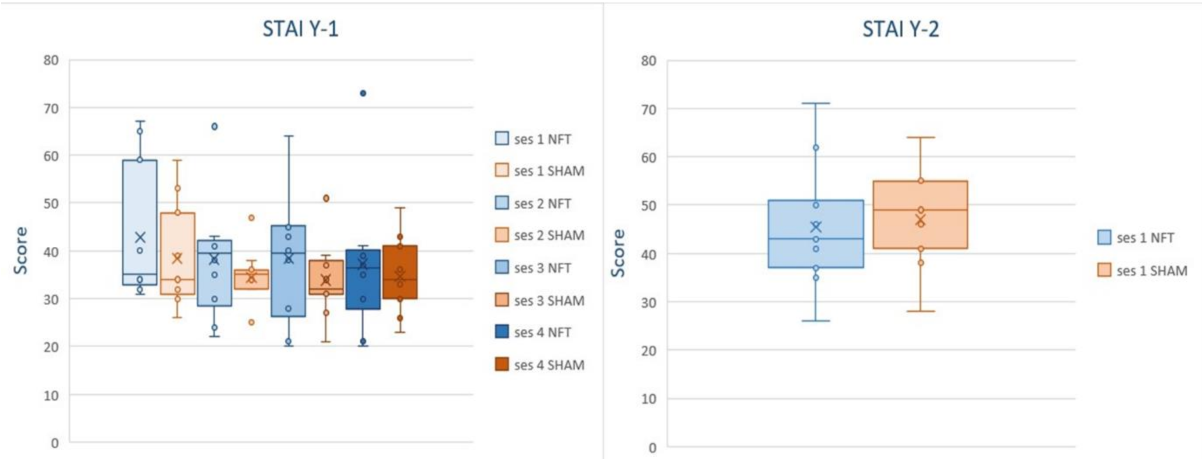

Figure 3-2 Distribution of scores of STAI Y-2 questionnaire (trait) from the first session, on the right, and STAI Y-1 questionnaire (state) from each session, on the left, presented with boxplots with the median line, divided in the two groups. The scores range from 20 (normal) to 80 (abnormal) (Spielberger et al., 1971)

A descriptive statistical analysis was performed for both questionnaires and each session (Y-1). When analysing the data from the first session it can be noticed that in Y-2 (trait) the minimum values reported are 26 for NFT group and 28 for SHAM group, the maximum values are 71 for NFT group and 64 for SHAM group, the median values are 43 for NFT group and 49 for SHAM group; in Y-1, considering both groups, the maximum value is 67 and the minimum is 26, the median values are 34 (SHAM) and 35 (NFT). In the other sessions the results are: i) session 2, maximum 66, minimum 22, median values 39 (NFT) and 35 (SHAM); ii) session 3, maximum 64, minimum 20, median values 39 (NFT) and 32 (SHAM); iii) session 4, maximum 73 (outlier), minimum 20, median values 36 (NFT) and 34 (SHAM). The Mann-Whitney U test was conducted between groups for the STAI Y-2 (trait), however no significant difference was found ($p = 0.576$). Based on this data, a noticeable decrease in anxiety levels is evident throughout the session according to the state questionnaires. The detailed values for each participant can be found in Annex B.

3.2 Current Motivation

Since one primary focus of this thesis was to explore the initial motivation levels of each participant at the task's outset to observe subsequent alterations in learning outcomes, a questionnaire assessing current motivation was employed, evaluating four distinct factors:

anxiety, challenge, interest, and the likelihood of success. Notably, the probabilities of success and failure were categorized separately for a more detailed analysis. The original questionnaire excluded the probability of failure while decreasing the emphasis on the probability of success (Vollmeyer & Rheinberg, 2006).

In the Figures 3.3 and 3.4 are presented the scores obtained through the four sessions and the median values of each factor to see if the motivation increased or not for both NFT and SHAM groups, respectively.

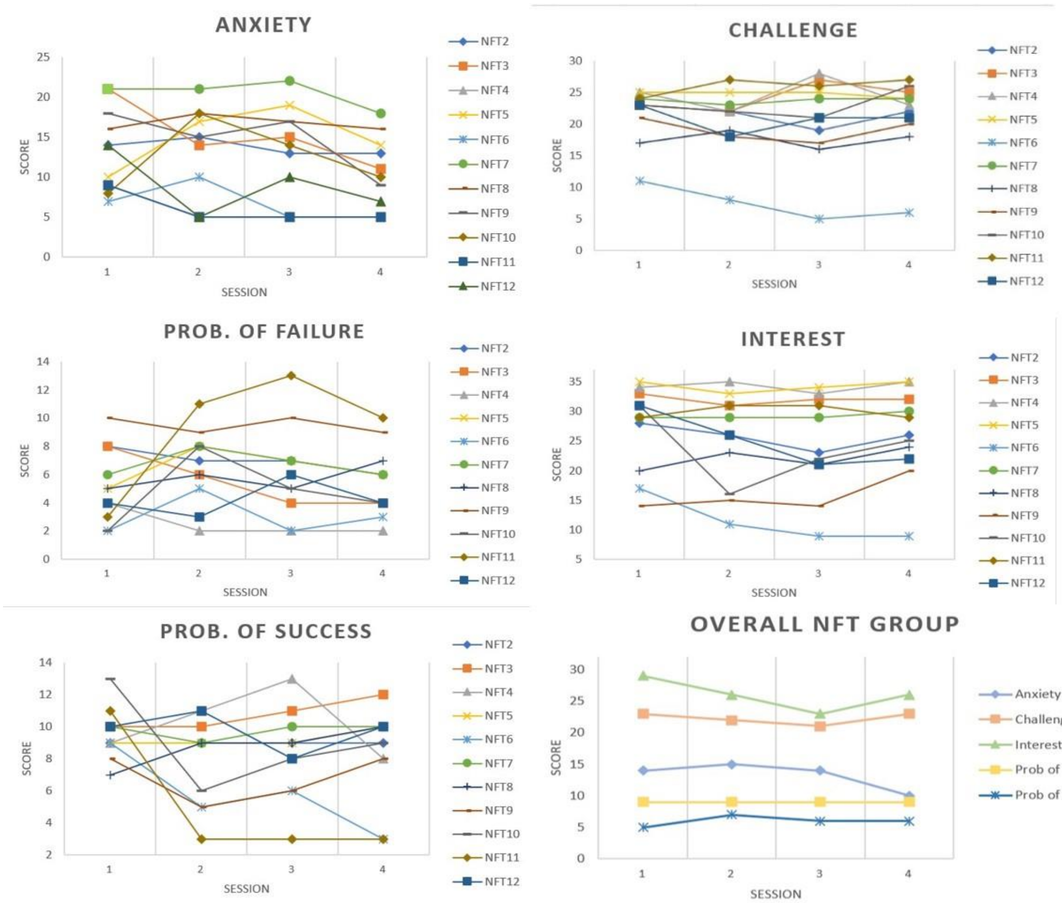

Figure 3-3 NFT Group QCM Scores: Individual presentation of the five factors across sessions for each participant, along with an overview of median values for each factor.

As it can be seen in Figure 3.3 in the NFT group the factors with higher values are interest and challenge, anxiety levels show a tendency to decrease from the first to the last session, while other factors tend to be stable or exhibit a slight increase. It is also clear that participant NFT6 shows a very low level of interest and challenge combined with a decreasing probability of success, which may lead to a non-learner due to the little motivation. On the other hand, the subject NFT11 shows a low level of probability of success with an high value of probability of failure, but she has also high level of interest.

In the Figure 3.4 that represent the SHAM group's results, it can be noted that in this group there is not a general decrease in anxiety factor, which is in overall lower than in the NFT group, and the probability of failure has a slight increment, but also in the SHAM group the higher values are challenge and interest. The probability of failure values fluctuates considerably across the sessions, possibly indicating stress due to difficulty in understanding the workings of NF. This pattern is similarly reflected in the declining values of the probability of success. The high levels of interest and challenge are promising since one of the goals of this protocol was to design an engaging and motivating environment, irrespective of the group assignment.

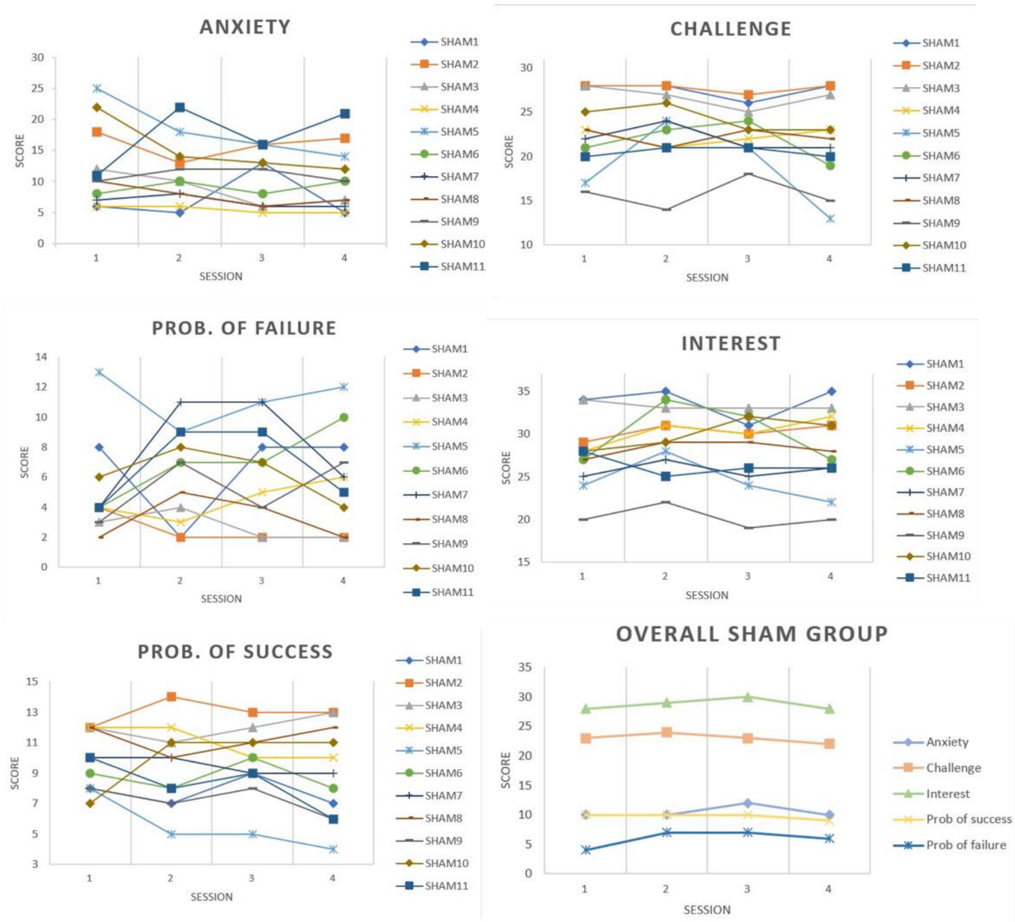

Figure 3-4 SHAM Group QCM Scores: Individual presentation of the five factors across sessions for each participant, along with an overview of median values for each factor.

3.3 Mental State

To investigate potential correlations between sensations and a participant's training capacity, each participant completed a questionnaire assessing their mental state. They were asked to rate their feelings after each session on four distinct factors: sleepiness level, motivation level, concentration level, and stress level.

The Figure 3.5 presents the median scores of each factor for the two groups (NFT on the left, SHAM on the right). It can be noticed that the values of concentration and stress are stable, the sleepiness is higher in SHAM group then NFT group, probably due to the incapacity to control the feedback, but the level of motivation remains the same. In the NFT group the sleepiness decreases and the motivation increases, which is encouraging.

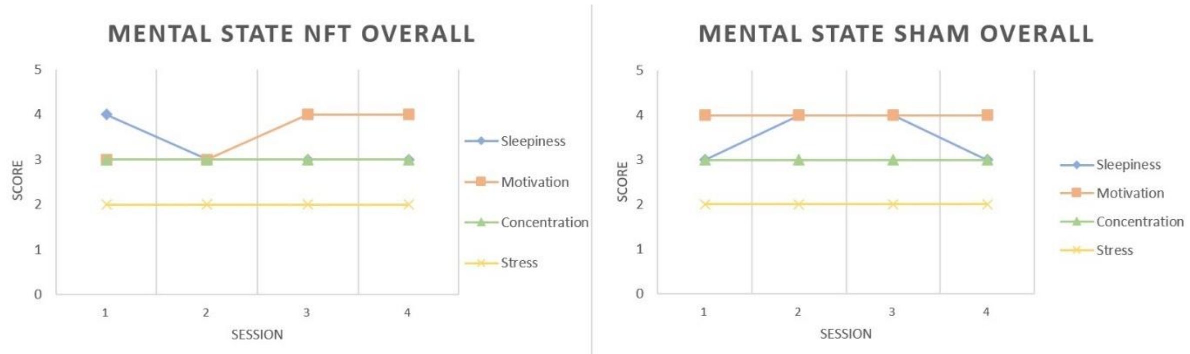

Figure 3-5 Median scores of the four factors evaluated at the end of each session, on the left NFT group, on the right SHAM group.

3.4 FKS

An overall of the results obtained from FKS questionnaire are reported in Figure 3.6 in which the median values for both flow and worry are shown, comparing the values of the NFT and SHAM groups. These findings indicate a higher overall flow level in the SHAM group compared to the NFT group, while conversely, the worry level is higher in the NFT group than in the SHAM group. Moreover, within the NFT group, the worry level diminishes across the sessions. Additionally, there is a slight increase in the flow level observed in both groups.

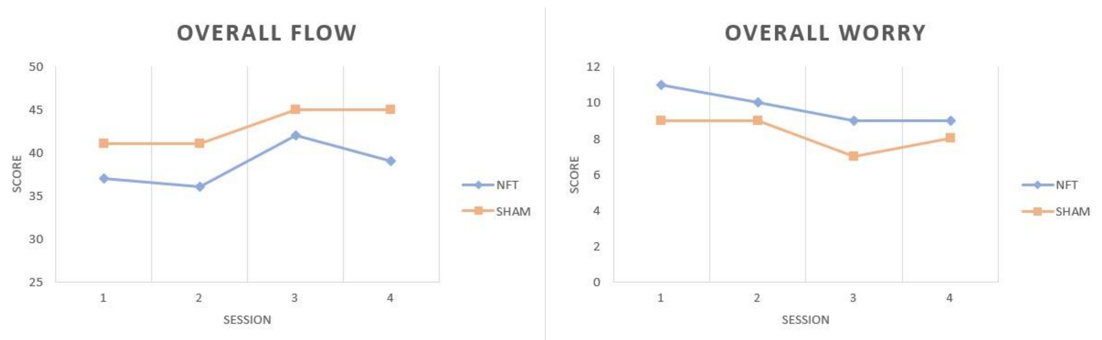

Figure 3-6 Overall of FKS questionnaire, the median values are presented comparing the two groups. On the left, Flow, on the right, Worry.

3.5 Attention & Memory

The results obtained from the self-evaluation of memory done by each participant at the beginning of the experiment are presented in Figure 3.7 for both NFT group (left) and SHAM group (right). The results show that only one participant in the NFT group (NFT4) has rated their memory with the highest value (7), which means that they considered to have a perfect memory. One participant in the SHAM group (SHAM2) reported a very low level of memory (2), indicating major memory problems. In general, most of the participants rated their memory with a middle score (5).

Figure 3-7 Memory scores assigned by each participant before the first session, ranging from 1 (indicating significant memory issues) to 7 (indicating no memory problems).

3.6 Cognitive Tests

This section examines the outcomes of the working-memory tests conducted at the commencement of the initial session (PRE) and at the conclusion of the final session (POST).

3.6.1 Digit Span

The scores obtained from both the Digit Span-Forward and the Digit Span-Backward, before the first session and after the last one, are graphically represented in the Figure 3.7. The Forward condition in the NFT group showed an increment in most of the participants. In the same group, two participants (NFT7; NFT10) had the same values (PRE and POST) and only the subject NFT4 showed a lower score at end of the training. It can be interesting to notice that in the SHAM group, in the Forward condition, only six participants obtained higher scores, whereas four of them have worsened performances, only one was stable (SHAM5). On the other hand, in the Backward condition both groups had similar results, with six participants who increased their scores, two subjects obtained the same score and three of them worsened it. The pre- and post-training condition were compared with a Wilcoxon signed-rank test with the alternative hypothesis that measure 1 (pre-) is less than measure 2 (post-) and a significant difference was found in the Forward condition in NFT group (p = 0.009), the same pattern is not present in the SHAM group (p = 0.117). This was not found in the Backward condition (NFT: p = 0.315; SHAM: p = 0.236).

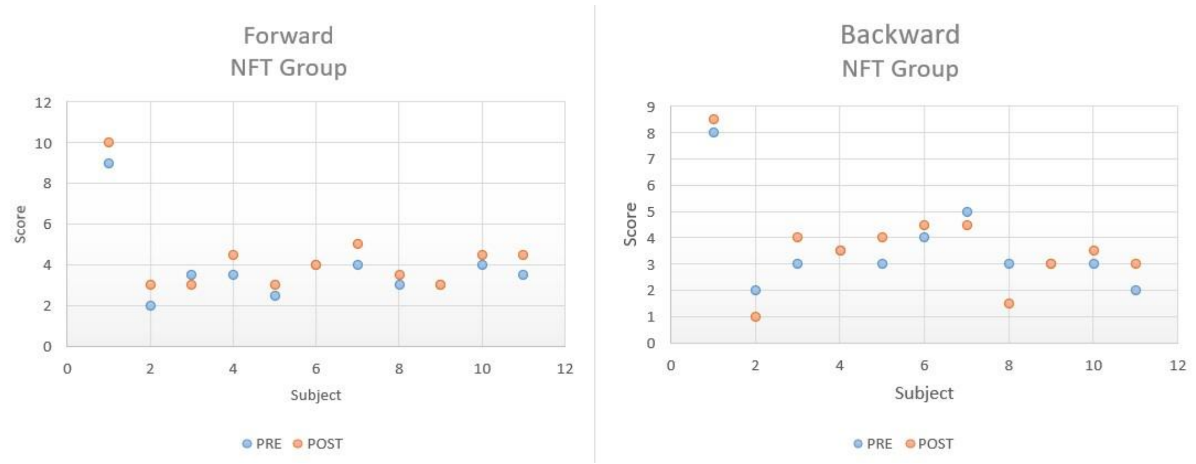

Figure 3-8 Scores of Digit Span-Forward (left) and Digit Span-Backward (right) of the NFT group comparing the first try before the first session (PRE) and the second try at the end of the last session.

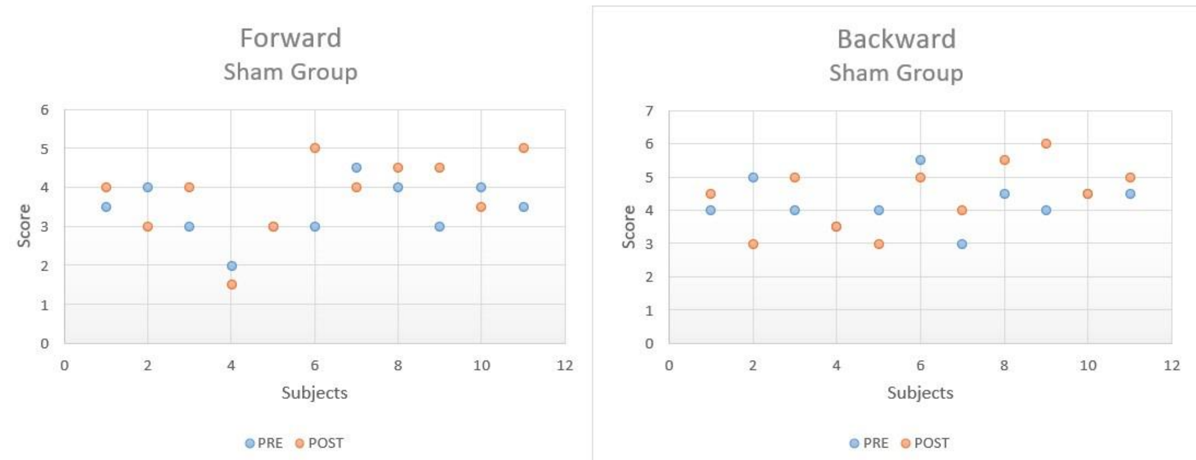

Figure 3-9 Scores of Digit Span-Forward (left) and Digit Span-Backward (right) of the SHAM group comparing the first try before the first session (PRE) and the second try at the end of the last session.

3.6.2 CPT-X

This study incorporated continuous cognitive tests to evaluate the participants' attention performance. In the following Figure 3.10 and Figure 3.11 are presented the scores of the CPT-X test regarding Accuracy, which represent how many times the participant took the target/non-target correctly, and Reaction time, which is the time interval to click on the mouse. Figure 3.10 shows NFT group's results, it can be noticed that in the target six participants obtained a better accuracy in the POST condition, three subjects had the same score and only two worsened it. In the non-target condition, nine participants out of eleven had the same or better score equal to 1 (perfect accuracy) in the final test, two of them had lower scores.

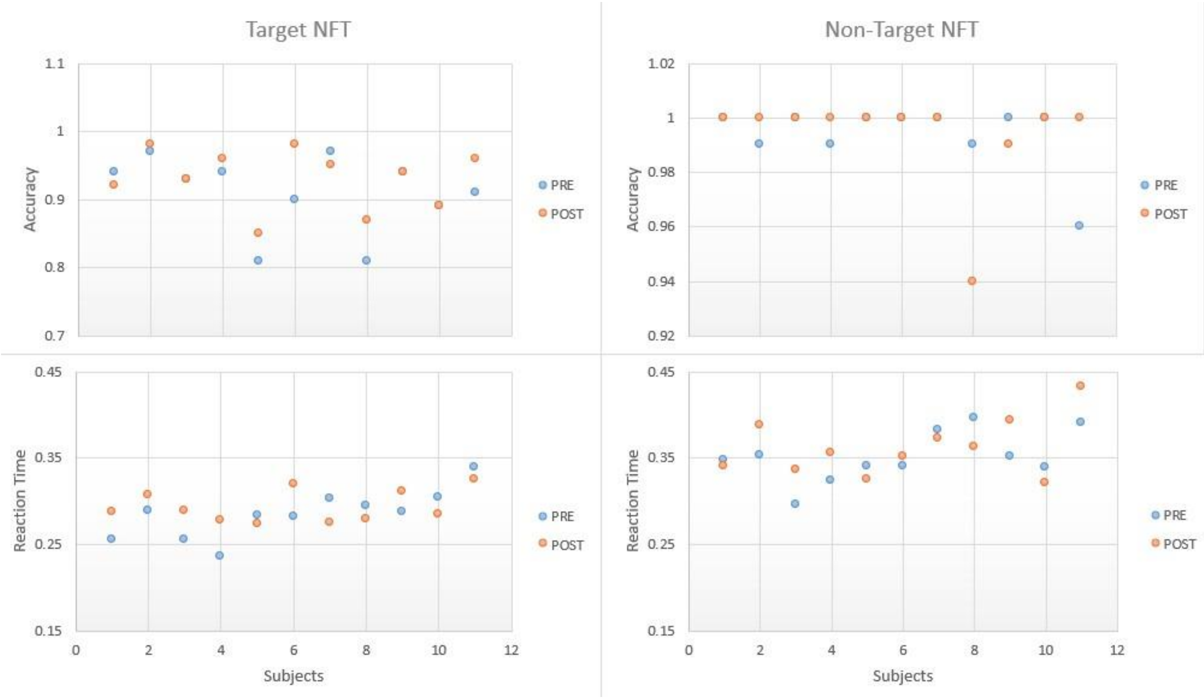

Figure 3-10 Scores of Accuracies and Reaction time for CPT-X test in the NFT group. Target condition in the left and non-target condition on the right.

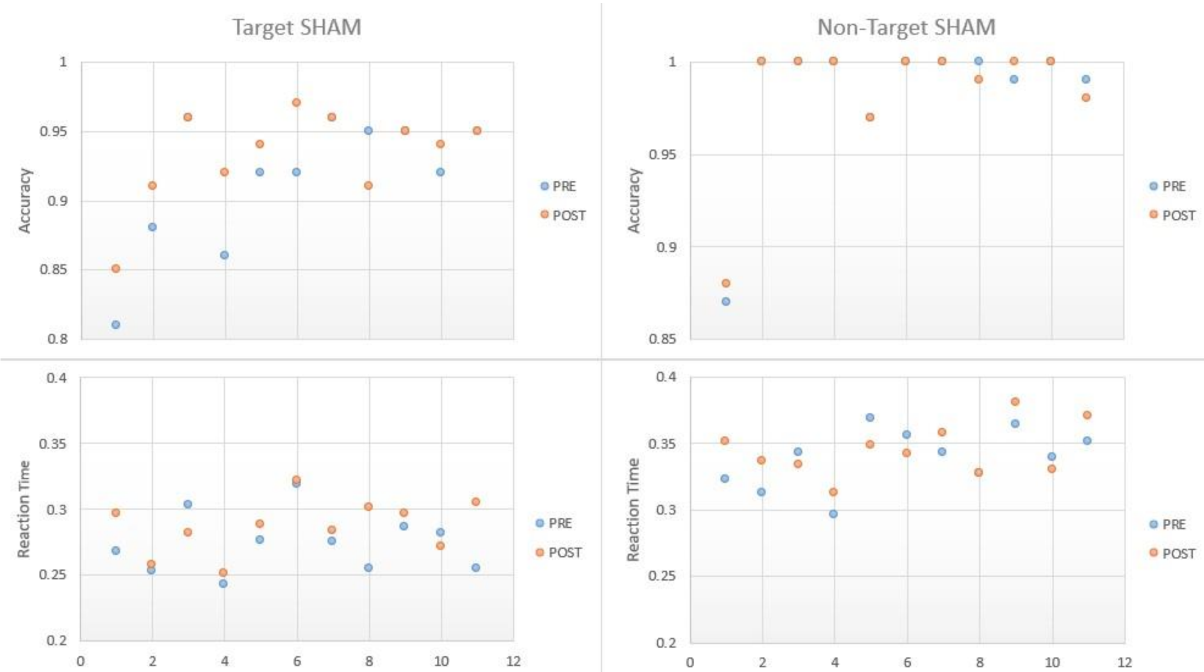

Figure 3-11 Scores of Accuracies and Reaction time for CPT-X test in the SHAM group. Target condition in the left and non-target condition on the right.

Regarding the reaction time, it is increased in the second test in six participants for the target and in five subjects for the non-target.

Figure 3.11 shows the scores of the SHAM group, in which most of the participants had the same or better accuracy in both target and non-target, only two of them had lower scores. The reaction time increased in nine subjects in target condition, and it increased in six participants in non-target condition. To have a statistical description of these data, the Wilcoxon signed-rank test was conducted comparing the pre- and post-training condition within group, a significant difference was found in the Target Accuracy when it was used as alternative hypothesis that measure 1 (pre-) is less than measure 2 (post-), with p values equal to $p = 0.046$ for the NFT group, and $p = 0.063$ for the SHAM group; no statistical significant difference was found for the reaction time.

3.7 Individual Alpha Frequency

In this section the distribution across participants of LTF, IAF and HTF obtained during the EO-EC baseline recording are reported in Figure 3.12. The lowest recorded IAF belongs to the participant NFT9 and is equal to 7.99 Hz, and the highest is from the subject NFT8, which is equal to 11.79 Hz.

The big differences across these values make it clear how much it is important to have a tailored interval of frequencies. All the detailed values are reported in the Annex C.

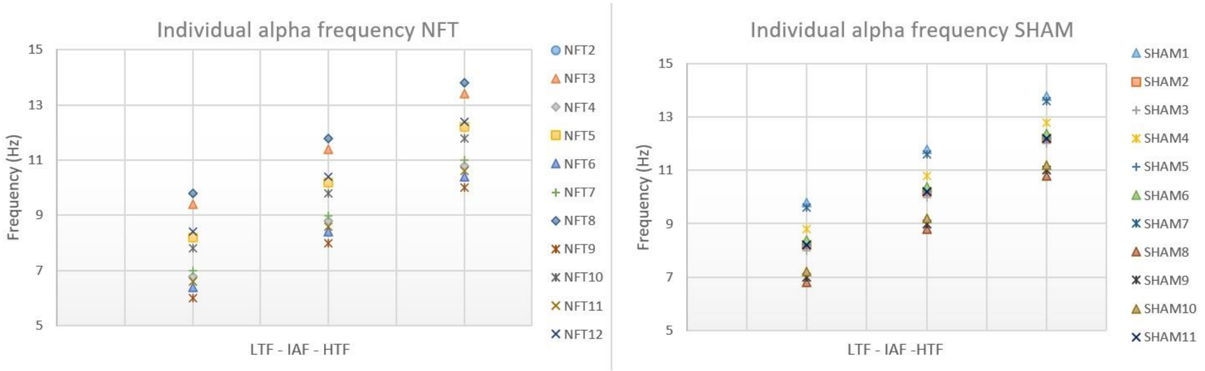

Figure 3-12 Distribution of Individual alpha frequency (LTF-IAF-HTF) in both NFT group (left) and SHAM group (right) obtained pre-session one (EO-EC baseline).

3.8 Training Effect on Target Location

The learning impact on self-regulation of brain activity was evaluated, specifically focusing on RAUA at electrode site Cz (channel 24), by examining changes in levels both intra- and intersessions. Additionally, we analysed other frequency bands like theta, LA, and IAB to gauge the training's comprehensive influence on brain activity.

3.8.1 Training Effect on RAUA Band

In Figure 3.13 and Figure 3.14 are reported the averaged values with the standard deviation of the RAUA across the session for both groups NFT and SHAM, respectively.

Observing the trends in the two figures, it's evident that the NFT group displays more variability in RAUA compared to the SHAM group, where values remain relatively stable across sessions and sets. This suggests that the group receiving actual NF training experienced a significant effect among participants, an effect not present in the other group. All the values of minimum, maximum and threshold per session for each participant are presented in Annex D.

The Table 3 and Table 4 showcases all slope values of the development of RAUA through the sets in each session for each participant, categorized by the two groups respectively, aiming to highlight individuals who obtained a negative value (decreased RAUA) in more than two sessions. These subjects are possible non-learners, and this information will be combined with percent time results.

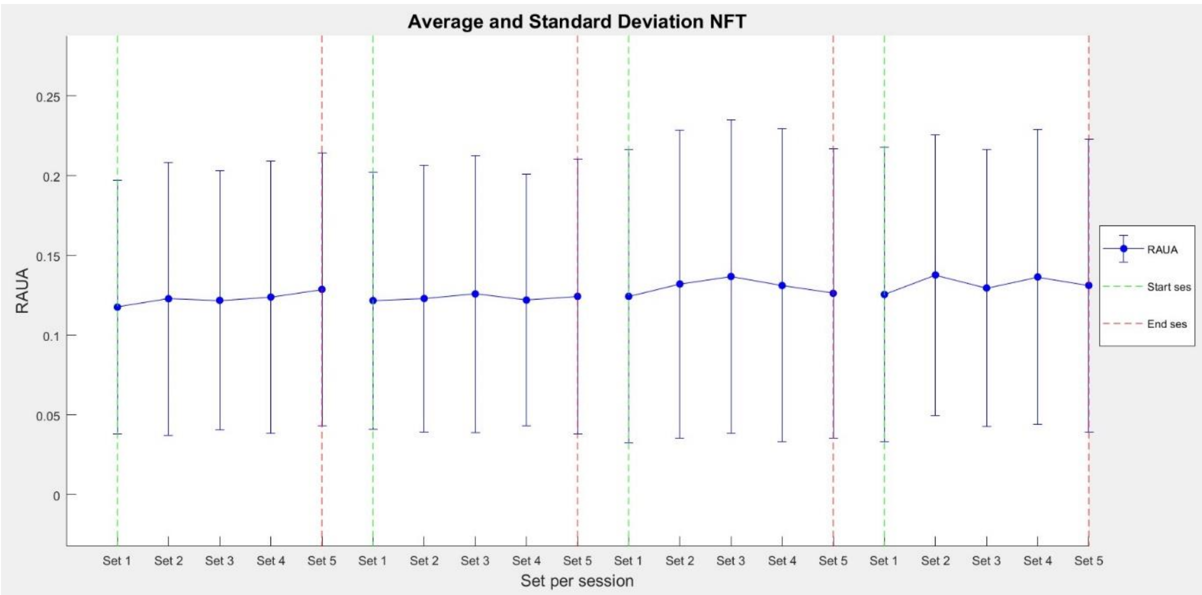

Figure 3-13 Averaged values with the standard deviation across the five sets and four sessions for the NFT group. Green line indicates the start of the session and the red line the end of that session.

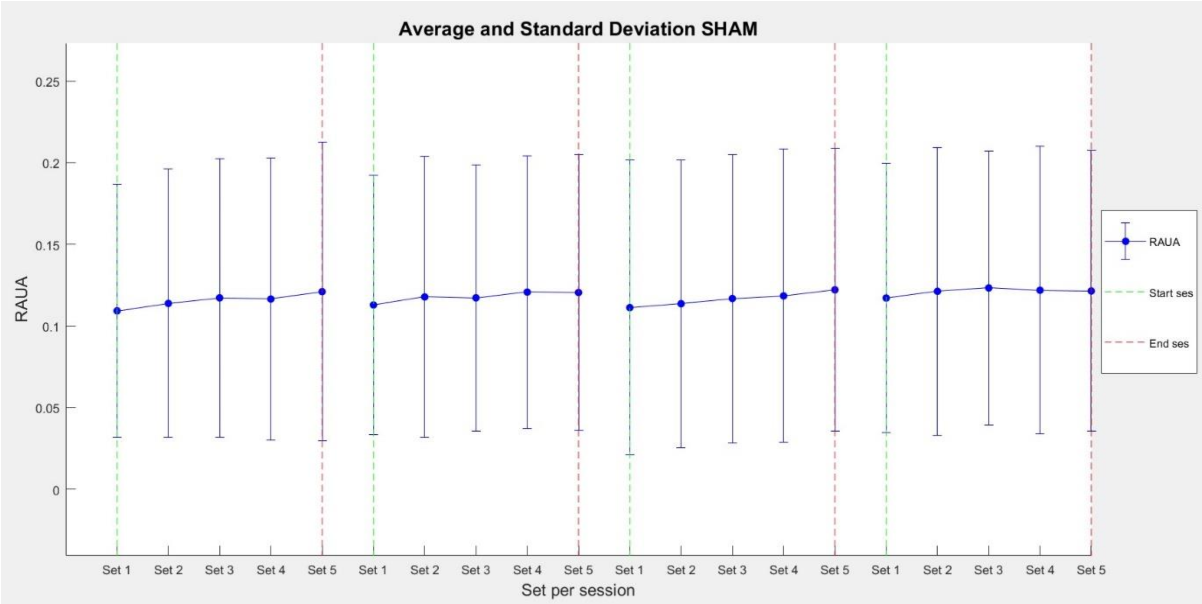

Figure 3-14 Averaged values with the standard deviation across the five sets and four sessions for the SHAM group. Green line indicates the start of the session and the red line the end of that session.

Table 3 - IntraS values of each participant of NFT group across the sessions. The subjects with negative values in more than two sessions are highlighted to show a possible non-learner to verify.

NFT ID\IntraS	Sess 1	Sess 2	Sess 3	Sess 4
NFT2	0.0059	0.0028	0.003	0.0017
NFT3	0.0073	0.0051	0.0035	-2.635e-04
NFT4	-0.0034	0.0011	-0.0022	-0.0012
NFT5	-0.0027	0.0014	0.0055	-2.012e-04
NFT6	0.0021	-0.0096	8.326e-04	-7.841e-04
NFT7	0.0080	0.0060	0.0025	1.692e-04
NFT8	0.0043	0.0020	9.410e-04	0.0046
NFT9	0.0016	9.487e-04	2.626e-04	-0.001
NFT10	0.0041	0.0062	0.0028	0.009
NFT11	-0.0012	-0.0023	-3.447e-04	0.0023
NFT12	-6.072e-04	-0.0089	-0.0137	-0.0032

Three participants in the NFT groups showed three or four negative values of slope across the session, they were not able to modulate the amplitude with the training (NFT4, NFT11 and NFT12). Anyway, also NFT6 has two negative slopes and a third which is very low, which could indicate another possible non-learner. NFT5 and NFT9 also had low slope values and they may identify as non-learners depending on other features. A Friedman test was conducted across the session for the learners in the NFT group, the result is statistically significant with a p-value equal to 0.025.

Table 4 - IntraS values of each participant of SHAM group across the sessions. The subjects with negative values in more than two sessions are highlighted to show a possible non-learner to verify.

SHAM ID\IntraS	Ses 1	Ses 2	Ses 3	Ses 4
SHAM1	6.445e-04	-0.0022	6.0908e-04	-1.209e-04
SHAM2	5.569e-04	2.8106e-04	-9.117e-04	6.766e-04
SHAM3	-0.0019	4.452e-04	0.0022	0.0015
SHAM4	0.0131	0.0063	0.0019	0.0016
SHAM5	0.0015	-9.684e-04	-0.0077	-7.351e-04
SHAM6	0.0024	0.0077	0.0035	0.0019
SHAM7	0.0013	0.0012	0.0060	0.0030
SHAM8	-3.222e-04	0.0016	6.189e-04	0.0026
SHAM9	4.516e-04	7.648e-04	0.0120	2.025e-04
SHAM10	0.0039	0.0055	-	-0.0018
SHAM11	0.0072	-4.132e-04	0.0076	0.0015

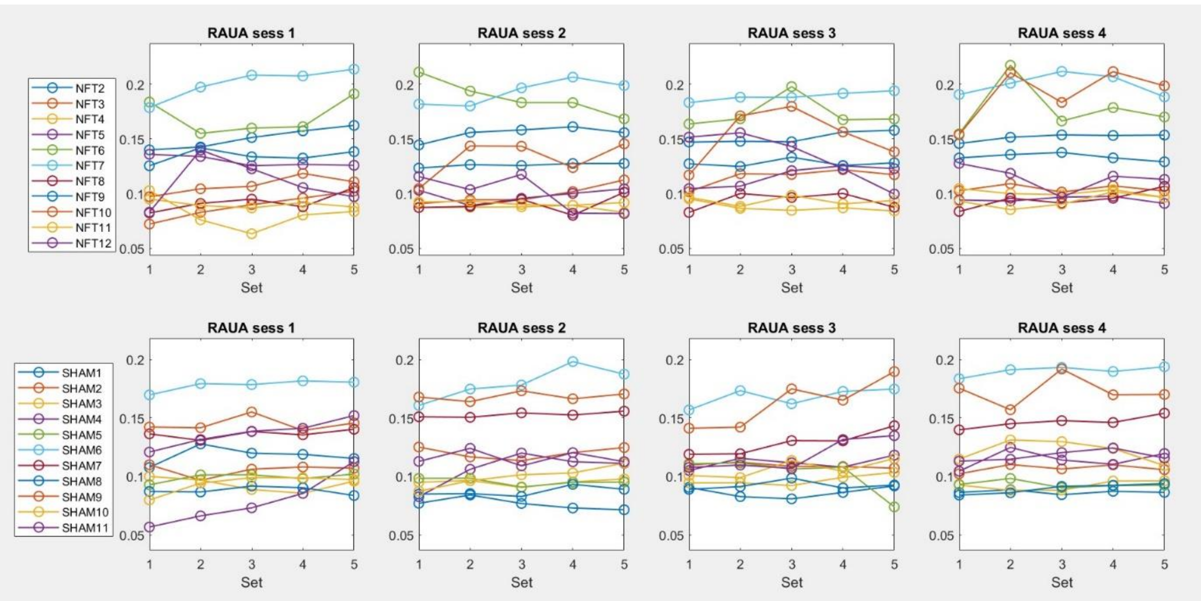

Figure 3-15 Development of RA of UA frequency across the sets in all sessions. The NFT group are presented on the top, the SHAM group is at the bottom, each participant is shown in a different colour.

In Figure 3.15, RAUA development of each participant is shown.

In the SHAM group one participant had three negative values (SHAM5), identified as a possible non-learner, and another one has exhibited two negative slope values and two values proximate to zero, leading to their identification as a potential non-learner (SHAM1). Also, SHAM2 had all slopes around zero, it cannot be identified as a learner or not with this feature alone. Participant SHAM10 who had technical problems with the recording of the third session is considered a possible learner since two values are positive and the recorded values for session three showed an increasing trend.

In Table 5 and Table 6, the results of the two other learning metrics for both NFT group and SHAM group, respectively, and all sessions are summarized. For the NFT group the same participants already identified with IntraS are highlighted, but it can be noticed that there are other subjects with two out of four negative values in at least one metric.

Table 5 – Results of Intra A1 (left) and Intra A2 (right) for the NFT group. Participants with more than two negative values across the sessions are highlighted.

IntraA1	Ses 1	Ses 2	Ses 3	Ses 4	**Intra A2**	Ses 1	Ses 2	Ses 3	Ses 4
NFT2	0.0536	0.0530	0.0211	0.0285		0.1599	0.078	0.0735	0.0527
NFT3	0.0823	0.0398	0.0677	0.0092		0.4188	0.2395	0.1524	-0.0031
NFT4	-0.1077	0.0072	-0.0385	-0.0193		-0.1866	0.0512	-0.1166	-0.0767
NFT5	-0.0319	-0.0228	0.0579	0.0019		-0.0742	0.0128	0.1753	-0.0336
NFT6	-0.0676	-0.1159	0.0474	0.1139		0.0407	-0.2026	0.028	0.10
NFT7	0.1125	0.0549	0.0289	0.0455		0.1968	0.0938	0.0589	-0.0111
NFT8	0.0501	0.0155	0.0528	0.055		0.2818	0.1608	0.0566	0.2756
NFT9	0.0445	0.0137	0.0027	0.0045		0.1028	0.0342	0.0066	-0.0266
NFT10	0.0519	0.1379	0.1777	0.1888		0.1412	0.3923	0.1818	0.2911
NFT11	-0.0248	-0.0142	-0.0152	0.0015		-0.0771	-0.1034	-0.0296	0.037
NFT12	0.133	-0.0773	-0.0857	-0.0661		0.1703	-0.2926	-0.3437	-0.1144

In the SHAM group, it is identified the subject SHAM2, which was not clear in IntraS index and is highlighted, additionally the two participants already identified are highlighted.

Table 6 - Results of Intra A1 (left) and Intra A2 (right) for the SHAM group. Participants with more than two negative values across the sessions are highlighted.

IntraA1	Ses 1	Ses 2	Ses 3	Ses 4	Intra A2	Ses 1	Ses 2	Ses 3	Ses 4
SHAM1	0.0512	-0.0027	-0.0208	0.0015		0.0715	-0.0721	0.0138	9.42e-04
SHAM2	-0.0219	-0.0253	-0.0029	0.0233		-0.0265	-0.0035	-0.0246	0.0348
SHAM3	-0.0325	3.07e-04	0.0112	-0.0017		-0.04	0.0296	0.0936	0.0392
SHAM4	0.1107	0.1193	0.0329	0.051		0.9894	0.3455	0.1249	0.1451
SHAM5	0.0315	-0.0137	-0.0438	7.3e-04		0.0992	-0.0314	-0.3335	-0.0063
SHAM6	0.0415	0.0956	0.0557	0.0338		0.0642	0.1661	0.1142	0.0556
SHAM7	-5.8e-04	0.0092	0.048	0.0336		0.0287	0.0319	0.2053	0.1018
SHAM8	0.0039	0.0109	0.0168	0.0276		-0.0396	0.0483	0.0416	0.1167
SHAM9	0.0128	0.0025	0.1071	-0.0131		0.0242	0.0155	0.3436	-0.0307
SHAM10	0.0701	0.0629	-	0.035		0.219	0.2759	-	-0.0481
SHAM11	0.0801	0.0147	0.0522	0.0227		0.2584	-0.002	0.2524	0.0229

3.8.2 Training Effect on Other Frequency Bands

As it has been previously mentioned, given the specificity of training in neurofeedback targeting a particular frequency band, it was also important to determine whether additional frequency bands were influenced by the neurofeedback training. This section presents the data regarding the Relative Amplitude (RA) of other frequency bands.

In Figure 3.16 are presented the development of relative amplitude (RA) of theta frequency over the electrode Cz across the sets and in each session for all the participants (NFT above, SHAM below). Regarding the NFT group, there is an increment in the values from the first to the last session in particular in subjects NFT4 and NFT11, who were identified as non-learners for the RAUA. The behaviour regarding the LA and IAB are showed in Figure 3.17 and Figure 3.18 (NFT above, SHAM below), all the participants' values across the sets and in all the sessions are represented, respectively.

The evolution of LA resembles that of IAB, which is also similar to the trend of RAUA, whereas the outcomes observed in the theta band portrayed an almost opposite trend, where increased RAUA values corresponded to decreased RA Theta values.

The analysis excluded beta values due to the presence of persistent physiological artifacts (muscle activity) that remained unresolved despite attempts at denoising through Independent Component Analysis (ICA).

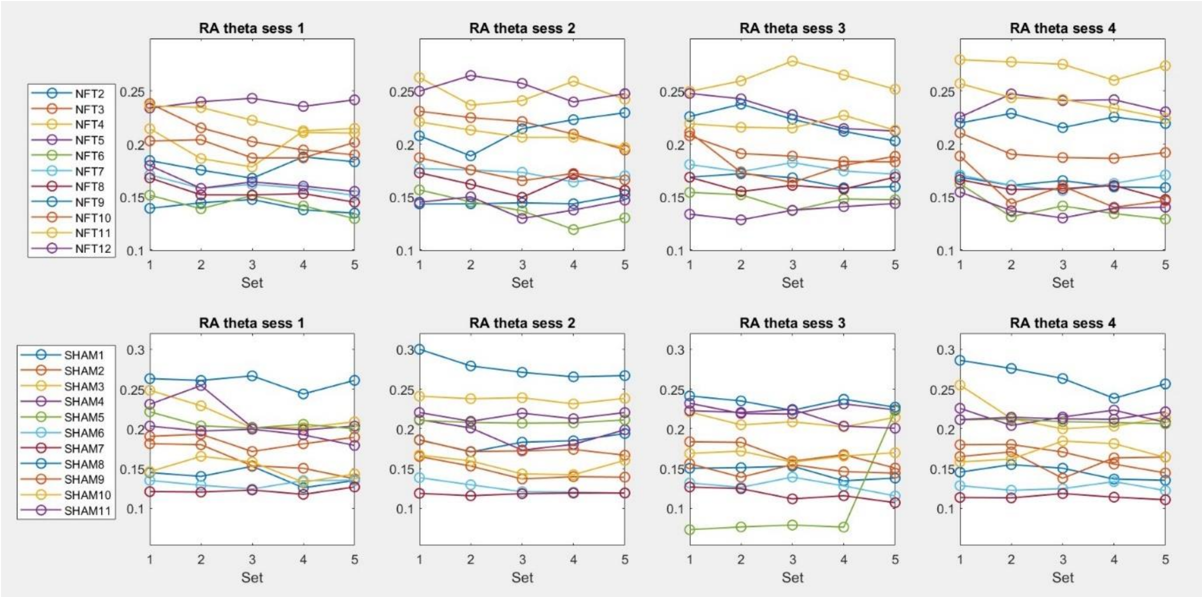

Figure 3-16 Development of RA of theta frequency across the sets in all sessions. The NFT group are presented on the top, the SHAM group is at the bottom, each participant is shown in a different colour.

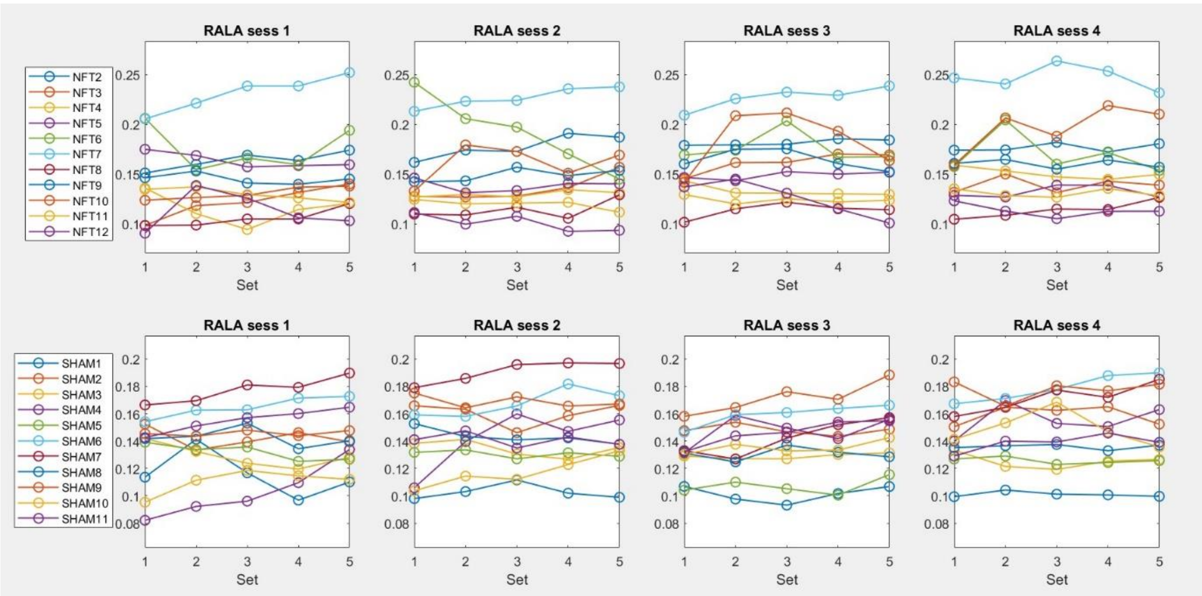

Figure 3-17 Development of RA LA frequency across the sets in all sessions. The NFT group are presented on the top, the SHAM group is at the bottom, each participant is shown in a different colour.

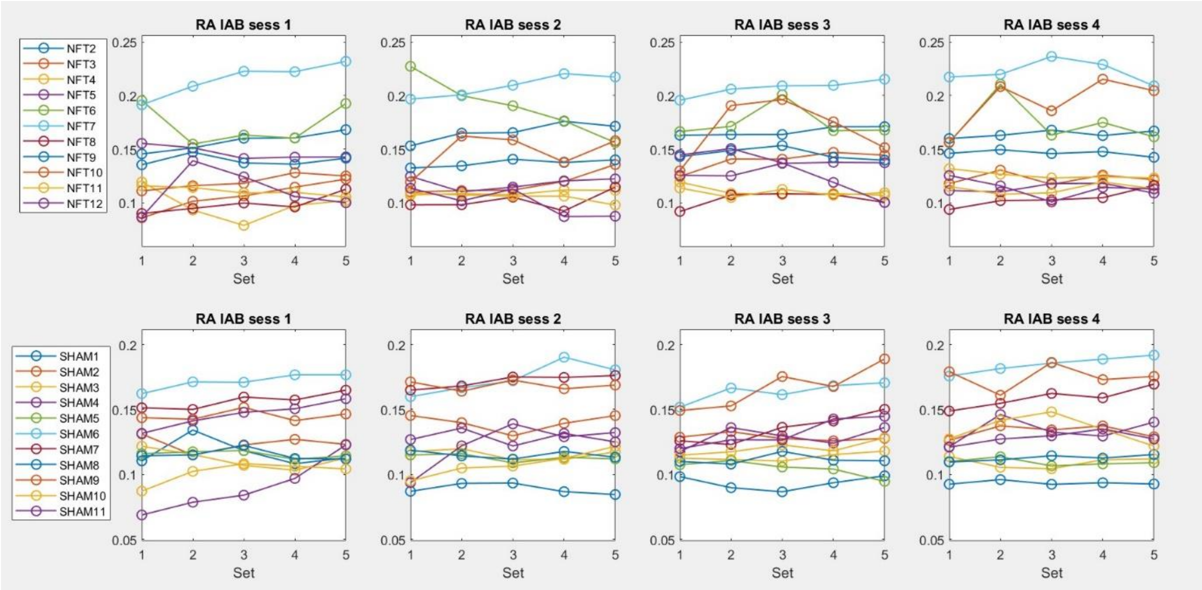

Figure 3-18 Development of RA IAB frequency across the sets in all sessions. The NFT group are presented on the top, the SHAM group is at the bottom, each participant is shown in a different colour.

3.9 Time Rewards Effect

In order to assess the effectiveness of adding a reward every 2.5 seconds on the modulation of time above the threshold, the development of this feature has been evaluated. This has been performed in two conditions, within session and across sessions, to establish if participants had a positive effect on the self-regulation during the training or from the first to the last session.

3.9.1 Percent Time Variation Intra-session

In this section, the trend of time above the threshold is graphically presented for each participant across the epochs, in Figure 3.19 the NFT group is shown and in Figure 3.20 the SHAM group is represented. The relative slope from each session is also reported in the Table 7 (NFT) and Table 8 (SHAM). Looking at NFT results, it is seen that the same subjects identified as non-learners with RAUA are not able to self-regulate the time above the threshold, this suggests that they can be considered non-learners. One more subject is found with more than two negative slopes, the NFT9, which had low values of slopes for RAUA, so it could be part of the non-learners. All the detailed values per session of each participant are reported in Annex D. A Friedman test was conducted for the learners of NFT group to study the development across sessions, the obtained value was p = 0.067.

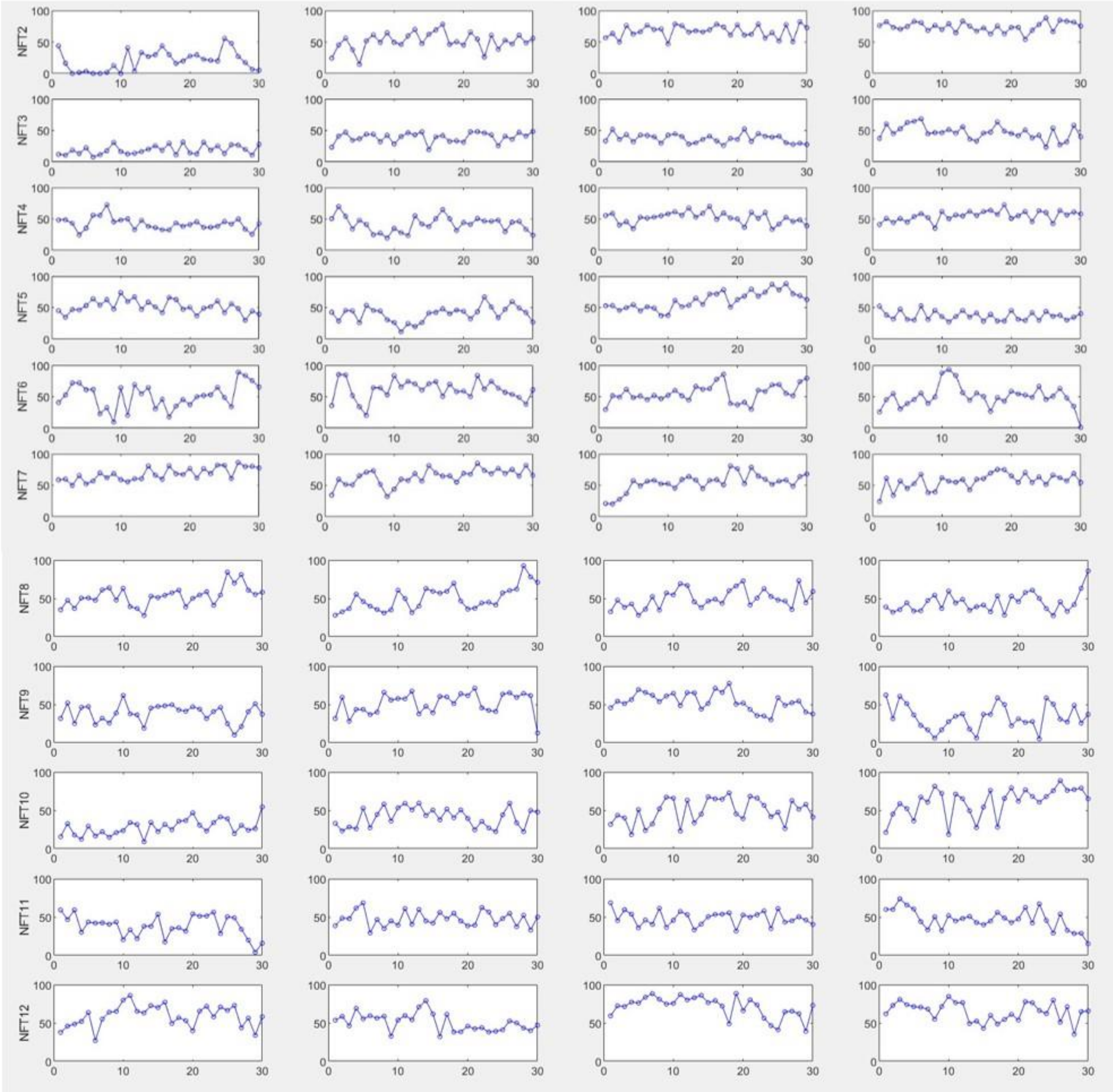

Figure 3-19 Development of time above the threshold through the 30 epochs in the 4 session of each NFT participant.

Table 7 – Slopes of the trend of percent time through the epochs in each session of the NFT group. The participants with more than two negative values are highlighted as possible non-learners.

Slope intra session	Ses 1	Ses 2	Ses 3	Ses 4		Ses 1	Ses 2	Ses 3	Ses 4
NFT2	0.5874	0.3261	0.1233	0.0081	NFT8	0.7022	1.1002	0.5130	0.5194
NFT3	0.3031	0.1689	-0.2283	-0.525	NFT9	-0.0861	0.3466	-0.5577	-0.0699
NFT4	-0.3464	-0.1228	-0.1933	0.4044	NFT10	0.6103	0.0454	0.535	1.1076
NFT5	-0.2706	0.3755	1.728	-0.178	NFT11	-0.5332	-0.0471	-0.1594	-0.8288
NFT6	0.5293	-0.0255	0.5987	-0.194	NFT12	0.1621	-0.597	-0.7642	-0.3947
NFT7	0.8215	0.8567	0.9914	0.6813					

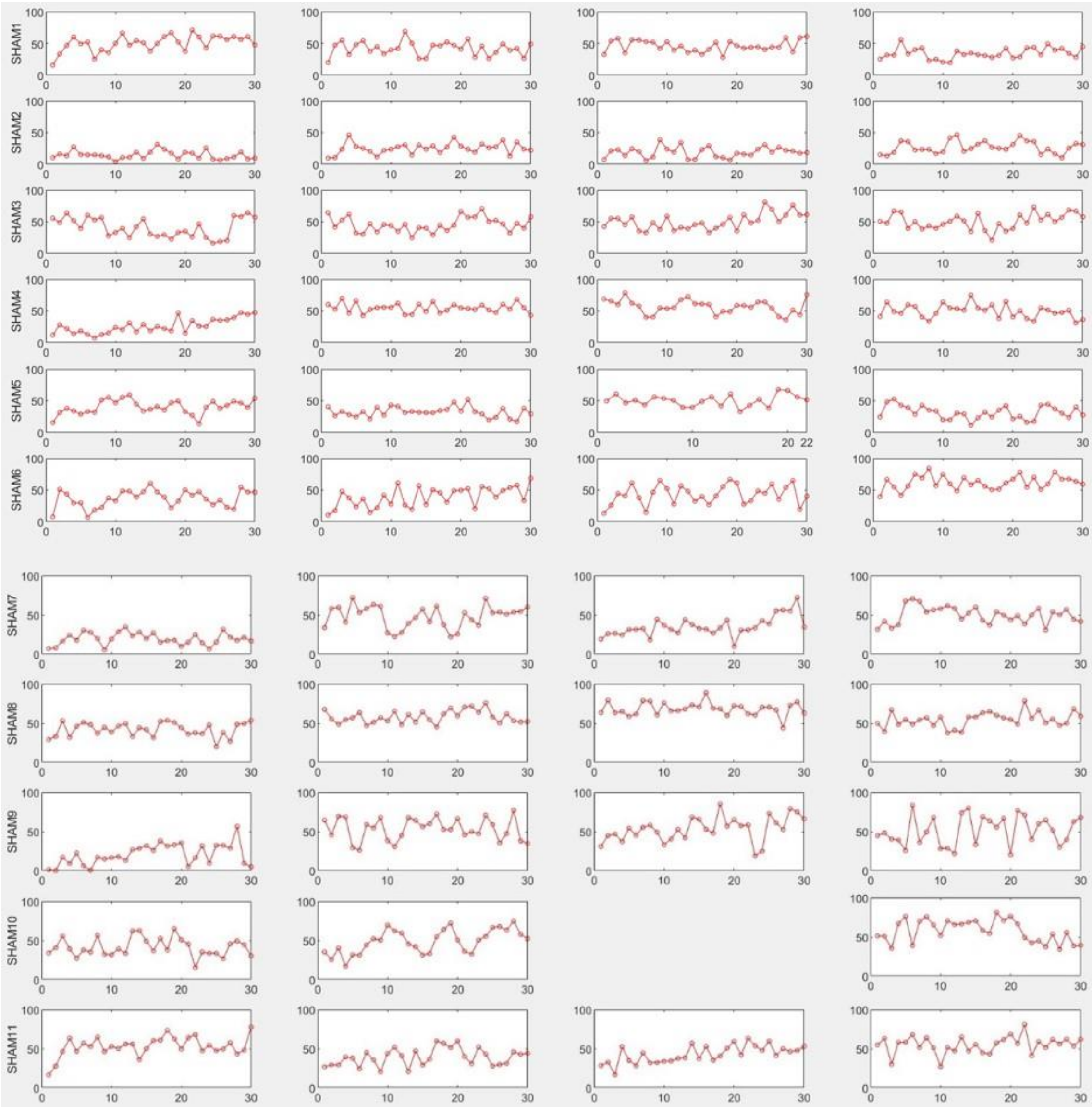

Figure 3-20 Development of time above the threshold through the 30 epochs in the 4 sessions of each SHAM participant.

Table 8 - Slopes of the trend of percent time through the epochs in each session of the SHAM group. The participants with more than two negative values are highlighted as possible non-learners.

Slope intra session	Ses 1	Ses 2	Ses 3	Ses 4		Ses 1	Ses 2	Ses 3	Ses 4
SHAM1	0.737	-0.0735	0.0528	0.2367	SHAM7	0.0080	0.0518	0.8397	-0.1289
SHAM2	-0.1029	0.220	0.0885	0.1159	SHAM8	0.0303	0.140	-0.0891	0.3444
SHAM3	-0.3959	0.2048	0.7082	0.3511	SHAM9	0.6914	-0.0808	0.7431	0.4419
SHAM4	0.9962	-0.0712	-0.3418	-0.3370	SHAM10	-0.0816	0.9758	-	-0.5136
SHAM5	0.3112	-0.0933	0.178	-0.256	SHAM11	0.5308	0.3698	0.8211	0.2577
SHAM6	0.3965	1.0107	0.3495	0.2399					

Regarding the SHAM group, it is present just one participant (SHAM4) who had negative slopes in three sessions and one (SHAM10) who had two out of three negative slopes, while none of the already identified non-learner subjects are recognized. Since this pattern is present in the SHAM group, this could be explained by the non-correlation of the variations with the training.

3.9.2 Percent Time Variation Inter-session

In this section the development of percent time above the threshold across the session is represented in Figure 3.21 and Figure 3.22 for SHAM and NFT groups, respectively. The variations of threshold across the session are indicated by a circle, it is green if the threshold was diminished from the previous session, and red if it was increased. The slopes of each participant are also presented in Table 9. The slopes values reported in the Table 9 don't show any correlations with the other features already seen, just one participant (SHAM1) corresponds to the identification as non-learner.

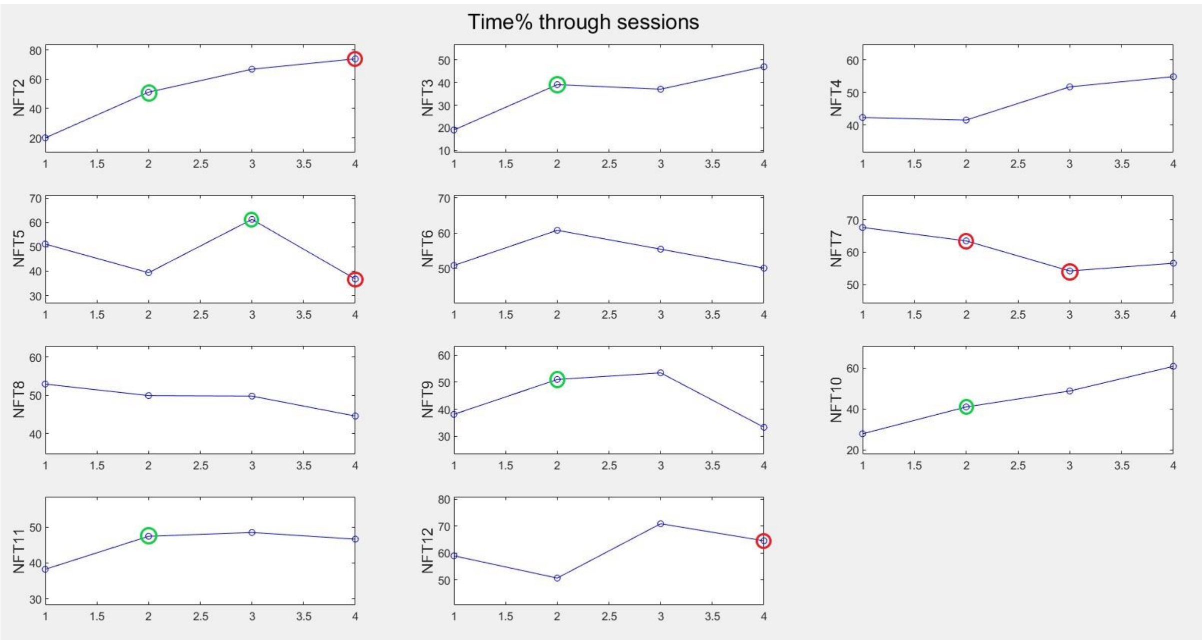

Figure 3-21 Trend of percent time above the threshold across the sessions for each participant in NFT group. Red circle = threshold increased from previous session; Green circle = threshold decreased from previous session.

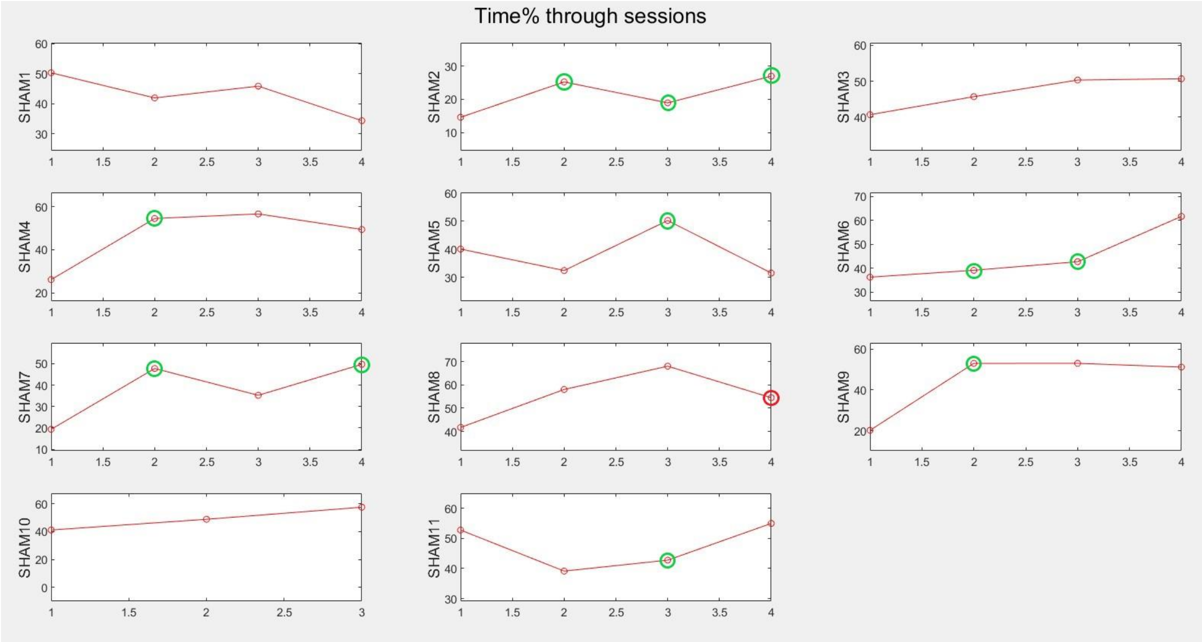

Figure 3-22 Trend of percent time above the threshold across the sessions for each participant in NFT group. Red circle = threshold increased from previous session; Green circle = threshold decreased from previous session.

Table 9 - Slopes of the trend of percent time through the sessions in both groups. The participants with more than two negative values are highlighted.

NFT ID	Slope	NFT ID	Slope	SHAM ID	Slope	SHAM ID	Slope
NFT2	17.7313	NFT8	-2.5251	SHAM1	-4.3964	SHAM7	7.8483
NFT3	8.1947	NFT9	-1.1914	SHAM2	3.0696	SHAM8	4.8247
NFT4	4.7903	NFT10	10.673	SHAM3	3.4601	SHAM9	9.2672
NFT5	-2.1167	NFT11	2.6344	SHAM4	7.2164	SHAM10	-11.4703
NFT6	-0.7652	NFT12	3.680	SHAM5	-0.7787	SHAM11	1.025
NFT7	-4.2348			SHAM6	7.9699		

3.10 Training Effect on Spectral Topography

In this section the variations in the spectral topography throughout the NFT are presented for the averaged RA of all the considered bands. Figure 3.23 shows the topographic maps through the five sets of session one for each frequency band, the values were averaged across the NFT group participants. The same representation is done for the SHAM group in Figure 3.24.

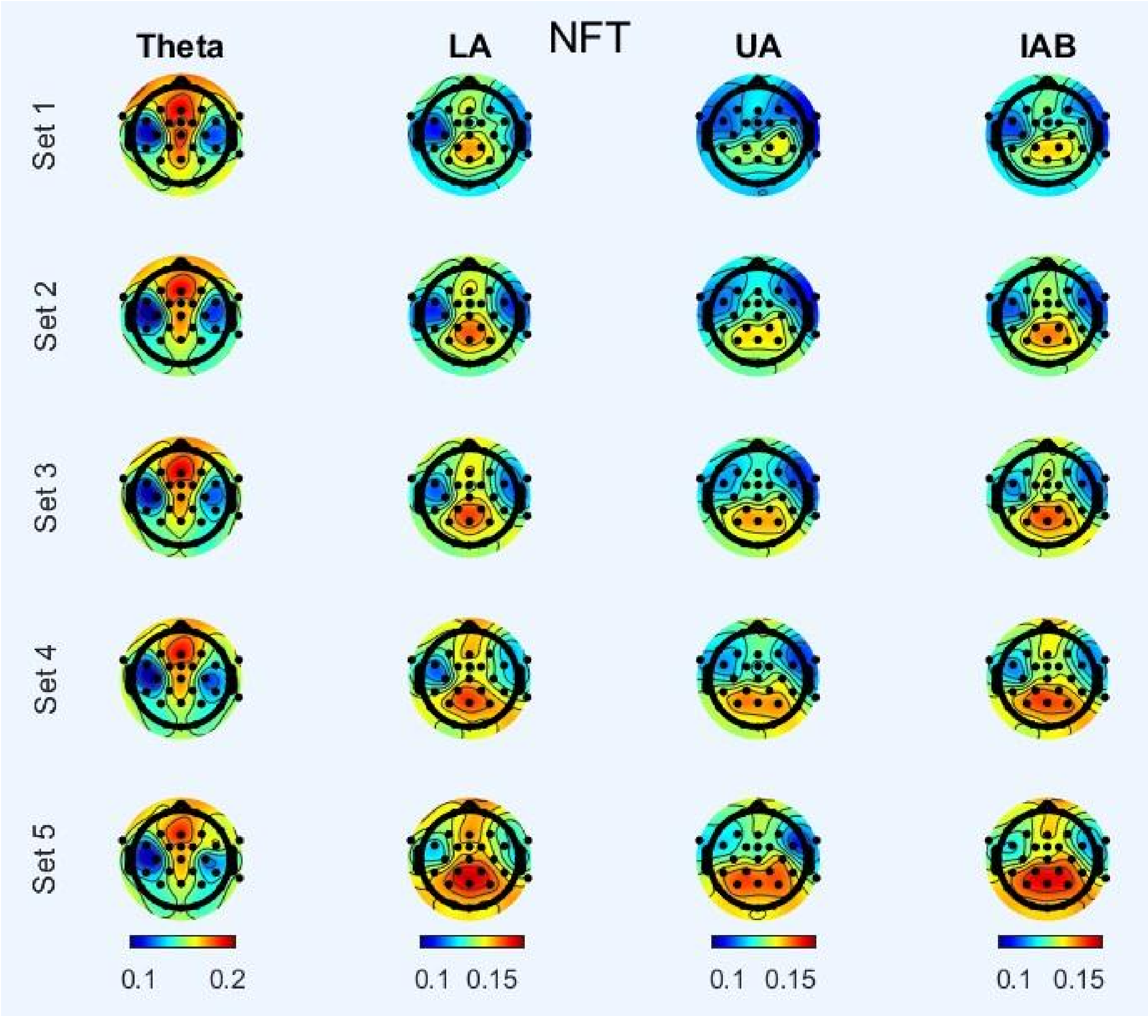

Figure 3-23 Topographical distribution of the averaged RA for all the frequency bands analysed along each of the five sets in the first session for NFT group.

The results showed an increase through the sets when analysing the RA for LA, UA and IAB frequency bands, the increment is concentrated near the Cz electrode location and there is a slight increase also in the frontal area. On the contrary, the RA of theta frequency band shows a decrease in the frontal area from the first to the last session, this decrement is significant in NFT group, while it is less present in the SHAM group, probably due to a lower effect of the placebo training. In the Figure 3.25 and Figure 3.26 are represented the spectral topographies of the averaged RA of all the examined frequencies of the learners from NFT and SHAM group, respectively, of the pre- and post-condition.

Pre-training indicates the mean of the first two sets of session one, while post-training is the mean of the last two sets of session 4. The subjects considered as non-learners were excluded from the values averaged for these spectral topographies. In the NFT group: NFT4, NFT9, NFT11, NFT12. In the SHAM group: SHAM1, SHAM5.

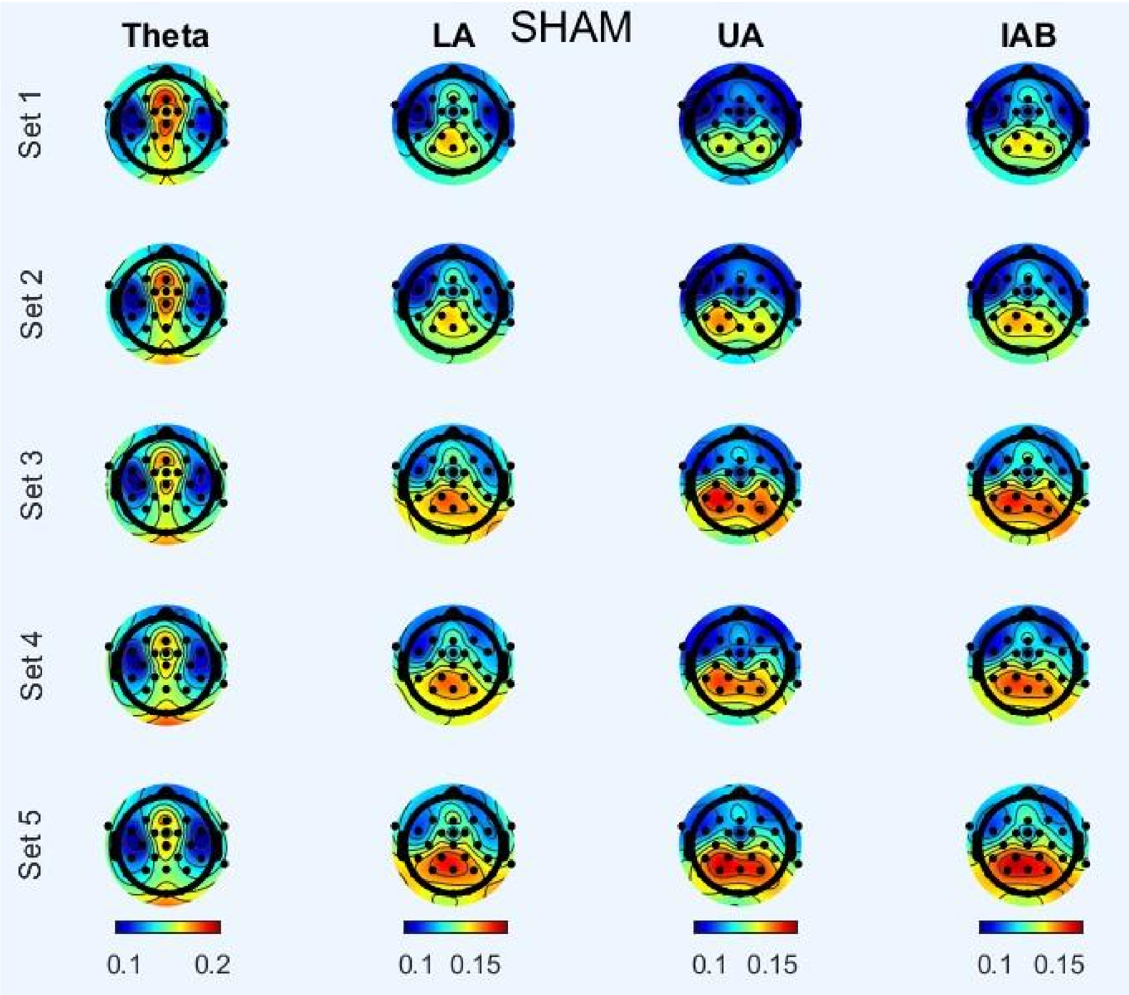

Figure 3-24 Topographical distribution of the averaged RA for all the frequency bands analysed along each of the five sets in the first session for SHAM group.

In these two figures (3.25 and 3.26) the same scales are used to make the comparison simpler. In the NFT group it can be seen a significant increase of RA in UA, LA and IAB frequency bands, at the same time there is a decrease (inhibition) of the RA in theta frequency band in the frontal area. In the SHAM group the increment of RA in UA, LA and IAB frequency bands is lower and more dispersed throughout the brain than in the other group, although the effect of training can be seen from the first to the last session near the Cz electrode location, additionally it should be kept in mind that the values were already lower in the first session for these subjects. The inhibition of theta frequency band is present in the SHAM group, too.

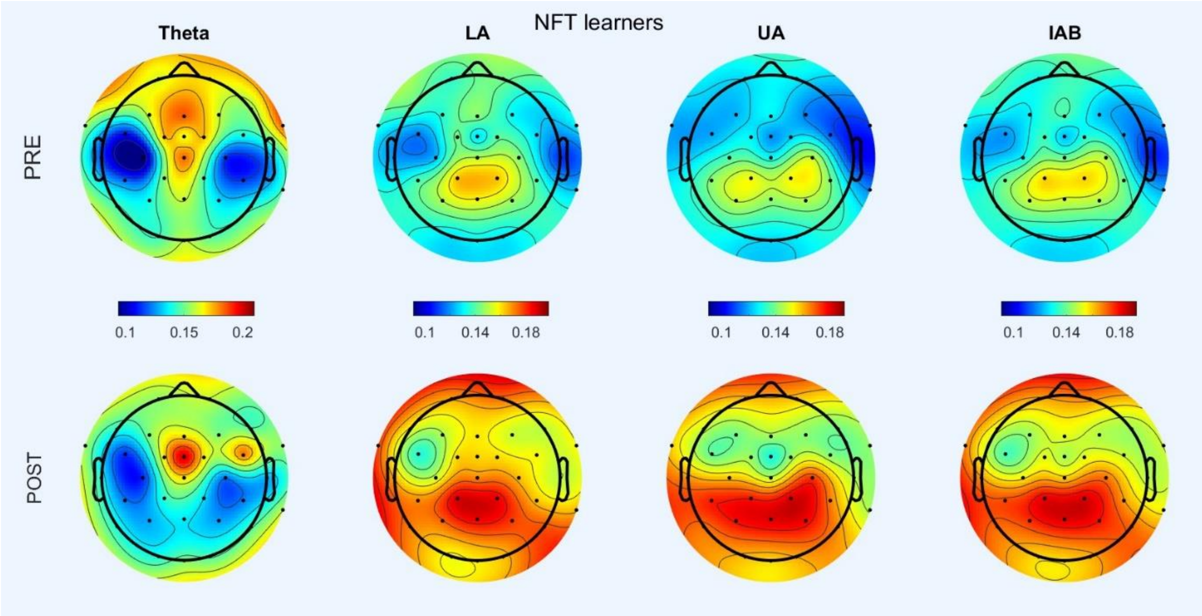

Figure 3-25 Topographical distribution of the averaged RA of each frequency band across learners from NFT group in the pre-training and post-training conditions (PRE=mean of two first sets of session 1; POST=mean of two last sets of session 4).

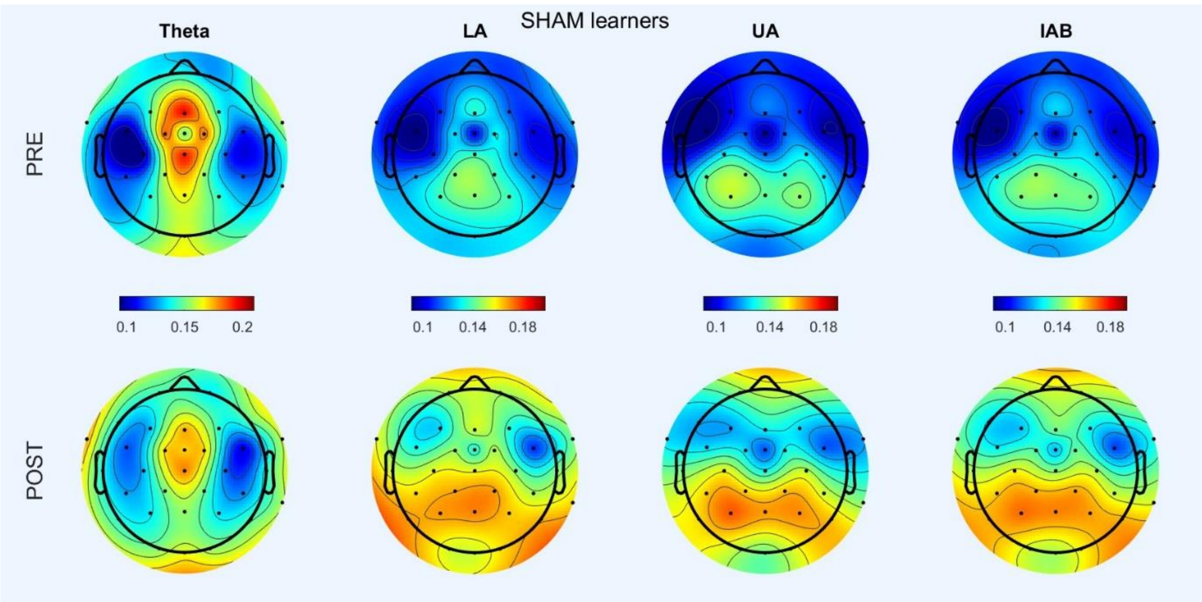

Figure 3-26 Topographical distribution of the averaged RA of each frequency band across learners from SHAM group in the pre-training and post-training conditions (PRE=mean of two first sets of session 1; POST=mean of two last sets of session 4).

3.11 Classification into Learning Groups with Machine Learning

In this section, the results of the classification tests using the two machine learning techniques employed (K-means and SOM) are presented (classes and clusters). Both methods have been tried with three combinations of features: i) RAUA IntraS, percent time slope within session; ii) RAUA IntraS, percent time slope within session, percent time slope across session; iii) RAUA IntraS, percent time slope within session, percent time slope across session, percent time above threshold in each session. Since it was not clear the effect of the training in the SHAM group, for this part only NFT group was considered.

3.11.1 K-means Classifier

The number of cluster was set at 2 (learner/non-learner), and it was applied considering each session individually. The second and third combination of features (ii; iii) led to bad classification, so those results will not be reported. In Table 10 the classes regarding the combination of the first two features with NFT group's session are reported, cluster 1 corresponds to non-learner, cluster 2 identify a learner. If a subject is classified in more than two sessions as class 1, it is considered a non-learner.

Table 10 - Classification obtained with K-means method considering the sessions from NFT group and 2 clusters.

NFT ID\classes	Ses 1	Ses 2	Ses 3	Ses 4	Classification
NFT2	2	2	1	1	Learner
NFT3	2	1	1	1	Non-learner
NFT4	1	1	1	2	Non-learner
NFT5	1	2	2	1	Learner
NFT6	2	1	2	1	Learner
NFT7	2	2	2	2	Learner
NFT8	2	2	2	2	Learner
NFT9	1	2	1	1	Non-learner
NFT10	2	1	2	2	Learner
NFT11	1	1	1	1	Non-learner
NFT12	1	1	1	1	Non-learner

This technique recognized five non-learners, four of them are the same identified with the classic method.

3.11.2 Self-organizing map Classifier

When analysing the results obtained with the SOM method, it was noticed that also in this case the second and third combination of features led to misclassification, with cluster that had no correlation with the results already obtained. The slope of percent time across the session was removed, as well as the total percent time in each session, leaving only the first combination of features (i). Figure 3.27 shows the clusters obtained (A), the SOM hits (B), which are the number of victories obtained by each neuron, and the SOM neighbour weight distances (C).

The classes obtained with this technique are reported for each session in Table 11, the clusters 1 and 2 are identified as the non-learners and the clusters 3 and 4 are the class of learners. If a subject is assigned in more than two sessions to the cluster 1 or 2, it is classified as non-learner.

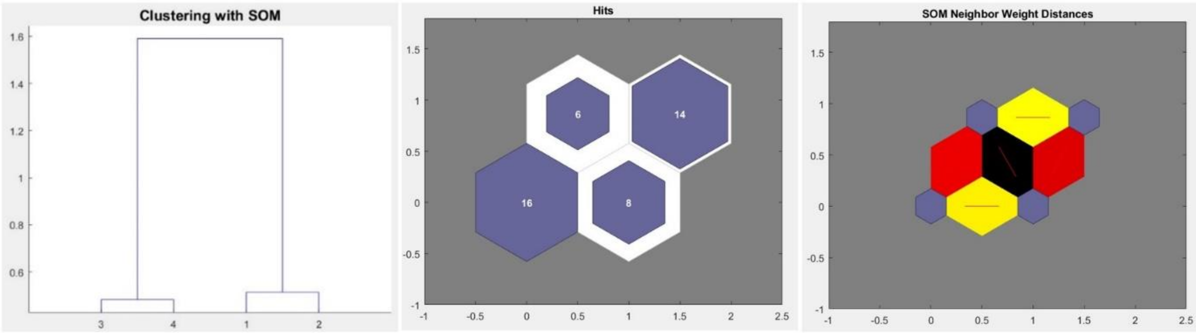

Figure 3-27 SOM network obtained with 2x2 topology and two features. (A) on the left, the clusters obtained, assigned to 2 classes: 1-2=non-learner; 3-4=learner. (B) in the middle, SOM hits which represent the number of victories for each neuron. (C) on the right, SOM neighbour weight distances: darker colours mean greater distance, lighter colours indicate smaller distances.

Table 11 - Classification obtained with SOM method considering the sessions from NFT group and 2x2 topology.

NFT ID\classes	Ses 1	Ses 2	Ses 3	Ses 4	Classification
NFT2	4	4	1	1	Learner
NFT3	4	1	1	2	Non-learner
NFT4	2	1	1	4	Non-learner
NFT5	1	4	3	1	Learner
NFT6	4	1	4	1	Learner
NFT7	3	3	3	4	Learner
NFT8	4	3	4	4	Learner
NFT9	1	4	2	1	Non-learner
NFT10	4	1	4	3	Learner
NFT11	2	1	1	2	Non-learner
NFT12	1	2	2	2	Non-learner

The classification obtained results the same obtained with K-means method, both techniques recognize as non-learner NFT3, in addition to the already identified NFT4, NFT9, NFT10 and NFT11.

4. DISCUSSION

This chapter explores six specific topics for comprehensive discussion. Initially, a critical review of the outcomes of the QCM and FKS questionnaires is performed, which hold significance in evaluating participant motivation and engagement before and during each session. Subsequently, the cognitive test results are examined in relation to existing literature. Following this, the chapter presents insights into the IAF and the impact of training on RAUA at the Cz target location. Next, the effect of time-based reward is examined, investigating the fluctuation in the percentage of time spent above the threshold. The application of sham feedback alongside visual feedback in NFT is then analysed, drawing insights from existing literature. The last topic is relative to the classification with machine learning problem, in the current thesis this method was tested for further investigations, however, due to the limited dataset size, it wasn't employed for the final classification.

4.1 Current Motivation

It is known from the study by Vollmeyer & Rheinberg (2006) that the motivation at the beginning of the task can influence the results of the performance, since more motivation encourages the participants to do better. This work is aimed to understand if this protocol can increase the motivation and, consequently, boosted engagement, an asset at optimizing outcome performance in learners who would otherwise act as non-learners.

Among the four motivational factors considered, Kleih et al. (2010) demonstrated that interest and the likelihood of success are higher in new participants, as seen in this case. Moreover, when interest and challenge are higher, motivation tends to be greater. In another study, Nijboer et al. (2010) found a difference in anxiety levels between the control and NFT groups, noting lower anxiety levels among NFT participants post-exercise compared to the control group. However, contrary to this finding, the present study observed a decrease in anxiety levels among nearly all NFT participants, but their anxiety levels didn't significantly differ from those in the SHAM group. Interestingly, the anxiety level was generally lower in our SHAM group, even if drawn from random sampling of the population.

The challenge and interest levels were the highest scoring properties in both groups, in particular in the NFT group the interest decreased until the third session and then increased in the last one, whereas the challenge was stable and had a slight decrease in the last session. On the other hand, the interest in the SHAM group had an opposite behaviour, it increased upon the third session and decreased in the fourth session. The highest variation is seen in NFT6, SHAM5, SHAM6 (decrease), and NFT9, SHAM10 (increase). Regarding the likelihood of fail and success, as expected, when the first increased the second decreased, this is the case of NFT11 and SHAM5, both identified as non-learners.

In the present study it wasn't find a diminishing number of non-learners caused by the motivation, but it was noted a correlation between the feelings experienced by the participants and the outcomes of the training, for example in NFT6 the decreasing interest led to worse results in both RAUA and time above the threshold, even if it is still considered a learner.

4.2 FKS Questionnaire

The aim of this questionnaire is to monitor the development of flow and worry across the session in the two groups, since the capacity to experience flow during an activity is considered an internal motivator that influences the engagement in a task.

Looking at the results obtained, it can be noted that in the NFT group the level of flow is smaller than the one in control group, the opposite happened for the level of worry. Despite these general considerations, it is interesting how the worry level decrease across the sessions in NFT group, which may indicate an increased confidence in performing the task among the participants, whereas in the SHAM group worry decreased in the third session but showed again an increment in the last session. On the other hand, the level of flow increased in SHAM group, while it shows a peak in the third session and a decrease in the fourth one in the NFT group. This behaviour could be caused by an under or over challenging in the participants, as explained in a study by Reinhardt et al. (2015); in this case, considering the participants at the end of the experiment, this could be due to over challenging or boredom during the training.

In the study conducted by Vollmeyer & Rheinberg, in 2006, they explained that the level of motivation reported in the QCM questionnaire (interest and challenge) influence the results of flow perceived at the end of the session, subsequently impacting the final learning outcome. As participants consistently experienced high levels of flow throughout the study, they felt like having gained substantial learning from the training, and they are more confident. This confidence is not always related to the real results, as it can be seen, for instance, in NFT4 and NFT9, both identified as non-learners but with increasing motivation, increasing flow levels across the sessions and, consequently, increasing motivation in their performances, even if it was ineffective.

4.3 Cognitive Tests

The two cognitive tests, Digit Span and CPT-X, submitted to all subjects at the beginning of the first session and at the end of the last one were used to evaluate their short-term memory capacities and sustained attention skills, respectively.

Indeed, as proven in a study by Nan et al. (2012), an increase in RAUA may be related to an improvement in memory skills, reflected in a better score in Digit Span test. Looking at these scores in the NFT group, in forward condition most of the participants experienced an improvement, while two obtained the same score (NFT7 and NFT9) and only one had worse performance, which is the NFT4, identified as a non-learner. Despite these promising results, in the backward conditions the outcome is different, NFT4 increased the score, whereas NFT3, NFT8 and NFT9 lowered it, although the first two are considered learners. This might be due to the more challenging condition or to the tiredness caused by the length of session or, for those who did the training in the afternoon, their work during the day. In the control group, the pattern is not significant, since half of the participants increased the score and the other half decreased it, in both conditions, which can be explained by the non-correlation of the training and the effect obtained.

Regarding the CPT-X, four factors were considered to evaluate the performance of participants: the accuracy, which means how many times they answered correctly, and the reaction time, which indicates how long it took to answer, for both target (X) and non-target letters (Sherwood et al., 2019). Indeed, they had to click on the mouse every time a non-target letter appeared on the screen and the expected outcomes after the training were a better accuracy combined with a reduced reaction time, according to the study led by Sherwood et al. in 2019. In the current study, the first was assessed in both groups, as most participants managed to increase accuracy. Conversely, the reaction time showed the opposite effect, exhibiting a general increase, perhaps due to the desire to avoid mistakes, leading them to slow down their responses.

4.4 Individual Alpha Frequency

It has been proved in the past that a customized training protocol raises the trainability level, in this case a personalized training is obtained by evaluating for each participant an individual alpha band (IAB), following the methodology by Escolano et al., (2013) and Kober et al. (2015). The peak in this band was identified as the individual alpha frequency (IAF) used to obtain the UA value (IAF+2Hz). There are some studies where the IAB was evaluated in two conditions, pre-training baseline and post-training baseline, to see if the NFT had some effect over these values (Kober et al., 2015; Miguel & Bucho, 2018). However, in the presented work the post-training baseline was recorder for future purposes, but it wasn't considered.

The values of IAF found here range from 8 Hz to 11.8 Hz, they are near the standard value of 10 Hz.

4.5 Training Effect on RAUA Band

To assess the effectiveness of the training, among the three intra-session metrics evaluated, IntraS was used to identify non-learners when it displayed a negative value in at least three sessions. However, this classification wasn't conclusive and was supplemented by considering the slope of the percent time above the threshold, which will be discussed later. From this first feature, five participants were identified as possible non-learners: NFT4, NFT11, NFT12, SHAM1 and SHAM5.

Choosing to utilize intra-session metrics instead of inter-session ones is based on past studies indicating a more pronounced effect during training, particularly when the number of sessions is small, as in this case (Hanslmayr et al., 2005; Bucho et al., 2018).

From the results showed in Figure 3.15 it is seen an increasing value of RAUA across the sessions for the learners in NFT group, although there is a slight decrease at the end of each session and it is clearly seen in the average value reported in Figure 3.13, maybe caused by tiredness or fatigue after the whole training, this is more significant in the last session. The control group had less variations of RAUA across the sessions, as it is seen in Figure 3.14, although the expectations were that this groups wouldn't have been able to learn the self-regulation, most of the SHAM participants was classified as a learner and only SHAM1 and SHAM5 was non-learners. It is possible that for this group different learning metrics should have been considered, since the effect of the training didn't have the wanted results in the cognitive tests and the outcomes may not be related to NFT.

This feature will be combined with the features about time in following sections to obtain the final identification of non-learners as those who was recognized as non-learners in at least two features, always keeping in mind also the third one.

4.6 Training Effect on Other Frequency Bands

The training effect when trying to increase or decrease the RAUA band can influence the frequency band close to that, which may be modulated unintentionally by the participant, as was proved in previous studies (Esteves et al., 2021; Hanslmayr et al., 2005; Nan et al., 2012).

Analysing the results of the trend of these frequencies in this study, they showed two different behaviours. The RA theta tended to decrease concurrently with the increase in RAUA, which is the expected outcome considering studies conducted in the past, like those from Esteves et al. (2021) and Bucho et al. (2018). On the other hand, the LA and IAB bands exhibited a similar pattern to that of RAUA, mirroring its trend: as RAUA increased, the values of these other bands also showed higher values.

Over the years, studies have also been conducted where modulation was achieved only in the RAUA without impacting other bands, such as the one by Zoefel et al. (2011). A final consensus remains to be achieved.

4.7 Time Rewards Effect

The obtained results regarding the percent time above the threshold are discussed in the next two sections, discussing separately the modulation within session and across sessions.

4.7.1 Percent Time Intra-session

Unlike the approach used for RAUA, for the time above threshold, the decision was made to use individual epochs rather than the five sets, this was done to offer a more detailed insight into its development during a training session. Then the same feature is studied, corresponding to the slope of the line approximating this trend, the same approach was used and the participants with more than two negative slope values were identified as non-learners. The expected outcome is that the so-called learners from RAUA analysis should also have an increasing time above the threshold, the results obtained in the NFT group align with this hypothesis, as the three previously identified subjects (NFT4, NFT11 and NFT12) also exhibit three or more negative values in this feature. One additional subject has been recognized, NFT9, and upon rechecking their RAUA values, it's apparent that although the slope is positive, the values are very small. This indicates that rather than increasing, the values remained stable, and it could be considered a non-learner, this classification will be confirmed when checking the percent time inter-session. On the contrary, in the SHAM group it wasn't present the same pattern, indeed only two subject was identified as non-learner with this method, SHAM4 and SHAM10, and they don't correspond to those recognized with RAUA,

However, it can be noticed that the values obtained in the control group are generally lower than the ones in the real NFT group, except for some exceptions. It is possible that the slight positive slopes are due to participants in this group not being able to understand how to control the feedback and becoming distracted from the task, relaxing, and closing their eyes, which leads to a natural increase in alpha waves.

4.7.2 Percent Time Inter-session

To analyse this feature, it's important to note that the thresholds used in different sessions vary based on the subject's performance in the previous session. It begins at the 60th percentile threshold and increases by 5 when the percentage of time exceeded 60% or decreases by 5 when it was below 40%. In Figure 3.21 and Figure 3.22 these variations were indicated with a green circle when the threshold was decreased and a red circle when it was increased, compared to the previous session. This calculation choice was made to represent the feedback displayed to the NFT group, and accordingly, the same approach was followed for the SHAM group. In these two figures it is clearly seen that the NFT group managed to increase the threshold more, indeed four participants had an increment, whereas in the SHAM group only one participant was able to do it (SHAM8) and seven of them needed easier tasks.

Keeping that in mind, it is not surprising that there are a higher number of negative slope values in the NFT group than in the control one, each case of negative slope should be analysed separately. For example, NFT5 and NFT7 have negative slope values, but they have also one and two increment in the threshold, respectively, and since they were not identified as non-learners for the previous features, they are considered learners. NFT6 and NFT8 also have negative slopes and no variation in the threshold, despite this they were not classified as non-learners because their behaviour was positive in the other features. Regarding the NFT9 instead, it's observed that it has a negative slope despite the decrease in threshold. Given its minimal increases in RAUA and being flagged as a potential non-learner based on the intra-session percentage of time, this subject is ultimately classified as non-learner. Looking at the control group, two subjects were highlighted, SHAM1 and SHAM5, both already identified with the RAUA. The first hadn't change the threshold across the session, while the latter had a lower threshold in the third and fourth sessions, and still, they had negative slope values, combining these results with the first feature, they both are classified as non-learners. It can be argued that the calculation should have been made considering always the same threshold, although in this way the information relative to the perception of the participants would have been lost.

Another important factor that should be considered is that this kind of training shows long-term effects after a great number of sessions, and four days might not be enough to see a significant difference from the first to the last session.

4.8 Classification with Machine Learning

The use of unsupervised machine learning methods in this study was a trial for future investigations. Due to the limited dataset of subjects, using each individual as input for the classifier was impractical and wouldn't have yielded consistent results. Hence, the decision was made to employ each session as a separate input to train the networks with a larger volume of data, which led to an inherent challenge in choosing suitable features. While considering the variation in the percentage of time across sessions and the total percentage of time above threshold in each session, the classification resulted in random outcomes where the machine couldn't accurately interpret the data. Several combinations of features were tested, and the findings showed that the best classification with the limited amount of data is achieved using only the first two features. The third feature would be interesting to consider in cases where each subject is an input, incorporating the data from each session.,

The K-means and the SOM network were the chosen machine learning techniques, in the first the binary classification was defined a priori by choosing the number of cluster equal to 2, in the second approach, as using only two neurons to achieve binary classification is not recommended, a 2x2 topology was utilized, resulting in the division into 4 clusters that can be grouped into two main ones. The association between the class and the definitions 'learner' or 'non-learner' was done manually by analysing which subjects belonged to the two obtained classes. The same criterion already used was applied, if more than two sessions belonged to the non-learner class, the subject was assigned to that category.

The results are encouraging since both methods identified as non-learners the same subjects, they are the same four already found with the standard approach (NFT4, NFT9, NFT11 and NFT12) and in addition to them, also the NFT3. Its values were checked again, and this participant had decreasing slope values across sessions for both RAUA and time above the threshold, in particular this last feature had negative values in the third and fourth sessions which indicate that it isn’t really learning the self-regulation. The machine was able to recognize this pattern better than a human eye and associate this behaviour to the non-learner class in three sessions out of four.

These classifiers still have some limits, in literature there are few studies with large enough database to train consistently a network, in addition to that, the learning metrics to use are not standardized yet, which means that there are few cases of labelled training set to be used with a supervised machine learning technique.

4.9 Comparison between Visual Feedback and SHAM

All the participants were aware from the beginning of the existence of the control group, even if none of them knew its real belonging, they might remain uncertain about their ability to influence the game since determining if they are effectively modulating brain activity is challenging. It was proven in a study by Sorger et al. (2019) that in continuous real-time NF the individuals belonging to the control group are more likely to understand it than when using feedback delayed or intermittent, which may lead to lose interest in the game or a feeling of frustration or demotivation, for this reason it is important to use a method that the participant cannot understand on its own. In this case, it was done by showing them a real and reliable feedback, recorded during another subject's session, so that they were not actually able to control the game but continued to make an effort to do it, which could explain their capacity in learning the self-regulation. Although another possible explanation is that not finding the right strategy may have led them to be more composed, which would increase the amplitude of RAUA unintentionally.

There are other possible approaches to use the Sham group, for example they could receive the NF targeting other frequency bands or brain locations, as well as be provided with different scenarios. It would be also possible to give them mental strategies to use during the training, to see if with them they would learn to self-regulate and enhance their activity, even without the visual feedback.

5. CONCLUSION

This thesis introduced and executed an NFT protocol to assess the impact of incorporating reinforcement levels in two distinct groups: the NFT group and the SHAM group. All participants were healthy individuals who had no prior experience with NFT sessions. The study centred on evaluating the effectiveness regarding both the amplitude of UA and the time spent above the threshold. The EEG signal was acquired and pre-processed using the OpenViBE programme, and the feedback parameter was sent to Unity, where it was displayed and given to the participant.

The participant's performance in accordance with the UA's relative amplitude controlled the game's two scenarios, which were a tropical forest and a diving deep in the ocean. Three values were set: a threshold, a minimum, and a maximum. A dimmer was used if the participant's value fell between the minimum and threshold values; otherwise, the scene would zoom in or out without the use of a dimmer, based on the amplitude of the RAUA with higher amplitude corresponding to more zoom. The second level of reinforcement regarding the time above the threshold consisted in giving rewards (animals appearing on the screen) every 2.5 seconds spent above the threshold, so that the participant was conscious of its performance. The SHAM group participants were shown feedback relative to another participant’s recording in another session, so they didn’t have any real feedback about their brain activity.

The results showed that the NFT group had individuals who were able to modulate and increase the RAUA in the electrode Cz and the time above the threshold, whereas a similar but blunted pattern could be observed in the SHAM group, even though real self-regulation or brain activity did not occur. The study sought to explore further the criteria used for classifying participants into learners and non-learners, namely using: (i) the slope of RAUA within session (across sets); (ii) the slope of percent time within session (across epochs); (iii) the slope of percent time across session. It was also verified that this training had a similar impact on the nearby frequency bands, the LA and the IAB, whereas it had an opposite effect in the theta bands, since an increase in RAUA led to a decrease in the relative amplitude of theta band. In addition, topographic maps were able to demonstrate the effects, which were observed in different brain regions. The effect of the training was assessed through the cognitive tests and the expected outcomes were achieved in the NFT group, with an increased performance in working memory. Finally, the extracted features were used to test the possibility to automatically identify learners using two machine learning techniques: K-means and SOM. These methods identified the same participants as non-learners; however, the dataset is too small to obtain consistent results with these techniques. These should be regarded as an innovative proof of concept, whilst further studies and investigations will need to be conducted on larger datasets.

This project holds numerous potential future developments, for instance, having a larger dataset would be intriguing for generalizing information. There's the possibility of computing time above the threshold differently, employing a consistent threshold across all sessions to observe trends. Additionally, further exploration into the field of classification using machine learning and potentially delving into deep learning methods could be beneficial.

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ATTACHMENTS

Annex A – HADS

Table 12 - HADS questionnaire values for each participant obtained in the first session.

	HADS Anxiety	HADS Depression
NFT2	14	2
NFT3	17	7
NFT4	3	3
NFT5	8	0
NFT6	6	6
NFT7	9	1
NFT8	5	6
NFT9	18	2
NFT10	15	11
NFT11	9	0
NFT12	4	4
SHAM1	10	4
SHAM2	12	6
SHAM3	10	7
SHAM4	11	3
SHAM5	11	5
SHAM6	12	7
SHAM7	11	3
SHAM8	12	1
SHAM9	6	3
SHAM10	11	8
SHAM11	12	2

Independent Samples T-Test between groups

	W	p
HADS A	47.500	0.409
HADS D	47.500	0.408

Note. Mann-Whitney U test.

Annex B – STAI Questionnaires

Table 13 - STAI questionnaires values for each participant, STAI Y-2 (trait) from the first session, STAI Y-1 (state) one value per session.

	Y-2	Y-1 ses 1	Y-1 ses 2	Y-1 ses 3	Y-1 ses 4
NFT2	50	34	30	28	30
NFT3	71	65	42	45	41
NFT4	26	31	22	20	20
NFT5	46	32	35	43	35
NFT6	43	40	42	39	40
NFT7	41	35	43	38	37
NFT8	37	41	38	40	36
NFT9	62	67	66	64	73
NFT10	51	59	41	46	39
NFT11	38	35	24	21	21
NFT12	35	33	32	33	36
SHAM1	38	48	36	31	33
SHAM2	55	26	25	27	23
SHAM3	50	31	38	32	30
SHAM4	41	32	25	21	26
SHAM5	64	53	47	51	43
SHAM6	28	34	36	39	49
SHAM7	56	30	32	32	31
SHAM8	49	39	35	31	36
SHAM9	41	31	35	34	34
SHAM10	46	39	34	38	36
SHAM11	49	59	35	37	41

Independent Samples T-Test STAI Y-2

	W	p
STAI Y-2	51.500	0.576

Note. Mann-Whitney U test.

Annex C – Individual Alpha Band

Table 14 - Values acquired during the first session's calibration phase include the Individual Alpha Frequency (IAF), the Lower Transition Frequency (LTF, IAF minus 2 Hz), the High Transition Frequency (HTF, IAF plus 2 Hz), and the Upper Alpha (UA) frequency band, representing the interval between IAF and HTF.

	LTF	IAF	HTF	UA
NFT2	8.1959	10.1959	12.1959	[10.1959: 12.1959]
NFT3	9.3954	11.3954	13.3954	[11.3954: 13.3954]
NFT4	6.7965	8.7965	10.7965	[8.7965: 10.7965]
NFT5	8.1959	10.1959	12.1959	[10.1959: 12.1959]
NFT6	6.3966	8.3966	10.3966	[8.3966: 10.3966]
NFT7	6.9964	8.9964	10.9964	[8.9964: 10.9964]
NFT8	9.7953	11.7953	13.7953	[11.7953: 13.7953]
NFT9	5.9968	7.9968	9.9968	[7.9968: 9.9968]
NFT10	7.7961	9.7961	11.7961	[9.7961: 11.7961]
NFT11	6.5966	8.5966	10.5966	[8.5966: 10.5966]
NFT12	8.3958	10.3958	12.3958	[10.3958: 12.3958]
SHAM1	9.7953	11.7953	13.7953	[11.7953: 13.7953]
SHAM2	8.1959	10.1959	12.1959	[10.1959: 12.1959]
SHAM3	7.996	9.996	11.996	[9.996: 11.996]
SHAM4	8.7957	10.7957	12.7957	[10.7957: 12.7957]
SHAM5	8.1959	10.1959	12.1959	[10.1959: 12.1959]
SHAM6	8.3958	10.3958	12.3958	[10.3958: 12.3958]
SHAM7	9.5954	11.5954	13.5954	[11.5954: 13.5954]
SHAM8	6.7965	8.7965	10.7965	[8.7965: 10.7965]
SHAM9	6.9964	8.9964	10.9964	[8.9964: 10.9964]
SHAM10	7.1963	9.1963	11.1963	[9.1963: 11.1963]
SHAM11	8.1959	10.1959	12.1959	[10.1959: 12.1959]

Annex D – Reward Threshold

Table 15 - Values of RAUA minimum, maximum and threshold per session for each participant in the NFT group. In the last column is presented the value of percent time spent above threshold per session.

Participant	Session	Min	Threshold	Max	Percent time
NFT2	1	0.8604	1.5935	2.8712	20%
	2		1.5435		51.17%
	3		1.5435		66.83%
	4		1.5935		73.89%
NFT3	1	0.7182	1.4932	2.4599	19.03%
	2		1.4346		40%
	3		1.4346		40%
	4		1.4346		47%
NFT4	1	0.5995	1.0023	1.7159	42.31%
	2		1.0023		41.51%
	3		1.0023		51.73%
	4		1.0023		54.87%
NFT5	1	0.7467	1.5073	3.0107	51.13%
	2		1.5073		39.37%
	3		1.4424		61.25%
	4		1.5073		36.78%
NFT6	1	0.8321	1.5673	3.2446	50.82%
	2		1.5673		60%
	3		1.5673		55.43%
	4		1.5673		50.06%
NFT7	1	0.9133	1.8451	3.8917	67.61%
	2		1.9025		63.47%
	3		1.9716		54.2%
	4		1.9025		56.59%
NFT8	1	0.6216	1.1562	2.1112	52.92%
	2		1.1562		49.89%
	3		1.1562		49.76%
	4		1.1562		44.55%
NFT9	1	0.4705	1.321	2.522	39.09%
	2		1.2642		51.01%
	3		1.2642		53.47%
	4		1.2642		33.29%
NFT10	1	0.8841	1.5198	2.8492	27.82%
	2		1.4821		40.93%
	3		1.4821		48.75%
	4		1.4821		60.8%
NFT11	1	0.5431	1.1023	2.1165	38.21%
	2		1.0788		47.43%
	3		1.0788		48.49%
	4		1.0788		46.64%
NFT12	1	0.6002	1.024	1.7982	58.97%
	2		1.024		50.74%
	3		1.024		70.84%
	4		1.0566		64.54%

Friedman Test on IntraS from NFT group's learners

Factor	Chi-Squared	df	p	Kendall's W
RM Factor 1	16.000	7	0.025	0.571

Friedman Test on slope of percent time from NFT group's learners

Factor	Chi-Squared	df	p	Kendall's W
RM Factor 1	11.786	6	0.067	0.491

Table 16 - Values of RAUA minimum, maximum and threshold per session for each participant in the SHAM group. In the last column is presented the value of percent time spent above threshold per session.

Participant	Session	Min	Threshold	Max	Percent time
SHAM1	1	0.8334	1.2215	2.6701	50.33%
	2		1.2215		41.95%
	3		1.2215		45.87%
	4		1.2215		34.36%
SHAM2	1	1.0436	1.9179	3.5611	14.64%
	2		1.8656		25.22%
	3		1.8225		18.96%
	4		1.7702		26.95%
SHAM3	1	0.6355	1.1861	2.3293	40.68%
	2		1.1861		45.7%
	3		1.1861		50.31%
	4		1.1861		50.7%
SHAM4	1	0.581	1.0545	2.161	26.22%
	2		1.0257		54.58%
	3		1.0257		56.71%
	4		1.0257		49.45%
SHAM5	1	0.7241	1.1067	2.0099	40%
	2		1.1067		32.4%
	3		1.0863		49.99%
	4		1.0863		31.5%
SHAM6	1	0.9704	1.7394	3.4647	36.33%
	2		1.6875		39.2%
	3		1.6457		42.77%
	4		1.6457		61.7%
SHAM7	1	0.7569	1.4603	2.5417	19.35%
	2		1.3929		47.73%
	3		1.3929		35.23%
	4		1.3447		49.68%
SHAM8	1	0.5883	1.0089	1.8788	41.71%
	2		1.0089		58%
	3		1.0089		67.98%
	4		1.0403		54.46%
SHAM9	1	0.9905	1.7922	3.3419	20.28%
	2		1.7348		53.02%
	3		1.7348		53.02%
	4		1.7348		51.17%
SHAM10	1	0.6108	1.0839	1.9385	41.12%
	2		1.0839		48.82%
	3		1.0839		-
	4		1.0839		57.47%
SHAM11	1	0.7089	1.4556	2.6901	52.76%
	2		1.4556		39.13%
	3		1.4082		42.76%
	4		1.4082		54.96%