Evaluation and algorithmic adaptation of brain state control through audio entrainment

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A dissertation submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in fulfilment of the requirements for the degree of Master of Science in Engineering.

Johannesburg, December 2022

Declaration

I declare that this dissertation is my own, unaided work, except where otherwise acknowledged. It is being submitted for the degree of Master of Science in Engineering to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination to any other university.

Signed 13$^{\mathrm{th}}$ December, 2023

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Abstract

This dissertation presents the design and evaluation of a system that can alter the dominant brain state of participants through audio entrainment. The ‘rch broadly aimed to identify the possible improvements of a dynamic entrainment stimulus when compared to a set entrainment stimulus. The dynamic entrainment stimulus was controlled by a Q-Learning (QL) model. The experiment sought to build on previous research by implementing existing entrainment methods in Virtual Reality and dynamically optimising the entrainment stimulus. The neurological effects of the stimuli were evaluated by analysing electroencephalogram measurements. It was found that a set 24 Hz entrainment stimulus increased the power of Beta band brain waves relative to a control condition. Further, contrary to existing research, it was found that the entrainment stimulus did not have a notable effect on brainwave connectivity at the entrainment frequency. The study subsequently evaluated if the QL agent could learn to optimise the entrainment stimulus. The agent was allowed to switch between an 18 and 24 Hz entrainment stimulus and succeeded in learning an optimised policy. The QL driven stimulus yielded results that generally exhibited the same characteristics as the set entrainment stimulus when using power and connectivity analysis methods. Furthermore, the power analysis indicated that the QL driven stimulus was able to affect a broader range of frequencies within the targeted band. The QL driven stimulus, additionally, resulted in higher meta-analysis metric values in some aspects. These factors indicate that it was able to have a more consistent impact on targeted brain waves. Lastly, results from participants whose stimulus was controlled by a QL driven stimulus using optimal actions indicated that the optimised actions created a more sustained increase in Beta band activity when compared to any other results, indicating the impact of the optimised policy learned.

Acknowledgements

I would like to thank the project supervisors, Dr Adam Pantanowitz and Professor David Rubin, for their assistance and guidance throughout this study. I would further like to thank all the study participants for their time, excitement, and patience during the study. Without you this research would not be possible! I want to extend a massive thank you to the NeuRL unit at the University without whom this research would not have left the ideation phase! Thank you for the use of the electroencephalogram (EEG) machine, for the constant support and thought-provoking questions. In particular thank you to Professor Kate Cockcroft and Dr Sahba Besharati. Lastly, thank you to Heinrich Zentgraf and Sarah Higgins for your assistance and support during the early piloting phase of the project! I am incredibly grateful for the energy and positivity you both brought when the path looked very murky at times.

Contents

List of Figures

List of Tables

List of Algorithms

Nomenclature

AWS Amazon Web Services.

BB Binaural Beat.

BCI brain computer interface.

CCA Canonical Correlation Analysis.

CSV comma severated value.

C-MAB Contextual Multi-Armed Bandits.

EEG electroencephalogram.

DFT discrete Fourier transform.

EMD Empirical Mode Decomposition.

EMD Empirical Mode Decomposition.

EMG Electromyograph.

EOG electrooculography.

ERP event related potential.

ERS event related synchronisation.

FT Fourier transform.

FFT fast Fourier transform.

HDF5 Hierarchical Data Format version 5.

ICA independent component analysis.

MAB Multi-Armed Bandits.

MEG magnetoencephalography.

ML Machine Learning.

MR mixed reality.

MRI magnetic resonance imaging.

NIRS near-infrared spectroscopy.

NN Neural Network.

PLV phase locking value.

QL Q-Learning.

SMR sensory motor rhythm.

SNR signal-to-noise ratio.

STFT Short-time Fourier transform.

RL reinforcement learning.

VR virtual reality.

Chapter 1

Introduction

As we build an increased understanding of the brain, we can begin to harness an increased knowledge base to augment our daily lives. This can take shape in the development of brain computer interface (BCI) devices that augment how we interface with technology and the world around us.

BCI devices currently exist both in academia and industry [1, 2]. These systems generally fit into one of two categories:

- Systems in which devices interface with the brain, but no feedback from the brain exists.
- Systems where the brain interfaces directly with a system, but the system has no means to feedback to the brain.

If we are to build upon these devices, we should aim to develop a system that can do both simultaneously. That is: a system that will interface with the brain directly, reading its state, while employing a feedback mechanism to influence neural activity. Ideally, the resultant brain state will have potential real-world benefits and be able to augment how well a task is performed. This might be achieved through priming neural activity before executing a task or using neural activity to explain reduced proficiency in tasks. Research has been conducted into how brain state control can be achieved and thus how priming might be implemented.

Existing research on BCI devices and brain state control methods has largely focused on how brain state control can be achieved using a set stimulus [3, 4, 5]. The research has indicated positive results when using Binaural Beat (BB) entrainment stimuli, implying that systems which can interface with the brain and affect its state are functional [3, 4, 5]. Binaural beat entrainment is essentially an audio stimulus that utilises two separate audio signals which differ by a set frequency of a targeted brain wave [3, 4, 5]. Additionally, research has shown how brain state control might be leveraged to improve memory tasks, indicating the potential real-world applications of brain state control and thus the potential value of brain state control research [6, 7, 8, 9]. No research has been conducted to assess how a brain state control stimulus might be dynamically optimised to better impact a targeted brain wave. Research into a dynamically optimised stimulus would aim to close the loop though providing feedback to the brain and, therefore, build on both existing research on brain state control and BCI devices.

Augmenting existing control methods would aim to optimise the speed at which brain state changes can be stimulated and allow these changes to be directed. These improvements would allow targeted brain states to be reached efficiently and allow leveraging the stimulus modality in real-world tasks. Given that improvement in real-world tasks has been shown when leveraging stimulated brain states, the latter provides a good basis for the value that this research might achieve if it is successful. [6, 7, 8, 9]

A dynamically optimised stimulus would build on existing research, attempting to improve brain state control methods. The process of building on existing knowledge would start by evaluating existing stimulus modalities and identifying where they might be optimised through a dynamic algorithm. Subsequently, the effect of a researched stimulus should be evaluated against the dynamic stimulus and a control stimulus while using the same experimental setup. This allows the effect of the dynamic stimulus to be objectively compared.

The research aims to evaluate if traditional entrainment stimuli can be optimised. Given that entrainment has been used to assist in memory tasks, optimising its effects may improve the assistance provided and lead to real-world applications for the stimulus method [6, 7, 8, 9].

Given the broad potential benefits of the study, its outcomes can be concisely listed. The research outcomes and goals are to:

- Evaluate findings from existing entrainment research when using an experimental design that includes a separate control recording.
- Establish the feasibility of a dynamic entrainment stimulus that can have an

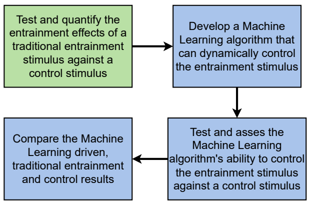
improved effect on targeted brain waves when compared to a traditional set frequency entrainment stimulus.

This study forms its research question by building on previous research in varying fields of neuroscience and engineering. The study focuses specifically on building from existing research in BB entrainment and aims to build on both the entrainment stimulus and electroencephalogram (EEG) evaluation of its effects. The research question of the study can be formulated to reflect the objectives of the study. The research objectives can be distilled into one research question, namely:

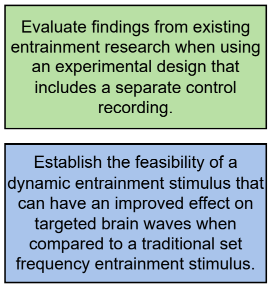
- What measured neural differences result from a dynamic and set entrainment stimulus targeting Beta brain waves?

Given the iterative nature of the research goals and question proposed, the study needs to be completed in phases. These phases relate to different research outcomes at different points of the project and are carried out after one another. An overview of the phases that make up the research is outlined in Figure 1.1. Figure 1.1a provides the workflow of the phases, which have been coloured based on which research outcome is primarily addressed at different points. Figure 1.1b outlines the key for the colours used in Figure 1.1a and which research outcomes they relate to.

This dissertation unpacks the development and testing of a system that uses a dynamic stimulus to change the brain state of participants. It presents results when this system was tested against a previously researched entrainment stimulus as well as a control stimulus. The research focuses on methods which can alter the dominant brain wave frequency of participants and whether traditional methods of achieving this may be improved. Chapters 2 and 3 outline an overview and evaluation of existing research related to this study, while Chapter 4 outlines the study design and considerations. Following these, Chapter 5 outlines the results of the study and discusses their implications. Lastly, Chapter 6 provides a conclusion of the study conducted.



(a) A flow chart of the workflow involved to address the research objectives.



(b) A key for the research objective addressed at different points of the workflow.

Figure 1.1: A workflow of the steps involved to address the research objectives, and a key indicating which research question is most investigated at different steps of the project.

Chapter 2

Background

2.1 Introduction

A background of existing work is evaluated to contextualise this study within the existing body of knowledge. Existing work in the fields of brain wave measurement, entrainment, Machine Learning (ML), and virtual reality (VR) are reviewed to provide a representation of relevant existing work that grounds the present study.

The study aims to evaluate existing brain state targeting methods in VR as well as potential optimisations of the methods. Background knowledge in brain wave measurement is required to sketch a summary of accepted neurological data recording methods and knowledge. Neurological recording is used to quantify any changes in brain state during the experiment. Background information on entrainment is presented, as it is a researched method of brain state targeting that is a useful reference for the intervention in the study. Similarly, contextual research in VR technology is outlined for its potential application to the intervention used. Lastly, ML algorithms are outlined as they form a good reference point for a dynamic feedback mechanism. This contextualises how the feedback algorithm is chosen and developed to control the entrainment stimulus.

This Chapter provides a narrative unpacking of the required background to support the research goals and question. The background is used to provide a solid basis for the research presented and aims to outline various concepts required to critically evaluate existing research.

2.2 Brain Wave Measurement

Brain waves/neural oscillations are electrical voltages measured as a result of neural activity [1, 10]. These voltages can be recorded from the surface of the scalp using an electroencephalogram (EEG) and are constantly fluctuating during the day [10]. Brain waves fluctuate based on the changes humans go through in a 24-hour cycle, also known as circadian rhythms [11, 12, 13]. Circadian rhythms respond especially notably to light and dark in the environment [11, 12, 13]. Furthermore, brain waves change due to concentration levels and what tasks humans are engaged with [14, 15, 16, 17, 18, 19]. They have additionally been linked with emotional states and level of alertness [20, 21, 22].

Measured brain waves exist due to local field potentials forming as a result of synchronous electrochemical signalling from communicating neurons [10, 23]. They indicate synchronisation of the underlying neural communication near an EEG electrode, and this synchronising can either be enabling or blocking to various neural circuits [1, 23, 24]. EEG measurements are a combination of different brain waves, at different levels of prominence [1, 23, 24]. Analysis techniques in the spectral domain, evaluating the frequency properties of data, have been critical in understanding EEG measurements [1, 10, 24, 25].

Spectral analysis carried out on brain wave data has resulted in interesting correlations that have helped describe their relation to neurological activity [1, 3, 10, 24]. Probably the most notable finding of the spectral analysis carried out on EEG data is the existence of distinct frequency bands in brain waves [1, 3, 10, 24]. These frequency bands have commonly been attributed to different broad categories of neural functioning and are in flux throughout the day [1, 3, 10, 24]. A description of the bands can be seen in Table 2.1; note that the frequency definition of these bands can differ slightly in literature, as they are not standardised [1, 3, 10, 24].

EEG cap data can provide a non-invasive window into the dominant characteristics of brain waves [3, 10, 21]. Some drawbacks of EEG cap data lies in its spatial challenges [21, 26]. These include the fact that it will pick up signals from several brain structures close to it and that it can only accurately measure signals from cortical structures of the brain [21, 26]. As a result, accurate measurements of neural activity from structures within the cerebellum, one of the most important structures within the brain, might not be achieved using an EEG cap [27]. Recent research has indicated that EEG measurements may be able to pick up cerebellar signalling,

Table 2.1: A high-level summary of brain waves and their broad characteristics, adapted from [1, 3, 10, 24].

Brain wave	Frequency (Hz)	General characteristics/most prominent brain state
Delta	0.5 - four	Deep sleep, meditation, often associated with a loss of awareness of one's body.
Theta	four - eight	Artistic expression, movement planning, meditation, working memory, encoding, and recalling learned tasks.
Alpha	eight - 13	Wakeful state, REM sleep, creative thought, meditation, and memory encoding. Prominent during tasks requiring a high cognitive load.
Beta	13 - 32	Normal waking state, concentration, alertness, anxious thinking, sensorimotor processing, emotional control, tasks requiring a high cognitive load.
Gamma	25 - 140	Vision/visual consciousness, high mental activity, problem-solving, processing high sensory input.

however with various guidelines regarding experimental methodology and data processing [27]. Further, data recorded from an EEG cap has both non-stationary and stochastic properties that need to be accounted for when analysing and forming results [21, 28].

The standardised 10 - 20 system is an accepted configuration for electrode placement that is widely adopted in EEG studies [21, 29]. The "10 - 20" name is derived from the positioning of electrodes on the scalp relative to key anatomical landmarks [29]. Variations may exist in the 10 - 20 system to tailor EEG measurements to a specific application and based on the number of electrodes used [29]. Electrodes are named based on the cortical structures or region of the brain that they overlay [29]. The name is a combination of a set of letters and a number; excepting electrodes that lie over the corpus callosum / mid-line of the brain, which have a z in place of a number [29]. The letters assigned define the region overlaid, being the first letter of temporal, frontal, occipital, parietal, and auricular [29]. Multiple letters may be used when an electrode is found bordering two regions, this convention is employed in the extended 10 - 20 system [29, 30]. The number assigned to an electrode defines which hemisphere it lies on, odd numbered electrodes exist on the left side of the head, while even numbered electrodes occur on the right side of the head [29, 30].

Figure 2.1 outlines a possible electrode placement when using the extended 10 - 20 EEG system, and a non-invasive EEG cap with 64 electrodes [29, 31]. The figure was produced using EEGLab [29, 31]. The ground electrode has been omitted in Figure 2.1, this would commonly be placed along the mid-line and be a "z electrode" [21, 29].

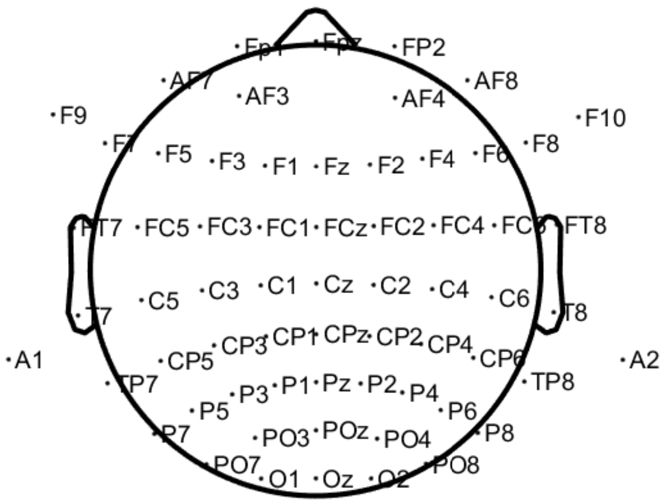


Figure 2.1: Channel locations of EEG electrodes used.

EEG electrodes reflect extracellular potentials of underlying neural structures [1, 23, 24, 29]. The field potentials are converted to voltages using active, often wet, or passive EEG electrodes [32]. EEG voltages recorded from active or passive electrodes are amplified due to their low amplitudes, this is key to measuring usable EEG data [32]. Wet electrodes use a gel or saline solution to reduce skin-electrode-impedance, this has been shown to increase the signal-to-noise ratio (SNR) of recorded signals while leading to a faster response time to changes in neural signalling [32, 33]. Active electrodes, additionally, amplify recorded signals before they are transmitted which provides an even higher SNR based on existing research [33]. Together, these factors make active wet electrodes a good choice for EEG research. It should be noted that the gel used in wet electrodes may become dehydrated during prolonged use which needs to be addressed through re-applying gel and interrupting recording, which is a drawback to the electrode type [32]. Wet electrodes, further, have a long setup time required to gel all electrodes [32].

A further drawback of EEG electrodes stems from how the recording method captures neural signalling [21, 28, 34]. Since EEG electrodes use field potentials and high amplification to record neural data, the method is susceptible to several artefacts [21, 28, 34]. These include movement artefacts, eye blinks, eye movement, cardiac artefacts if the electrode is placed near a superficial blood vessel, and sensor popping which occurs when the impedance of an electrode suddenly changes [21, 28, 34]. The artefacts identified have an increased amplitude when compared to valid EEG data [21, 28, 34]. This is a useful characteristic when cleaning recorded EEG data [21, 28, 34].

2.3 Analysing EEG data

2.3.1 Data cleaning

Algorithms and cleaning techniques have been researched to identify and remove artefacts from recorded EEG; however, these artefacts can lead to data being unusable, which is an inherent risk with EEG [21, 34]. Cleaning methods have been implemented using ML, transforms such as Empirical Mode Decomposition (EMD), adaptive filtering, statistical properties of the noise, and morphological component analysis [34, 35, 36, 37, 38, 39, 40, 41, 42]. Various methods of artefact removal can be used without manual input such as algorithms using ML, EMD, and statistical properties of EEG signals, however, methods such as independent component analysis (ICA) require manual input [34, 35, 36, 37, 38, 39, 40, 41, 42]. Additionally, some algorithms cannot realistically run in real time when 64 channels are used in EEG recording due to their computational requirements, even if they can be automated [35, 40]. Therefore, careful consideration of the application and feedback required in EEG systems is required so that artefact cleaning is appropriately conducted on recorded data.

2.3.2 ERP's

Within EEG measurement, the event related potential (ERP) needs to be outlined. An ERP is a voltage change generated by neural tissue in response to a stimulus [43, 44, 45]. The voltage changes are temporally aligned with the beginning of a stimulus or motor action [43, 44, 45]. ERP's essentially measure the brain's measured response to a stimulus [43, 44, 45]. This is achieved through an analysis of EEG data and allows the quantification of neurological changes as a result of a stimulus [43, 44, 45]. It is believed that ERP's reflect the summed postsynaptic potentials of synchronous signalling of underlying neural structures [43, 44, 45].

ERP's are averaged EEG signals which are recorded relative to a stimulus event. This creates an averaged waveform representing the brain's response to the stimulus. Therefore, several trials are required to reduce the SNR involved with ERP analysis. ERP's consist of different waveforms based on the polarity, amplitude, and latency of the waveform post stimulus. The different waveforms correspond with different cognitive functioning related to neural communication, and information processing. ERP analysis methods often look at the voltage peak values at specific latencies pre- and post-stimulus to observe the effect a stimulus had on the brain. This is particularly useful when a a series of stimuli are presented to a participant over the course of a recording [43, 44, 45].

2.3.3 Power Analysis

The spectral information of cleaned EEG data can be extracted using different power analysis methods [21, 25]. These methods apply different algorithms to measured data and have different underlying assumptions and benefits [21, 25]. Many popular power analysis methods are based on the Fourier transform (FT), the methods provide practical extensions to the FT, allowing its context specific application [21, 25]. Some commonly used methods branching off the FT are: the Short-time Fourier transform (STFT), fast Fourier transform (FFT), and discrete Fourier transform (DFT) [21, 25]. The equation defining the FT is given by Equation 2.1 [21, 25].

$$F[\omega] = \int_{\infty}^{-\infty} f(t) * e^{-j\omega t} dt \tag{2.1}$$

Where:

$F[\omega]$ is FT of the signal as a continuous function of the frequency, ω.

$f(t)$ is the time varying signal f.

The Fourier transform assumes stationarity of data, which is not the case in EEG data [21, 28, 25]. Assuming stationarity essentially entails inferring that the data's statistical properties do not vary with time [21, 25]. This does not hold true for EEG data, especially when a stimulus is attempting to change the frequency content of the brain, as is the case in entrainment research[21, 25]. If a FT is used to analyse non-stationary data, the heights of the peaks generated in the frequency domain can be smaller, leading to less conclusive results due to the analysis not picking up dynamics present in the data [21, 25]. Resultantly, methods including: the STFT, wavelet transform, and the Hilbert transform have been favoured when analysing EEG data [21].

The STFT, wavelet transform and the Hilbert transform use windowing methods [21, 25]. These allow temporal localisation of analysed EEG data [21, 25]. Thus, allowing the stationary assumption to hold up when the time window employed for localisation is made suitably small [21, 25]. An additional benefit to using power analysis methods which employ temporal localisation is their ability to measure changes in the frequency content of a signal over time[21, 25]. This is an important benefit for studies looking at quantifying the altered frequency content of the brain in response to a stimulus[21, 25]. Several windowing/taper function are available when using methods that apply temporal localisation [21, 25]. Windowing methods include: the Hann/Hanning, Hamming, Gaussuan, and Kaiser windows [21, 44, 46, 47, 48]. The Hann window is often preferred due to it tapering signals outside the window to zero, allowing better temporal localization and reducing artefacts [21, 44, 46, 47, 48]. Further, the Hann window has been used to effectively aid in feature generation in studies using ML models with EEG data [44, 48]. Due to this, methods discussed will use a Hann window to denote windowing functions in their mathematical definitions. Figure 2.2 provides an overview of a Hann window with a window length of 256 samples[21].

The STFT, wavelet transform, and Hilbert transform are appropriately applicable analysis methods for EEG data [21]. The methods are all able to generate distinct peaks in response to neural data recorded and, therefore, allow meaningful analysis of derived results [21]. However, only one analysis method is required. Several existing studies employ an STFT in their analysis of EEG data, and it has been noted that the Wavelet transform is often a suitable alternative for EEG analysis [49, 50, 51]. In particular, the STFT and wavelet transform have been noted as appropriate algorithms to use for real-time EEG feature generation for their computational time and accuracy in providing an accurate frequency characteristics of neural signalling [52, 53]. Further, research looking into the computational complexity of various Time-Frequency based power analysis algorithms has noted that of the three, the STFT has the lowest computational time required [54]. The

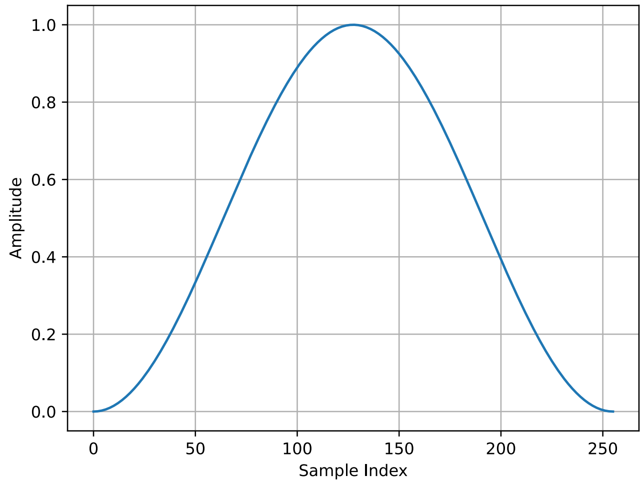


Figure 2.2: A Hann window of 256 samples.

time reduction was significant, leading to a large justification to use an STFT in the present research [54]. The present study will use an STFT; given that the research will require real-time analysis of EEG data, and the STFT has been shown as faster, and at least as good as the Wavelet transform [54]. The subsequent background given around the power analysis algorithm used will, therefore, only describe the STFT algorithm.

The STFT

The STFT is an extension of the FT that looks to address the two limitations of the FT that hinder its effectiveness when analysing EEG data [21, 25]. The improvements allow the analysis of the frequency characteristics of a non-stationary signal across time [21, 25]. At it's most basic, the STFT performs a FT on short segments of a signal after a windowing function was applied to the overall signal [21, 25]. Over the course of the STFT, the windowing function is applied to the signal at different points and produces a time - frequency representation of the signal [21, 25]. Equation 2.2 provides a mathematical overview of the STFT function [21, 25].

$$X[m, f] = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-ifn} \tag{2.2}$$

Where:

$X[m, f]$ is STFT of the signal at frequency f.

m is the location of the window along the time axis.

f is the frequency analysed / frequency bin.

$x[n]$ is the time domain signal at time n.

$w[n - m]$ is the Hann window shifted by n and of length m.

The STFT has two parameters not explicitly defined by Equation 2.2 that relate to the functioning of the method. These parameters further interact with the sampling rate used to provide contextual considerations. The sample window used in windowing functions affects the results derived from the STFT. The window size affects the frequency content that can be derived from the data. Shorter time windows obtain a higher temporal precision, and ensure a more stationary signal; while, using a longer window allows for better frequency resolution. The frequency range and precision is affected by the window as a set window size limits the number of complete waves a given window might contain of different frequencies, which in turn affects the frequencies that the STFT can analyse. Secondly, the overlap used in an STFT can affect the results derived. Temporal overlap has several benefits, improving time-frequency smoothness, removing data loss and improving temporal precision, however no hard guidelines have been provided to advise the best value to use [21].

2.3.4 Connectivity Analysis

Connectivity analysis methods are notable in the context of EEG analysis. Within connectivity analysis methods, different metrics exist, the metrics exist to perform graph analysis. This measures the degree to which a graph of interconnected nodes are linked. The connectedness is measured using different mathematical models and is useful in EEG research to measure the connectivity between different regions. Different connectivity metrics exist, however, the present study only requires one method of connectivity analysis [21].

The clustering coefficient is a coherence class of metric, representing the synchronicity of neural signalling. The value represents the proportion of adjacent nodes/electrodes that are interconnected and to what degree this is achieved. When an electrode is analysed using the clustering coefficient, the analysis essentially attempts to quantify the information flow from that electrode to groups of electrodes as a means of measuring synchronisation. However, to calculate the clustering coefficient of an electrode, a metric is needed that assesses the synchronisation of signalling between all electrode pairs. To this end, the phase locking value is selected, which can be calculated using the Hilbert transform. The clustering coefficient is calculated most effectively for a narrowband filtered signal. Equations 2.3 and 2.4 define the equations used to calculate the phase difference and phase locking values respectively. Further, Equations 2.5 to 2.7 provide the equations used to calculate the clustering coefficient [21, 55].

$$\phi_{hi}(t) = (\phi_h(t) - \phi_i(t))mod2\pi \tag{2.3}$$

$$PLV_{hi}(t) = |\frac{1}{N}\sum_{k=0}^{N} exp(i * \phi_{hi}(k * \Delta * t)| \tag{2.4}$$

Where:

$\phi_h(t)$ is the instantaneous phase of electrode h at time t, calculated using the Hilbert transform.

$\phi_{hi}(t)$ is the complex phase difference between electrodes h and i at time t.

$PLV_{hi}(t)$ is the Phase Locking Value between electrodes h and i at time t.

N is the number of discrete steps used for the PLV averaging.

$$cc_i(t) = \frac{2}{k_i(t)(k_i(t)-1)}\sum_{j}^{n}\sum_{h}^{n}(\widetilde{w_{ij}(t)} * \widetilde{w_{ih}(t)} * \widetilde{w_{hi}(t)})^{\frac{1}{3}} \tag{2.5}$$

$$k_i(t) = \sum_{j=1}^{n} |sgn(w_{ij}(t))| \tag{2.6}$$

$$\widetilde{w_{ij}(t)} = \frac{w_{ij}(t)}{\max_{i,j=1,....,n} w_{ij}(t)} \tag{2.7}$$

Where:

$cc_i(t)$ is the clustering coefficient of electrode i at time t.

$k_i(t)$ is the unweighted degree of electrode i at time t.

$w_{ij}(t)$ is the weight of the connection between electrode i and j. This is equal to PLV_{ij} at time t.

$\widetilde{w_{ij}(t)}$ is the normalised weight at time t.

2.4 Entrainment

2.4.1 History of Entrainment

Entrainment, as a concept, is rooted in physics and is defined as the frequency matching process in which a system's frequency matches that of another. The phenomenon can be seen due to a difference in energy between two systems. This causes energy to move through a transmitting medium between two systems and causes a negative feedback loop. This negative feedback loop causes the energy difference between the systems to minimise and thus their frequencies begin to converge. If two systems are linked within this paradigm and one has a set frequency, the other system's frequency will move towards that of the set value [56].

Entrainment in a neuroscience context is a phenomenon found as a result of advancements in EEG, magnetic resonance imaging (MRI), magnetoencephalography (MEG), and near-infrared spectroscopy (NIRS) technology [3, 4]. It is an effect where the brain will synchronise its internal dominant frequency to that of an external stimulus when the frequency of the stimulus exists within the frequency range of brain waves [3, 4, 5]. Furthermore, in changing the dominant brain wave frequency of a participant, the brain state that they are in can be altered [3, 4, 5]. This might temporarily influence the brain's functioning due to characteristics of different brain wave frequency bands [3, 56].

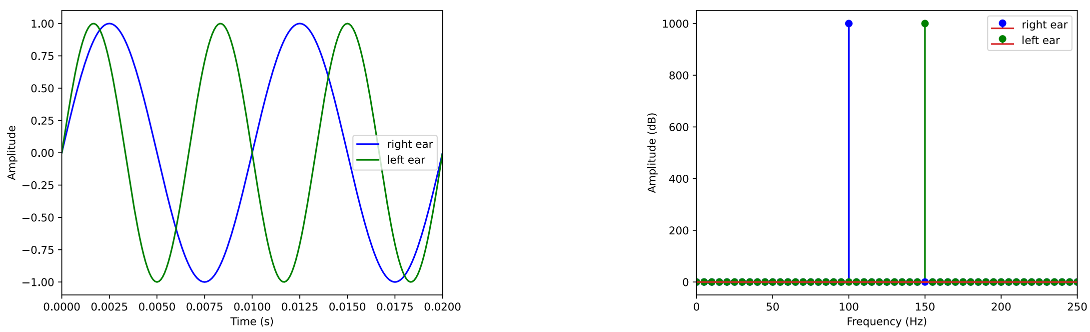
Awareness of the phenomenon of neurological entrainment preceded its formal recognition [3]. It was first formally identified in 1934 when researchers observed that a pulsating light could alter and evoke brain waves of the same Alpha band frequency [57]. However, Ptolemy, the Greek scientist and thinker, noted that patients who stared at a flickering light caused by a spinning spoked wheel exhibited feelings of euphoria and reduced anxiety [3]. Similarly, Plateau used flickering light as a diagnostic tool in the 17$^{\text{th}}$ century through the flicker fusion phenomenon [3].

2.4.2 Entrainment Techniques

Audio and visual entrainment techniques are popular and well-researched methods of entrainment [3, 4, 5]. Audio entrainment can be achieved through Binaural Beats (BB) [4, 5, 6]. These are audio stimuli where the left and right channels differ by a frequency within a brain wave frequency band being targeted [4, 5, 6]. Given that audio entrainment is noted, the frequency range of normal hearing should be mentioned. The average maximum frequency at which adult humans can hear is 20 kHz [58]. Therefore, any audio entrainment stimulus applied can have a maximum frequency of 20 kHz or below, given the diminishing frequency sensing capabilities of humans as they age [59].

Visual entrainment can be achieved through a flashing light which pulses at a targeted frequency [4, 60]. This is often achieved in tandem with a black/coloured background to induce a degree of visual perceptual deprivation, through the Ganzfeld effect [4, 60]. The Ganzfeld effect has been reported to enhance the effect of visual entrainment [4, 60].

Figure 2.3 provides an illustration of an audio entrainment stimulus's characteristics, when guided by knowledge gained from previous studies [5, 6, 61]. Figure 2.3 outlines the time and frequency characteristics of an audio entrainment stimulus in Figures 2.3a and 2.3b respectively. The entrainment stimulus has a carrier frequency of 100 Hz, presented to the right ear, and a targeted entrainment frequency of 50 Hz. This is due to the signal on the left and right ear differing by 50 Hz.



(a) Time varying entrainment stimulus signals.

(b) Frequency content of the entrainment stimulus signals.

Figure 2.3: An illustration of the time and frequency content of a 50 Hz audio entrainment stimulus.

2.4.3 Entrainment Effects

The area of the brain that entrainment effects depends on the stimulus presented to participants [56]. Audio and visual entrainment techniques primarily elicit a brain wave frequency shift in the: auditory areas, visual areas, motor areas, inferior colliculus, inferior frontal gyrus, and the cerebellum [56]. If neural activity is recorded using an EEG, the related brain wave changes will only be recorded at the auditory areas, visual areas, and to a lesser degree the motor areas [56]. The 10 - 20 EEG recording system outlined in Figure 2.1 would record the related brain changes most prominently at the T, TP and FT regions [21, 29, 56, 62].

Audio entrainment has been shown to affect both the power and connectivity of neural tissue at Temporal sites [3, 4, 5, 61, 63, 64]. A BB stimulus has been shown in literature to increase the power of Beta and Alpha band brain waves when the corresponding stimulus was used [3, 4, 5, 61, 63, 64]. The effects of BB stimuli appear to differ slightly across different studies [65, 66]. The differences appear to stem from the Band of neural activity targeted by the Binaural beat stimulus[67].

Research into BB stimuli targeting the Beta band of brain waves have one large trend when looking at the power of stimulus induced neural changes [3, 4, 5, 61, 63, 64]. The studies found that the entrainment stimulus increased the power of Beta band brainwaves, however the studies largely did not assess how the stimulus affected different frequencies within the Beta band [3, 4, 5, 61, 63, 64]. One study differed in this regard, however, the study investigated Alpha BB entrainment [68]. This is a limitation of existing studies, as the behaviour of the entire Beta band is of interest, as individual frequencies and as a whole. This is particularly apparent when assessing a stimulus aiming to influence it. As a result, an analysis looking at the entire Beta band as well as other frequency bands could provide a meaningful improvement to results presented by existing research on Beta band BB stimuli.

Further, research assessed the neural response in different Bands to a BB stimuli targeting the Beta band [65, 66, 67, 60, 69, 70]. Research largely found that the stimulus had a large effect on the power and connectivity in the Beta band, and that the effect was not prominently seen at other frequency bands; with some research indicating that the BB stimulus had weak effects at frequencies around the stimulus [65, 66, 67, 60, 69, 70]. Alpha and Theta bands were most prominently investigated in comparison [65, 66, 67, 60, 69, 70]. One study found that a Beta entrainment stimulus affected the Theta band, however the effect was not seen in Temporal sites [65, 66, 67, 60, 69, 70]. Therefore, Alpha and Theta bands at the Temporal sites represent a relatively good measure of brainwave activity that is not affected by a Beta entrainment stimulus

Studies have indicated that BB entrainment causes a connectivity increase at temporal sites. Research looking at the connectivity effects of entrainment stimuli are more conclusive on its effects when compared to studies looking at the power changes resulting from the stimulus Connectivity increases have been shown for a variety of connectivity metrics and studies have indicated that entrainment stimuli increase the connectivity of the targeted band at Temporal electrodes. Further, the research has indicated that control stimuli have no effect on the connectivity, however control periods were employed in existing research as opposed to control recordings. The connectivity increases seen in response to entrainment stimuli were shown in narrow-band filtered EEG data as it is a requirement of most connectivity analysis methods employed [21, 71, 72, 73, 55].

Specifically, connectivity increases have been shown in response to Beta entrainment stimuli [67]. These connectivity increases were prominently seen regarding the connectivity of Temporal sites to several other regions assessed [67]. This further indicates that a Beta entrainment stimulus causes an increase in connectivity. Further, studies have indicated that entrainment stimuli induce coherence increases that are more prominent than power increases over time [60]. These studies did not use separate control recordings and did not present a comparative assessment of connectivity increases when compared to other Bands that were not targeted [60, 67].

A study conducted looking at how entrainment could affect the mood of participants should be noted for its findings in the context of this research [5]. It found that Theta wave entrainment could impact the mood of participants [5]. It is notable that entrainment methods could result in potential mood changes. These mood changes could be necessary when altering the dominant brain wave frequency of participants in the study. Additionally, the potential change in mood should be noted for its ethical implications and accounted for in information given to participants.

Further, a study looking at the effects of a closed eye condition on Alpha band power should be noted. The study found that Alpha band power increases in response to participants maintaining a closed eyes condition [74]. The paper proposes that increases in Alpha Band power relate to inhibition of the visual processing region in the brain [74]. Given that the study will include a closed eyes condition for participants, this is an important finding to note as an increase of Alpha band power can be expected; or at the least a maintenance of Alpha band power can be expected. The characteristic would be beneficial to note in recorded data as it would validate observing expected Alpha band activity. This would, in turn, validate the recording and cleaning of EEG data, which would imply validity of derived results and data in other bands.

Research has looked at leveraging BB entrainment to impact both working and long-term memory [6, 7]. The studies found that BB entrainment could have a positive impact on working and long-term memory when entrainment was toward the correct dominant brain wave frequency [6, 7]. These studies provide a good justification as to why entrainment research should be conducted. If BB entrainment could have a positive impact on real-world tasks, it follows that research looking at evaluating and improving entrainment effects is justifiable, as it may have benefits outside improving knowledge in the field.

2.5 Immersive Virtual Environments

VR and mixed reality (MR) provide an augmenting layer over the world as we perceptually experience it. In both VR and MR, this is largely achieved by overlaying or replacing the visual field of someone wearing a VR headset [1].

Several studies have been conducted around the use of VR environments for entrainment and similar applications [1, 3, 75, 76, 77]. Two notable findings are applicable to the current study from the studies reviewed:

- Several studies found that virtual environments provided an increased sense of presence/self in the virtual world leading to increased levels of focus and entrainment [3, 75, 76]. The increased sense of presence is due to a lack of distractions in the lab environment / real world as well as the immersion provided by the VR world that mimics perception in the real world [3, 75, 76].
- Two studies found that VR environments were able to increase participant focus and mastery of mindfulness meditation when used to facilitate the practice, even when their eyes were closed [1, 77]. This indicates that participants had an increased ability to take in stimuli and control their brain state in the VR environment.

In addition to immersion, VR environments provide more freedom when compared to closed laboratory tests that operate in the real world in terms of the scope of activities that can be tested [14, 16]. This allows testing participants learning complex skills when compared to those found in previous EEG motor learning research [14, 16]. These studies often focus on tasks which are more trivial in nature such as mirror drawing tasks, ankle dorsiflexion and the pursuit rotor task [15, 78, 79].

2.6 Machine Learning

The research has set out to use a dynamic algorithm to augment traditional entrainment techniques. To this end, a background to ML algorithms should be outlined. This provides a description of an adaptive algorithm that can dynamically adjust itself based on inputs [21, 80]. ML algorithms can adjust their output through a process called training [21, 80, 81, 82]. ML algorithms adjust their outputs based on the statistical properties of inputs, known as features, so that the algorithm can "learn" [21, 80, 81, 82].

2.6.1 ML Model Selection

ML algorithms have several layers through which they can be classified [81, 82]. Possibly most broadly, ML algorithms can be divided into supervised, unsupervised, and reinforcement learning (RL) algorithms [81, 82]. Supervised models are trained based on pre-recorded data that has been labelled with a desired output, while unsupervised learning models use pre-recorded data that does not have labels [81, 82]. Supervised learning models can further be divided into classification and regression models based on their output; classification models attempt to output a discrete class that a given input falls into, while regression models output a continuous-valued output based on the input [81, 82]. RL differs from supervised and unsupervised learning in that it does not use any pre-recorded training data [81, 82]. RL models / agents can dynamically learn what to output based on a feedback algorithm, called a reward function, that is defined to optimise some condition [81, 82]. RL agents are, therefore, useful in situations where learning data does not exist and scenarios that might require a highly adaptive and dynamic algorithm that can learn while interacting with a system.

Machine learning models of all categories can exist through pre-defined algorithms and models as well as deeper and newer models [81, 82]. These deeper models are called Neural Network (NN) and they require a higher amount of data to generalise [81, 82]. This means that NNs require a higher amount of data to accurately predict / output a value that is expected [81, 82]. Pre-defined NN architectures also exist, and they similarly require large amounts of data, while being optimised for certain tasks [81, 82].

RL agents might be well suited to developing a ML model for the application of dynamic entrainment control as the agent would be able to learn an optimal policy function as it interacts with the system [80]. A policy function will define what the agent will output for a given input, essentially what decision the RL agent will take for any scenario [80]. A more detailed description of RL agents and algorithms will therefore be sketched for context as the algorithms would be useful in this study.

At it's core, an RL agent evaluates an environment or system that it interacts with to define what state, s, the system is in [80]. The RL agent then uses this state to define what action, a, it takes and evaluates what new State, s', the system transitions to as a result of the action [80]. Lastly the RL agent uses information around the states s and s' along with a reward function to define how favourable the action was and updates the RL algorithm [80]. The reward function defines a quantitative reward to update the algorithm with based on a set goal that the algorithm is trying to achieve [80].

The rewarding process is iterated whenever the RL agent makes a decision and interacts with the system, thus improving the RL model's information and accuracy around the system [80]. The iterative process is summarised broadly in Figure 2.4 [80]. Through this process, the RL agent is attempting to find the optimal action set based on any state that the system can be in [80]. The intricacies of finding an optimal action set and updating the algorithm can differ based on the RL model used [80].

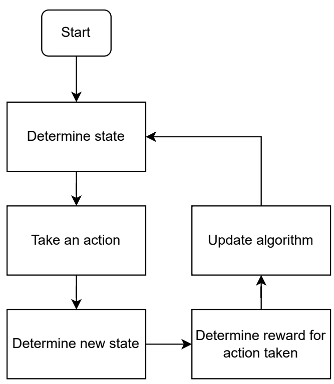


Figure 2.4: An overview of the loop a reinforcement learning model follows.

RL learning can be further subdivided most broadly into model-free and model-based algorithms which govern how the RL agent defines the environment / system that it interacts with [80]. Model-based learning attempts to use previously learned information about an environment, while model free learning purely relies on an iterative approach to determine what the correct policy function is, i.e. what actions to take for different states [80]. Further subdivisions exist to divide algorithms between control and prediction models [80]. Control RL agents attempt to create / find an optimal policy function to maximise the defined reward, while prediction-based models attempt to evaluate an already formed policy function [80]. Therefore, within RL models, model-free control agents provide a suitable option in scenarios where a dynamic algorithm is required to learn how to best interact with a system / environment without any prior knowledge of it. The one big requirement of such a model is that an objective goal is defined for the model to work towards optimising [80]. The goal needs to be converted from a state-based goal to a reward function that allows the RL agent to optimise actions which maximise the reward gained [80].

Within model-free control RL agents several algorithms exist that have been researched and can be adapted to use in different scenario's [80]. The algorithms either use a function approximation or a lookup table-based approach to determine the correct action, this is called a policy function [80]. Function approximation-based algorithms work well in scenarios where numerous state - action pairs exist as a lookup table in these scenarios would be incredibly large [80]. However, function approximation algorithms require a lot of data when compared to lookup table algorithms and therefore take longer to converge / generalise [80]. A good example of a model-free function approximation algorithm is the Deep Q Network, this is a type of NN [80].

As mentioned, lookup table-based algorithms are an alternative to function approximation models [80]. There are a variety of different lookup table based model-free control RL algorithms including: Q-learning (the lookup table alternative to Deep Q Networks), Multi-Armed Bandits (MAB), Contextual Multi-Armed Bandits (C-MAB) and SARSA to mention a few [80]. These algorithms operate well on both episodic and non-episodic scenarios with some tweaking of the application; however, they are all used to develop an optimal policy function that can determine which action to take in a given state [80].

C-MAB is based on the MAB algorithm [80]. The MAB algorithm can essentially be thought of as a set of slot machines, each with its probability distribution [80]. Each slot machine represents a potential action and the probability distribution represents the possible reward for selecting an action [80]. The MAB algorithm aims to learn the probability distribution for all actions and in doing so, determine what action is best [80].

The C-MAB and MAB algorithms look solely at reward and therefore look to optimise moving to a favourable new state for the reward associated with the state itself [80]. The algorithms, therefore, do not consider the possible future benefits of being in the new state [80]. Both C-MAB and MAB may use different algorithms to update it's state - action pair, probability distribution, based on the reward function which may have different implications to the optimal actions defined [80]. However, regardless of the reward function used, the same loop is repeated for an MAB algorithm [80]. At time t arm n is pulled, action n is taken, and a reward is assigned to the action [80]. This reward is used to create the probability distribution associated with the action [80].

The C-MAB algorithm essentially operates in the same way as MAB, however a set of states / contexts are used to define different action sets, probability distributions [80]. The state is initially evaluated, and the relevant action set is used and updated [80]. This, essentially, creates a MAB for every independent state [80].

Q-learning sets up a Q-table of state - action pairs as shown in Table 2.2 and uses the Bellman equation, outlined in Equation 2.8, to update the Q-table every time it takes an action [80]. The Bellman equation allows the Q-learning algorithm to balance returns versus rewards essentially allowing the algorithm to balance rewarding finding new states that maximise the immediate reward and potential future rewards [80]. The Q-table allows the algorithm to determine the optimal action for any given state once it has been filled with values [80]. Initially, the Q-learning algorithm"explores" the state action space, often through a greedy epsilon policy, which essentially allows the algorithm to occasionally take a random action that improves exploration of unknown state - action pairs [80].

$$Q(s,a) = Q(s,a) + \alpha * (r + \gamma * max(Q(s',a)) - Q(s,a)) \tag{2.8}$$

Where:

Q is the Q table value.

s is the state in which the action was taken.

s' is the new state that the system is in after the action was taken.

Table 2.2: An overview of a Q-learning Table.

State \ Action	a_1	a_2	$\cdots$	a_n
s_1				
s_2				
$\vdots$				
s_n				

a is the action taken or an action that could be taken.

α is the learning rate.

γ is the discount factor.

2.6.2 Useful Techniques

Within ML and applying algorithms such as Q-learning several useful techniques should be outlined. These techniques allow inputting of different data to generalised algorithms that have been previously studied. The techniques focus on parameters of the model as well as methods to ensure data from different participants/recording sessions can be used as an input to the same algorithm. The techniques will be described in the context of a Q-learning model as this is the model employed in the current study [80].

Models have been shown to utilize a greedy epsilon policy to balance exploration and exploitation. The pseudocode for a well-used greedy epsilon policy can be seen in Algorithm 1. When a random action is taken, the action is decided purely pseudo-randomly between the two possible actions for a state. When choosing the best action, the Q table is employed to select the action with the highest Q value. If both elements in the Q table are equal, the best action is also selected pseudo-randomly [80].

The greedy epsilon policy outlined in Algorithm 1 requires a set value of epsilon. Due to the benefits of exploiting when possible and exploration - exploitation balancing, a decaying epsilon policy is often implemented. The pseudocode for a decaying epsilon policy can be seen in Algorithm 2. A decaying epsilon policy allows for a lower probability to select a random action as the model gains more information from the environment. This, by extension, allows a more exploitative model to exist when the

Algorithm 1 Pseudocode for greedy epsilon policy.

function DETERMINEACTION*(epsilon)*
  $p \leftarrow$ random() ▷ Generates a random number between [0, 1]
  if $p < epsilon$ **then**
    $action \leftarrow$ random action
  else
    $action \leftarrow$ best action
return action

Q table is fully formed. Figure 2.5 provides further insight into the values of epsilon that this algorithm produces as steps of table updates are completed [80].

Algorithm 2 Pseudocode for decaying epsilon policy.

function CALCULATEEPSILON*(step)*
  $nEpsilon \leftarrow 25$
  $pinit \leftarrow 1$
  $pend \leftarrow 0.15$
  $r \leftarrow max(nEpsilon - step)/nEpsilon, 0)$
  $epsilon \leftarrow (pinit - pend) * r + pend$
  $step \leftarrow step + 1$ $return$ $[epsilon, step]$

The next technique outlined is normalization; this is a useful technique when using a feature set that varies in magnitude. This is especially apparent in EEG research due to participant and set-up differences. Different normalisation methods exist that may affect different properties of the feature set. Min-max/scaling normalisation is a popular method which essentially takes a set of possible inputs and reduces the possible magnitudes to a set range, most often between: [0, 1]. Z-normalisation is another method, which reduces the mean of the input data to zero and the standard deviation to 1. Normalisation is a useful technique as it can reduce the training time a model requires and improve its performance [83, 84, 85].

It is valuable to define what optimise and optimal entail in the context of this study. When a ML model, especially a RL model, is discussed the term optimisation will be used. This optimisation will not define some absolute optimal value or the search for one as this is not realistically practical in any system. The optimisation defined will look at the improvement of the selected feature and action set, in addition to how the model interacts with them to make decisions.

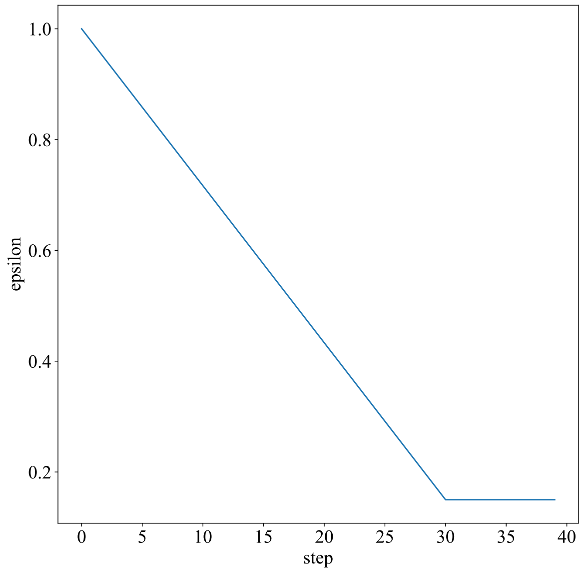


Figure 2.5: A graphical overview of the decaying epsilon policy used.

2.7 Summary of Findings

The background required for the research is outlined. This background draws from existing research in various fields to provide a framework to ground the present study. The existing research provides support for concepts that facilitate the objectives of the study.

Research in the field of brain wave measurement provides a good basis for a measurement system to evaluate the brain state of participants. EEG can measure neurological signals and has been shown as a widely accepted method of non-invasive brain state measurement. This research justifies that quantifying brain state changes is possible and well documented.

Research into entrainment techniques provide a basis for the study's intervention, and its expected effect on measured EEG data. The research provides a non-invasive stimulus, BB entrainment, that can modify the brain state of participants. Furthermore, existing research provides evidence that brain state targeting though audio entrainment can improve functioning in tasks, thus providing a justification for researching improving the techniques. Lastly, research into VR technologies provides an additional tool that can potentially enhance the entrainment techniques employed.

ML methods are outlined as a dynamic algorithm that can control the dynamic entrainment stimulus. Specific algorithms in the field of RL are identified as potential algorithms in the context. The two algorithms most suited for the application are outlined so that their benefits might be weighed up during a discussion around the experimental set-up.

Chapter 3

Literature review

3.1 Introduction

Building on sketched background information, a critical review of notable literature is required. This review aims to provide a justification for the research question posed and the experimental design outlined.

The research question and experimental design are justified by identifying research gaps arising from previous studies. Research gaps are identified in the field of entrainment research.

3.2 Research Gaps From Entrainment Research

Existing research into neurological entrainment provides a solid base on which future knowledge can be built. The research generally looked at entrainment performance and how it can be achieved. The studies evaluated either used a constant entrainment stimulus or alternated a set entrainment stimulus with pink noise [3, 4, 5, 61, 63, 64, 71].

Past the stimulus modalities that produce entrainment effects, the electroencephalogram (EEG) markers of entrainment have been reported in previous research [3, 4, 5, 61, 63, 64]. These markers have been commonly noted using a power or connectivity analysis and should be discussed as they provide possible research gaps for further investigations into entrainment [3, 4, 5, 61, 63, 64].

3.2.1 Frequency of Entrainment Stimulus

The power changes of different brain waves in response to audio entrainment has been assessed [3, 4, 5, 61, 63, 64]. Results using this analysis has differed along with other varying experimental factors including: the entrainment frequency used, the duration of the stimulus, and the frequency analysis employed [3, 4, 5, 61, 63, 64]. Further unpacking of existing research is required to identify research gaps presently investigated. It is notable that all existing research did not employ the same frequency analysis methods and parameters [3, 4, 5, 61, 63, 64]. While their methods differ, the underlying dynamics of the EEG signal would remain constant regardless of the analysis. Therefore, while different methods might better highlight differences in neural signalling, all valid methods would produce similarly correct results. It can further be assumed that existing research used adequately scoped EEG analysis methods with correct parameters to account for the non-stationary and stochastic nature of EEG recording.

Previous research into audio entrainment stimuli utilised a carrier frequency for the two audio signals presented to a listener [5, 6]. This is the base frequency which is used for one of the audio channels [5, 6]. The remaining channel will differ by the targeted frequency from the base frequency [5, 6]. An optimal carrier frequency has been reported by previous studies, and claims regarding the true optimal value vary between 200 Hz and 500 Hz [5, 6]. The true optimal carrier frequency is the base frequency used by an audio entrainment stimulus that can create the most pronounced frequency following effects at the targeted brain wave frequency [5, 6]. In the practical case, optimal refers to a previously utilised stimulus which is able to evoke the most notable change in brain wave measurements.

The variation seems partly dependent on the brain wave targeted, however the optimal frequency also differed between studies targeting the same brain wave [5, 6]. Notably, a 400 Hz carrier frequency has been reported as a reliable optimal carrier frequency to use for Binaural Beat (BB) entrainment [5, 6]. While this does not directly relate to a research gap, it informs the current study around what carrier frequency is likely to yield the best results. Further, it provides minor credibility to the idea that traditional entrainment stimuli might be improved upon as different studies reported different optimal carrier frequencies. This might imply that a dynamic stimuli could provide benefits to entrainment effects, as the stimulus's effects do not appear absolutely consistent across different groups of participants.

While the audio entrainment frequency and duration of the stimulus used varied in existing research, two common threads relating to the entrainment frequency occurred when positive results were found. Studies that had conclusive findings indicating that entrainment affected neural dynamics generally applied an entrainment stimulus for more than three minutes – typically over 10 minutes. Conversely, studies applying an entrainment stimulus for less than three minutes mostly did not have conclusive findings. Secondly, the positive findings indicated that entrainment stimuli increased the power of brain waves at the targeted frequencies/frequency bands. Power changes were consistently present in the temporal regions of the brain. Lastly, findings generally indicated that a marked increase in brain wave power occurred after around 10 minutes of participants being exposed to the entrainment stimulus [3, 4, 5, 61, 63, 64].

The common threads indicate a framework for achieving positive, frequency following entrainment effects within a targeted band when using entrainment. Further, existing research had two features that lead to a potential research gap [3, 4, 5, 61, 63, 64]. All existing research reviewed used a set entrainment stimulus and applied this stimulus constantly [3, 4, 5, 61, 63, 64]. Secondly, the literature did not mention a distinct reason for choosing a specific frequency, and results when using the same frequency of entrainment differed between participants, groups, and studies [3, 4, 5, 61, 63, 64]. Resultantly, a research gap exists to improve on existing set frequency entrainment stimuli by creating a stimulus that can dynamically adapt to participants.

The research gap focuses on creating a dynamic algorithm/system that can switch between entrainment frequencies within a band of neural activity. More specifically, the gap exists to evaluate if a dynamic entrainment stimulus, confined to a set number of frequencies, might have similar effects when compared to a traditional entrainment stimulus. Further, the research gap is to evaluate if the algorithm can either find a general optimal entrainment frequency, within a set number of frequencies, or develop a frequency switching method that will improve the entrainment effects experienced.

The research gap would evaluate to what degree the dynamic entrainment stimulus could improve on frequency following effects when compared to a traditional entrainment stimulus. Further, the research gap would evaluate what method/policy the dynamic entrainment algorithm developed within its entrainment frequency set, and determine if this method indicated that one entrainment frequency in particular was favourable. This would evaluate if a set entrainment stimulus appeared optimal when compared to a frequency switching option, within the bounds of the frequency set used. The research gap would necessitate selecting the carrier frequency based on existing research and keeping it constant. This would assist in focussing on the specific research gap identified. A carrier frequency of 400 Hz would, therefore, provide the best option, given the findings of existing literature.

3.2.2 Habituation

One further layer to the reported effects of audio entrainment exists in literature [71, 86, 87]. Several studies have reported that habituation occurs when an entrainment stimulus is presented to participants over a longer period of time [71, 86, 87]. The period that this occurs has not been conclusively evaluated [71, 86, 87]. The studies propose that the brain begins to filter out the stimulus as noise and resultantly the effects of the entrainment stimulus are minimised or negated after extended exposure [71, 86, 87].

Studies have proposed that habituation effects can be negated when a stimulus consists of entrainment blocks that are alternated with pink noise or control blocks [71]. These studies used identical stimulus blocks of between one and three minutes long and had total stimulation periods of over 10 minutes long [71]. Studies using shorter entrainment block sizes had less conclusive results, while studies using a block size of three minutes found large power changes from 7 - 10 minutes [71]. More specifically, studies found that a change could be seen at around six minutes, while a large change occurred at around nine minutes [71].

The neural response to audio entrainment has been further assessed regarding the associated connectivity changes. The studies have varied results: they indicate that connectivity did increase at temporal sites as a result of entrainment; however, there are mixed results regarding connectivity increases across other regions of the brain. Notably, some distinction may exist due to the nature of the connectivity analysis methods available. These methods may have differing implications and use different metrics. The results were derived when BB entrainment was used for differing periods and for differing targeted brain waves. Additionally, two studies evaluated alternated the entrainment stimulus with pink noise. Overall, the common finding in existing research is that entrainment causes an increase in connectivity at temporal regions of the brain [21, 71, 72, 73, 55].

The connectivity studies provide an interesting parallel when compared with studies focussing on habituation. Both sets of studies appear to have used a similar stimulus, while in some studies the stimulus was explicitly designed to reduce habituation effects [21, 71, 72, 73, 55]. This parallel will enhance any possible research gaps identified relating to the stimulus used in studies, as the research gap will relate to both a power and connectivity analysis of derived data. Further, the studies did not individually conduct a comprehensive power and connectivity analysis [21, 71, 72, 73, 55]. Therefore, results exist distinctly assessing the connectivity and power dynamics in response to the entrainment stimulus. The present study would benefit in analysing the same participant data using both power and connectivity metrics. This would allow the simultaneous assessment of both dynamics.

The research gap provided in this context looks to subvert the effects of habituation when using an entrainment stimuli. Habituation was accounted for in literature by alternating the entrainment stimulus with blocks of control stimuli [21, 71, 72, 73, 55]. Given the nature of a pink noise control stimulus, it is not expected that it would have any effect on neural activity [21, 71, 72, 73, 55]. Therefore, the periods where a control stimulus was presented can be seen, broadly, as periods in which entrainment effects were not present [21, 71, 72, 73, 55]. A research gap exists to develop a dynamic stimulus that can provide a varying entrainment stimulus that does not exhibit habituation. This stimulus would need to dynamically switch between entrainment frequencies in an attempt to avoid habituation effects. Evaluating this stimulus's ability to avoid habituation effects would require comparing it to both a set entrainment and control measurement. It would further benefit from both a power and connectivity analysis to assess its impact from multiple analysis modalities that have been previously researched.

3.2.3 Experimental Setup

Studies looking into the power dynamics of habituation effects did not have a separate control group or control recording and compared entrainment blocks to control blocks [71, 86, 87]. This was mirrored in studies looking at the connectivity changes present in participants [21, 71, 72, 73, 55]. The entrainment blocks used a set frequency stimulus in all studies reviewed. and were alternated with control blocks in selected studies [71, 86, 87]. Resultantly, the studies were unable to compare the entrainment effects to that of a control stimulus when both were applied to a participant in the resting state. The control stimulus, therefore, may have exhibited a response that was due to lingering effects of the entrainment stimulus and vice versa, or it may have exhibited a placebo effect.

Existing research frequently used control periods instead of separate control recordings to benchmark and separate entrainment stimulus periods[3, 4, 5, 61, 63, 64, 71]. While the research used a control period at the beginning of sessions, this can be seen as an oversight in the research for two reasons[3, 4, 5, 61, 63, 64, 71]. First, if a separate control group and control recordings for the test groups were recorded, any results observed would be more substantiated. These control recordings would illuminate any group-specific dynamics, as well as provide two equally valid benchmarks against which to compare test recordings. The control recordings would have the same experimental conditions aside from the entrainment stimulus to test recordings. The addition of control recordings would, therefore, limit the number of extraneous variables present in the study and assist in highlighting the true impact of the stimulus investigated. Further, having pink noise in between entrainment periods assumes that the control stimulus was presented for a sufficient time so that any lingering entrainment effects would have dissipated. Lastly, it assumes the control stimulus was presented for enough time to affect the neural processing of the participant. Given that this was not independently investigated, it is a substantial assumption, especially given the short amount of time given for control periods which is around one minute on average. This research gap extends to analysing recorded data using a power and connectivity analysis.

The study would benefit from using both a power and connectivity analysis, as previously noted. This would provide additional insights around the effects of entrainment. It would provide information around how both dynamics are impacted by an entrainment stimulus in the same participant set. Further, existing studies largely did not apply a power analysis across multiple frequencies within brain wave bands [3, 4, 5, 61, 63, 64]. The present study would benefit in individually analysing different frequencies within bands analysed to improve on existing findings around entrainment effects. The research gap, therefore, exists to apply both analysis methods to recorded EEG data and expand on how the methods are presented.

A research gap exists when evaluating the experimental setup used in existing research. The use of separate control recordings within habituation and entrainment research could serve to provide a more objective marker when evaluating results around the stimuli's effectiveness. The addition of a separate control group can, therefore, be seen as a valid research gap when combined with a research gap aiming to gain additional insight around the neural response to entrainment.

3.3 Identified Research Gap

An overlap exists between the research gaps identified in literature focussing on entrainment stimuli and its related habituation effects. The research gaps focus on exploring the possible benefits and validity of a dynamic entrainment stimulus. The dynamic stimulus would look to create a stimulus that is able to switch between entrainment frequencies. The stimulus would aim to reduce the effects of habituation, while increasing the effects of entrainment. The research gap looks to evaluate the effects of a dynamic entrainment stimulus relative to a traditional set frequency entrainment stimulus.

The assessment of the dynamic stimulus would benefit from including a separate control recording, which would further distinguish it from existing studies and provide an examination of a research gap identified. This allows the study to isolate the entrainment effects and contextually evaluate them between recordings. This is a gap in existing research which is aided by including both a power and connectivity analysis. Adding multiple analysis methods allows more insights to be drawn regarding the difference between control and test recordings, which improves the results derived from a single set of participants.

Existing research provides a good base to build the present study on. The study uses a virtual reality (VR) environment to enhance effects of a BB entrainment stimulus. Two entrainment stimuli are used in two separate recordings: a set entrainment stimulus that follows previously researched entrainment stimuli is leveraged, further a dynamic stimulus is used. The dynamic stimulus is controlled by an Q-Learning (QL) agent that can switch the entrainment frequency of the stimulus. In addition to recordings using the two entrainment stimuli, a control measurement is recorded to provide an objective reference point. The control measurement is recorded for the test group that is exposed to the two entrainment stimuli, as well as a separate control group. Given the background sketched and critically analysed, the study's implementation should be outlined to describe how the research question and goals are addressed.

Chapter 4

Materials and Methods

4.1 Introduction

Detailing the study implementation allows it to be both reputable and reproducible which is a key aspect of research. This chapter outlines the experimental design and justifies decisions made while presenting metrics used in deriving results from recorded data.

At its core, the experiment looked to enhance Beta band activity in participants using audio entrainment in a virtual reality (VR) environment. Two audio entrainment stimuli were used: a set entrainment stimulus and one controlled by a reinforcement learning (RL) agent, implemented as a Q-learning agent. The RL agent used electroencephalogram (EEG) data to inform how the stimulus was adjusted. Further, a pink noise control measurement was taken for all participants. Analysis methods were applied to recorded EEG data to quantify the neurological changes associated with the different stimulus sets. This chapter unpacks how this was achieved in more detail.

4.2 EEG recording

EEG measurements were taken while the experiment was running and participants had a VR headset on. The measurements were taken at a sampling frequency of 512 Hz. Data was recorded using a 64 channel g.tec wet electrode EEG with a g.tec high impedance amplifier. A sampling rate of 512 Hz was selected as a trade-off between the computational complexity of processing data in real time, the size of data recorded, and sampling quickly enough to negate any problematic aliasing effects (the Nyquiest frequency of the band evaluated was 100 Hz). 64 g.SCARABEO active electrodes were used to record EEG data. Each electrode, except the earlobe reference electrodes, were mounted on a cap that was adjusted to fit participants.

The g.GAMMAcap was employed, this ensured that electrode placement agreed with the extended 10 - 20 system. Therefore, all electrode placements can be assumed to lie in the correct location relative to the respective neural structures measured. The 64 channels were set up in a standardised 10 - 20 configuration with two electrodes being used for earlobe re-referencing and one electrode serving as the ground electrode, placed at the AFz position. The electrode configuration used can be seen in Figure 2.1. The EEG cap recorded data from 61 regions due to the configuration employed.

Due to the nature of the active electrodes used, conductive gel was applied to each electrode. The gel was employed to obtain an optimal impedance value. Gel was applied to each electrode until its impedance check, measured relative to a reference electrode at the $Fp1$ position, was below 30 $k\Omega$. The EEG cap setup took between 20 and 40 minutes.

Using the g.tec high impedance amplifier, a hardware bandpass and notch filter was applied to every EEG channel. Table 4.1 outlines the parameters of the hardware filters used during data recording. A notch filter was implemented to remove 50 Hz power line noise and the bandpass filter removed insignificant frequencies as well as DC noise.

Table 4.1: A description of filters applied to all EEG channels.

Filter	Order	Lower cutoff frequency (Hz)	Upper cut-off frequency (Hz)
Notch	4^{th}	48	52
Bandpass	8^{th}	0.5	100

4.3 Participants

4.3.1 Recruitment

The study required participation both to create and give confidence to its results. Participants were invited to participate in the study; however, some groups were excluded from the study. The study has 12 participants with acceptable results, those without artefacts that compromise the ability of the data to be analysed. The participants were split into a control and test group, with six participants in each group.

A study population of 12 was chosen for two major reasons. In the context of the research timeline, having 12 participants was a practical necessity due to the complex nature of EEG experiments and the unpredictability of participation on the study. A relatively low number of participants allowed for adequate time to collect data within the timeline allotted for masters research. Secondly, the sample size has implications on the study's results. A sample size of 12 allows for the study to form a proof of concept on the specific goals and research question investigated. This is useful given the novel nature of the research question asked.

Participants over the age of 18 were invited to participate in the study. However, anybody with a history of photosensitive epilepsy and related conditions were excluded from participating due to the nature of the stimulus used. Participants were invited using any of the University's channels available to the investigators.

Control participants were recruited in the same way that test participants were recruited. Both investigators and participants were not informed as to which group participants belonged to while recording was in progress.

4.3.2 Participant demographics

Table 4.2 provides an overview of the participant demographics involved with the study. The table provides information around any biases that might exist due to differences in the participant groups which should be noted. The implications of these biases will be further explored in Section 4.9.

The test and control groups have a similar median age, despite the maximum age of the two groups differing significantly. Therefore, age differences should not provide a significant bias in the study when comparing recording groups. However, the results will note if the participant with a higher age in the test group exhibits any distinct behaviour from the rest of the group. Secondly, both groups consisted entirely of students which will, further, not introduce any bias. One notable area where bias may exist is in the sex distribution between the two groups. The control group had a higher number of male participants than female participants, while the test group had an even mix. This may introduce a bias into the study and needs to be noted.

Table 4.2: An overview of the participant demographics.

Group	Test	Control
Maximum age	59	26
Minimum age	22	22
Median age	26.5	24.5
Number of male participants (sex)	3	4
Number of female Participants (sex)	3	2
Number of students	6	6

4.4 Experimental Test environment

The final experimental setup is outlined for completeness and reproducibility of the study. This section details the high level technical considerations of how data recording was accomplished.

Figure 4.1 provides a description of the high-level layout of components used for data recording during each session. It additionally provides an overview of how the custom entrainment suite, run on the Oculus Quest 2, was controlled. The entrainment software on the Oculus was developed in Unity and polled an API, created and hosted on Amazon Web Services (AWS), to query what stimulus was presented to participants. The API returned what stimulus to use and was polled every 10 s by the Oculus.

EEG data was recorded on a g.tec EEG device and data was retrieved using the g.tec Python API. The EEG data was saved on a Hierarchical Data Format version 5 (HDF5) file as it offered better Input/Output speeds, and a smaller disk size in comparison to data structures such as a comma severated value (CSV) file [88].

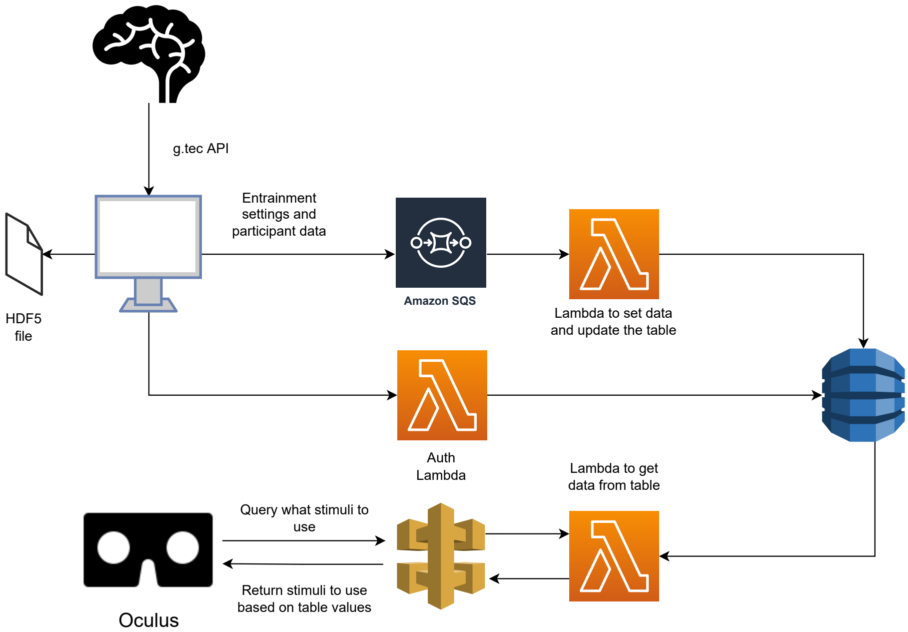


Figure 4.1: An overview of the architecture setup of the system relating to data capture during recording sessions.

Figure 4.2 outlines the abstraction between any investigators and the code used to run the experiment. Two Docker containers have been created to handle infrastructure deployment and running the experiment. The docker container in charge of infrastructure deployment used Terraform to deploy all necessary changes to the AWS infrastructure and stored a state file with required details to run the experiment. Similarly, the docker container in charge of running the experiment used the state file and a python installation with all necessary packages to run the experiment.

The effectiveness of the system developed was tested before participation in the study. This was only conducted once ethics clearance had been provided for the study and encompassed testing that the entrainment system was working as expected, and that all components of the system were adequately linked and scoped. These tests do not form part of the formal results of the study.

Participant privacy was of the utmost importance during the study. This was

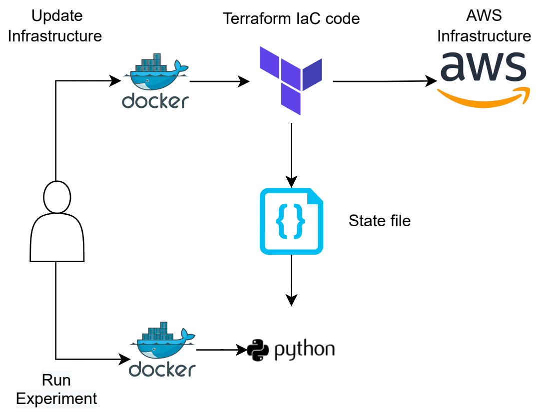


Figure 4.2: An overview of the components used to run the experiment and deploy changes to the experimental setup.

to avoid bias in the study and so that anonymity was maintained to protect participant privacy. How data was stored had been considered before measurement to ensure that this was maintained. Data recorded from the EEG were tied to a Participant ID which did not directly relate to any personal information.

Separate to recorded data, the Participant ID was associated with a hashed value, created using the participant's name and a secret key that was emailed to the participant. None of the investigators had access to this key, and it was only available to the participant, it was not stored anywhere. Therefore, only the participant was able to allow the investigators to identify them as a particular Participant ID while data were recorded. The hashed value was never shown to the investigators while recording data and the Participant ID was randomised so that it could not be used with session times to "reverse engineer" the database and relate records to participants.

After recording was completed, the hash values identifying all participant IDs were removed. This removed data linking to any personal details, even though the link was incredibly obscure and secured to be one way only. This ensures that the data remaining were completely anonymous and will allow the investigators to publish the data once the study results have been published. Publishing the data will enable further research to be conducted on the dataset. The participants were informed that this is the intent of the investigators when consenting to be a part of the study.

Figure 4.3 provides a timing diagram as an overview of the authentication system that ensured anonymity. The system was designed with a user interface that was convenient for participants to use.

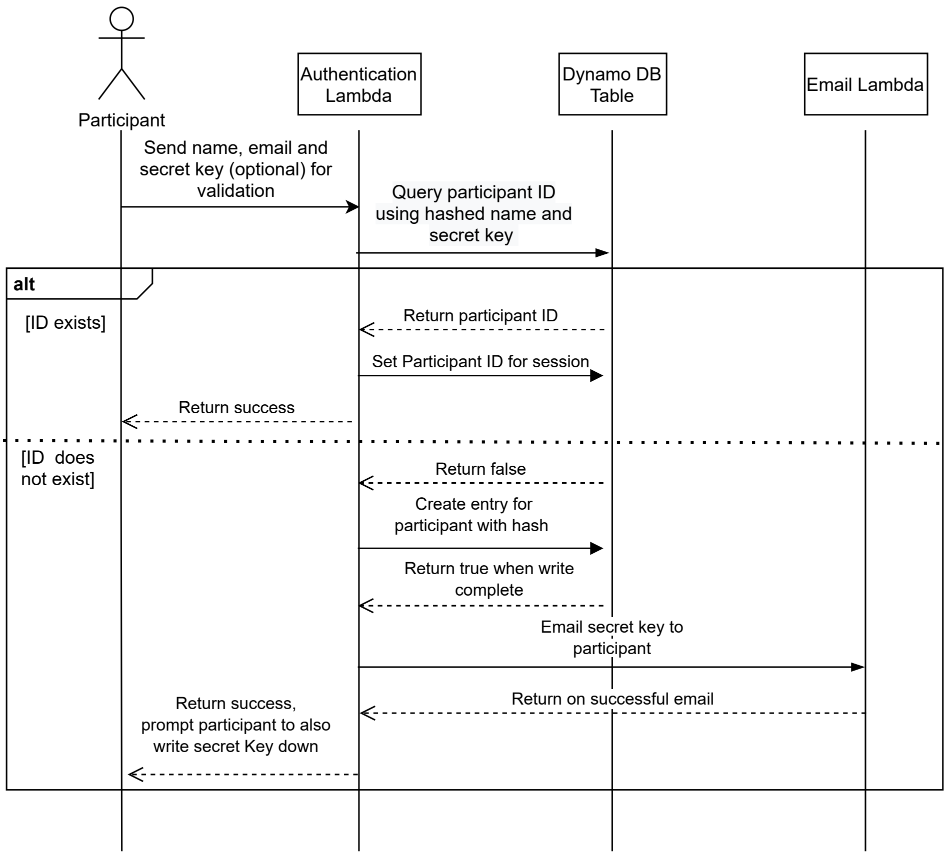


Figure 4.3: An overview of the authentication system used to ensure anonymity for participants.

4.5 Experiment Overview

The study consisted of one control group and one test group. The test group had three EEG measurements recorded while different stimuli were presented to participants: a measurement with a constant audio entrainment frequency of 24 Hz, one where the entrainment frequency was controlled by a Q-Learning (QL) agent and a control recording in which pink noise was used as a stimulus. The separate control group had one session in which a pink noise stimulus was presented to them. The addition of separate control recordings allows for additional confidence in any results derived as an objective comparison point exists both as an intra-group and separate group measurement. All stimuli were presented to participants in a VR environment using a pair of noise-cancelling headphones.

The VR environment built allowed participants to focus only on the stimuli presented to them. The environment had a black background, two visual elements, and an audio stimulus. The visual elements can be used for visual entrainment and neurofeedback in future experiments. However, for the present study these elements were not used and were made invisible. Therefore, participants were immersed into a completely black world with an audio stimulus, reducing the potential distractions within the world that they could focus on. The left and right channels of the audio stimulus could be independently modulated, both channels presented a sinusoidal tone at a set frequency to participants. The modulation allowed the frequency of the signal on both channels to be changed. An example of the VR environment when the elements for visual entrainment and neurofeedback are in use can be seen in Figure 4.4. The audio stimulus was provided to all participants using the same pair of headphones to ensure that constancy in the setup was achieved.

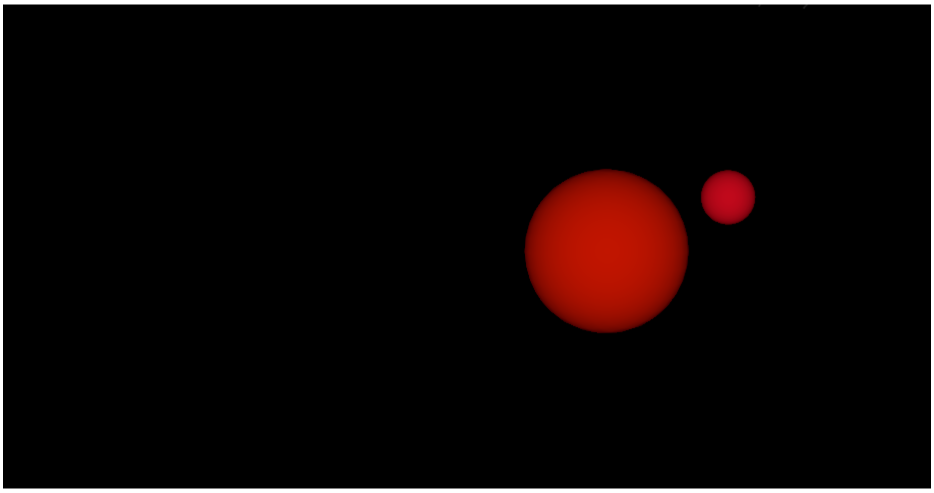


Figure 4.4: A view of the VR game world, with visible visual entrainment (left) and neurofeedback (right) elements.

An overview of what a recording session entailed for participants in each group can be seen in Figures 4.5 and 4.6 for sessions one and two respectively. Test participant workflows are shown in blue, while control participant workflows are shown in orange. Data recorded were stored using information that did not relate to any identifying information of the participants.

4.5.1 Recording Session 1

The experimental setup for test and control groups was the same during recording session 1, excluding the stimulus presented to participants. During the first 30 s

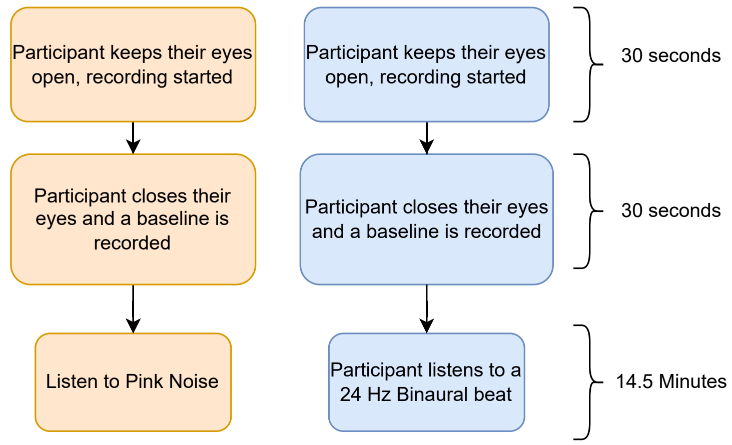


Figure 4.5: An overview of the experiment as experienced by a participant in each group during the first session.

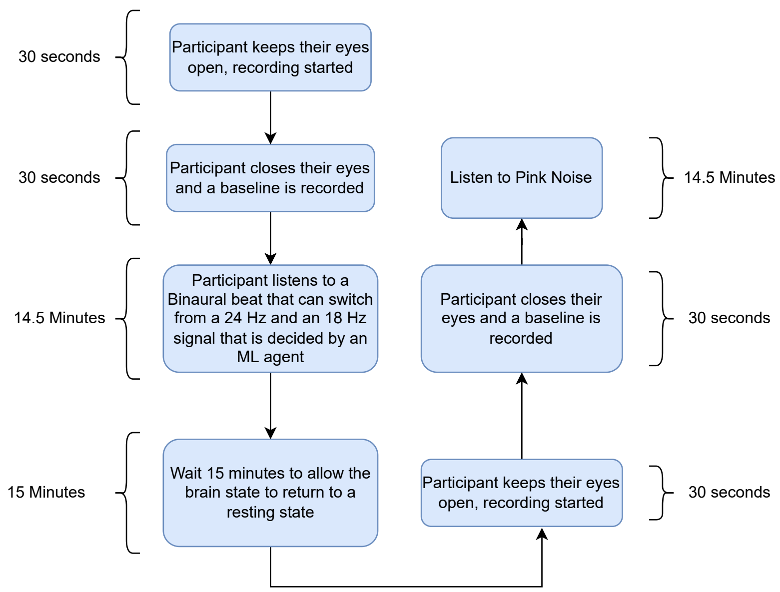


Figure 4.6: An overview of the experiment as experienced by a participant in the test group during the second session.

of the experiment, participants had their eyes open while in the VR environment, did not hear any audio stimulus, and did not have any EEG recording carried out. During this time, the g.tec high impedance amplifier's hardware filters exhibited a step response before reaching a steady state condition. Data could not be recorded until the steady state condition was reached, necessitating this stage of the experimental setup. Subsequently, participants closed their eyes and EEG recording began - participants eyes remained closed for the rest of the recording session. These two stages of the first recording session were the same in both groups, after which participants heard an audio stimulus in the VR environment which differed.

Control participants listened to pink noise in the VR environment. The pink noise presented to participants was generated using the Matlab Audio toolbox to ensure that it had the correct frequency characteristics. Pink noise was chosen as the control audio stimulus because it exhibits a 1/f proportional spectral density, while being Gaussian noise [89, 90]. This means that it has the same general spectral density as the brain and should not affect brain waves as the Binaural Beat (BB) entrainment stimulus aims to [21]. The pink noise stimulus sought to highlight effects of the test stimulus, as it should not alter the brain waves of participants using the same stimulation modality targeted by the test stimulus. Further, a pink noise stimulus allowed participants to focus on an audio stimulus in the VR environment. Having an audio stimulus for control participants to focus on meant that the main difference between test and control conditions was the frequency content of the stimulus and not the existence of one. Furthermore, it minimised potential placebo effects that might occur due to participants knowing that they were not listening to any audio stimulus [90].

Participants in the test group listened to a 24 Hz BB entrainment stimulus. This stimulus aimed to induce a change in their Beta band brainwaves. The BB stimulus used a sinusoidal carrier tone of 402 Hz. As a result, the entrainment stimulus used a pure sine wave audio tone of 402 Hz and 426 Hz in the left and right channels respectively.

Overall the first session took 15.5 minutes, aside from setup. In total sessions practically took between 40 and 60 minutes.

4.5.2 Recording session 2

Recording session two was only run with test participants. The scheduling of this session was, additionally, started once the majority of test participants had measurements complete for session 1. Participants returned to have two sets of measurements recorded during the second session. Additionally, the EEG cap was set up once for each participant.

The general flow of a single measurement in recording session two followed the same protocol as in session 1: it consisted of an open eyes condition that was not measured, followed by a measurement using a closed eyes condition in tandem with a specific stimulus. During recording session 2, test group participants were initially recorded for their response to a machine learning controlled stimulus. Subsequently, after a 15-minute break to allow their brain to return to a resting state, their response to a pink noise stimulus was recorded. The QL model employed during recording session two used EEG measurements to decide what stimulus was presented to participants. The model's design and considerations are presented in Section 4.8. The discussion of the QL model's design follows an explanation of the analysis methods employed in the study as the features used for the model rely on these methods.

Aside from the setup, recording session two took around 46 minutes. At this point in the study, investigators were more experienced at the setup, therefore recording sessions on average took around 70 minutes. Participants were briefed on this before scheduling the recording session.

4.6 Data Pre-processing

Data analysis was an important process required to formulate results and draw conclusions for the study. The analysis initially consisted of cleaning / pre-processing recorded data. Pre-processing allows: artefact removal from EEG data, re-referencing data to reduce common noise, and filtering data to scope any analysis to a specific frequency band.

A pre-processing pipeline was used to clean data in real-time. Unless otherwise stated, all processing and cleaning algorithms employed and listed in this section were applied in real-time. This was a practical necessity due to the QL algorithm using data that had been processed by the pipeline. The general pipeline can be seen in Figure 4.7. Once this process was completed, the data could be analysed using frequency and time domain analysis techniques that draw insights regarding the underlying neural signalling. As outlined in Figure 4.7, data was filtered specifically to brain wave bands analysed when creating results. Filtering data to the relevant band would confine data to a specific band; i.e. if the beta band was analysed, the data would be filtered between [13 - 32] Hz to isolate the analysis to Beta waves.

EEG data was re-referenced to change the reference of recorded data from the AFz electrode to an average of electrodes placed on the earlobes. This removed the common-mode-noise when re-referencing to an electrode that is close to others, but records less neural activity. The mathematical basis for re-referencing can be seen

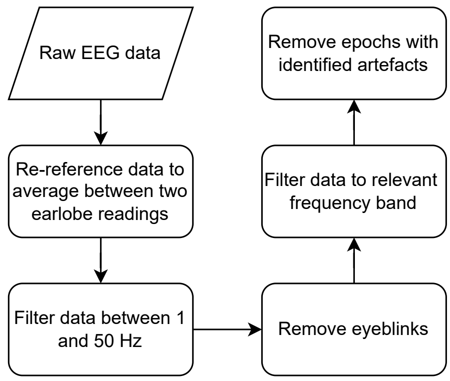


Figure 4.7: An overview of the final pre-processing step for EEG data recorded.

in Equation 4.1. This illustrates how the reference measurement is changed for any electrode from e_{gnd} to a. [21]

$$e_{\text{re-ref}} = [e - e_{gnd}] - [a - e_{gnd}] = e - a \tag{4.1}$$

Where:

e is the reading from an electrode.

e_{gnd} is the reading from the original ground (AFz) electrode.

a is the reading from the earlobe reference electrode.

e_{re-ref} is the re-referenced electrode.

The final step in the pre-processing pipeline shown in Figure 4.7 was used to remove the artefacts that could not be cleaned. Identifying these artefacts was conducted before running the pre-processing pipeline. An overview of the broad algorithm used to identify epochs with artefacts that could not be cleaned can be seen in Figure 4.8. This analysis technique used a Bandpass filter between one and 50 Hz constructed using a Hamming window and having a lower and upper transition bandwidth (-6 dB) of 0.50 and 56.25 Hz respectively. A frequency range of one to 50 Hz was chosen as it is commonly referenced as the frequency range in which brainwaves prominently operate [21]. Therefore, any potential artefacts that exist in this frequency band may have an impact on brainwaves analysed in the different sub-bands and should be removed. Identified epoch regions were stored and removed later in the pre-processing pipeline. These regions contained areas of EEG data where artefacts that could not be cleaned existed. A threshold of 90 μV was manually determined for the algorithm, and a buffer of 2 s of data (1024 data points) was used around the first and last point that the data crossed the threshold.

The threshold was identified through manual inspection of recorded EEG data with known artefacts and after evaluating data recorded during recording session 1. Data evaluation looked at the voltage characteristics of both clean and artefact impacted data to identify a useful aspect of the recorded data that could identify artefacts. Further, existing literature informed the decision. Literature indicated that eye blinks and Electromyograph (EMG) artefacts would have an increased magnitude when compared to valid EEG data [21, 28, 34]. Existing literature, therefore, supported the use of a voltage threshold to identify epochs where the artefacts existed. However, no absolute threshold existed due to differences in measurement equipment and a threshold needed to be manually determined.

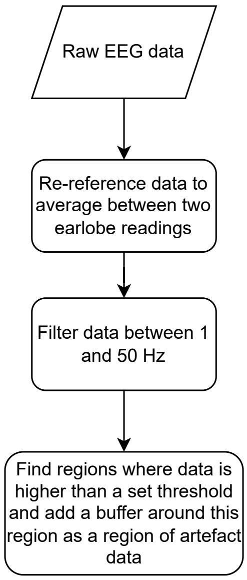


Figure 4.8: An overview of the process used to find epochs with artefacts in EEG data recorded.

4.6.1 Online artefact cleaning

The QL algorithm employed required data to inform its decision-making process. The data was derived from processed online EEG. The pipeline outlined in Figure 4.7 was used to process the data for online EEG data. Due to limitations in the algorithms employed, only eye blink artefacts were removed from online data. Artefacts not fully removed through signal processing tools outlined were epoched and removed when the system was run in real-time. The algorithm used to identify epochs in which artefacts occurred, outlined in Figure 4.8, removed artefacts that could not be cleaned. These artefacts include movement artefacts, sensor popping and other artefacts types. Due to the conditions of the study, this was determined to be acceptable. Participants had their eyes closed for the duration of the study and were asked to keep their head as stable as possible while recording was in progress. Therefore, eye movement and movement artefacts due to EMG were mitigated acceptably by the experimental paradigm.

Methods exist to remove eye blink artefacts online while preserving the underlying EEG data. Despite participants having their eyes closed, eye blinks might occur and these artefacts could be removed while maintaining an acceptable level of data integrity. The algorithm used to remove eye blink artefacts employed a hybrid of Empirical Mode Decomposition (EMD) and Canonical Correlation Analysis (CCA) to remove artefacts. If eye blink artefacts were present, a Fast EMD-CCA algorithm was applied to the dataset to remove the eye blink artefacts. The algorithm implemented has been previously researched for its efficiency at reliably removing artefacts. The algorithm can be split into two parts: one that identifies a generic eye blink template for a dataset and one that removes eye blinks from the dataset. Initially, the algorithm looked to create a generic template of an eye blink using correlation, displacement metrics, and Empirical Mode Decomposition. The algorithm subsequently used a correlation metric to match the template to data, which located eye blinks. The eye blinks were removed using Canonical Correlation Analysis. This algorithm was chosen from existing research as it is unsupervised, scales well to 64 channels, and could be run in real time if needed [36, 37].

4.6.2 Off-line artefact cleaning

Data was analysed after recording sessions had concluded. This analysis was able to take advantage of slower algorithms and methods that required supervision/input to effectively remove artefacts. This subsection details the only algorithms applied offline regarding data pre-processing.

The online pipeline was applied to recorded data before any off-line analysis was carried out. However, when analysing recorded data post-recording, the data did not have epochs removed where data could not be cleaned using classical signal processing methods and the Fast EMD-CCA algorithm applied to remove eye-blink artefacts; instead these epochs were identified. Once the pipeline was applied, a visual inspection was conducted on the data, the visual inspection was applied to identify any further regions where artefacts existed and reduced data integrity. If any artefacts were identified using the visual inspection, independent component analysis (ICA) was applied to further clean the data. Additionally, processing/validation was applied to the data using the MNE python package which identify if any "bad channels" existed. Once this was completed, the data was visually assessed a second time to ensure that no artefacts were visually present before analysis was run on recorded data.

4.7 Analysis Techniques

Analysis methods were applied to pre-processed EEG data. Two notable analysis techniques are discussed which focus on the power content and connectivity of data. Both analysis methods have been applied over the entire time window and are presented as time varying metrics. The analysis methods have been selected as they offer distinct insights into the dynamics of the EEG signals analysed.

Measured EEG data are known to have both random and stochastic properties when compared to the true value of the data [21]. Random and stochastic properties of recorded signals mainly account for noise and background biological processes that do not relate to the underlying neural signalling [21]. Owing to this, averaging was applied to data recorded to better represent the neural processes measured. Each analysis method employed a different suite of averaging techniques that were applicable to the analysis. Additionally, EEG data are generally non-stationary, meaning that its dynamics change across time; however, it has been found that stationarity can be assumed when EEG data are analysed for under 200 ms [21]. Therefore, windowing methods needed to be applied for less than 200 ms.

4.7.1 Power analysis

A power analysis was applied to the EEG data recorded. The power analysis assessed the prominence of various brainwave bands as a time varying metric. The analysis would need to be as computationally light as possible so that it could be run in real time, would need to assess the signal at discrete periods, and it would need to be able to calculate the power of the signal at different frequency bands. Power analyses were applied to results from Temporal electrodes in regions T, TP, and FT because the Temporal lobe is the auditory processing centre of the brain [21].

A Short-time Fourier transform (STFT) was decided as the power analysis method used. This was partly due to its lower computational complexity when compared to methods such as the Morlet wavelet as well as its ability to analyse the power content of the EEG signal over time [21]. The STFT would, therefore, allow an analysis to be run in real time and assess how the power content of EEG data are changing over time. Additionally, previous research has indicated that the STFT would have more distinct peaks at frequencies with a higher power content than a Discrete Fourier Transform or Fast Fourier Transform when applied to EEG data [21]. The STFT analysis method was applied over a 100 sample (195 ms) window with a 10 % overlap and was buffered to 512 samples. A window of 100 samples was employed to ensure that a relatively stationary EEG signal was being analysed [21]. The lowest frequency which can be investigated was 2.56 Hz when using due to the chosen window parameters and Nyquiest's theorem. The slowest signal that the window can analyse is $195ms^{-1}$, 5.13 Hz. However, to agree with Nyquiest's theorem, the slowest signal that can be accurately sampled is $\frac{5.13}{2}$, 2.56 Hz. This is acceptable given that this is below the Theta band defined for this analysis [21, 25]. Secondly, a buffered sample of 512 data points was used to increase the frequency resolution of the STFT[21, 25].

Figure 4.9 outlines the overall power analysis method applied. Once an STFT was taken, the mean of the frequency band being analysed was calculated for every period, and time averaging was applied. Frequency averaging was only applied when brain wave bands were analysed, and was not when individual frequencies were assessed. Region averaging took the average of electrodes from the same region between the left and right hemispheres. After all averaging was carried out, every value at the end of the power analysis pipeline represented six seconds of data. These averaging methods were applied to the data to reduce the random, stochastic, and non-stationary properties of EEG data.

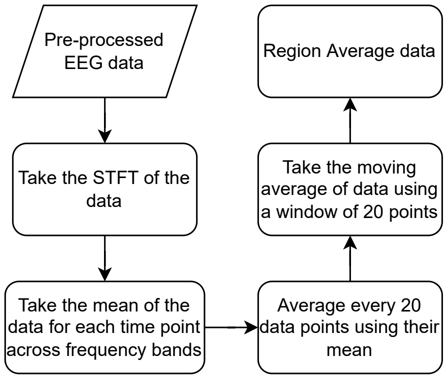


Figure 4.9: An overview of the power analysis techniques used.

4.7.2 Connectivity analysis

A connectivity analysis was applied to the EEG data. This analysis methodology took inspiration from analysis methods used to analyse computer networks. Although multiple network analysis metrics were assessed and implemented, the clustering coefficient was chosen to represent connectivity dynamics between electrodes in the context of the present study.

Figure 4.10 outlines the pipelines used to determine the phase locking value and clustering coefficient for each electrode at every period. The `NetworkX` Python package was used to calculate the clustering coefficient after constructing a graph of interconnected nodes. The weights associated with the graph were set to the phase-locking value between all pairs of electrodes. The earlobe reference electrodes were excluded from the graph and phase-locking calculation as they served as a reference point for the EEG measurement. Results regarding the clustering coefficient have been presented for Temporal electrodes in regions T, TP, and FT as the Temporal lobe is the auditory processing centre of the brain [21]. However, the clustering coefficient was calculated for the connectivity between every electrode, excluding the earlobe electrodes, and the Temporal electrodes presented.

4.7.3 Meta Analysis

Once a connectivity and power analysis was carried out on the EEG data a new challenge arose. Both sets of data analysis created results that were too large to quantitatively digest. Therefore, several meta analysis methods were applied to each set of data. The meta analysis methods produced concise and comparable metrics

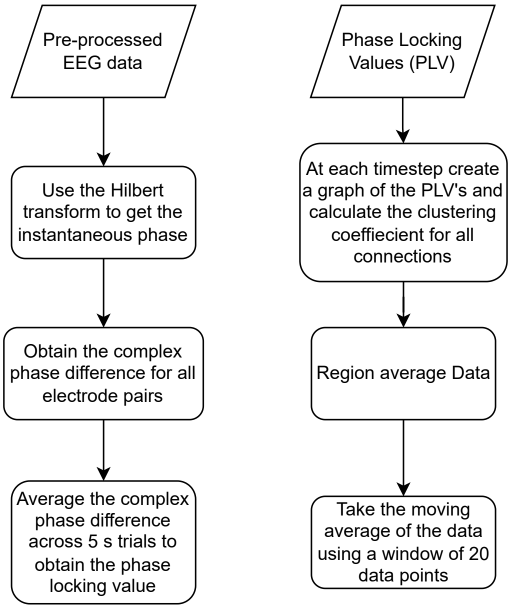


Figure 4.10: An overview of the connectivity analysis techniques used.

which allowed comparisons to be drawn regarding the differences between recording groups.

Table 4.3 summarises the meta analysis metrics used to provide these comparable metrics. Some metrics had averaging applied to them, however the nature of averaging applied to these metrics are expanded on in Chapter 5. All the meta analysis metrics outlined in Table 4.3 were applied to results from Temporal electrodes in regions T, TP, and FT [21].

Metric name	Description	Insights drawn
Increasing count	Counts the number of temporal electrodes, out of 3, that a participant had which increased from their initial baseline value.	Allows the quantification at a broad level over which participants had electrodes that increased for a particular metric.
Mean	Calculates the mean value of participant data at a given period within the dataset.	Allows a comparison to be made regarding the average metric value across groups. Again this has a similar drawback to the standard deviation metric. However, since confounding variables will be relatively consistent the metric will be used.

Mean absolute difference	Calculates the mean of the absolute difference participants had from the start to the end of the recording.	Allows a comparison to be made regarding the amount of displacement a participant had during a session. While there are other confounding variables regarding the measurements being compared such as skull morphology, electrode gelling, hair type e.t.c., all participants were set up to have $< 30\ k\Omega$ resistance values for all electrodes and these factors will be relatively consistent across the measurements. These reasons, therefore, allow the metric to be used as a comparison tool.
Percentage increase	Calculates the percentage of values that are above the initial recorded baseline for a participant. Notably, this has been calculated in three minute buckets and overall.	Allows participants to be compared more objectively as the baseline for this metric is the participant's initial state recorded. The metric allows comparisons to be made regarding whether a sustained increase is achieved for participants in any group.
t-test	Calculates the t-test value for different metrics using all three minute buckets that make up the overall change during the session.	An independent t-test has been used to allow the null hypothesis to be evaluated when comparing all measurement sets with one another. This allows all other metric values to be held up to some form of objective metric and determine whether they are significant or not. The critical value used to determine significance has been chosen as 0.05. If a t-test has a p value above the critical value the null hypothesis is not rejected. This means that the hypothesis / data tested against is not statistically different from the population being tested. If the p value is below the critical value, there is a high probability that it is substantially distinct from the data being tested against.

Table 4.3: Meta analysis metrics used for power and connectivity results.

4.8 Machine Learning

The design and considerations required for the Machine Learning (ML) algorithm are outlined to further elaborate on the experimental setup. The algorithm was used for test participants and could potentially use values from the power and connectivity analyses, or raw EEG data to derive a feature/feature set.

4.8.1 Requirements

The ML algorithm developed was used during recording session two. The algorithm was employed to control the entrainment stimulus presented to participants and aimed to enhance entrainment effects when targeting Beta band brainwaves.

Requirements were a key consideration in deciding what type of ML algorithm was implemented. The ML algorithm would run in real time while EEG measurements were taken in parallel. The algorithm would, additionally, need to periodically assess a segment of time series data. Therefore, the model needed to be relatively lightweight. Lastly, the ML algorithm would have further requirements:

- It would need to be transferable between participants so that inter-participant learning could be achieved.
- It should learn the optimal policy while driving the entrainment stimulus and not require previous training as this was not realistically possible.
- It would need to be stateful such that it could assess the change in a participant's brain state relative to an objective state.

4.8.2 Feature selection

Initially, the feature used for the algorithm was decided. The results of the STFT were selected as the feature for the algorithm.

There were several supporting motivations for this decision; however, one major reason should be noted. The STFT runs faster than the connectivity analysis and can be scoped to run only on the region selected, while the connectivity analysis needs to be run on every pair of electrodes from a selected region. The STFT, therefore, was practically a better option as the ML would need to run in real time.

More specifically regarding the chosen feature, data from the STFT of the TP region was chosen instead of data from the T or FT regions. The FT region was excluded as it would be most susceptible to eye movement and blinking artefacts due to its location, despite cleaning algorithms being implemented. While either the T or TP region would have been acceptable options, the TP region was chosen as only one region was needed. The feature used was pre-processed using the on-line processing outlined in Section 4.6.

4.8.3 Model selection and design

Given that the feature for the algorithm was chosen, the algorithm itself needed to be selected. The algorithm would need to learn the optimal policy while interacting with the live system, and with limited data. Due to these requirements, an algorithm from the RL family was selected. RL algorithms are well suited to learn an optimal policy function when working with live data and without any previous training. Within RL, the problem was one of control and was stateful as the current entrainment frequency and brain dynamics were necessary in choosing an action. Additionally, the task was not episodic in nature as each participant would have multiple entrainment blocks defined by the agent that did not start back at some starting point. A Q-learning and a Contextual Multi-Armed Bandits (C-MAB) agent were considered most prominently. Q-learning was chosen over C-MAB as it allowed for a reward and return aspect that could be useful in the application. Secondly, the number of contexts in a C-MAB implementation produced a similar model to Q-learning. Therefore, Q-learning was selected as the RL algorithm used [80].

The Q-learning algorithm implemented leveraged the Bellman equation to update its Q table [21, 80]. The Bellman equation is outlined in Equation 2.8. Additionally, it utilises a learning rate, α, and discount factor, γ, of 0.2 and 0.4 respectively. These values have been chosen as they result in a relatively slow update of information to the model. This was beneficial so that potential outliers would have a less pronounced impact on the model during earlier iterations as well as providing a closer match to the brain's relatively slow response to binaural beats [21, 71, 80].

The Q-learning algorithm used states that were defined by two parts: the direction that the brain state is moving and the current entrainment frequency. The brain state direction was determined using the first and last data point during the window evaluated. The EEG measurements used for this were narrowband filtered to the entrainment frequency shown to a participant; this data was used for the STFT and any reward calculations performed. The direction has been bucketed into two possible values: up for a positive change or down for a negative change. The current entrainment frequency is self-explanatory as the stimulus experienced by a participant during a block. The state notation was defined as: $brain\ state\ direction\_entrainment\ frequency$.

QL stimulus-driven blocks were divided into three minutes each. The blocks meant that every three minutes the QL agent would evaluate the previous three minutes of EEG measurements, and the stimulus used during the block. The information would inform the audio entrainment employed during the subsequent block and what reward to assign the previous action. This decision was based on existing research and practicality [71]. Practically, three minute periods were acceptable given a 15-minute recording session as three is a factor of 15 and the period allows the QL agent multiple decision-making points. Existing research indicated that habituation commonly occurred after three minutes and that this was an optimal period to switch the stimulus presented; however, the research reviewed alternated an entrainment stimulus with pink noise [71]. The QL driven blocks would start after the first three minutes of stimulus, in which all participants would be exposed to an entrainment stimulus of 24 Hz. This was employed due to the Q table requiring a direction and entrainment frequency applied to define the initial state. Therefore, during any 15 minute test run, the algorithm would be able to take four actions and similarly update the Q table four times.

It was decided to limit the action and state space to two actions resulting in an initial Q table shown in Table 4.4. This was chosen for two reasons: firstly the number of actions that could be taken with six test participants was considered as it would allow 24 actions to be taken in total. A Q table with two actions had eight values, while a table with three actions would have 18 values. Therefore, any more than three actions would require a significantly higher number of exploring iterations, allowing very few actions to exploit a model during the study. Furthermore, the state - action space explored was not completely causal; when an action was taken it was not guaranteed that a specific state would be reached. Therefore, when there is a state - action space with 18 values, the number of exploratory steps to truly reach all pairs would be between 18 and infinity actions. Consequently, it was more practical to have a smaller state space and increase the probability that all state - action pairs were reached at least once. Additionally, it was decided that the study should have at least one participant who had their brainwaves driven by a purely exploitative QL agent. This was to evaluate the possible effect that it might have and becomes significantly more probable with an action space of two actions. Lastly, given that no existing study evaluated dynamic switching between entrainment frequencies, it was decided that the QL agent should evaluate the feasibility of this method of stimulus switching. This evaluation was optimised when using fewer entrainment frequencies in the action space.

Table 4.4: An overview of the Q-learning Table used for the study.

State \ Action	24	20
up_24		
down_24		
up_20		
down_20		

Entrainment frequencies of 24 and 20 Hz were chosen for the stimuli. 24 Hz was chosen as it was used for the set frequency Beta entrainment stimulus, while a 20 Hz entrainment frequency was chosen as it still falls within the Beta band and is spaced from the 24 Hz frequency. Additionally, it was determined that despite audio processing on the Oculus or headphones both 24 and 20 Hz pure sinusoidal entrainment frequencies were possible.

The Q-learning algorithm employed the greedy and decaying epsilon policies outlined in Algorithms 1 and 2. Once the Q table was fully populated, the value of epsilon was set to 0 for the following participants to ensure that the model only selected what it deemed as optimal actions. This decision was made to increase the number of exploiting steps that the QL model took given the small sample size and the goal of having at least one participant that only used optimal actions as defined by the model.

4.8.4 Reward function

The final step in designing the RL agent used was its reward function. RL agents have reward functions that define how well actions are rewarded. This allows the agent to “learn” what actions are better than others and make decisions. The reward function needed to be comparable between participants so that the model could learn between participants. This was due to possible changes between participant setups regarding how they were gelled, the morphology of their head, and the exact placement of electrodes among other factors [21]. With this in mind, the reward function was created and the pseudocode for the reward function can be seen in Algorithm 3. In essence, the reward function returned the percentage of STFT values that were either increasing or decreasing at the entrainment frequency depending on the general trend of the data. The reward function developed would reward both upward and downward movement based on how it was sustained for cases where participants had a sustained and significant decrease in power at the entrainment frequency.

In addition to the reward function having a return value that depends on which direction the brain state was moving, it also relied on the amount that it was changing. If the brain state’s overall change was below a set percentage of the initial value, eight %, a separate reward of 0.5 was used. This was chosen as it is in the middle of all possible reward values that could be obtained from the function. Scenarios where the agent was maintaining a particular brain state were useful when the QL agent had induced a brain state that was optimal. In this case, it was not ideal to punish the algorithm for maintaining the state, and thus it was rewarded with the mean reward.

The reward function created a percentage value from the feature, the STFT data for a participant. While the STFT data may have variability regarding setup and participant dynamics, the reward function converted this into a percentage. Therefore, no feature normalisation was required before the reward function, as the reward function had an output that was between: [0, 1] for all participants. This feature of the reward function ensured that learning could occur between participants.

Algorithm 3 Pseudocode for reward function.

function CALCULATEREWARD*(STFTData)*
    $diff \leftarrow dy(STFTData)$ ▷ Take the derivative of the STFTData
    $increasingCount \leftarrow$ count positive values in $diff$
    $decreasingCount \leftarrow$ count negative values in $diff$
    $totalValues \leftarrow$ length($diff$)
    $fractionalChange \leftarrow |(diff[end] - diff[start])/diff[start]|$
    if $fractionalChange > 0.08$ **then**
        if $increasingCount > decreasingCount$ **then**
            $reward \leftarrow increasingCount/totalValues$
        else if $decreasingCount > decreasingCount$ **then**
            $reward \leftarrow decreasingCount/totalValues$
        else if $decreasingCount == decreasingCount$ **then**
            $reward \leftarrow 0$
    else
        $reward \leftarrow 0.5$
    return reward

4.9 Study Bias

Several forms of bias may affect the results of the study. While these biases can be accounted for, fully eliminating them is impractical. Therefore, potential sources of bias should be noted along with potential mitigations.

Using the University's network to invite participants might introduce bias to the study due to the population group it provides: a University's network is heavily biased towards youth and is in the top percentage of society in terms of education, to name two possible biases. This may be accounted for by asking participants to invite others to the study, if they are willing to, however this may do little to curb the bias due to the social strata often associated with University students. Beyond this, the bias is noted but not further accounted for due to the scope and timeline of the research.

Participants of differing sexes were invited to participate in the study. Statistically, male participants will be more likely to have experience playing computer games [91, 92]. Therefore, having more male participants in one of the groups might bias the study due to VR being a gaming-like environment. Additionally, the University has a student population with a higher percentage, 55.26 %, of females than males [93].

The age of participants may also impact on biases of the sample group, this should be noted as the study might have participants from different age groups. While the majority of gamers are over 18, there is a drop-off of percentage gamers for an age population as age increases [94]. Therefore, having a group with a higher mean age might reduce participant's experience of gaming.

Given these gender and age statistics in the context of a study that looks at immersing participants in a relatively gamified world, the gender, and age of participants has the potential to bias the study. The study will need to account for these biases, as they cannot be completely removed from the study.

4.10 Project Plan

Project management was required for the study to ensure that it was completed in a timely manner which aligns with the duration of a Masters set out by the University. To this end, a project plan with estimated timeframes was created.

Figure 4.11 provides a summarised Gantt chart describing the estimated timeline of the research, while Figure 4.12 provides a Gantt chart of the actual project's progress as it was completed. Appendix A provides a more in-depth look into the estimated timeline against real dates on which milestones were started and completed.

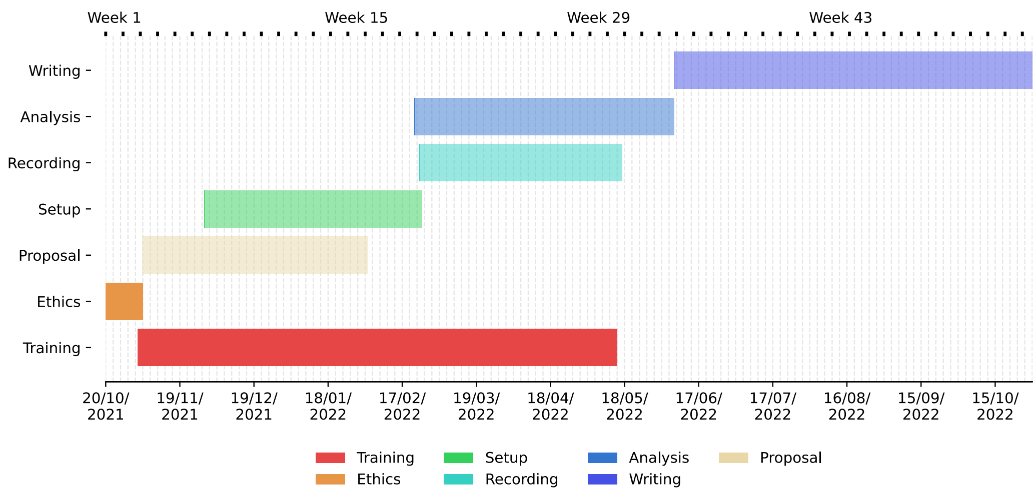


Figure 4.11: A summarised Gantt chart of the project management plan for the research.

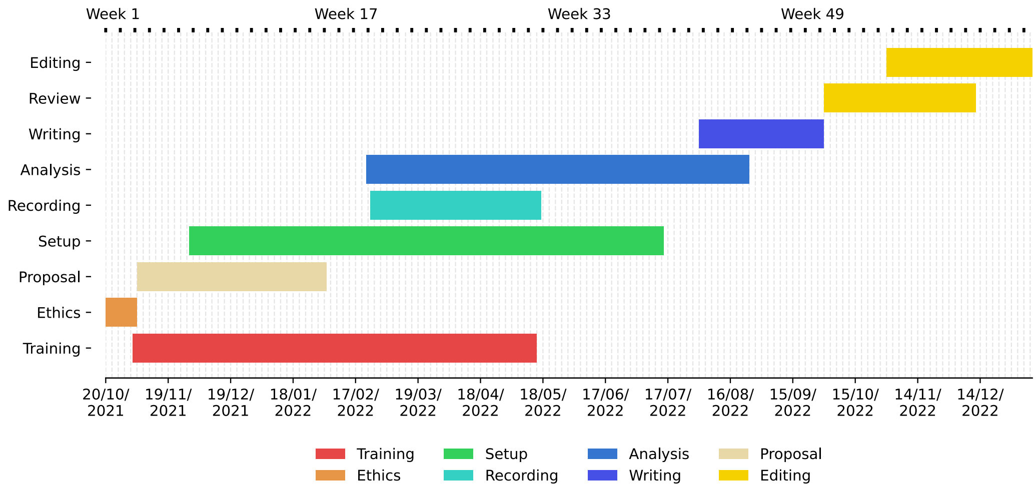


Figure 4.12: A summarised Gantt chart of the Final project timelines followed.

4.11 Funding

Funding was required for the project to be set up and for data recording to be carried out. The overall cost of the project can be seen in Table 4.5.

Funding required for equipment and resources not available at the University was provided by the project supervisor's research funds. The funding required was sufficiently low that this was feasible and external funding was not needed. No funding from participants was required.

4.12 Ethical Consideration

Ethical implications for the research need to be considered for several reasons. The research dealt with participants and was performed during the COVID-19 pandemic, therefore the impact of the research should be noted and evaluated.

An ethics application to the medical ethics committee was submitted and approved to ensure that the research was carried out ethically and that risks to the participants were adequately accounted for. The ethics protocol number is M211146 and the Clearance certificate and amendment can be seen in Appendix C Figures C.1 and C.2 respectively. Since the scope and title of the project was changed slightly, participants

Table 4.5: Cost of the project.

Equipment	Cost (R)
Oculus Quest two	11,999
Noise-cancelling headphones	0 (Personal pair of headphones)
g.tec EEG device	0 (EEG machine already at the University)
Sanitising equipment	150 (estimate)
Data storage and compute power on AWS	0 (Did not exceed free tier limits)
Total (R)	12,449.00

were advised that aspects of the information sheet were no longer being tested in the study and that the title had changed. Furthermore, ethics training was obtained by the principal investigator and supervisors of the study to ensure sufficient ethical knowledge to assess the project.

Informed consent is an important ethical step in studies involving participation. All participants received an information sheet and a consent form for study participation. The consent form was signed by participants and both the investigators and participant have kept a copy of the signed consent form.

Major ethical considerations around the study methodology centre around the entrainment methods used and the entrainment itself. Entrainment has been shown to potentially influence the mood of participants and participants were, therefore, informed regarding this [3, 4, 5, 61, 63].

Ethical considerations around the study in context of the COVID-19 pandemic should further be noted. The principal investigator was fully vaccinated against the COVID-19 virus and wore a mask during the entirety of the measurement phase where they interacted with participants; participants were also required to wear a mask at all times. Secondly all equipment was sanitised before and after any participant used them. Lastly, participants were given hand sanitiser before and after recording sessions and were required to complete and sign a COVID-19 questionnaire, in addition to the consent form. Participants were additionally asked to contact the investigating team if they exhibited any COVID-19 symptoms post recording. This allowed the investigators to let any participants that may have had any exposure know and so that the team could make an informed decision to pause recording until the team was certain that the principal investigator had not contracted COVID-19 and was not transmitting the virus.

4.13 Notable methodology points

The experimental setup and analysis methods are outlined for the study. Further, the addition of a control reading for both test participants and a control group increases the validity of results by adding two objective recordings. Lastly, considerations are presented regarding the study's ethical considerations and limitations which are necessary when conducting research.

The study's sample should be noted as it is relatively low. As a result, any conclusions drawn from the study are indications of likely trends more than definitive inferences. This is useful due to the novel nature of the study.

The study has been designed to address the research question and goals set out. It measured EEG recordings using a g.tec device to evaluate neural changes in participants. BB entrainment has been identified and implemented as an intervention that can alter the brain state of participants. Further, the entrainment stimulus was controlled by a Q learning agent in a separate recording which evaluated if the stimulus may be optimised when the agent switched between two entrainment frequencies.

The ML agent is outlined and was a Q learning RL algorithm. The Q learning agent was able to switch between an entrainment frequency of 20 and 24 Hz and had a reward function that focuses on the Power of Beta band brainwaves. The Q learning algorithm attempted to learn an optimal policy to control the entrainment stimulus and maximise the power changes in participant Beta band brainwaves. The parameters of the Q learning agent were designed so that at least one participant might have a stimulus guided by actions the agent deemed optimal.

Analysis methods used to derive results for the study are outlined. These analysis methods used power and connectivity analysis metrics to assess different aspects of recorded data. The methods produce metrics which allowed participant as well as recording group comparisons to be made. The next step required in the study is to present the analysis of recorded data.

Chapter 5

Results and discussion

5.1 Introduction

Results are derived from recorded electroencephalogram (EEG) measurements as well as the Q-Learning (QL) algorithm that controlled the stimulus. The results cover various aspects of the recorded data and have been derived using different mathematical methods. This chapter outlines and highlights various key findings of the analysis performed on the recorded data.

The key results presented look at power and connectivity dynamics during the recording sessions as well as the reinforcement learning (RL) model derived from exploratory actions. A variety of metrics constitute the results. These metrics provide a singular value that can be compared at different points during the experiment. Further qualitative analysis methods are applied in looking at visual trends present in results.

The results derived focus on the research outcomes of the study. These outcomes centre around evaluating existing entrainment techniques in virtual reality (VR) and how well these techniques can be improved though a dynamic algorithm. Results are formed to aid in addressing these outcomes with as much validity as possible. Multiple metrics have been developed to support conclusions and discussions with multiple layers of substantiation. A discussion is formed around both the nature of the stimulus used and various aspects of the results derived.

Notable for all discussion points made is the relatively small sample size of the study. This hinders any points from being made absolutely, as it would require more participation in the study. Points made in this Chapter will serve as indicators of potential trends and patterns that may arise if the study was run with more participants.

5.2 Audio Stimulus

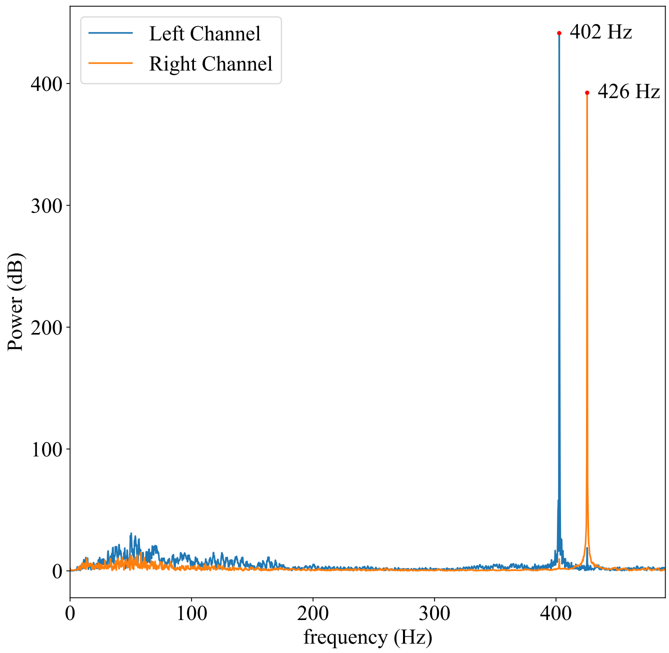
5.2.1 Results

Before participation in the study began, the stimuli used for the experiment were evaluated. This analysis was conducted to interrogate assumptions regarding the setup of the experiment and ensure that it was correct.

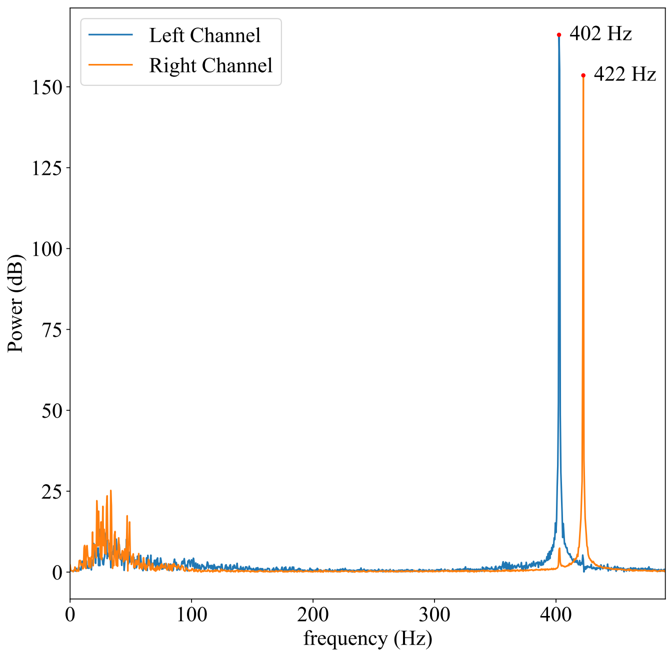
Figure 5.1 illustrates the frequency spectra of both the 24 Hz and 20 Hz entrainment stimuli used, obtained using a Short-time Fourier transform (STFT) with a window of two seconds. Figure 5.1 plots the frequency spectrum during one window of evaluation. Figure 5.1 was generated by data recorded from a microphone. The entrainment stimulus was played as if a participant was using the setup, and the microphone recorded the stimulus from each channel. A Steel Series Arctis Pro gaming headset microphone was used.

Due to the recording setup, any changes to the Oculus's volume or the relative position of the microphone to the headphone could cause minor changes in the power values seen in Figure 5.1. These differences are indicated in Figure 5.1, however, the power difference between the two channels is negligible.

A 402 Hz carrier wave was used for the entrainment stimulus and was sent to the left channel of the headphones. Figures 5.1a and 5.1b confirm that this occurred, they indicate that the left channel of both entrainment stimuli had a distinct peak at 402 Hz. Further, the figures indicate that entrainment frequencies of 24 Hz and 20 Hz were achieved by the stimuli. The Figures illustrate that the signals had distinct peaks at 426 Hz and 422 Hz for the 24 Hz and 20 Hz entrainment stimuli respectively. These differ from the 402 Hz carrier frequency by 24 Hz and 20 Hz respectively indicating that the entrainment stimuli were at the expected frequencies. Figures 5.1a and 5.1b indicate that some frequency content occurred at the lower end of the spectrum, below 200 Hz. However, these frequencies have a significantly lower power than at the entrainment frequency and can be attributed to noise. As a result, the noise should not impact on the entrainment's effects.



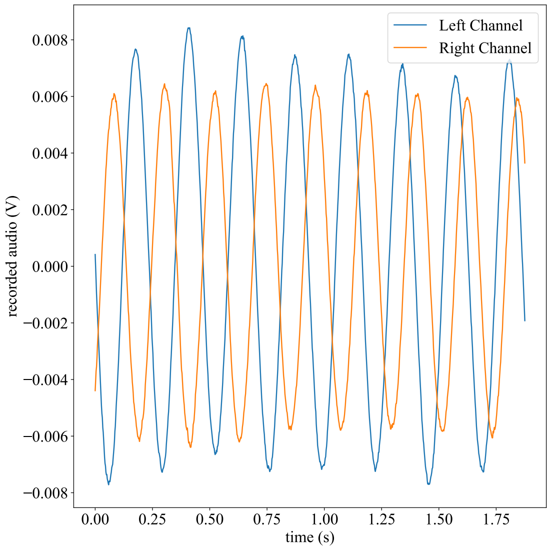
(a) Beta entrainment stimulus.



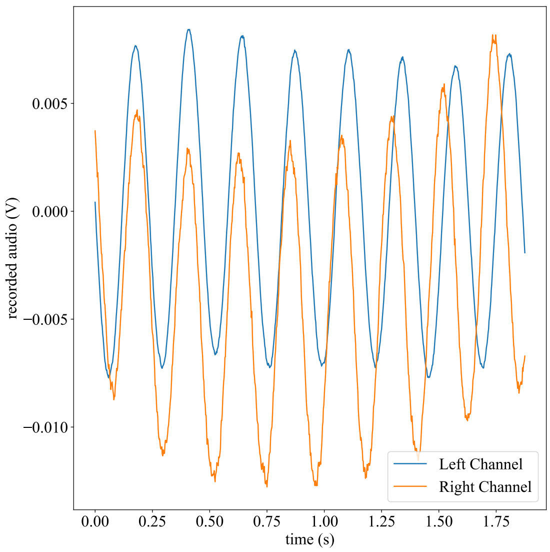
(b) 20 Hz entrainment stimulus.

Figure 5.1: The frequency spectrum of the two channels of entrainment stimuli used.

Beyond assessing the frequency content of the entrainment audio, the recorded stimuli are visually evaluated. The recordings used to analyse the frequency content of the stimulus are plotted for a subset of the two-second interval. Figure 5.2 illustrates the recorded data; both Figures 5.2a and 5.2b illustrate that the stimulus was relatively visually sinusoidal with some ambient noise distorting the recording.



(a) 24 Hz entrainment stimulus.



(b) 20 Hz entrainment stimulus.

Figure 5.2: The raw audio data recorded from the channels of entrainment stimuli used.

Lastly, the pink noise stimulus is considered. Pink noise was not generated dynamically as it was not practical given the computational complexity required. The pink noise was, therefore, pre-generated using Matlab and evaluated using an STFT with a window of two seconds. Figure 5.3 provides the frequency spectrum for one two-second window of the pink noise stimulus used. Figure 5.3 illustrates that the pink noise generated and experienced by participants had a $1/f$ frequency distribution.

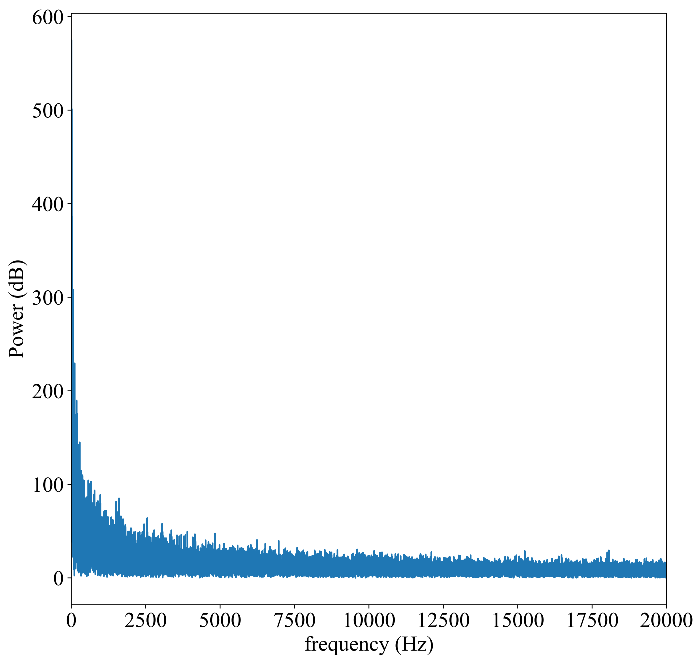


Figure 5.3: The frequency spectrum of the pink noise stimulus

5.2.2 Discussion

The frequency properties of the three audio stimuli are evaluated. This is conducted to ensure that participants were exposed to the expected stimulus during the experiment.

The entrainment stimuli are expected to be sinusoidal and produce an entrainment frequency of 20 Hz and 24 Hz. The left and right channels of both entrainment stimuli are visually sinusoidal with some noise effects. The noise effects can be assumed to originate from ambient noise and limitations of the recording method. This is due to the noise's relatively low prominence in both the raw data recorded and frequency spectrum plots of the stimuli. The results, further, indicate that the entrainment stimuli used a carrier tone of 402 Hz which was sent to the left channel. The stimuli achieved an entrainment stimulus of 20 Hz and 24 Hz through sinusoidal tones of 422 Hz and 426 Hz respectively in the right channel. The entrainment stimuli, therefore, acted as expected.

Further to the entrainment stimuli, the pink noise presented to participants is assessed. The pink noise presented is confirmed to have a $1/f$ power distribution and visually appeared as Gaussian noise. The pink noise, therefore, exhibits the expected characteristics required for the control stimulus.

The audio stimuli had characteristics that corresponded with the requirements set out in the experimental design. This provides an increased level of confidence in the results as assumptions made around the stimuli have been evaluated.

5.3 Nomenclature Used For Grouping

Groups are divided for analysis and results so that group averages can be calculated and compared using a single value. Divisions have been made based on the group, test or control, and stimulus experienced. The recording groups and a more explicit description of each group can be seen in Table 5.1.

For the purposes of brevity and clarity, discussions in this Chapter which reference test stimuli groups collectively refers to QL and Beta entrainment stimuli recordings. Control groups collectively refer to the intra-group control recording, the control recording for the test group, as well as the control recording for the separate control group.

5.4 Continuous Visual Time Analysis

The power and connectivity analysis methods are analysed and recorded as time varying metrics. The time varying results of the analysis methods are evaluated. The metric values are plotted using a participant whose data reflects the optimal general trend of the group so that visual trends can be discussed.

Table 5.1: Recording groups used for analysis.

Recording	Description
test group, Beta stimulus / entrainment	Recordings where participants were exposed to a constant 24 Hz Beta entrainment stimulus.
test group, QL stimulus	Recordings where participants had their stimulus modulated by QL agent that could switch between a 24 Hz and 20 Hz entrainment stimulus. The QL agent could change the stimulus every three minutes.
control group, control stimulus	Recordings where the separate control group participants were exposed to a pink noise control stimulus.
test group, control stimulus / intra-group control	Recordings where test group participants were exposed to a pink noise control stimulus.

5.4.1 Power Analysis

The power analysis results are plotted at the T, TP, and FT regions. These results are plotted using a participant whose data reflects the overall trend of the group, allowing a discussion around visual trends present. Appendix B provides the spectrogram and baseline plots for these results. Further, once visual trends have been identified, a table is presented which compares the identified characteristics across different recording groups.

Power analysis results are presented for the Beta, Alpha, and Theta brain wave bands. The Alpha and Theta bands provide an objective measurement with which to compare trends in the Beta band. The comparison is possible as the entrainment methods applied did not target the Alpha and Theta bands. The comparison point is not absolutely objective; however, it provides a good baseline. Further, different bands can be compared within a recording using the same experimental setup as the same data are filtered to different bands for the analysis. Additional analyses were run when narrowband filtering EEG data to 24 Hz and 20 Hz. However, these results were not reported as they had the same general trends and insights as the overall Beta band analysis.

Power analysis graphs are plotted as spectrograms which focus on the Theta, Alpha, and Beta bands. Red dotted lines are plotted at the edge of different bands to visually highlight where the borders exist. The spectrograms presented reflect the power changes from the participant's baseline power; this is beneficial as the study focuses on evaluating the effects of a stimulus aiming to change the baseline power. The baseline spectrum is plotted for every spectrogram plot to indicate the baseline resting state of participants, before the stimulus onset.

Results

Figures B.1 to B.3 and B.4 to B.6 outline the baseline spectra and spectrograms of the response exhibited in response to the control stimulus. Figures B.1 to B.3 and B.4 to B.6 describe the general trend seen in participants of test and control groups, respectively.

The figures outline baseline spectra that exhibits a 1/f power distribution and are therefore acceptable and expected baseline power recordings for participants. The magnitude of the baseline power spectra between the control and test participant highlighted are different, however the power dynamics have been presented for the change in participant power relative to this baseline. Therefore, the difference seen will not detract from the power results derived from the spectrograms. This extends to all spectrograms analysed. Figures B.1 to B.3 outline trends seen in test participants. Generally, the trends seen in Figures B.1 to B.3 agree with Figures B.4 to B.6. While some differences exist, these differences are transient and, therefore, will not be noted as stimulus related differences. Rather, they are likely participant specific differences.

Figures B.1 to B.3 and B.4 to B.6 have several notable characteristics. Due to the similarity of results seen for both groups, characteristics will be noted once for the control stimulus recording groups. Firstly, the Theta band exhibits a decrease in power during the recording session. This is generally seen across all participants in all regions analysed; the test group's control recordings deviated from this, increasing from the baseline. Secondly, both groups exhibit some varied increases in the Alpha band. These increases are at times transient, however a decrease in power is not seen in the Alpha band. Lastly, the Beta band does not exhibit a notable and sustained increase in power across either group. The lower end of the Beta band tends towards a decrease in power. However, the upper end of the band exhibits values indicating negligible changes in power values. This indicates that the upper band was unchanged, while the lower end of the frequency band exhibited a decrease in power as a result of the pink noise control stimulus.

Figures B.7 to B.9 outline the baseline spectra and spectrogram plots for a test participant exposed to the Beta entrainment stimulus. The baseline spectra indicate that the participant initially has a relatively 1/f frequency distribution, which is both expected and acceptable based on previous research.

The spectrograms presented by Figures B.7 to B.9 provide several interesting results. A decrease is seen in the Theta band for all three regions. This is less pronounced in the upper end of the Theta band for the TP region. Further, an increase in Alpha band activity for all regions is seen. This change is not initially present, however it was maintained after occurring. Lastly, and possibly most notable, are the results shown in the Beta band. There is a sustained and notable increase in the power of Beta band brainwaves in all regions analysed. This is distinct from the changes seen in the Alpha and Theta bands. Power increases are most prominently seen, both in the sustained nature and magnitude of the change, in the lower end of the Beta band, below the 24 Hz entrainment frequency. Lastly, the upper end of the Beta band indicates no notable power changes, there are some power increases by the end of the stimulus period. However, these changes are not as pronounced as changes seen in the bottom end of the Beta band.

Figures B.10 to B.12 outline the baseline spectra and spectrogram plots for a test participant exposed to the QL driven entrainment stimulus. The baseline spectra indicate that the participant initially has a relatively 1/f frequency distribution, which is both expected and acceptable based on previous research.

Figures B.10 to B.12 generally agree with the results seen in response to a set Beta entrainment stimulus. The figures indicate a maintained increase in the Beta band and Alpha bands. Additionally, one strong distinction exists between the two test groups; Figures B.10 to B.12 indicate that, across all regions, the QL driven stimulus increased the power of Beta band brain waves more comprehensively across all frequencies of the Beta band. The increase, additionally, appears to concentrate around the entrainment frequencies, the middle, and upper region of the Beta band.

The visual analysis of spectrogram plots resulted in several notable characteristics that were present in the data. However, the characteristics need to be reproduced across participant groups to have any validity as results. Table 5.2 provides a summary of spectrogram results across all participants. The table provides a count for the number of participants exhibiting different identified characteristics. The overall

Beta band listed refers to any increases seen anywhere in the Beta band. Similarly, the upper and lower bands are defined relative to the entrainment frequencies used in the experiment. The lower band refers to frequencies between 13 - 19 Hz, and the upper band refers to frequencies between 19 - 30 Hz. The frequencies were chosen due to identified trends seen in the spectrogram plots.

Table 5.2 indicates that the control recordings did not exhibit a notable increase in Beta band power, at any defined region of the band. This is less present at the FT region, however it is most prominent at the T region. Further, the table indicates that all but two recording groups showed an increase in Alpha band power across the T and TP regions for at least half of the participants. The finding is further supported as no participants show a notable decrease in Alpha band power in the T or TP regions, this is noted, but not shown in the table. No significant findings distinguishing test from control recordings are present in the Theta or Alpha band.

Table 5.2 illustrates that an increase in Beta band power is exhibited by both test groups on the whole. 2 participants do not exhibit an increase in Beta band power across both the QL and Beta entrainment recordings. It was verified that these two participants were common across both recording sessions. Further, the table indicates that the increase in Beta band power was not present in the control recordings. This differs from findings in the Alpha band, where a comparable number of participants exhibited an increase in the metric for both test and control stimuli.

Table 5.2 outlines a notable difference between the QL and Beta entrainment groups that was identified in the visual analysis. Table 5.2 provides evidence that the QL driven stimulus had an impact on a larger region of the Beta band, this is most prominent in the T and TP regions. The finding is highlighted by the difference in count values across recordings in all Beta frequency regions listed. The result indicates that the Beta entrainment stimulus increased the power of Beta band brain waves below the entrainment frequency and at the lower end of the band; while the QL driven stimulus was able to affect a larger range of frequencies in the Beta band, including the entrainment frequencies. Table 5.2, therefore, supports findings from the visual analysis indicating that the QL driven stimulus was able to increase the Beta band power across the Beta band, significantly at the entrainment frequencies used and at the upper end of the Beta spectrum.

Table 5.2: A summary of the spectrogram characteristics across recording groups

Region	Band	Test group, Beta stimulus	Test Group, QL stimulus	Control group, Control stimulus	Test group, Control stimulus
T	Overall Beta	4	4	1	1
	Upper Beta	2	4	1	1
	Lower Beta	4	4	1	1
	23 - 24 Hz	3	4	0	1
	19 - 20 Hz	4	4	1	1
	Theta	1	1	1	3
	Alpha	3	3	3	2
TP	Overall Beta	4	4	2	2
	Upper Beta	2	4	0	0
	Lower Beta	4	4	2	2
	23 - 24 Hz	1	2	1	0
	19 - 20 Hz	1	2	1	0
	Theta	1	2	0	4
	Alpha	3	2	3	4
FT	Overall Beta	5	3	3	2
	Upper Beta	2	3	1	2
	Lower Beta	5	4	3	3
	23 - 24 Hz	2	2	1	2
	19 - 20 Hz	2	3	0	2
	Theta	1	3	1	3
	Alpha	3	2	2	4

Discussion

The baseline power spectra of the visually analysed recording sessions was presented and determined to have a 1/f distribution. This finding was confirmed for all participants. A 1/f distribution agrees with existing literature regarding the frequency distribution of resting neural activity. Further, this confirms that data was adequately recorded and cleaned. Setup and data processing errors would result in a different baseline spectrum. Therefore, since no marked differences exist, it can be assumed that the data has been adequately recorded and processed.

The spectrogram plots of all participants were analysed visually, however an individual analysis is presented for one participant in each group. The individual visual analysis identified key characteristics which informed data consolidated into Table 5.2. The results presented in the individual analysis agrees with the overall trends shown in Table 5.2. Therefore, discussions regarding notable characteristics will be presented once for both results.

Theta band brain waves exhibit a relatively constant or decreasing trend across participants of all groups. Similarly, Alpha band activity is seen to either increase or remain relatively constant for all participants. This finding increases the confidence around any findings in the Beta band. Findings in the Beta band gain more credibility for their comparison, as the Alpha and Theta Band similarity justifies that setup and participant specific differences are not pronounced between recording groups. Further, it indicates that the entrainment stimuli did not affect the Alpha and Theta bands. This agrees with previous results, while improving their validity, as previous research did not have a separate control recording, and often did not evaluate multiple frequencies within the bands.

Increases seen in the Alpha band agrees with existing research. Prior studies have indicated that increases in the Alpha band during a closed eyes condition is linked with inhibition of visual processing in the brain. This was most present in the Occipital region of the brain in the majority of studies, however it has been reported to occur in all regions of the brain. Further, this agrees with the visual trend identified, where Alpha band power would reach and maintain a certain power level for the entire recording session, shortly after the session began. Cases where the Alpha band power remained constant instead of at an increased value are likely due to participants reaching the constant increased Alpha state during the baseline recording. Lastly, the presence of this trend across all recording groups agrees with existing knowledge, as the effect of the increased and/or maintained Alpha level was due to the closed eyes condition and not the audio stimulus.

The difference in Beta band activity between test and control recordings is notable. Beta band trends indicate that the test stimuli increased Beta band power in test participants, while control participants exhibited a decreased or maintained Beta power through the recording. Further, comparisons between results seen in the Beta band and results present in both the Alpha and Theta bands supports this. Trends in the Alpha and Theta bands are present in all recording groups, while trends in the Beta band differentiate groups that had test and control stimuli. This agrees with previous research, indicating that an entrainment stimulus targeting the Beta band would increase the power of targeted brain waves. Additionally, the results expand on existing research by indicating that the QL driven stimulus is able to have a comparable effect on Beta band brain waves when compared to the Beta entrainment stimulus, and that the effects in the Beta band are not common when control groups are added to the experimental setup.

The results indicate that the largest effect of the Beta entrainment stimulus was seen in the lower end of the Beta band spectrum, increasing the power of brain waves at these frequencies. Conversely, the pink noise stimulus is shown to result in a decreased or relatively constant power at the lower end of the Beta band. This is a notable difference between the Beta and control stimuli, as it exists in the same region of the Beta band. The finding indicates that a set Beta entrainment stimulus resulted in an increased power of Beta band brainwaves in the same frequency band where the pink stimulus, under the same experimental conditions, caused a decrease or negligible change. The finding is further supported as the difference exists between the Beta entrainment stimulus recording and both the intra and separate control recordings. The observed effect of the stimulus agrees with existing research, however the use of control recordings as a means of comparison provides new substantiation for this finding.

The frequencies which increased in power resulting from a set entrainment stimulus are notable in context of existing research. No existing research reviewed evaluated a continuous spectrogram at the Temporal regions in response to a Beta entrainment stimulus, further, the studies reported power increases in the overall band targeted. Therefore, no findings were presented regarding the specific brain wave frequencies that were affected by the stimulus. The result, therefore, presents new information that should be further investigated. The finding is that the entrainment stimulus did increase the power of Beta band brainwaves at the lower end of the band, at frequencies below that of the entrainment stimulus. This finding gains more credibility as it is compared to both an intra and separate control group recording.

The power analysis provides one further notable characteristic. The QL driven entrainment is shown to increase the Beta band power comparably to the Beta entrainment stimulus. Additionally, it is shown to increase the power of more frequencies within the Beta band than the set entrainment stimulus. This is notably present in the upper end of the Beta band and at the entrainment frequencies. Neither of these findings is present in existing literature as a dynamic stimulus is part of the research gap addressed by the present study. Further, no continuous spectrogram analysis has been previously presented to compare different frequencies within the Beta band.

Existing research into habituation may aid in explaining the phenomenon and justify that the QL driven stimulus was able to address a research gap identified. It is reported that habituation hinders the effects of entrainment stimuli. Given that previous studies looked at brain wave power within a band as a whole, it is possible that the habituation was, similarly, reducing entrainment effects in the upper end of bands targeted in the studies. When assessing the overall band, this would present as an overall reduction or stagnation of power increases. However, when assessing multiple frequencies within the band it presents as a reduction in brain wave power increases at specific frequencies.

Working on this as a premise, differences in the effects of the QL driven and Beta entrainment stimuli indicate that the QL driven stimulus was able to avoid habituation and improve the entrainment effects of the stimulus. This finding is based on existing findings in entrainment and habituation effects, however the finding itself is not present in previous studies. Therefore, it would benefit from further metric justification to look at the power analysis from different perspectives. Any Beta band analysis performed would further justify this finding if the overall Beta band power increased by more between the QL and Beta entrainment stimuli.

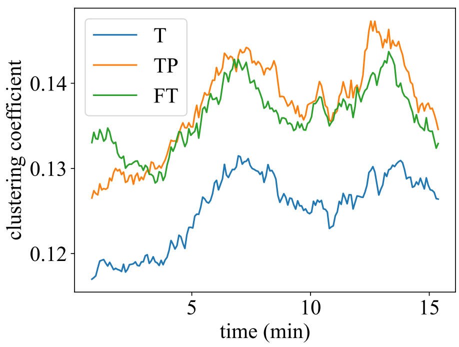
The findings presented are novel, while they are justified by trends previously identified in literature. However, due to the small sample size used in the study, the findings present likely features of the results more than absolute findings. Any novel findings identified should be investigated further to definitively identify their existence.

5.4.2 Connectivity Analysis

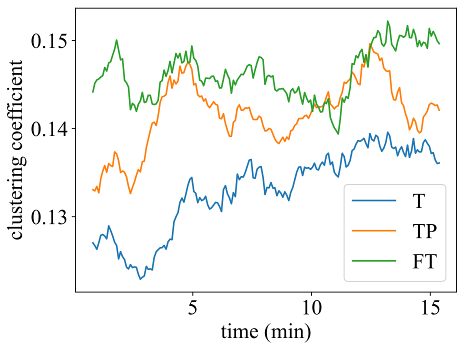
The connectivity analysis results are plotted at the T, TP, and FT regions. Additionally, these plots are grouped by the stimulus provided to participants. This is done to simplify comparisons between different frequency bands of the same EEG data.

Connectivity analysis took shape in calculating the clustering coefficient. This is carried out for the upper and lower entrainment frequencies used by the QL agent: 24, and 20 Hz respectively. The clustering coefficient is, therefore, calculated for a narrowband filtered signal as literature indicated. Consequently, there is no band to compare results to. The narrowband filtering requirement meant that analysis in the Alpha and Theta bands will not be as directed as in the Beta band, as the entrainment frequencies targeted were in the Beta band. Therefore, it is unrealistic to assess every real valued frequency within these bands as a means of comparison.

Results



(a) Connectivity at 24 Hz.



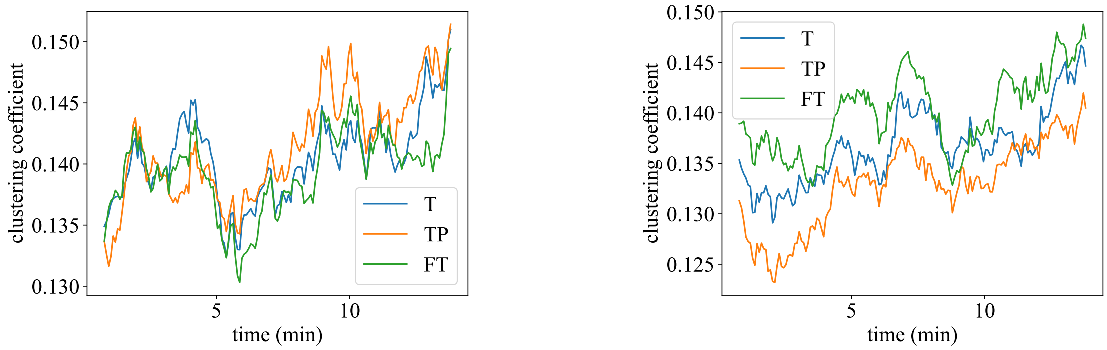
(b) Connectivity at 20 Hz.

Figure 5.4: Connectivity analysis values for a test participant that was exposed to the Beta entrainment stimulus.

Figure 5.4 provides the clustering coefficient as a time varying plot across a recording session for a test participant exposed to a Beta entrainment stimulus. Figure 5.4a shows that there is a maintained and early increase in the connectivity to all the Temporal electrodes at 24 Hz. The T and TP regions exhibit a dip in the metric value close to 14 minutes. Similarly, Figure 5.4b illustrates the connectivity at 20 Hz. Figure 5.4b illustrates a similar maintained increase for all Temporal regions.

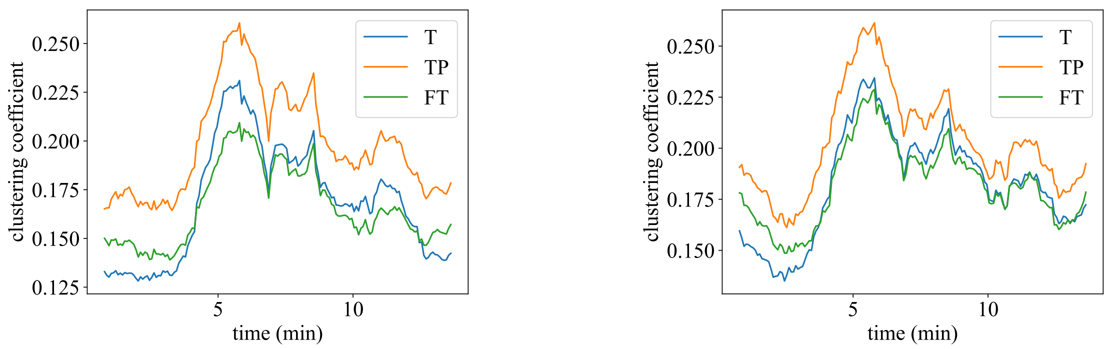
Figure 5.5 illustrates the time varying connectivity of the temporal electrodes when a test participant was exposed to the QL driven stimulus. Between Figures 5.5a and 5.5b all electrodes exhibit a sustained and relatively constant increase in the clustering coefficient metric. Some large dips occur in both Figures, however, after the dips the connectivity of the electrodes consistently increases to past the initial value.

Figures 5.6 and 5.7 provide insight into the time varying characteristics of the connectivity for a test and control participant exposed to the control stimulus. The Figures illustrate that at both 24 Hz, Figures 5.6a and 5.7a, and at 20 Hz, Figures



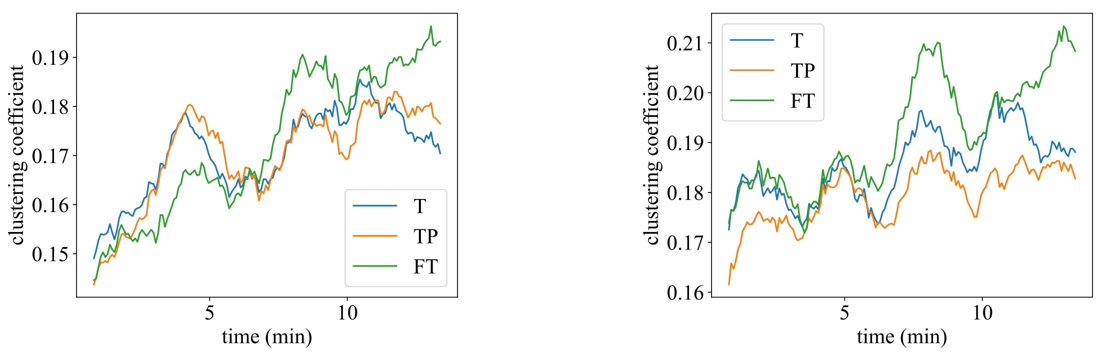
(a) Connectivity at 24 Hz. (b) Connectivity at 20 Hz.

Figure 5.5: Connectivity analysis values for a test participant that was exposed to the QL driven entrainment stimulus.



(a) Connectivity at 24 Hz. (b) Connectivity at 20 Hz.

Figure 5.6: Connectivity analysis values for a test participant that was exposed to the pink noise control stimulus.



(a) Connectivity at 24 Hz. (b) Connectivity at 20 Hz.

Figure 5.7: Connectivity analysis values for a control participant that was exposed to the pink noise control stimulus.

5.6b and 5.7b, there is a maintained increase in the connectivity metric. This is similar to the characteristics shown in both test conditions provided in Figures 5.4

and 5.5.

Discussion

A visual inspection of the connectivity analysis results indicates that the entrainment stimulus did not distinctly impact on the connectivity of temporal electrodes when contrasted to the results derived from control stimulus recordings. It additionally provides visual evidence that the connectivity increased from its initial value and maintained that increase across the session.

The results for both the 20 and 24 Hz frequencies show the same general trend for all recording conditions, both test and control. This exists with some differences and notable dips in the metric; however, the irregularities can be attributed to participant specific differences as well as the nature of brain waves and their relationship to attention and other soft factors that cannot be controlled. Across the board the results indicate that the connectivity at both frequencies either increased and maintained that increase or ended the session with a relatively similar value to the initial state. This provides evidence that the entrainment stimulus had no impact on connectivity when compared to the control stimulus and that the connectivity generally increased at the temporal regions for both stimulus conditions.

5.5 Meta Power Analysis

Meta analysis methods were applied to the results of the power analysis run on EEG data. Chapter 4 details the meta analysis methods used, how data recording was carried out, and how the power analysis was applied.

5.5.1 Mean Increasing Count Metric

The mean increasing count metric was determined across the recording groups. The metric counts the average number of temporal electrodes, out of three, which increased in power from their initial baseline value. This metric can be reliably averaged between participants as it does not vary based on any setup factors. The metric has a maximum value of three and a minimum value of one.

Results

Table 5.3 outlines different notable aspects of the mean increasing count metric. The table outlines the overall and maximum value of the metric to illustrate the maximum effect of the stimulus on different frequency bands analysed. Further, the consecutive minutes where the metric value was greater than one is outlined, this provides information around how sustained any stimulus effects were; this would have a maximum possible value of 12. The time was evaluated and incremented at three minute intervals. Three minute intervals have been chosen as the QL agent could change the entrainment stimulus at this interval, and because it allows for a zoomed out view of the data. A zoomed out view can be digested easily when compared to assessing every data point. The reference point used in Table 5.3 was the initial resting condition.

Table 5.3 indicates several notable characteristics in the Beta band regarding the overall change observed. Table 5.3 shows that the test group has a higher, over double, overall change in the metric for both the Beta (24 Hz) stimulus and the ML recording when compared to the control recordings. The Beta entrainment recording group has a slightly higher value of the two test group recordings. Lastly, the two control recordings have the same overall mean increasing count metric. This finding provides evidence that the test stimuli increased the power of Beta band brainwaves, while the control stimulus did not have a similar effect. Further evidence supporting this is provided by the maximum value of the metric in the Beta band. The table indicates that the test stimulus groups have the same maximum value, 1.5, while the control stimulus groups both have maximum values of less than one. Indicating that, at the maximum value observed, the control stimulus did not seem to have a notable effect increasing the power of Beta band brainwaves, while it was present as a result of the test stimulus.

Further, notable characteristics exist in the Beta band when jointly analysing the metric's value after 3 minutes, and overall value. The QL and Beta entrainment groups have an overall increase in the metric between these two periods. The Beta entrainment stimulus group has a higher final value than in the QL group, having a higher initial value too.

The two control groups have some notable characteristics past being lower than the test recording conditions. Both control groups have the same metric value at the end of the experiment, despite starting at different values. Secondly, the test group's control recording has the same initial value as the QL recording, but decreased by the

Table 5.3: A summary of important aspects of the mean increasing count metric

Band analysed	Statistic	Test group, Beta stimulus	Test Group, QL stimulus	Control group, Control stimulus	Test group, Control stimulus
Beta	Overall	1.5	1.25	0.5	0.5
	Initial value (3 min)	1.3	0.83	0.17	0.8
	Maximum	1.5	1.5	0.5	0.8
	Consecutive minutes greater than 1	9	3	0	0
Alpha	Overall	1.2	0.8	1.2	0.5
	Initial value (3 min)	1.0	0.83	1.16	0.83
	Maximum	1.2	1	1	1.2
	Consecutive minutes greater than 1	0	0	1	0
Theta	Overall	1.3	1	0.8	1.3
	Initial value (3 min)	1.0	1.66	1.16	1.83
	Maximum	1.8	1.6	1.2	1.1
	Consecutive minutes greater than 1	12	9	3	12

end of the session. These characteristics provide a clear distinction between groups that had a test and control stimulus. The finding indicates that the entrainment stimuli did affect the power of the Beta band of brainwaves.

Table 5.3, further indicates notable metric values in the Beta band regarding the sustained increase observed. The QL recording group sustains a metric value of above one for 9 minutes, while the Beta entrainment group exhibits this for around 3 minutes. Therefore, during this period, every participant consistently had at least one increasing electrode on average. The control groups do not display this metric characteristic in the Beta band; they have a maximum metric value of 0.8 which is correspondingly the minimum initial metric value in test stimuli groups. These findings provide evidence that the QL stimulus was able to have a notable effect sooner than the Beta entrainment group; in addition it indicates that the test stimuli had a distinct effect when compared to the control stimulus.

In the Beta band, two further characteristics differ between the QL and Beta entrainment stimulus recordings. The QL recording's metric proportionately increases by a larger amount, 60 % against 12 % relative to the metric value at 3 minutes. Given that the same participants were exposed to the QL and Beta entrainment stimulus, it can be proposed that this is due to the difference in the stimulus presented. The findings indicate that the QL stimulus had an increased effectiveness in increasing and maintaining the power of targeted brain waves. This could be due to the QL agent avoiding potential habituation effects.

Table 5.3, indicates the metric value in the Alpha and Theta band as a means of reference. The Alpha and Theta bands indicate a scattered and fluctuating metric for the different recordings. These fluctuations do not provide any consistent grouping trends between the test and control groups, indicating that the stimuli did not have a notable effect in the Alpha or Theta bands. This provides evidence that the stimuli effects were specific to the Beta band.

Discussion

The mean increasing count metric provides a strong grouping for recordings that had been exposed to test stimuli which separates them from those that were exposed to a control stimulus. This grouping is apparent in the Beta band and not in the Theta or Alpha bands. The finding indicates that the entrainment stimulus affected the power of temporal electrodes by increasing the Beta band power and that it did not impact the Theta or Alpha bands. Additionally, the finding indicates that the control stimulus did not affect the power of brain waves in the Beta, Alpha, or Theta bands at the temporal electrodes.

Evidence that the entrainment stimulus increased the brain wave power of participants in the frequency band targeted agrees with previous research. While existing research did not necessarily use an increasing electrode count metric, the underlying finding remains consistent. The novel finding presented is that the QL driven stimulus was able to achieve a similar result when compared to the constant Beta entrainment stimulus. Since existing research did not use a QL driven stimulus or a stimulus that switched between entrainment frequencies, this result has not been previously noted.

While varied results have been presented in literature, a set entrainment stimulus has been reported to have a marked effect after 9 - 12 minutes. Results for the Beta entrainment stimulus recordings are consistent with this finding. However, results from the QL recordings differ as participants exposed to the QL stimulus have a marked improvement from six minutes. The difference indicates that, of the two entrainment stimuli, the QL driven stimulus was better able to entrain participants. This needs to be contextualised to the small participant size of the study as it limits the finding past indicating a potential trend. However, given that the QL stimulus results are compared to existing results, the finding gains an increased level of credibility. The findings regarding the increased effectiveness of the QL driven stimulus are novel as this stimulus was not present in previous research reviewed.

A clear distinction between control and test recordings is not observed in the Alpha or Theta bands when the mean increasing count metric was evaluated. In literature, no impact was seen in brain wave bands not targeted by the entrainment stimulus. Therefore, the finding aligns with existing knowledge.

Notably, the Theta band exhibits a mean increasing count metric that is highest in the test group's Beta entrainment and control stimulus recordings. The metric provides no further evidence that the test stimulus affected the Theta band brain waves. Therefore, it can be proposed that the notable metric values in the Theta band are likely due to underlying neural dynamics that are naturally present in the test group. This proposed rationale cannot be firmly presented due to the limited participant pool used in the study.

The mean increasing count metric indicates that there is a difference between test and control groups in the Beta band. This is notable when the metric is evaluated at time intervals and for the overall difference observed. The difference indicates that the test stimuli were able to alter the Beta brain waves of participants, while the control stimulus was not. Further, the QL driven stimulus is shown to have an increased effectiveness in increasing and maintaining the power of targeted brain waves when compared to recordings using a constant Beta entrainment stimulus. The increase in effectiveness is indicated by the QL stimulus creating a notable increase earlier and having a greater proportional increase when compared to an early point in the experiment. Lastly, the metric indicates no notable grouping or characteristics in the Alpha and Theta bands, providing more validity to findings in the Beta band.

5.5.2 Mean Absolute Difference Metric

The recording group averages of the absolute difference in participant power values between the start and end of the session is analysed. The metric looks at the absolute value of the displacement in power values for recordings groups and uses mean averaging to create a single valued metric. This allows a comparison regarding the displacement experienced by participants in different frequency bands to be made. Possible setup and participant specific differences might impact the results of this analysis; however, the differences will be relatively constant across recordings and the analysis method will be used. Figures 5.8 to 5.10 illustrate the mean absolute difference metric across recording groups. A key aspect of this metric is its ability to distinguish region specific differences.

Results

Figure 5.8 illustrates the mean absolute difference metric for the Beta band. Figure 5.8 shows that the most significant difference can be seen between groups that experienced a test and control stimulus in the Temporal, T, region. It can be seen that the Beta entrainment group has the highest mean absolute difference, while the QL group has the second highest; these values are at least 0.1 dB greater than both control stimulus recordings. This is a significant difference given that the mean initial and final power values for all participants lie between 1 dB and 1.36 dB. The difference therefore represents a change of around 10 %. The distinction between test and control groups is not seen as comprehensively in the FT and TP regions. The QL stimulus group shows a significantly higher value in the FT region and the Beta entrainment group exhibits this in the TP region. The notable distinction between the test and control stimulus groups indicates that the test stimuli were able to have a notable effect on Beta band brainwaves when compared to control stimuli. This was most apparent in the Temporal, T, region.

Figure 5.9 outlines the mean absolute difference for Alpha brain waves. The figure shows that Alpha brainwaves in the test group's recordings have a consistently higher mean absolute difference than the separate control group. There are no further

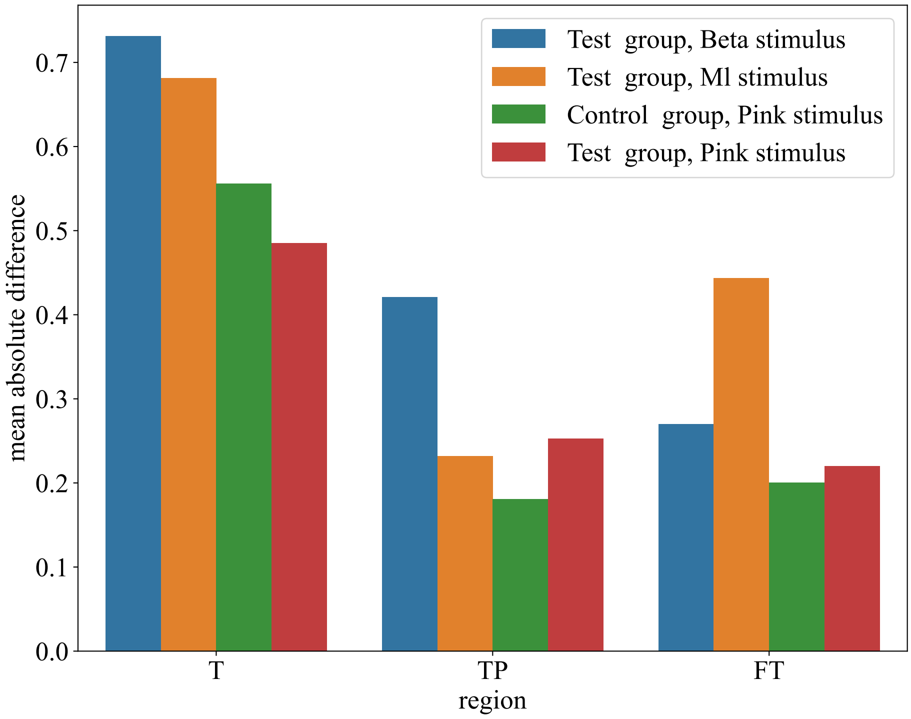


Figure 5.8: The mean absolute difference of recording groups across different EEG regions recorded in the Beta band.

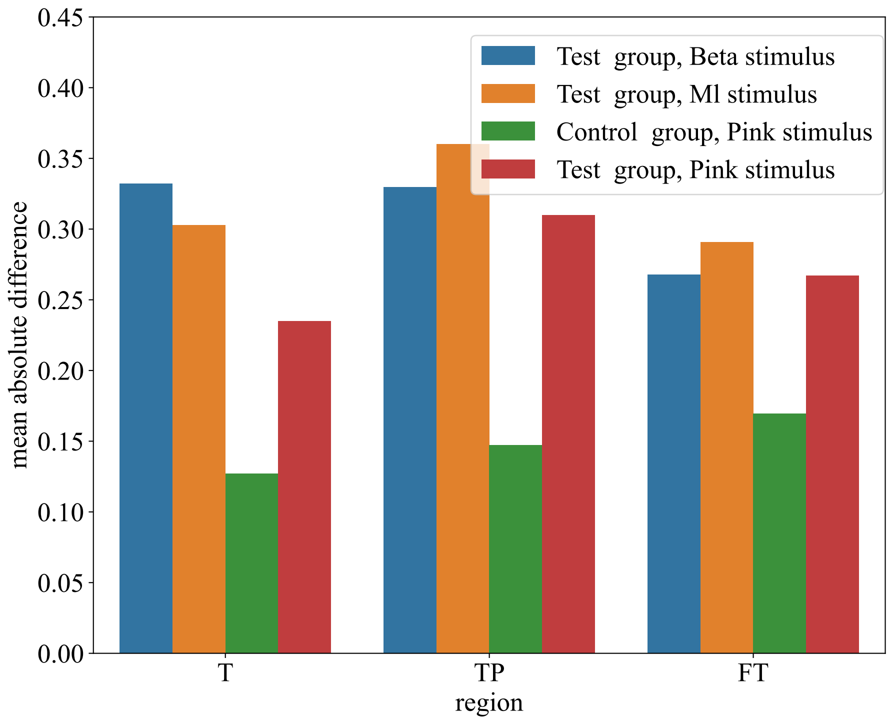


Figure 5.9: The mean absolute difference of recording groups across different EEG regions recorded in the Alpha band.

notable trends for the Alpha band.

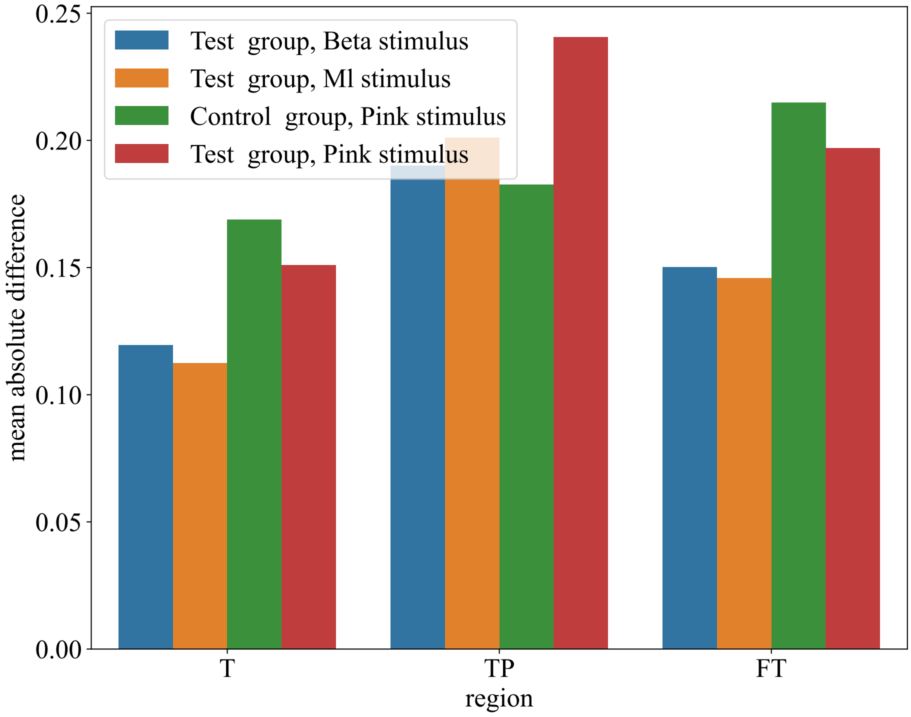


Figure 5.10: The mean absolute difference of recording groups across different EEG regions recorded in the Theta band.

Figure 5.10 illustrates the mean absolute difference metric in the Theta band. Figure 5.10 shows that the two control recordings have the highest mean absolute difference in the Theta band across all regions. This is less evident in the TP region for the separate control group's recordings.

Lastly, contextualised by the results presented in Figures 5.8 to 5.10 and findings in the visual spectrogram analysis, the data of two test participants are noted. The two test participants exhibited a decrease in their Beta brain waves during the Beta and QL entrainment recording sessions. These participants have absolute change values that are significantly higher than the values reported in Figures 5.8 to 5.10. Table 5.4 details the absolute difference exhibited by these participants, T1, and T2, in the Beta band. Table 5.4 shows that the participants have a significantly higher absolute difference metric when compared to the group averages shown in Figures 5.8 to 5.10. This difference is most notable in the Temporal, T, region, which is the region previously identified as most affected by the stimulus. The marked difference is, further, only seen in the Beta entrainment and QL driven stimulus recordings.

Table 5.4: The absolute difference of decreasing test participants in the Beta band.

Participant	Region	Absolute Difference	Stimulus
T1	FT	0.9444	24 Hz Beta entrainment
T1	T	2.3143	
T1	TP	1.7266	
T2	FT	0.4077	24 Hz Beta entrainment
T2	T	1.7928	
T2	TP	0.2381	
T1	FT	0.8085	QL driven
T1	T	0.8507	
T1	TP	0.6235	
T2	FT	1.2376	QL driven
T2	T	2.4651	
T2	TP	0.3603	
T1	FT	0.6134	Pink noise
T1	T	0.7743	
T1	TP	0.7934	
T2	FT	0.3122	Pink noise
T2	T	0.5061	
T2	TP	0.3297	

Discussion

The metric differences in the T region provide evidence that the entrainment stimuli had an effect on the power of Beta band brain waves; however, it does not allow for a notable difference to be seen between the Beta stimulus and QL groups. It, therefore, agrees with existing literature on a constant Beta entrainment stimulus impacting the power of Beta band brain waves, while providing new evidence for the similar effects that a QL driven stimulus can provide. It provides evidence that the effect is most apparent in the T region.

The results found in the Alpha and Theta bands are less conclusive. In the Alpha band, the test group's recordings for control and test stimuli show increased metric values relative to the separate control group's recordings. Conversely, the two control recordings have the highest values in the Theta band. This scattered set of results indicates that the entrainment stimulus did not have an effect on the Alpha or Theta bands. The control stimulus may have had an effect in the Theta band however more data would be needed to substantiate this. This provides additional substantiation of the entrainment stimulus's effect in the Beta band and agrees with existing literature on the effects of entrainment being limited to the band targeted.

The substantially higher decrease in power values in the two participants highlighted were analysed in isolation. The results indicate that the entrainment stimuli potentially had an effect, however, instead of increasing Beta band power it caused a decrease in power. This finding opposes existing research and requires more participants to confirm as only two participants exhibit a large decrease in power values in response to the test stimulus. Existing research found that entrainment causes an increase in the power of a targeted brain wave, while this result indicates that the opposite can be true too for the same entrainment stimulus. This disagreement with existing research and having two participants exhibiting the trend warrants further research with more participants in an attempt to reproduce the result with more data points. However, it can be used as an indication of a possible trend that previous research had not yet identified.

The absolute difference metric provides two major findings when discussed. Firstly, it provides evidence that the test stimuli had similar effects, and that the stimuli had an impact on Beta band brainwaves. This impact was distinct from that of the control stimulus and was not seen in the Alpha and Theta bands. It is possible that the stimulus may have affected Theta band brain waves however more data are needed to substantiate this notion. Secondly, the metric provides evidence that the two test participants, whom previous analysis indicated had no entrainment effects, may have had their Beta brain waves altered by the entrainment stimulus. The participants had their Beta band brain waves significantly reduced during the session. The cause of this may be the entrainment stimuli however more data are needed to substantiate the finding.

5.5.3 Percentage Increase Metric

The percentage increase metric evaluates the percentage of values that are above the initial recorded baseline for a participant. This is a metric that can be compared between participants as it does not relate to any setup or participant specific factors. The metric allows comparisons to be made regarding if a sustained increase is achieved for participants in any group. If entrainment influences brain state, it is expected that the entrainment stimulus provides a sustained increase in the power of brain waves.

Results

Figures 5.11 to 5.13 show a box and whisker plot for the recordings evaluated. The red line in Figures 5.11 to 5.13 represents the median, while the green arrow represents the mean. A box and whisker plot was used to illustrate several statistical properties that underlie the data. Data used to create Figures 5.11 to 5.13 are generated by evaluating the percentage increase for all three minute intervals in the data.

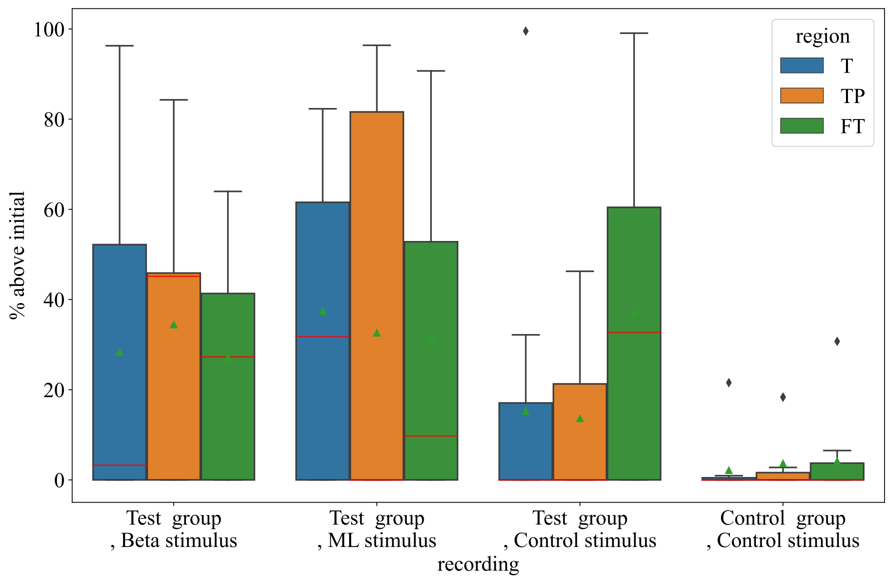


Figure 5.11: A box and whisker plot of the percentage increase metric when applied to different recording groups in the Beta band.

Figure 5.11 looks at the percentage increase metric for the Beta band and has various notable points. Excepting the FT region in the test group's control recording, test stimuli recordings have a significantly higher mean and median value across temporal regions when compared to control recordings. These recordings, additionally, do not have any outliers, while the control recordings both have at least one outlier in their data. Lastly, test stimulus recordings have median values that were non-zero, while control stimulus participants have median values that were generally equal to zero. This indicates that at least 50 % of participants in the test stimulus groups had EEG readings that increased for all electrodes from the initial value at some point during the session. It further indicates that during control recordings, at least 50 % of participants had no increase in any of their temporal electrodes. Indicating that both test stimuli resulted in an increase in Beta band power.

In the Beta band, Figure 5.11 illuminates further notable differences between the Beta entrainment and QL stimulus recordings. The QL group has a higher mean and median value than the Beta entrainment group for the T region and a higher mean for the FT region. Additionally, the QL group has a higher maximum and Q3 value for the T and FT regions. Notably, the QL and Beta entrainment recording groups have Q1 values that were above zero on average, while for both control conditions Q1 is most often 0. This indicates that the QL stimulus was able to create a more sustained increase in Beta band power when compared to the Beta entrainment stimulus.

Further notable features can be seen in Figure 5.11. The Beta band results for the intra-group control recording have a higher mean and Q3 value than those in the separate control group. The increased values, except the FT region, are not higher than those seen in the test stimulus groups. Therefore, the credibility of the entrainment stimulus's effects are still valid, especially as the two recordings being compared had the same participants. The difference does, however, differentiate the intra-group control recordings from the separate control group's recordings. Further, the two control recording groups have a median value that was comparable in the T and TP regions. This indicates that at least 50 % of participants behaved in the same way across the control groups. Therefore, the mean and Q3 values in these regions are likely being biased by outliers in the intra-group's recordings, this is apparent in the box and whisker plots. This indicates that while differences occur, the two control recordings are comparable and remain distinct from the test recordings.

Figure 5.12 illustrates the percentage increase metrics statistical properties in the Alpha band. It can be seen that all regions have a median value of above 0, except the QL recording group's T region. The mean and median values are comparable across groups, with control groups exhibiting a higher median value in all regions relative to the test stimulus groups. There is no further grouping possible between recording ses-

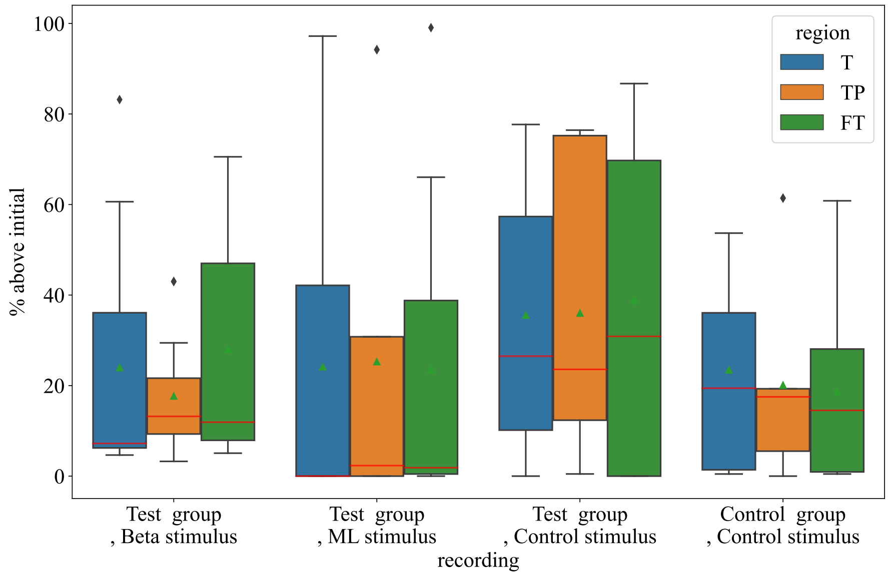


Figure 5.12: A box and whisker plot of the percentage increase metric when applied to different recording groups in the Alpha band.

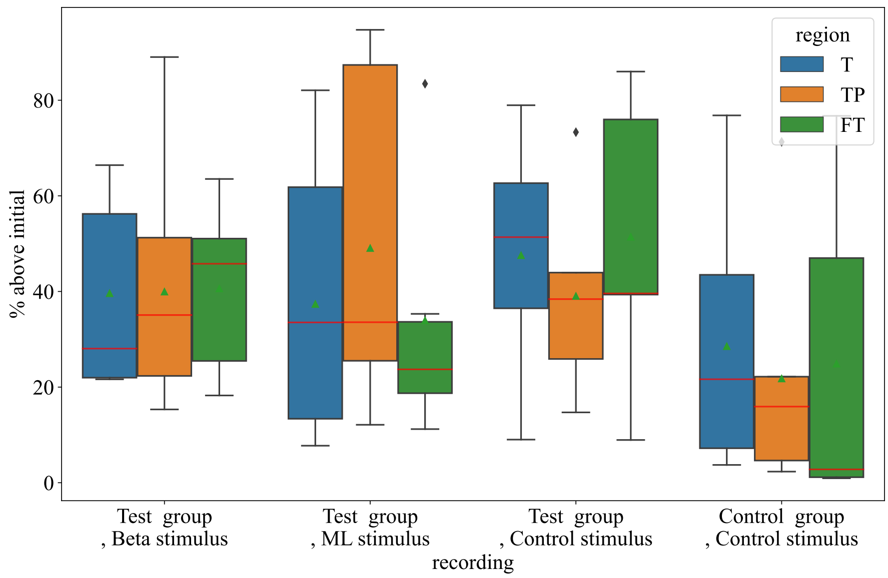


Figure 5.13: A box and whisker plot of the percentage increase metric when applied to different recording groups in the Theta band.

sions, indicating that no affect is seen in the Alpha band as a result of the test stimuli.

Figure 5.13 outlines the Theta band's percentage increase metric. The Theta band exhibits a more scattered metric when compared to those shown in Figures 5.11 and 5.12. In general, the median and mean values for the Test group's control recording are the highest, while the separate control group's results exhibit the lowest values.

Due to the novel nature of the percentage increase metric and the differences seen in the Beta band, a t-test is applied to the 3-minute intervals used to form the overall percentage increase metric. This allows the statistical validity of the results drawn from the metric to be assessed and evaluated. The t-test would either provide support or reject results and conclusions created using the metric. The results of the t-test are plotted in Figures 5.14 to 5.16. The figures plot the p value associated with comparisons made. The blue vertical line is the critical value, 0.05, used to evaluate the t-test results.

A t-test is used to compare two recording sets and determine if they are statistically distinct from one another. If the associated result of a t-test comparison is below the critical value the null hypothesis is conclusively rejected. This infers that the two populations associated with the t-test are significantly distinct. If the result is above the critical value the two populations are not significantly different and the null-hypothesis is not rejected. Lower t-test results indicate more conclusively different data, which correspondingly extends to values around the critical value. A p value, t-test result, of 0.6 for example does not reject the null hypothesis however it is not conclusive given how close it is to the critical value. This point has increased emphasis given the small population size of the study.

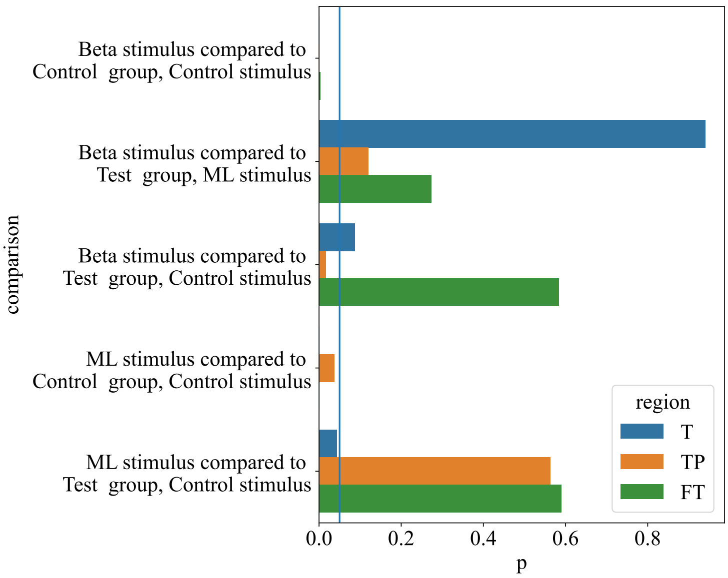


Figure 5.14: T-test applied to the percentage increase metric values across different recordings in the Beta band.

Figure 5.14 outlines the t-test run for the Beta band. Figure 5.14 shows that the null hypothesis is rejected absolutely when the QL and Beta entrainment recordings are compared to the separate control group's recordings. This indicates that the datasets are significantly different and that the entrainment stimuli had a marked effect. However, when test stimuli are evaluated against the intra-group control recording, the Beta entrainment recording can only reject the null hypothesis completely in the TP region, while the T region is close with a p value of 0.08. The QL driven entrainment only rejected the null hypothesis in the T region. This indicates that it is possible that participants differences between the test and separate control group recordings could have had an impact on the comparison as the intra-group control recording is less significantly different from the test recordings than the separate control group.

Figure 5.14 further shows that the QL recordings are not rejected when compared to the Beta entrainment recordings as a null hypothesis. The results do not indicate that the two are a perfect match. This indicates that the two recordings are not the same, despite the same participants making up the two recordings. The result indicates that the QL stimulus, even while exploring, had a different impact on the Beta band brain waves than the Beta entrainment stimulus. This finding would benefit from more participants to have a more conclusive finding.

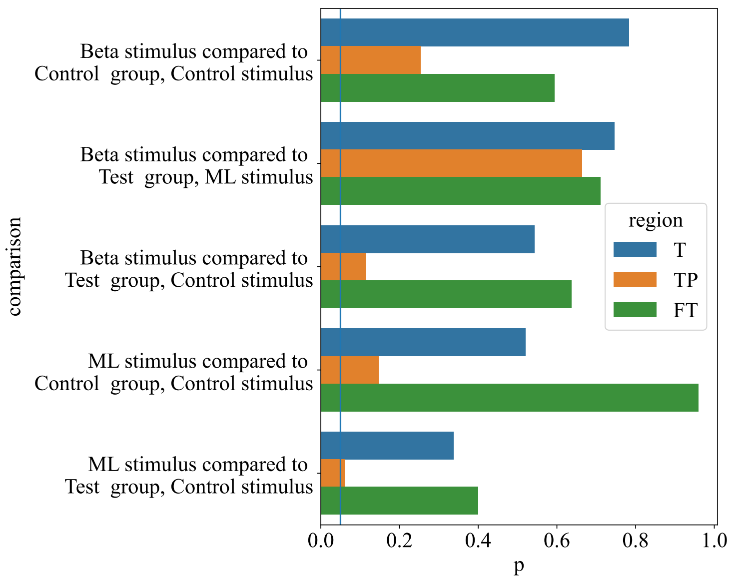


Figure 5.15: T-test applied to the percentage increase metric values across different recordings in the Alpha band.

Figure 5.15 provides the t-test results when run on Alpha brain waves. Figure 5.15 shows that the t-test is unable to reject the null hypothesis for any comparison criteria. It is only close to rejecting the null hypothesis in the TP region of the QL recording with a value of 0.06 when compared to the intra-group control measurement. This implies that no recordings compared are significantly different, indicating that the control and test stimuli had a similar impact, or lack thereof, on Alpha brain waves. Thus providing further evidence regarding the effect of the entrainment stimulus's in the Beta band.

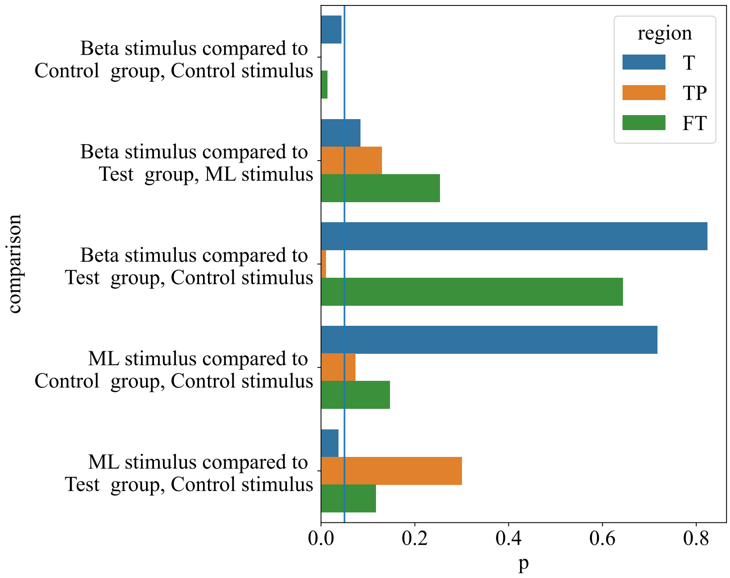


Figure 5.16: T-test applied to the percentage increase metric values across different recordings in the Theta band.

Figure 5.16 illustrates the t-test results in the Theta band. QL recordings are rejected as a null hypothesis when compared to the Beta entrainment recording. Further, the Beta entrainment stimulus rejects the null hypothesis in the separate control group for all regions and in the intra-group control recording at the TP region. Lastly, the QL recording rejects the null hypothesis when evaluated against the test group's control recordings for the T region but not any regions when compared to the separate control group.

Discussion

When looking at the percentage increase metric in the Beta band, these findings indicate that the Beta and QL stimuli impacted Beta band brain wave power and caused an increase in the power. This needs to be contextualised to the small sample space of the study and should be run with more participants to improve the validity of the results. The novel nature of the metric means that no existing research evaluated used a metric of this type. However, previous findings indicated that entrainment causes an increase in the targeted brain wave power. The metric supports this as it indicates that the test stimuli increased the Beta band power and maintained that increase relative to the baseline value. The result, therefore, both supports and provides a new layer of analysis to existing findings.

Notable findings exist in the T region of Beta band analysis. The findings indicate that the QL algorithm may have been more effective as a stimulus than the constant Beta entrainment, even while the model was exploring. This is due to various aspects of the metric having heightened values in the QL group's results. The results, additionally, indicate that this improvement was most apparent in the T region. However, this would require more participant data to be conclusively stated. When contextualised to existing research, the result indicates that the QL driven stimulus was able to most effectively subvert habituation effects in the T region and provide an improvement to the stimulus in this region. The results indicate that the Beta entrainment stimulus was distinct from the control measurements and agreed with previous research, therefore it is acceptable to assume that it had an effect and that this effect was due to the entrainment stimulus. Therefore, if the metric indicated that theQL driven stimulus had an improved effect, this indicates that the stimulus was able to improve on existing entrainment effects seen in previous literature. This is likely due to it overcoming the habituation effects as outlined in previous research.

Differences in the control recordings were identified by the metric. One cause of this might be participant specific differences, as the test group had different participants as the separate control group. However, due to the small sample size no definitive conclusion can be drawn to determine the certain cause in the metrics differences between the test and separate control group's control recordings. It can be stated that the intra-group control recording was distinct from the separate group's control recordings, but was not comparable to metric values in the test stimuli recordings. The difference is therefore most likely due to participant differences.

This finding was not present in previous research due to existing studies not using a distinct control group. Therefore, there is no specific basis to which this result can be compared.

The percentage increase metric in the Alpha and Theta band yields no conclusive trends or notable findings. Both sets of recordings have mean and median values that are comparable across recordings as well as being scattered leading to no notable trends. Data in the Theta band is more scattered than data in the Alpha and Beta bands, this may be due to the nature of Theta bands against Alpha bands in a closed eyes condition. This agrees with previous research, indicating that entrainment affects a specific band of brain waves based on the frequency of the stimulus.

Cumulatively, these findings indicate that the Beta and QL stimuli impacted Beta band brain wave power and caused an increase in the power. This needs to be contextualised to the small sample space of the study and should be run with more participants to improve the validity of the results. The novel nature of the metric means that no existing research evaluated used a metric of this type. However, the metric is based on previous findings indicating that entrainment causes an increase in the targeted brain wave power, which this result supports.

Results when applying a t-test to the percentage increase metric validate the results seen in the metric and, by extension, validate conclusions drawn using the metric. The results, particularly support the conclusion that the QL driven stimulus was able to have a significant improvement in the T region when compared to the Beta stimulus. When comparing results of the test stimulus conditions against the two control groups, a less conclusive p value was generated against the intra-group recording than against the separate control group.

The difference does not imply that entrainment was not effective as the null hypothesis is rejected in several regions, but that its effect may potentially be less pronounced than the separate control reading's comparison suggested. The drawback of participant size is notable here as it is possible that the small study size is limiting the QL and Beta entrainment recordings from more conclusively rejecting the intra-group's control recording due to common participant neural dynamics clouding the difference between the recordings. Using the t-test results in the Beta band, the percentage increase metric can conclusively determine that the entrainment had a significant impact in the T region and potentially the TP region. No existing research evaluated used a separate control group, therefore there are no existing results available as a comparison.

The Theta band exhibited mixed results for all recordings, as shown in Figure 5.16. When comparing the test and control groups, a null hypothesis is not rejected for the same region in t-tests applied to both control recordings, with one exception. This indicates that the distinctions seen are not likely valid as the trend should occur when comparisons are made to both control recordings. The t-test comparing the QL recordings with the intra-group control recording rejected the null hypothesis in the T region, however this is not the case when compared to the separate control group's recording. This does not indicate any conclusive evidence that the stimulus had a marked impact on the Theta band. Conversely, the Beta entrainment recording rejected the null hypothesis in the TP region when compared to the intra-group control recording and when compared to the separate control recording. This might indicate that the Beta entrainment had an effect on Theta brain waves that the QL driven stimulus did not, however given the rest of the results in the Theta band this would require more participants to be considered a possibility.

The percentage increase metric provides conclusive evidence that the test stimuli created a sustained increase in Beta band power when compared to control stimuli. It further indicates that the QL stimulus was more effective than the Beta entrainment stimulus in consistently increasing Beta band brain waves. These results are verified with a t-test which found that the Temporal region of the test stimulus's recordings are conclusively differentiated from control recordings in both groups. It is possible that more data are required to have a more conclusive separation in all temporal regions given the sample size. However, the result might, further indicate that the entrainment effects were seen most prominently in the T region. Similar findings are not apparent in Alpha and Theta bands, which provides further evidence for results in the Beta band. The results address both research outcomes, indicating that the test stimuli had effects scoped to increasing the power of brain waves in the Beta band. Further, they indicate that the QL stimulus was able to have an increased effect, when compared to the set entrainment stimulus, particularly in the T region.

5.5.4 QL Optimal Action Effects

Two participants had their stimulus controlled by QL agent that used actions it deemed optimal. These participants are compared with the rest of the QL participants who had their stimulus controlled by an exploratory agent to determine if any differences occur. Due to this comparison existing between groups of two and four participants, a lighter basis exists when contrasted to the rest of the results presented. The percentage increase metric is used to compare these groups as it is the most robust metric utilised; it does not relate to any setup or participant specific factors and provides an overview of neural dynamics across the entire recording session. Figures 5.17 to 5.19 provide a comparison of the percentage increase metric between the exploratory and exploitative QL groups. For the purposes of the discussion, the participants who had an QL agent that used optimal actions will be referred to as the optimal QL group and the others will be the exploratory QL group.

Results

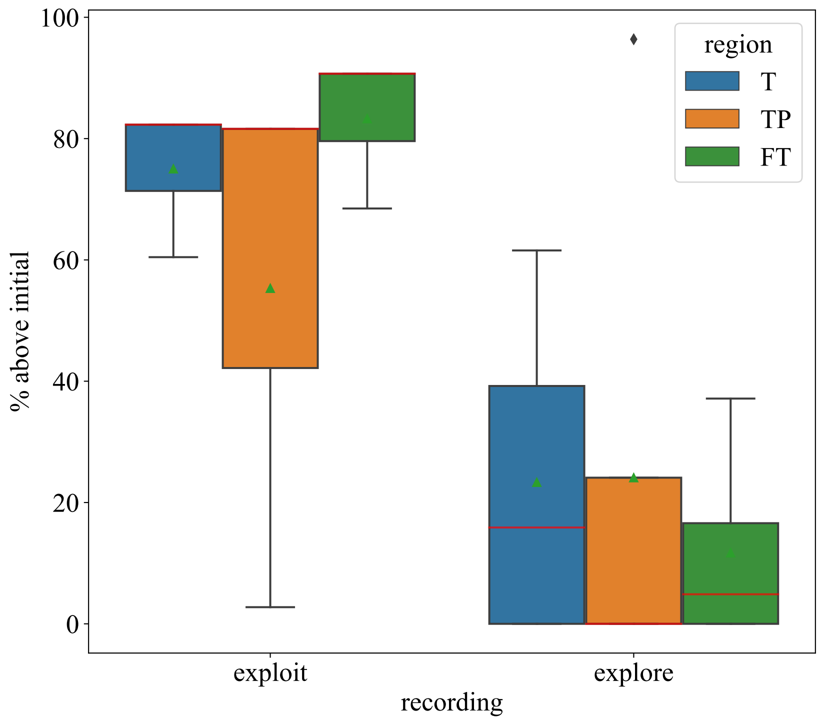


Figure 5.17: A comparison between QL participant' percentage increase metrics in the Beta band when using exploratory and exploitative actions, using a box and whisker plot.

Figure 5.17 provides a comparison of the percentage increase metric for Beta band brain waves. Figure 5.17 illustrates that the optimal QL group has a markedly higher percentage increase metric when compared to the exploratory QL group. Excepting the TP region, Q1, and the lower outlier bound of the optimal QL group is higher than the upper outlier bound of the exploratory QL group's metric. Additionally, the optimal QL group has a mean and median value that is significantly higher than that in the exploratory QL group. The difference in the median values between the optimal QL group and exploratory QL groups is between 60 and 80 %.

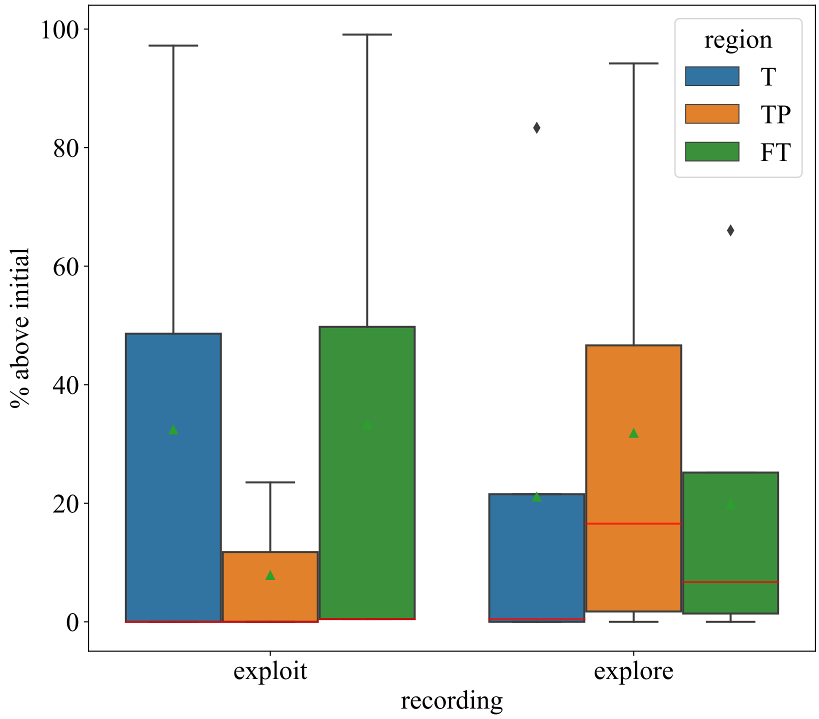


Figure 5.18: A comparison between QL participant' percentage increase metrics in the Alpha band when using exploratory and exploitative actions, using a box and whisker plot.

Figure 5.18 shows the metric comparison in the Alpha band. The median of the optimal QL group is around zero for all conditions, while the exploratory QL group has a non-zero median for the TP and FT regions. Secondly, the optimal QL group has a higher mean and Q3 for the T and FT regions. No significant differences are seen between the optimal and exploratory QL groups in the Alpha band. While differences in various statistical properties of the metric are apparent, these differences can be attributed to the limited sample space as they were relatively similar.

Figure 5.19 outlines the metric differences in the Theta band. In the Theta band, the exploratory QL group has a significantly higher metric value across all regions. Most notably the mean and median are higher than those in the optimal QL group, however not as significantly as in the Beta band. In the Theta band the exploratory group has a markedly increased metric when compared to the optimal QL group.

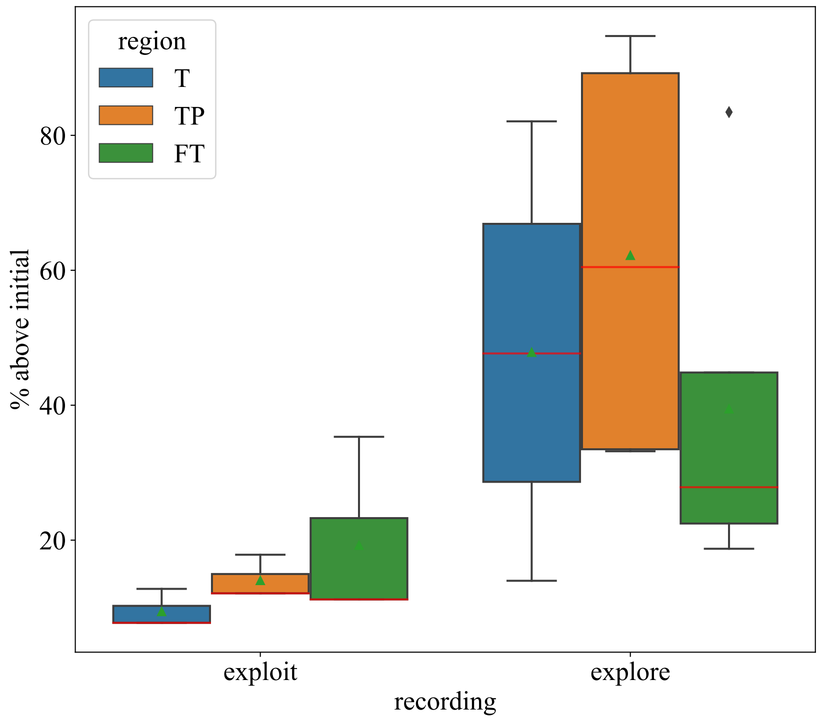


Figure 5.19: A comparison between QL participant' percentage increase metrics in the Theta band when using exploratory and exploitative actions, using a box and whisker plot.

This difference is less distinct than in the Beta band and could indicate that the exploratory actions served to enhance Theta band brain waves. However, due to the sample size and nature of the Theta band, this cannot be conclusively stated.

A t-test is applied to the percentage increase metric so that a comparison could be made between the optimal and exploratory QL groups. Figures 5.20 to 5.22 outline the results of the t-test applied.

Figure 5.20 outlines the t-test results for the Beta band. Figure 5.20 illustrates that the optimal QL group rejects the null hypothesis for all recordings that it is compared to. This is, except the Beta entrainment and intra-group control recordings in the TP region.

Figure 5.21 illustrates the t-test results in the Alpha band. Figure 5.21 indicates that the optimal QL group did not reject the null hypothesis for any compared recording in the Alpha band. Therefore, the optimal QL group was not distinct from any other recording in the Alpha band. Similarly, Figure 5.22 illustrates the results of the t-test when applied to the Theta band. Figure 5.22 shows that the null hypothesis is

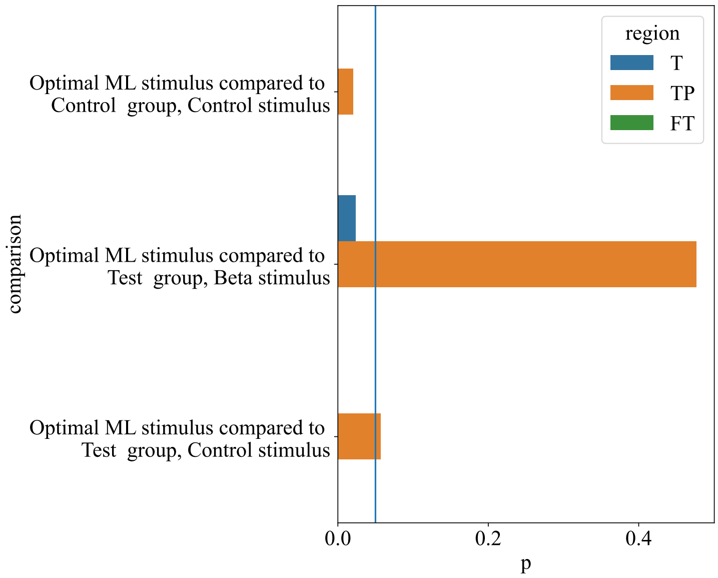


Figure 5.20: A t-test comparison of participants who had an exploratory contrasted with exploitative QL agent when using the percentage increase metric in the Beta band.

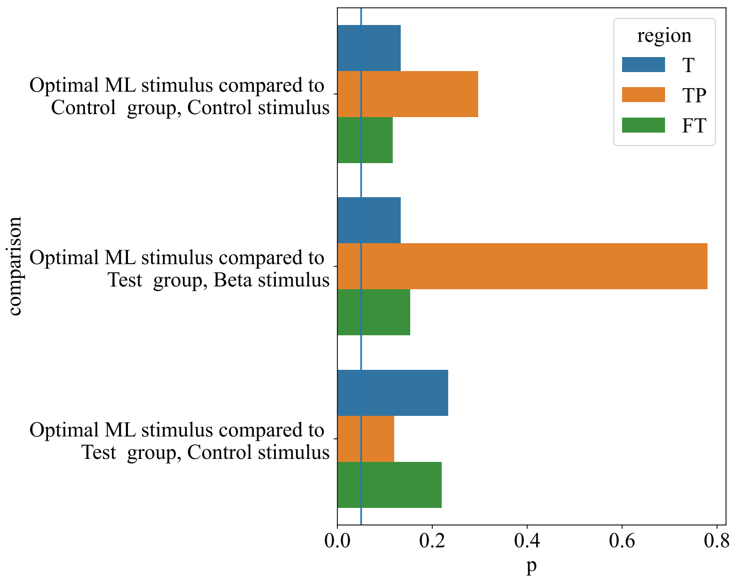


Figure 5.21: A t-test comparison of participants who had an exploratory contrasted with exploitative QL agent when using the percentage increase metric in the Alpha band.

rejected in the Beta entrainment group for all regions and in the intra-group control condition for the T region. Given the small sample size, this does not conclusively define any causality to the relationship. Since the two control groups are showing

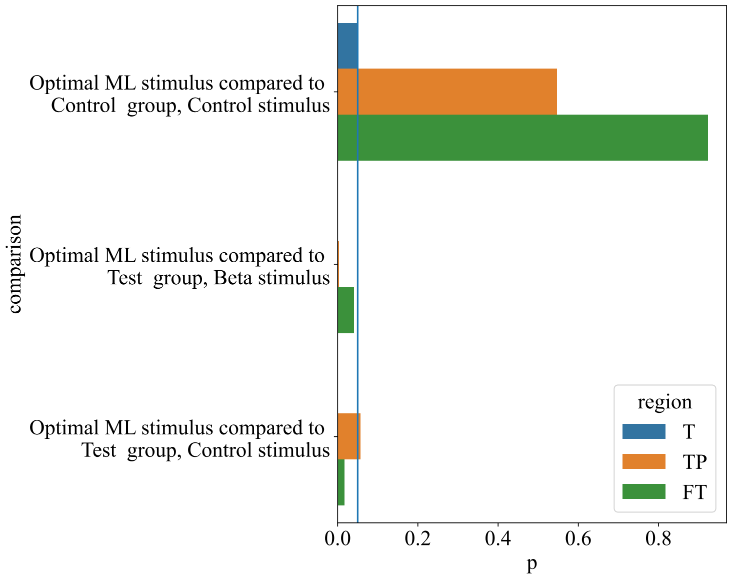


Figure 5.22: A t-test comparison of participants who had an exploratory contrasted with exploitative QL agent when using the percentage increase metric in the Theta band.

completely separate response's to the stimulus, it cannot be concluded that either result is a valid result of the stimulus. The rejection of the null hypothesis in the Beta stimulus recording might indicate a differing response in the Theta band between the two stimuli conditions; however, this is not conclusive due to the results in the two control conditions.

Discussion

Characteristics of the percentage increase metric indicate that the optimal QL stimulus had a significantly higher impact on EEG power in the Beta band than the overall QL group. This provides backing that the policy learned was able to optimise the entrainment stimulus. The finding should be contextualised to the overall comparison where the QL driven stimulus's recording has a notably higher percentage increase metric than the Beta entrainment recording, especially in the T and FT regions. The overall QL stimulus was determined to have had a more marked impact on EEG readings than the Beta stimulus in the Beta band. Since the optimal QL group exhibited an increased effect of the stimulus when compared to the exploratory QL group, which intern had an increased effect when compared to the Beta stimulus various conclusions can be drawn. It can be stated that the exploratory actions of the QL agent provided a degree of improvement to the Beta entrainment stimulus, however it can further be deduced that the optimal policy and actions learned by the QL agent were able to produce a substantial improvement to the stimulus. This indicates that the optimal policy was successfully learned by the model.

The exploratory actions were most likely effective in reducing habituation effects in the brain that were noted in previous research. Through switching frequencies, even within the Beta band, it appears that habituation effects were subverted as indicated by the increased percentage increase metric for the exploratory QL group when compared to the Beta stimulus group. Further, the optimal actions learned when switching between the two entrainment frequencies was most beneficial. This indicates that an optimal entrainment stimulus switching policy can be determined. However, it should be noted that given the small sample size and the fact that only two participants used an optimal action set, this result should be investigated when comparing larger groups of participants to draw any concrete conclusions. The investigation might benefit from further exploring a similar action space to that presently investigated.

Results discussed regarding the optimal QL actions taken have one large thread. They indicate that the QL model was able to learn an optimal policy to control the entrainment stimulus when switching between two entrainment frequencies. Furthermore, the results indicate that when using optimal actions, the QL driven entrainment stimulus was able to evoke a notably improved effect on Beta band brain waves when compared to all other stimuli used. Due to only two participants using the optimal QL driven stimulus, more data are required to state this outright; however, the results provide a good indication that the trend will hold true.

Regarding the t-test results, the rejection of the null hypothesis when comparing the optimal QL group to the Beta entrainment and intra-group control recordings has two large implications. Firstly, this indicates that the optimal QL actions had a significantly different impact on Beta brain waves than the Beta entrainment stimulus did. Given that the optimal QL recording has a higher percentage increase metric of the two, this indicates that the optimal QL stimulus had a more sustained power increase, except in the TP region. The finding is distinct from the comparison made between the entire QL groups and the Beta entrainment recording which found that the two groups were not significantly different, indicating that the optimal QL stimulus had an effect that was distinct even in comparison with the overall QL group.

Secondly, the result indicates that the optimal QL recording was significantly different to the intra-group control measurement, except in the TP region. This highlights a notable difference when contrasted with the overall QL comparison. The overall QL group was similar to the intra-group control recording except in the T region. These two results indicate that results derived when using optimal QL actions are significantly different from all other results recorded. This indicates that the QL policy developed was able to optimise the entrainment effects of the stimulus. However, it needs to be further investigated with more participants using an exploratory and optimal QL agent to further base the finding; because it's completely novel when contextualised with existing research and having a limited number of participants using optimal QL actions. Lastly, it should be noted that the optimal QL group rejected other recordings with markedly lower p values. This indicates that the optimal QL recording was even more statistically distinct from other recording groups. This may be due to the low number of participants using optimal actions and the overall low population count; however, the finding is significant enough to warrant noting.

5.5.5 Overall insights

Metrics associated with the power analysis are presented and discussed individually. The insights from each of these metrics are discussed together to form a clearer picture of implications derived from the power results.

The metrics all individually indicate that both the QL driven and Beta entrainment stimuli had a marked effect on Beta brainwaves when compared to the control stimulus. Aside from two test participants, this effect resulted in increased power of Beta band neural activity. As a group, the metrics did not provide a clear indication that any stimulus related effects occurred in the Theta or Alpha bands, both for the control and test stimuli; while isolated metrics identified novel trends in Theta and Alpha bands. As a result, no concrete findings in the Theta or Alpha bands exists.

These results indicate that the entrainment stimuli were able to affect the power of Beta band activity, which the control stimulus was not. The finding agrees with existing research on entrainment, indicating that entrainment stimuli increase the power of neural activity in a targeted band. Additionally, the finding provides new evidence that a QL driven stimulus can have a comparable effect when measured against a set frequency entrainment stimulus.

The mean increasing count metric, and mean absolute difference metric indicate that the QL driven and Beta entrainment stimuli had similar effects on Beta band neural activity. These metrics indicate that the QL driven stimulus was able to entrain participants at least as well as a traditional entrainment stimulus. This finding gains additional credibility as multiple metrics support it. This provides new knowledge to existing studies, as no reviewed research assessed a dynamic entrainment stimulus.

The time related characteristics of the mean increasing count metric indicates that the QL driven entrainment stimulus was able to have a more pronounced effect on Beta band brainwaves than the traditional Beta entrainment stimulus. This finding is further justified by the percentage increase metric and the analysis run on the metric. The finding indicates that the QL driven entrainment was not only able to function as well as a traditional entrainment stimulus, but that it was able to have an increased effect on Beta band brainwaves. This is additionally supported when analysing the results of an QL agent taking actions it deemed optimal. The optimal actions taken by the QL algorithm resulted in further improved effectiveness of the stimulus in the Beta band. This finding supports results discussed around the spectrogram of different participants, which indicated that the QL driven stimulus was able to effect more frequencies within the Beta band of neural activity. These findings are unique when compared to existing research.

Generally, the intra-group and separate control recordings have similar characteristics which differ from those in the test recordings. However, some differences are noted between the control recordings that could be due to participant specific differences. These may stem from the small sample size of the study and are most apparent when analysing the percentage increase metric. The differences do not indicate that the intra-group control recordings were similar to the recordings using test stimuli.

The mean absolute difference, and percentage increase metrics looked to identify the regions most affected in different recordings past the impact itself. The mean absolute difference metric found that the test stimuli recordings exhibited the most pronounced entrainment effects in the T region when looking at the Beta band. The percentage increase metric agrees with this; however, its results were not conclusive when comparing the Beta entrainment recording to the intra-group control recording. This comparison was close to absolutely supporting the finding and the difference can therefore be attributed to the small sample size. This finding gains additional credibility when contextualised with the analysis run on spectrogram of recordings in Section 5.4. The spectograms indicated that the T and TP regions had the most distinct results of the three regions analysed. Therefore, the meta analysis methods present a filtering of this result to isolate the most objectively affected region.

Two outliers are present across analysis run on the test recordings. These outliers exhibit a decreasing trend in power values in response to the test stimuli. The absolute difference metric is used to analyse the distinction between these participants and the rest of the participants. This metric found that the participants were impacted by the test stimuli, as their absolute difference is significantly higher than the rest of participant. This finding was distinct from existing research and should be investigated further.

Overall meta analysis metrics augmented and agreed with spectrogram analysis results presented. The meta analysis methods confirmed that Beta and QL entrainment stimuli had an effect on the Beta band of brainwaves. This effect was confirmed to result in the increasing of Beta band power. Further, meta analysis metrics were able to qualify that the Machine Learning (ML) stimulus was able to have improved entrainment effects; this was identified in the spectrogram analysis of data and presented as a difference in the frequencies excited within the Beta band by the stimulus. Two of the meta analysis metrics were able to observe this effect from different perspectives, further confirming the result.

5.6 Meta Connectivity Analysis

Meta analysis methods are run on the results of the connectivity analysis. Chapter 4 outlines the meta and connectivity analysis methods used. Results are presented for two meta analysis metrics applied to connectivity analysis data, subsequently the results are discussed in the context of existing research.

5.6.1 Mean Increasing Count Metric

Figures 5.23 and 5.24 outline the mean increasing count metric analysis applied to connectivity results. This metric value has the same characteristics present during the power analysis results, having possible real values between [0, 3].

Figures 5.23 and 5.24 respectively outline the metric values for the 24 Hz and 20 Hz narrowband filtered results. The figures show similar results, indicating that on average participants in all recording groups have at least one increasing electrode.

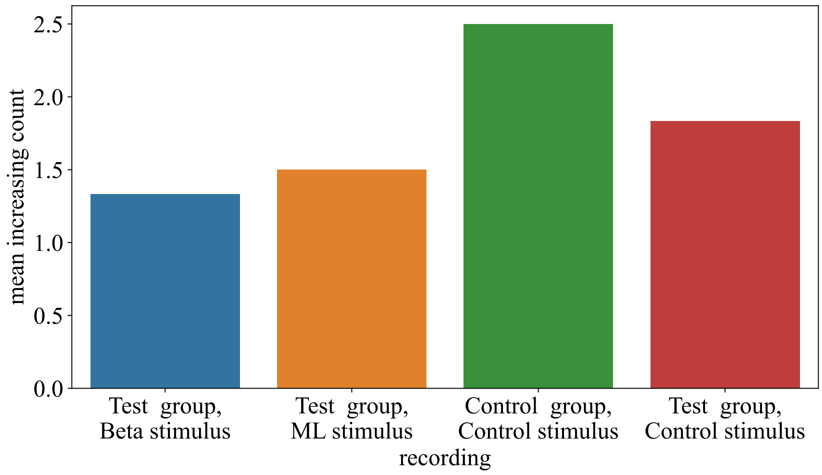


Figure 5.23: The mean increasing count metric between the start and end of the session for the 24 Hz narrowband filtered signal.

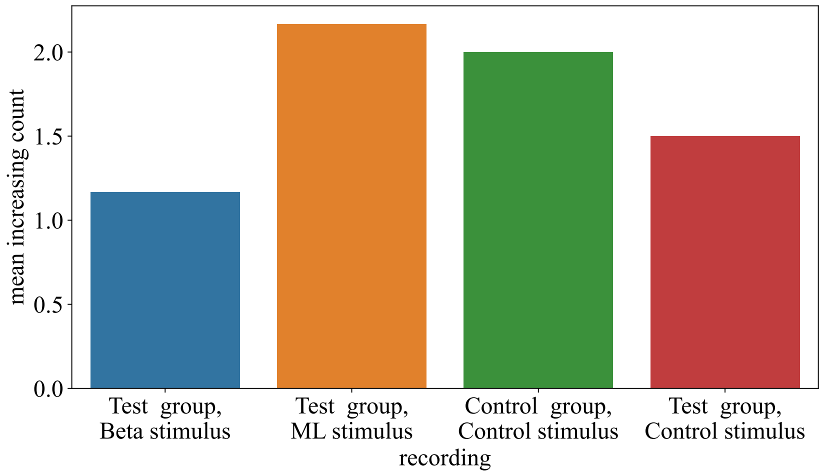


Figure 5.24: The mean increasing count metric between the start and end of the session for the 20 Hz narrowband filtered signal.

This is more apparent for results at the 20 Hz frequency, shown in Figure 5.24. Additionally, no distinct grouping exists to separate the test and control recordings for this metric. Lastly, the control group has the highest mean increasing count followed by the test group's control and QL recording between the two frequency bands.

The time varying characteristic of the mean increasing count metric are investigated and can be seen in Figures 5.25 and 5.26. Figure 5.25 illustrates the metrics value for the 24 Hz frequency. At this frequency, only the control recordings have an increase in

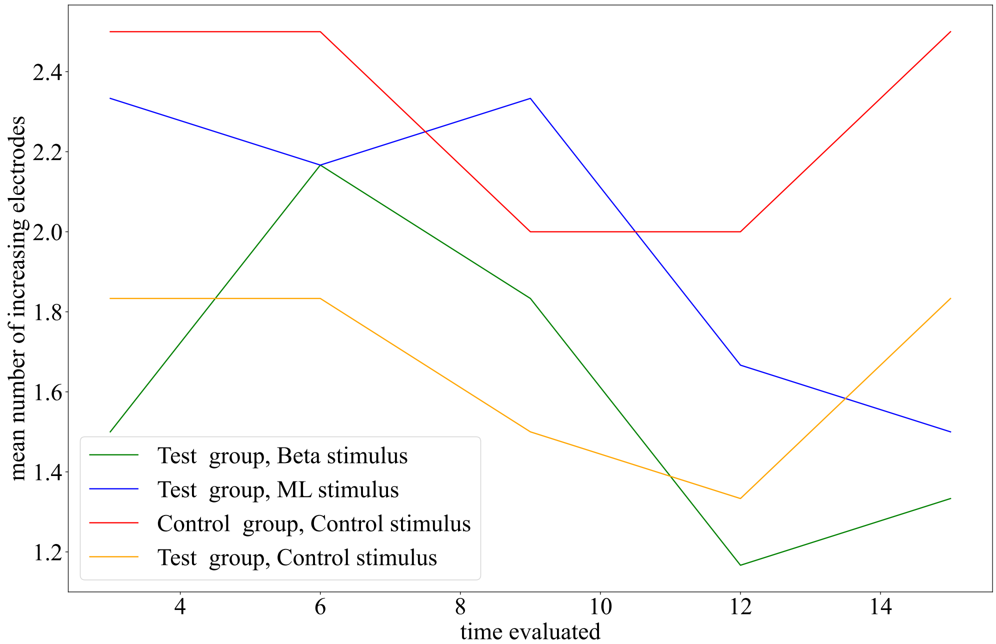


Figure 5.25: The mean increasing electrode count metric at different time intervals measured relative to the start of the session for the 24 Hz narrowband filtered signal.

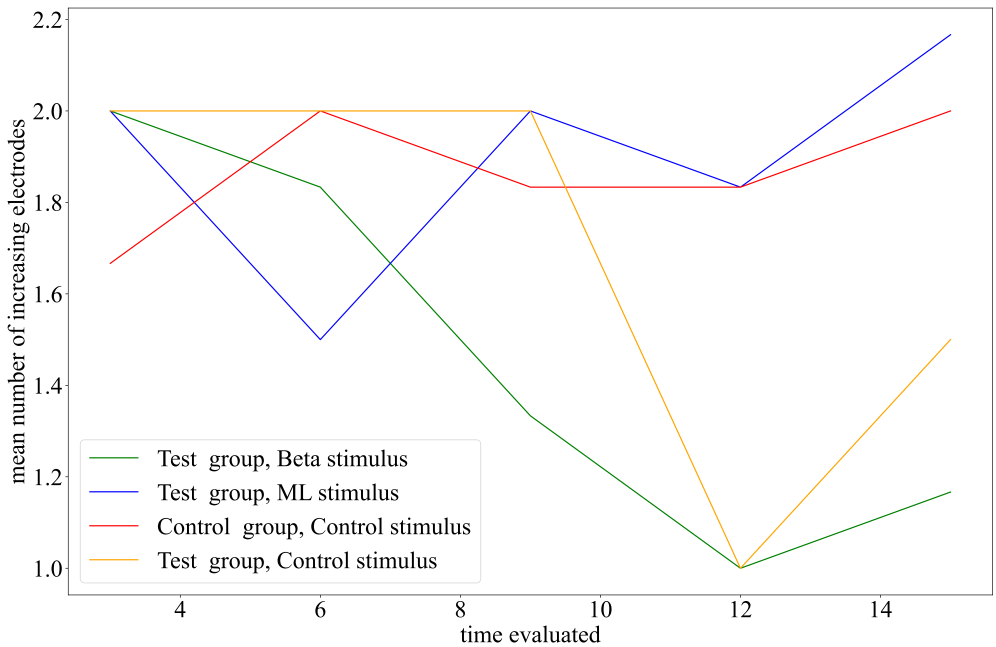


Figure 5.26: The mean increasing electrode count metric at different time intervals measured relative to the start of the session for the 20 Hz narrowband filtered signal.

the metric value. Figure 5.26 illustrates the metrics value for the 20 Hz narrowband filtered signal. Figure 5.26 shows that the QL and control group's recordings have an increase in the metric, while the other two recordings exhibit a decrease in the metric value. It should be noted that both Figures 5.25 and 5.26 indicate that at no point during the recording session did the metric value drop below one. Indicating that throughout the experiment, all participants, on average, had at least one electrode with an increasing connectivity.

5.6.2 Percentage Increase Metric

The percentage increase metric is applied to connectivity analysis results. The metric allows comparisons to be made regarding whether a sustained increase was achieved for participants in any group. Figures 5.27 and 5.28 provide a visual description of the statistics underlying the percentage increase values for each group analysed. The red line in Figures 5.27 and 5.28 represent the median, while the green arrow represents the mean.

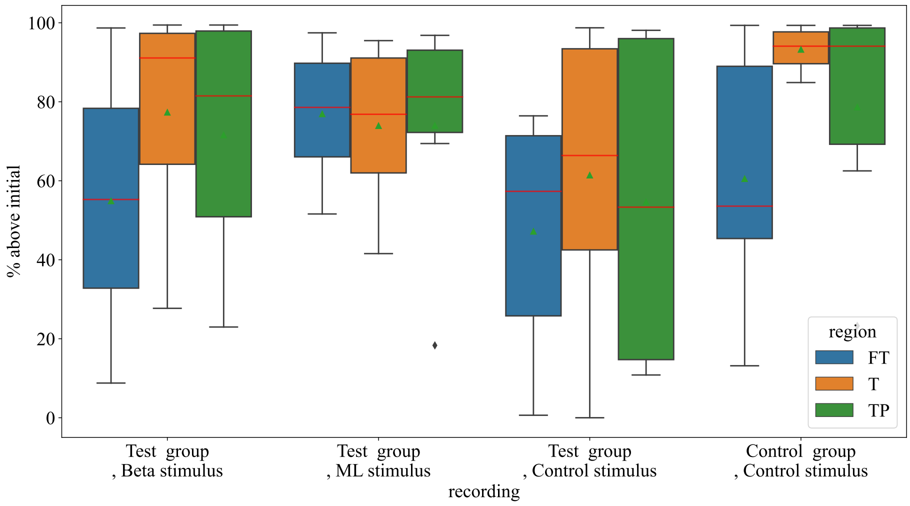


Figure 5.27: A box and whisker plot of the percentage increase metric when applied to different recording groups for the 24 Hz narrowband filtered signal.

Figure 5.27 outlines the metric for the 24 Hz filtered signal. Notably, all mean and median values are above 50 %. Additionally, the highest median values for the T and TP regions belong to the separate control group's recordings. Lastly, no grouping between test and control groups can be achieved when looking at the median and mean values. The test group's QL and Beta entrainment recordings have mean values that are within 5 % of one another in the T and TP regions. However, the separate control group and intra-group control measurements are not grouped similarly. Figure 5.28 displays a similar trend for the metric at 20 Hz. Across the

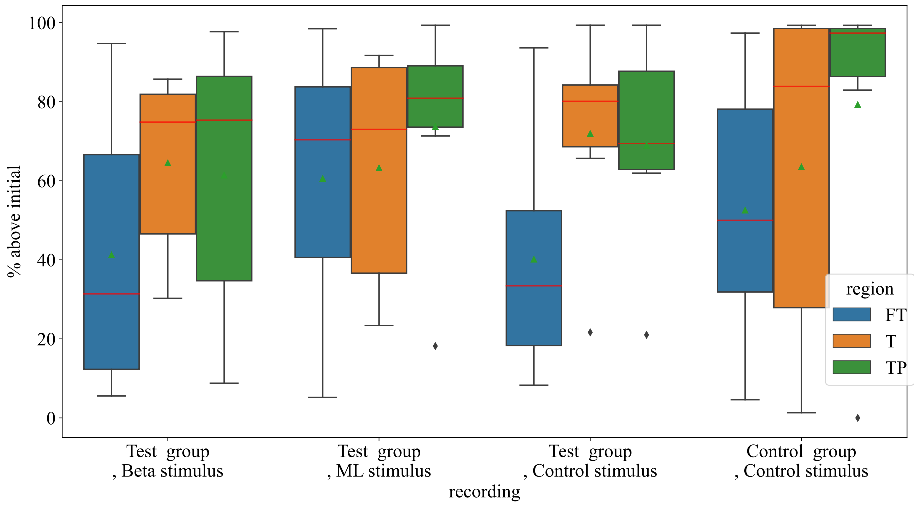


Figure 5.28: A box and whisker plot of the percentage increase metric when applied to different recording groups for the 20 Hz narrowband filtered signal.

20 Hz and 24 Hz metric values, the mean values are relatively comparable with one another, and no recording appears to deviate greatly from the rest.

5.6.3 Discussion

A connectivity analysis is carried out on EEG data recorded at temporal regions. The connectivity analysis is applied to EEG data at the two stimuli frequencies used, 20, and 24 Hz. The connectivity analysis creates many data points to analyse and therefore meta analysis methods are applied to the results of the connectivity analysis. The meta analysis methods provide a set of singular values that can be compared and are computed based on the recording group that recording sessions are clustered in.

Results of the connectivity analysis show a consistent trend, therefore, the individual methods of analysis are not separately discussed. Generally, the results indicate that participants in both control and test stimulus groups had an increase in their connectivity at temporal electrodes. This common increase could potentially imply that the change in connectivity was a result of the stimulus modality or closed eyes condition, but not the frequency characteristics of the stimulus. It is possible that only having an audio stimulus to focus on increased the connectivity of Temporal electrodes, as it is the audio processing centre of the brain. However, more participants would be needed to fully substantiate this claim. The finding that both test and control participants exhibited an increase in connectivity conflicts with existing research which indicated that the increase in connectivity was a result of the entrainment stimulus. The conflict may arise from the study design of existing research not having separate control readings using a pink noise stimulus. Various aspects of the meta analysis metrics used substantiate this conflicting finding in the context of the present research.

The mean increasing count metric indicated that on average participants in all recording groups have at least one increasing electrode at 20 and 24 Hz and that there is no grouping between control and test recording sessions when using the metric. This indicates that all recording groups exhibited an overall increased connectivity.

The mean increasing count metric is further evaluated and plotted as a time varying signal. The analysis shows that while the metric did not generally increase from three minutes during the recordings, it consistently remains above one. This indicates that participants mostly had an overall increase in their connectivity from at least one region. The metric does not provide any grouping trends between the two frequencies, past indicating that all recordings maintained at least one increasing electrode on average for participants from three minutes until the end of the recording session.

Lastly, the percentage increase metric is applied to the connectivity results. Notably, at 24 Hz all mean and median values were above 50 %. Further, the separate control group exhibits the highest mean and median values, however, the difference against other groups is not significant. The mean and median values of all recording groups are highly comparable, existing within 5 % of one another. A similar trend is seen at 20 Hz, with no notable differences seen between the results at the two frequencies. Between the two frequencies, it can be determined that on average participant connectivity increased relative to its initial point as most regions exhibited a percentage increase metric of above 50 % for all recordings. Additionally, no large differences between control and test groups exist, it can, therefore, be determined that the increase was not likely due to the nature of the audio stimulus used.

Given the relevant metrics, it is apparent that test stimuli did not cause any increase in connectivity. No marked difference is present between recordings using test and control stimuli. The assertion requires further data to be stated absolutely due to the limited sample size of the study. However, given the apparent lack of outliers, this result is fairly well substantiated in its objection to existing research.

5.7 Machine Learning Model Insights

The final QL model generated after all participant's in the test group had their QL driven session can be seen in Table 5.5. This model is briefly discussed and analysed as the table itself has some interesting results due to the nature of Q-learning.

Table 5.5 defines a model that broadly maintains the current entrainment frequency when the power of the targeted brain wave is increasing. Alternatively, it switches the frequency of the stimulus when the power is decreasing. The exact values of the table items are not assessed as they are more reliant on how many times, and when a state - action pair was visited. This is especially apparent given the sample size of the study.

Table 5.5: The final Q table after all QL driven sessions.

State \ Action	24	20
up_24	0.55377406	0.11839484
down_24	0.27656361	0.42190746
up_18	0.11956283	0.30234323
down_18	0.24249081	0.108

The machine learning model's structure and weights are discussed. The model developed was allowed to switch between two frequencies as entrainment stimuli. This was to allow the model to serve as a proof of concept and determine if switching between entrainment frequencies would be able to optimise the entrainment effects of the stimulus. Given that the power results have indicated that this is possible, extensions to the model should be looked at: expanding the action space of the Q-table to allow different frequencies from different brain wave bands to be targeted as well as allowing pink noise to be used by the QL model.

The model would, additionally, benefit from allowing more exploratory steps to be taken. This would require many more participants and would allow the model's weights to truly begin to converge. At present, the model only had four participants that used exploratory steps and, therefore, would not necessarily have fully converged.

Lastly the Q values associated with the model are discussed. The model broadly maintains the current entrainment frequency when the displacement in the power of the targeted brain wave is increasing. This both agrees and disagrees with existing research on the concept of habituation. The model defines an action space that would switch the entrainment stimulus' frequency when habituation was occurring. This agrees with previous research in that the phenomenon exists. However, the model also defines that maintaining an entrainment frequency can be optimal. This indicates that previous research, which indicated that habituation occurred after three minutes and that this was the optimal time to switch stimuli, was not entirely correct. The finding implies that the habituation phenomena is not as defined as previous research implied, occurring at different rates and needing to be dynamically avoided. It is, therefore, possible that a period of shorter than three minutes may be optimal for the QL agent to decide to change the entrainment frequency.

5.8 Overall Study Strengths And Limitations

The study has several areas where it has both strengths and limitations. This is unavoidable, as no research experiment can exist without either.

Bias may be introduced into the study that cannot be removed, these biases have been outlined in Section 4.9. Additionally, limitations exist in the methodology of the study, five notable extensions have been identified for the project:

- A longer period with more entrainment sessions might result in more conclusive results.
- Separately entraining participants towards more than one brainwave band would yield interesting results regarding assessing potential limitations of entrainment in affecting different bands of brainwaves.
- Having more participants with the current experimental setup to improve the confidence in the results.
- Having more actions in the Q table and participants using a stimulus controlled by an QL agent might improve insights and results when using the QL agent.
- Using different entrainment techniques as the type of entrainment might impact the effectiveness of the intervention.

However, the research also has several strengths which should be noted. Firstly, the research builds on and combines previously separate research in neuroscience, VR, engineering, and psychology in a novel application that might have real-world benefits. Secondly, the study provides a good basis for future research whether its results are positive or negative.

5.9 Summary of Results

Results are presented that illuminate different dynamics involved with both test and control recordings. Sufficient evidence has been provided to differentiate between test and control recordings when a power analysis is applied to data; however, this is not true for a connectivity analysis.

A discussion of the results derived has been presented to further explore the meaning of differences noted. The discussion looked to find possible meaning and implications of various results. The discussion specifically looked at the implications of results on different recording groups to evaluate if the set entrainment stimulus and RL controlled entrainment stimulus differed from one another and the control recordings. The discussion, therefore, looked to address answering the research question of the study.

Several differences between the recording groups were notable. These differences indicated that the RL controlled stimulus was optimised when compared to the set entrainment stimulus in several aspects of the results. Further, the entrainment stimuli were shown to have had an effect on the Beta band brainwaves of participants when compared to control readings when a power analysis was employed. More elaborate conclusions should be drawn regarding the results and discussion presented in context of the research question of the study. The discussion presented provides good insights that will allow conclusions to be drawn regarding the results of the experiment.

Chapter 6

Conclusion

The study conducted allows conclusions to be drawn from the derived results. These conclusions must be contextualised to the relatively small sample size of the study. Any conclusions drawn represent identified trends and likely connections more than conclusive relationships. The conclusions are, further, derived using results from temporal regions. More participation is needed to create more decisive conclusions; however, conclusions have been carefully created to improve their basis. Conclusions formally outlined draw evidence from multiple metrics analysed to provide an increased confidence that attempts to account for the low participant size of the study.

Due to the low sample size of the study, and its methodology several extensions are identified for the research. The extensions centre around increasing the confidence of results and expanding on the neural mechanisms examined. Results can be improved by increasing the population size of the study, and increasing both the period and number of entrainment sessions. Similarly, expanding on how the study investigates entrainment: more brain wave bands might be entrained towards, more actions could be used by the Q-Learning (QL) driven stimulus, and different entrainment techniques might be employed together.

The study looked to determine what neural differences exist due to a dynamic and set entrainment stimulus targeting Beta brain waves. For this purpose, the power, and connectivity results of recorded electroencephalogram (EEG) data were observed. Results were observed in response to a pink noise control stimulus, a set 24 Hz Beta entrainment stimulus, and an QL agent controlled stimulus. A separate control group was included to ensure that the findings did not indicate a placebo effect or any dynamics involved with the conditions of the experiment separate to the stimulus.

Power analysis results derived meaning from spectrogram and meta analysis metrics applied to Short-time Fourier transform (STFT) data The results indicated that the entrainment stimuli uniquely increased the power of Beta band neural activity in participants. The increased Beta band power was only present in test stimuli recordings and was not present in control recordings, confirming that the increase was not a result of a placebo effect or experimental conditions outside the test stimulus. Further, it was confirmed that the entrainment stimuli did not affect the Alpha or Theta band of neural activity as results in these two bands were relatively consistent across both test and control recordings. The findings agreed with existing research and provided new evidence regarding the effect as previous research did not employ separate control recordings.

The impact seen on Beta band brain waves largely agreed with existing research. Results found that a 24 Hz Binaural Beat (BB) entrainment stimulus increased the power of Beta brain waves. However, two test participants had a distinct difference which leads to a unique conclusion. The participants had a significant decrease in the Beta band brain wave power when exposed to the 24 Hz and QL driven entrainment stimuli. It can be concluded that this large decrease was due to the entrainment stimulus and should be investigated further due to the limited data points supporting this finding. The finding disagrees with existing research which found that entrainment serves to increase the power of targeted brain waves.

No evidence indicates that the 24 Hz entertainment stimulus had any notable effect on the connectivity of brain waves from the temporal regions. The results from all recordings indicated a trend of increasing connectivity in response to all stimulus conditions. The increasing trend was apparent for both entrainment and control recordings. This finding provides evidence that the connectivity increase was due to the closed eyes condition imposed on participants and the fixation on an audio stimulus. The conclusion opposes those in existing literature and should be further investigated to confirm. The same finding is valid for the QL driven stimulus, which did not indicate any stimulus related connectivity changes.

Conclusions can be drawn around the QL driven stimulus and its effectiveness as an alternative to a set entrainment stimulus. The QL driven stimulus was shown to have comparably effective or improved results relative to the set entrainment stimulus when analysing the power increase of Beta band brain waves. The findings around the comparable nature of the QL driven stimulus are present across all meta analysis power metrics presented as well as the spectogram plots assessed. The metrics outline similar behaviour as that seen in response to a set Beta entrainment frequency: an increase in Beta band power at Temporal sites which was stimulus related, while power changes in Alpha and Theta bands were present in all recording groups. This is a new finding when assessing existing research and indicates that the dynamic entrainment stimulus was able to affect the Beta brain waves of participants at least as well as the 24 Hz set entrainment stimulus. However, several metrics and characteristics of recorded data distinguish results seen due to the QL driven stimulus

Notably, the spectrogram based analysis of recorded EEG power had one key findings around an improvement seen due to the QL driven stimulus. The QL driven stimulus increased the power of Beta band brainwaves across the band more comprehensively than the set entrainment stimulus; it was able to increase the power of more frequencies within the band, including at the upper end of the Beta band and at the entrainment frequencies used. It is proposed that this is due to the QL driven stimulus avoiding habituation effects as it set out to achieve. Building off this, meta analysis metrics aimed to quantify this difference and ensure that it was present when assessing the power data from multiple angles.

Several meta analysis metrics indicate that the QL driven stimulus had an improved effect on the power of Beta band brain waves than the set 24 Hz entrainment stimulus. The mean increasing count metric and percentage increase metric provided the most conclusive evidence of the QL driven stimulus's increased efficiency when increasing the power of Beta band brain waves. These metrics support the idea that the QL driven stimulus was able to increase the power of different frequencies in the beta band. Further, the metrics indicate that this occurred earlier than notable effects were seen in response to a set entrainment stimulus. This occurred even when the QL agent was searching for the optimal policy.

Participants who had their stimulus controlled using an QL agent that only used actions that it deemed optimal were compared to all other groups of recordings. Conclusions drawn from this comparison need to have an additional qualifier added. Since only two participants had optimal actions taken by the QL agent, further testing should be conducted for this finding; however, it provides an indication of the potential impact of an QL agent optimised stimulus.

The optimal QL agent actions produced two recordings that were significantly different from recordings using all other stimuli presented to participants. The difference saw increased entrainment effects in the Beta band, while having no notable impact in the Alpha or Theta bands. This indicates that the QL agent was able to learn an optimal policy and that the optimal policy was able to notably improve entrainment effects in the Beta band. This improvement was in comparison to the 24 Hz entrainment, exploratory QL, and control stimuli. The conclusion indicates that further research should be conducted using a larger state - action space, and using the same Q-table developed with more participants to solidify the finding.

Findings around the increased effectiveness of the QL agent in entraining participants, and increasing their Beta band neural activity is novel when comparing it to existing research. The finding does ground itself in existing findings regarding the effect of entrainment on the power of brain waves and habituation. However, no previous research used a dynamic entrainment stimulus similar to the QL driven stimulus.

Lastly, conclusions can be drawn regarding the Q-table developed by the QL algorithm. The Q-table does indicate that habituation was occurring. It can, therefore, be concluded that previous research was correct in indicating that this phenomenon exists. However, the Q table indicates that the onset of habituation is not as clear-cut as previous research indicated. Three minutes was not the default time for habituation to occur as the Q-table found maintaining an entrainment frequency after three minutes of it being presented optimal at times. Therefore, while the Q-table was able to adequately learn a policy to avoid habituation, the QL agent should be further investigated using shorter periods between decisions to further investigate the time dynamics of habituation. This finding indicates a narrative unpacking of the dynamic stimulus developed more than its feasibility. It, therefore, provides a brief explanation around why the dynamic stimulus developed achieved improved results rather than directly describing its feasibility.

The experiment can conclude several factors, which assess the difference between a dynamic and set entrainment stimulus. The effect of a 24 Hz entrainment stimulus was confirmed to agree with existing research when applied in virtual reality (VR). This effect was further confirmed to be a result of the entrainment stimulus and not any possible placebo effects or experimental conditions. Further, it was determined that the 24 Hz stimulus increased the power of the lower end of the Beta band of brain waves. This is a new finding as existing research only looked at the Beta band power as a whole and not at distinct frequencies within the band. Further, the study can conclude that connectivity increases seen are not a result of the entrainment stimulus, as it was previously reported. These findings were validated using an analysis of spectrogram data, and meta analysis metrics to justify the findings from different aspects of the data. The findings, further, address the first research objective, evaluating existing findings when using a separate control measurement as a reference. Secondly, the study can conclude that a QL controlled dynamic algorithm is a feasible method of improvement to traditional entrainment stimuli. The study has shown that the QL controlled stimulus is able to increase the power across the entire Beta band, leading to a more significant increase in power when compared to the set entrainment stimulus.

Together, addressing the research objectives provides a conclusive answer to the overall research question. A dynamic entrainment stimulus, targeting the Beta band, is able to provide an increase in power across the whole Beta band as opposed to only in the lower end of the band when compared to a set entrainment stimulus. The increased range of frequencies affected leads to a more significant overall power increase when assessing the Beta band as a whole.

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Appendix A

Project management

Task	Phase	Start	End
EEG training	Training	2021-11-02	2022-05-15
Ethics submission	Ethics	2021-10-20	2021-11-04
Writing proposal	Proposal	2021-11-04	2021-11-26
Proposal defence and comments	Proposal	2022-01-26	2022-02-03
Oculus Entrainment setup (virtual environment)	Setup	2021-11-29	2021-12-10
Testing Oculus Entrainment setup	Setup	2022-02-08	2022-02-10
AWS resources and script setup	Setup	2021-12-10	2022-01-16
Oculus Entrainment API setup	Setup	2021-12-27	2021-12-30
EEG Testing environment setup	Setup	2022-01-20	2022-02-14
Setup EEG code linking to AWS	Setup	2022-02-07	2022-02-14
Test system	Setup	2022-02-17	2022-02-21
Setup Piano MR environment and experiment	Setup	2022-02-21	2022-02-22
Test overall system	Setup	2022-02-22	2022-02-25

Data collection and participation	Recording	2022-02-24	2022-05-17
EEG analysis Ramp-up	Analysis	2022-02-07	2022-02-22
Setup analysis tools for data	Analysis	2022-02-22	2022-02-28
Setup tools/workflows to clean data of artefacts	Analysis	2022-02-07	2022-02-25
Setup potential ML based on initial data and test	Analysis	2022-02-07	2022-02-07
Analyse results	Analysis	2022-05-18	2022-06-03
Summarise results	Analysis	2022-06-03	2022-06-07
Write up dissertation	Writing	2022-06-07	2022-10-15
Edit dissertation	Writing	2022-10-15	2022-10-30

Table A.1: An extended estimated breakdown of tasks for the project management of the research

Task	Phase	Start	End
EEG training	Training	2021-11-02	2022-05-15
Ethics submission	Ethics	2021-10-20	2021-11-04
Writing proposal	Proposal	2021-11-04	2021-11-26
Proposal defence and comments	Proposal	2022-01-26	2022-02-03
Oculus Entrainment setup (virtual environment)	Setup	2021-11-29	2021-12-10
Testing Oculus Entrainment setup	Setup	2022-02-08	2022-02-10
AWS resources and script setup	Setup	2021-12-10	2022-01-16
Oculus Entrainment API setup	Setup	2021-12-27	2021-12-30
EEG Testing environment setup	Setup	2022-01-20	2022-02-14

Setup EEG code linking to AWS	Setup	2022-02-07	2022-02-14
Test system	Setup	2022-02-17	2022-03-21
Test overall system	Setup	2022-03-21	2022-03-24
Setup and test cleaning workflows	Setup	2022-04-01	2022-05-10
Setup ML algorithm integration to system	Setup	2022-07-01	2022-07-14
Test ML integration and overall system	Recording	2022-07-15	2022-07-16
Data collection and participation	Analysis	2022-05-01	2022-08-04
EEG analysis further investigation	Analysis	2022-06-05	2022-06-16
Setup analysis tools for data	Analysis	2022-06-03	2022-07-30
Setup tools/workflows to clean data of artefacts	Analysis	2022-05-10	2022-06-10
Investigate potential ML based on initial data and test	Analysis	2022-06-18	2022-07-01
Analyse results	Analysis	2022-06-03	2022-08-25
Summarise results	Writing	2022-06-03	2022-06-30
Write up dissertation	Writing	2022-06-07	2022-09-20
Edit dissertation	Writing	2022-09-20	2022-09-30
Supervisors review dissertation	Editing	2022-09-30	2022-12-12
Editing dissertation based on feedback	Editing	2022-10-30	2023-01-08

Table A.2: An extended breakdown of task completion during the research

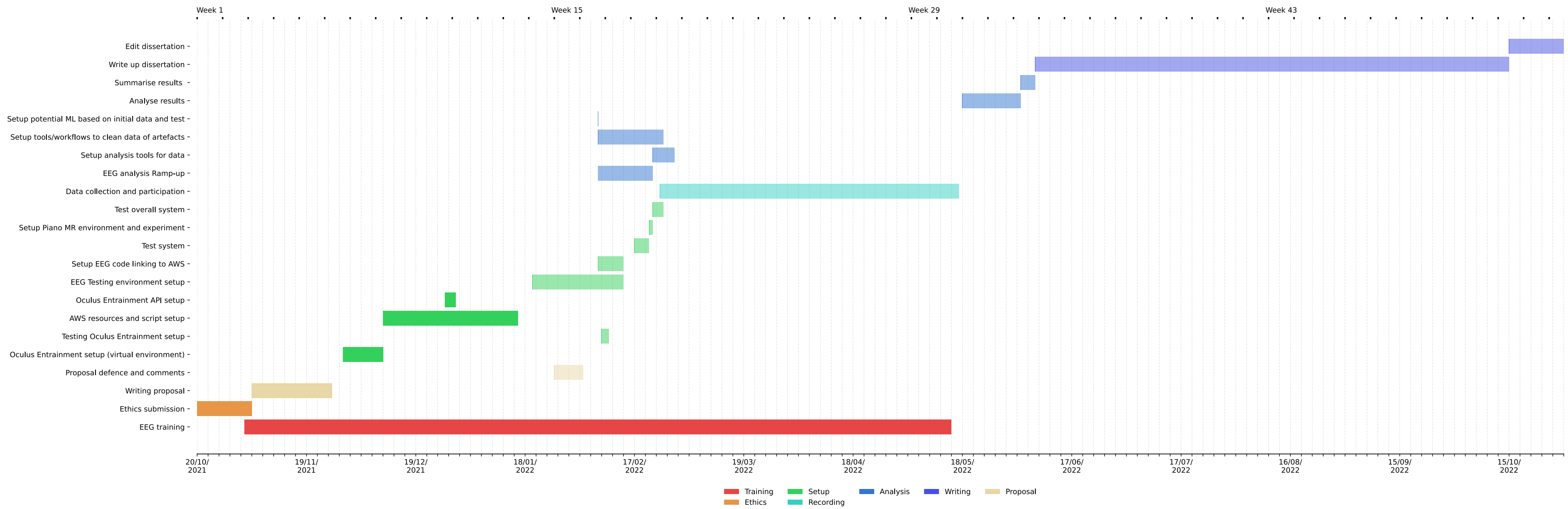


Figure A.1: An extended Gantt chart the project management of the research

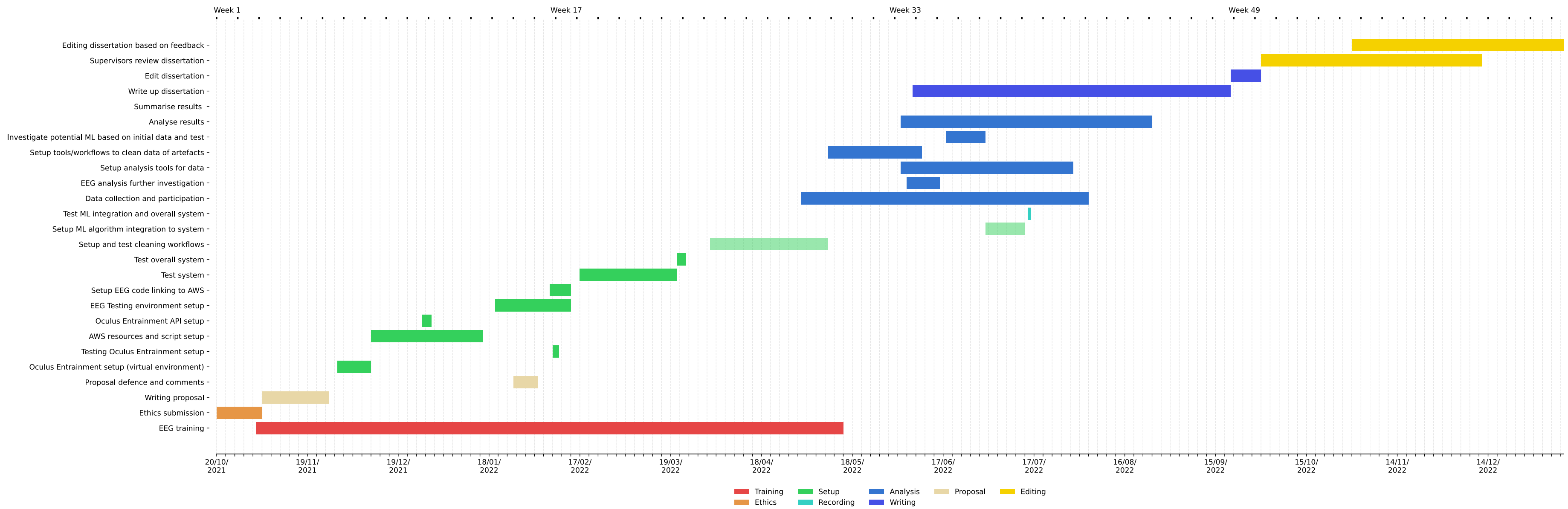
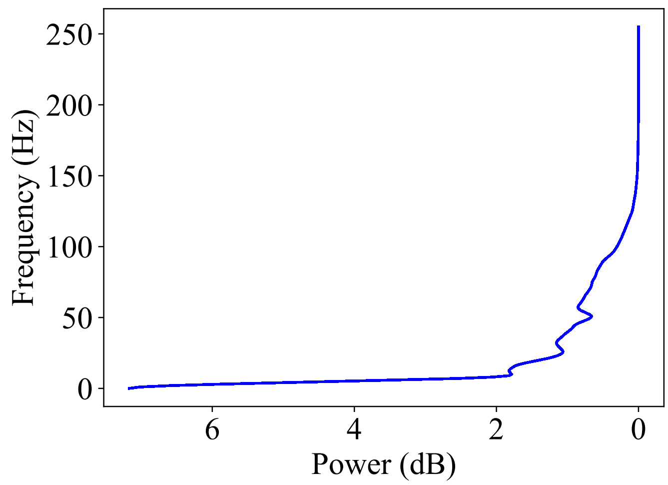


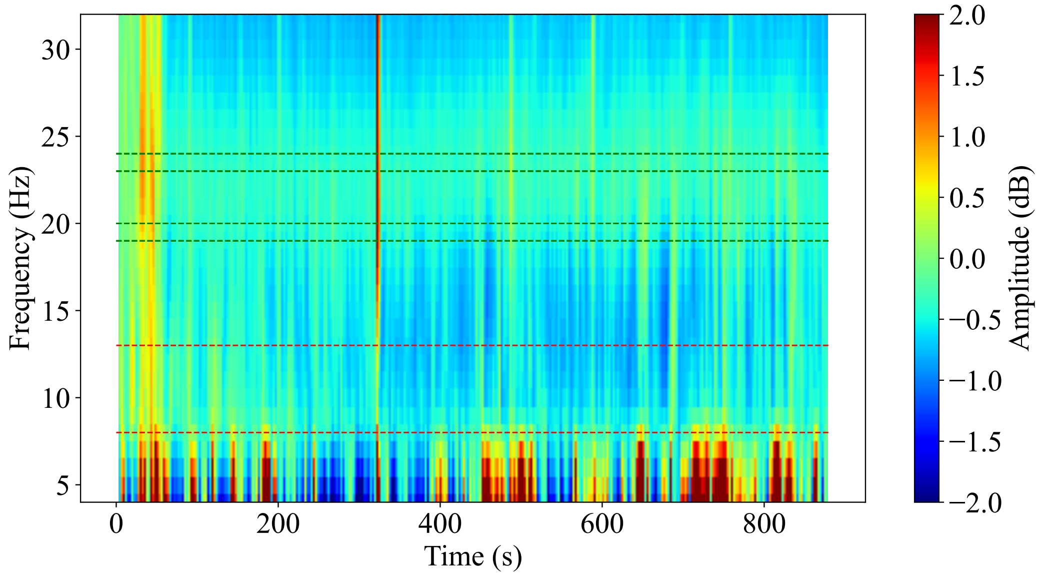
Figure A.2: An extended Gantt chart of task completion during the research

Appendix B

Spectrogram plots

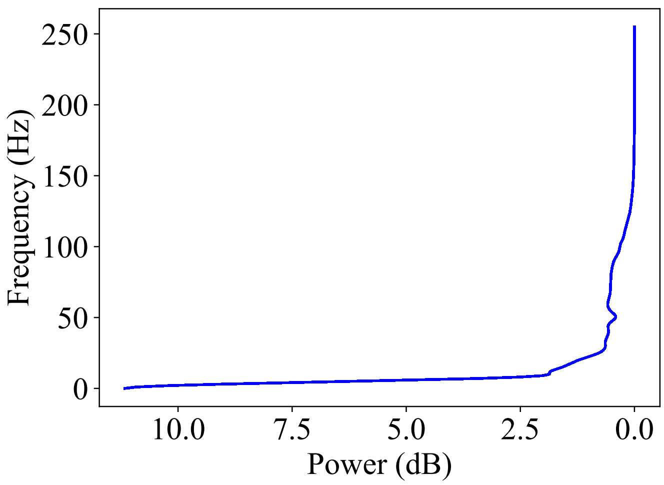


(a) Baseline power spectrum

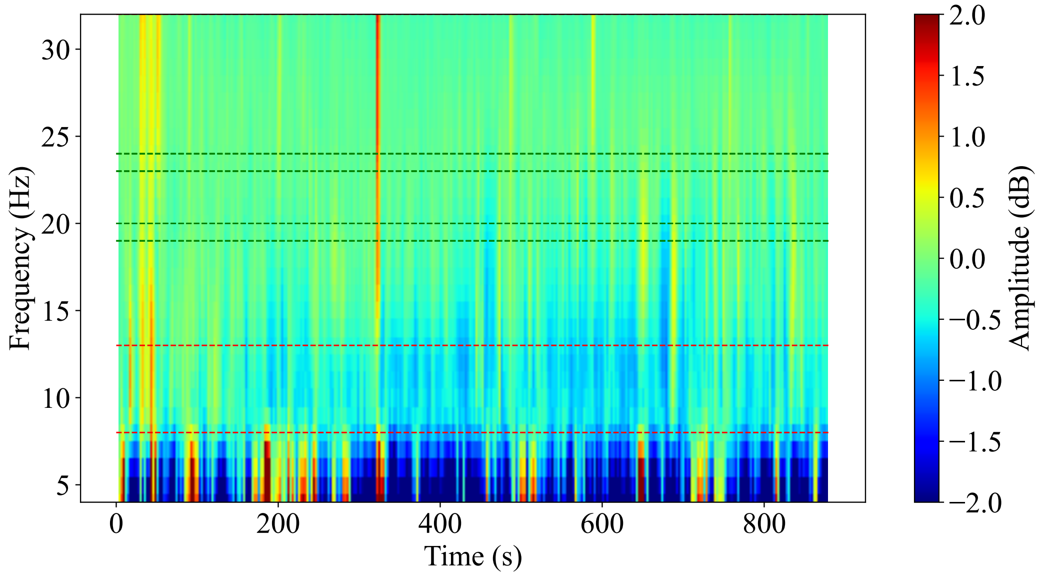


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.1: Spectrogram of T region for a test participant that was exposed to the control stimulus

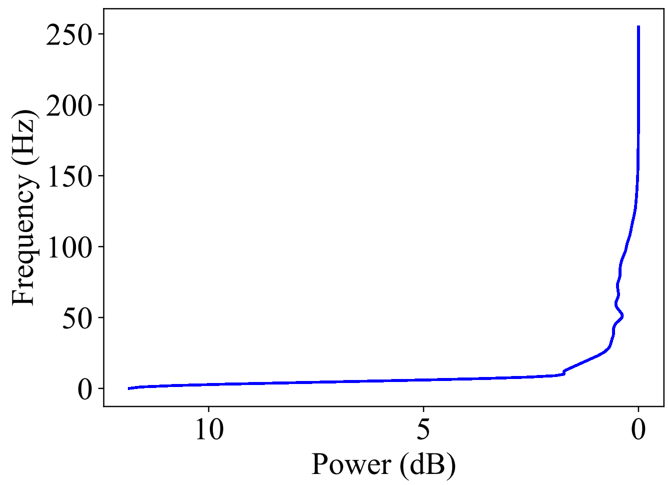


(a) Baseline power spectrum

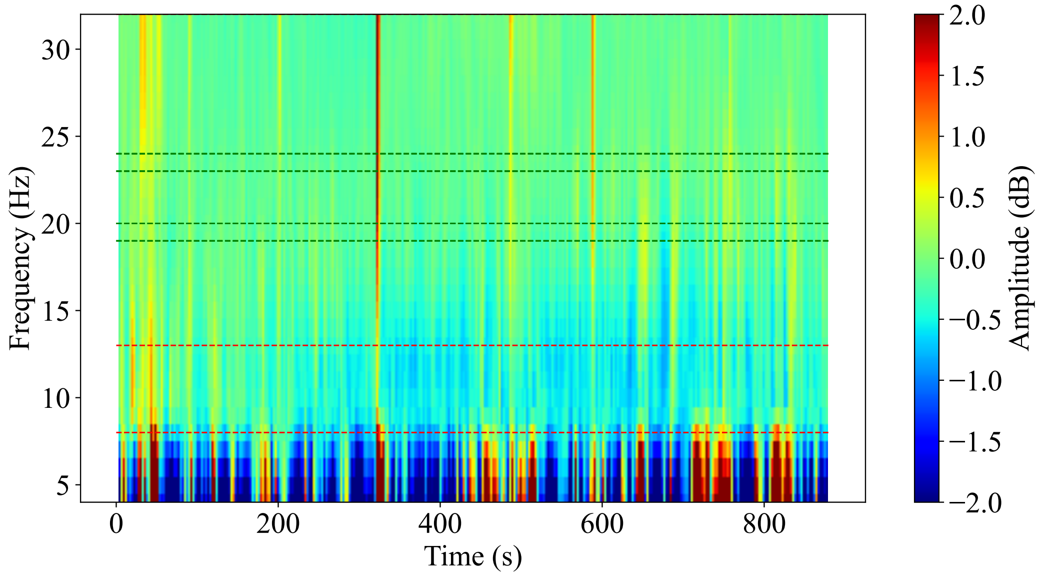


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.2: Spectrogram of TP region for a test participant that was exposed to the control stimulus

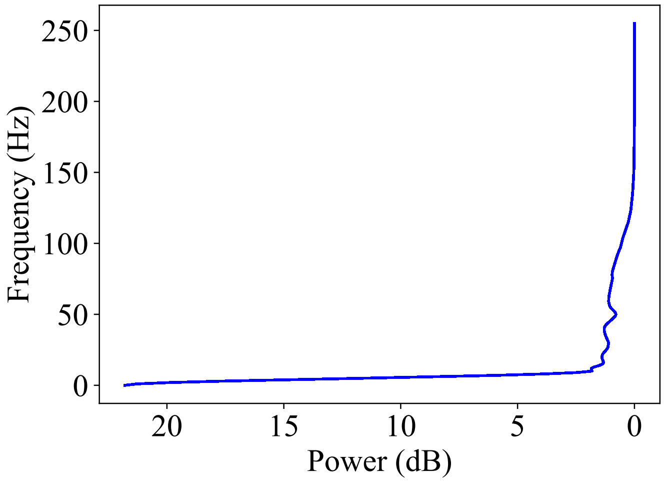


(a) Baseline power spectrum

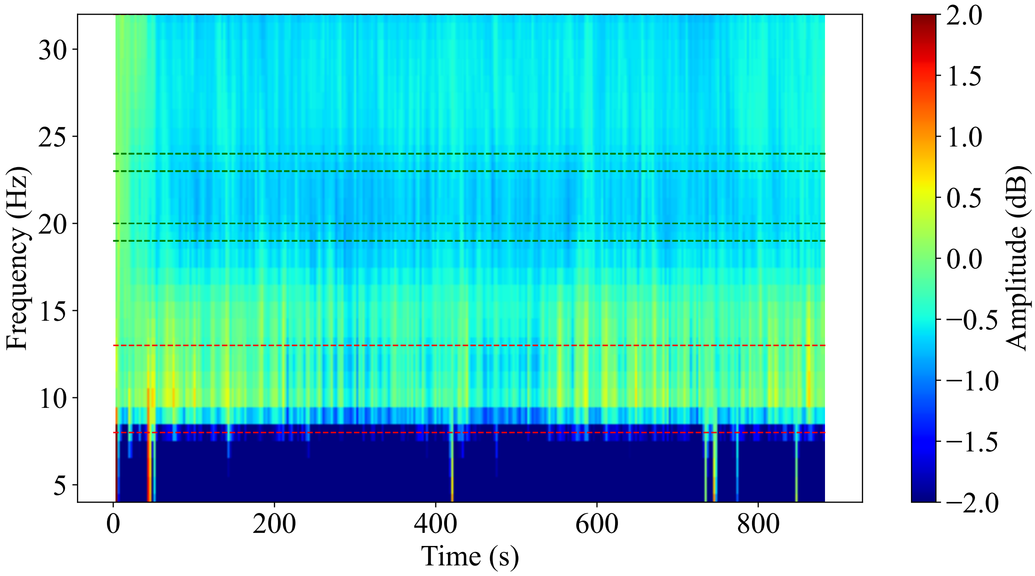


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.3: Spectrogram of FT region for a test participant that was exposed to the control stimulus

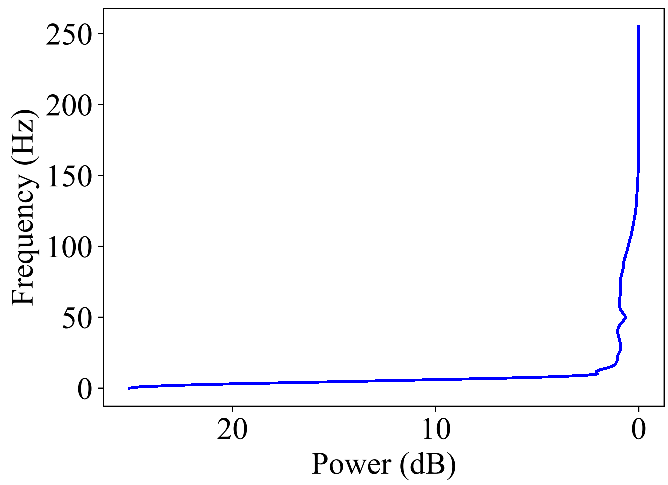


(a) Baseline power spectrum

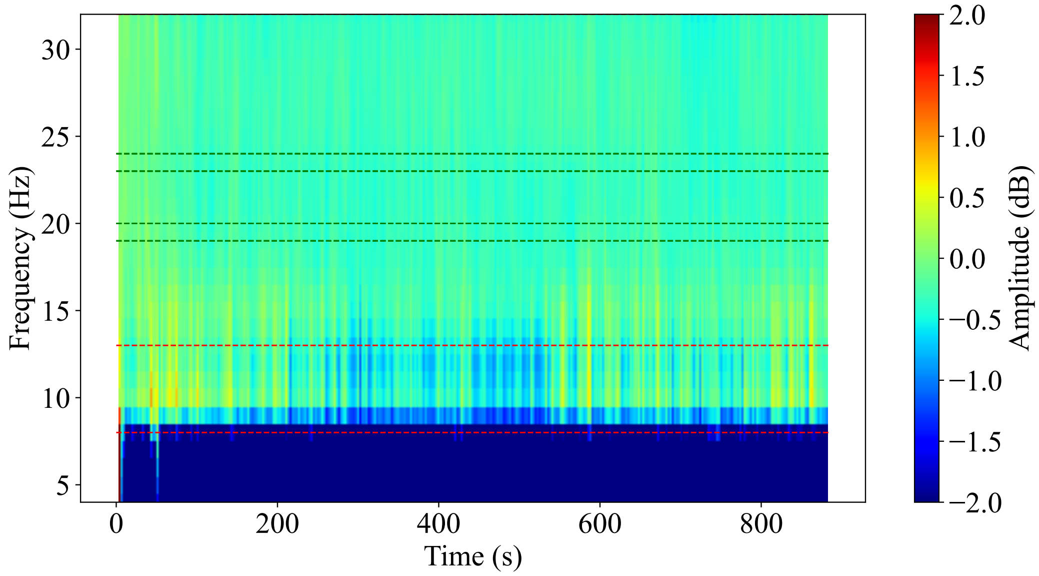


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.4: Spectrogram of T region for a control participant that was exposed to the control stimulus

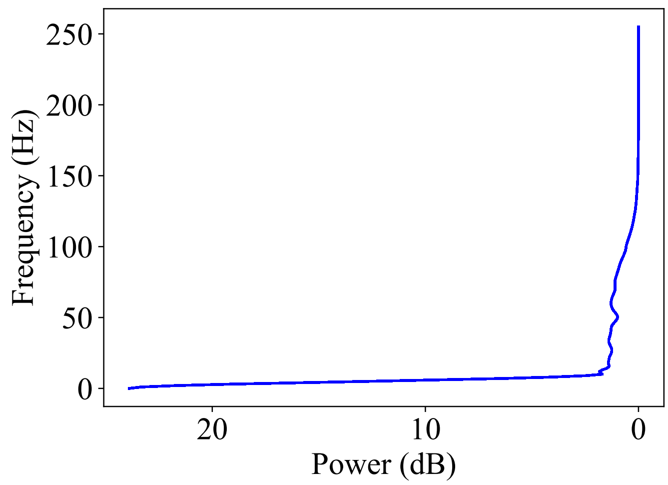


(a) Baseline power spectrum

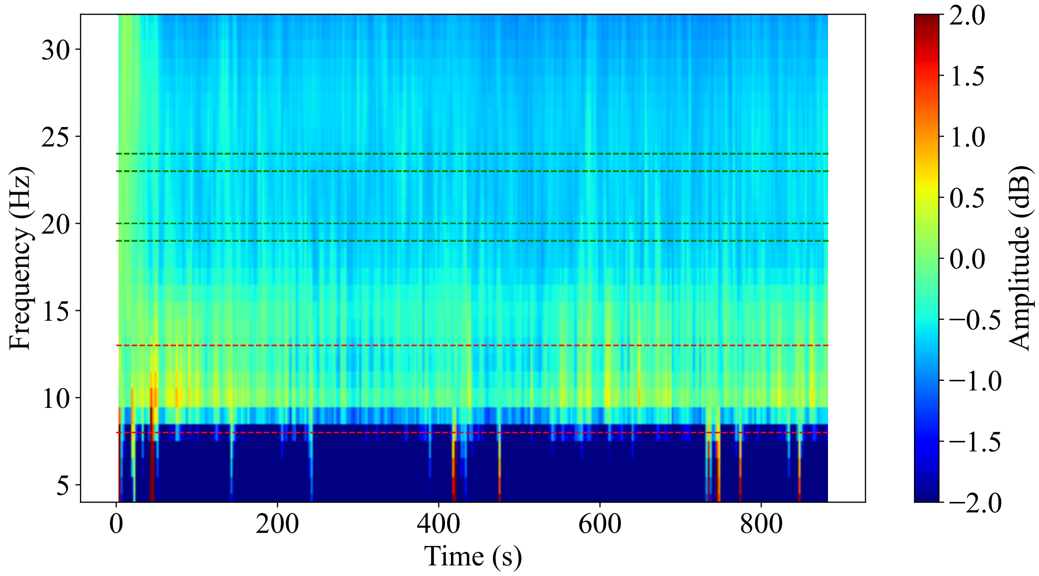


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.5: Spectrogram of TP region for a control participant that was exposed to the control stimulus

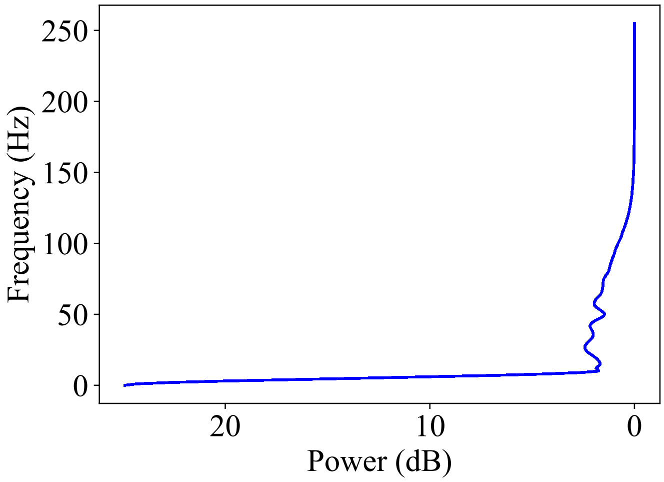


(a) Baseline power spectrum

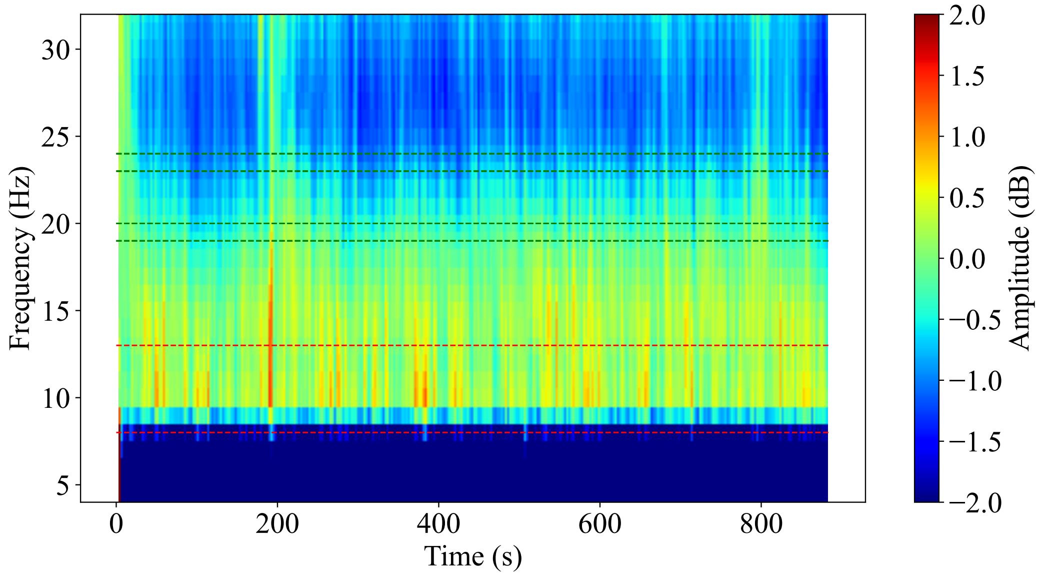


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.6: Spectrogram of FT region for a control participant that was exposed to the control stimulus

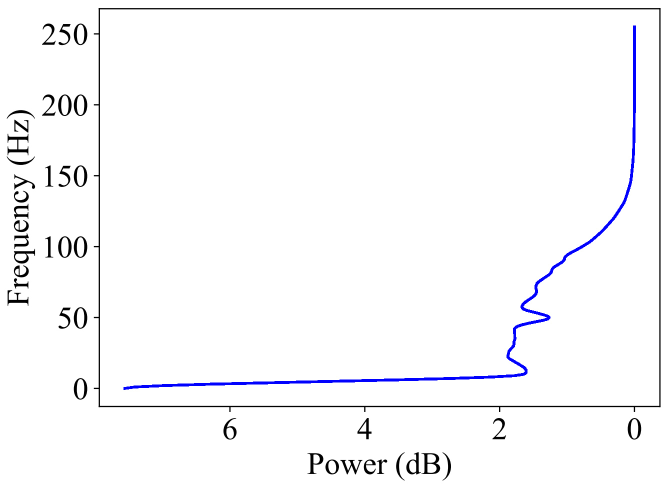


(a) Baseline power spectrum

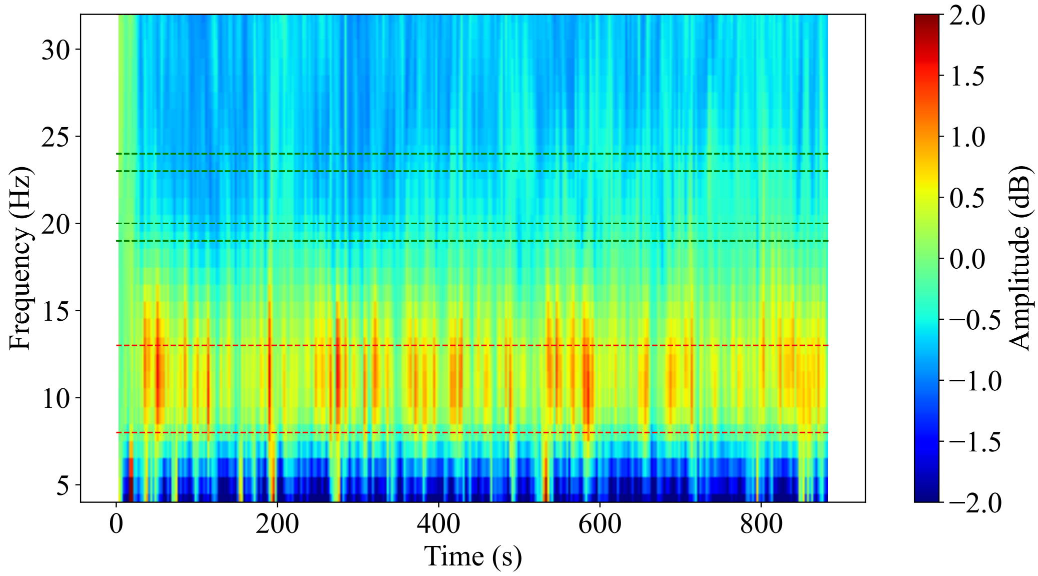


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.7: Spectrogram of T region for a test participant that was exposed to the Beta entrainment stimulus

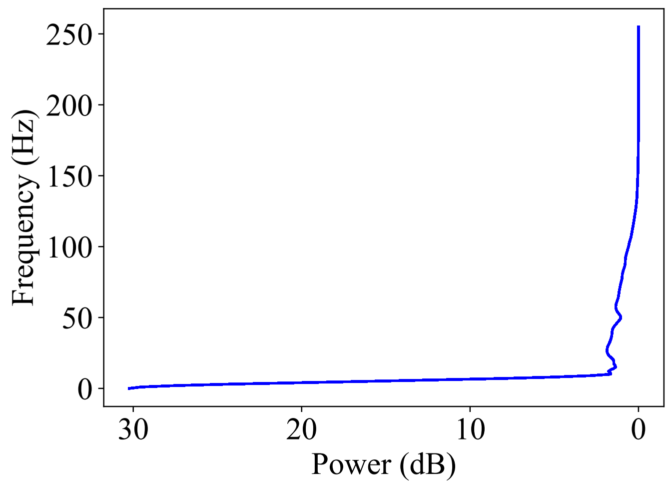


(a) Baseline power spectrum

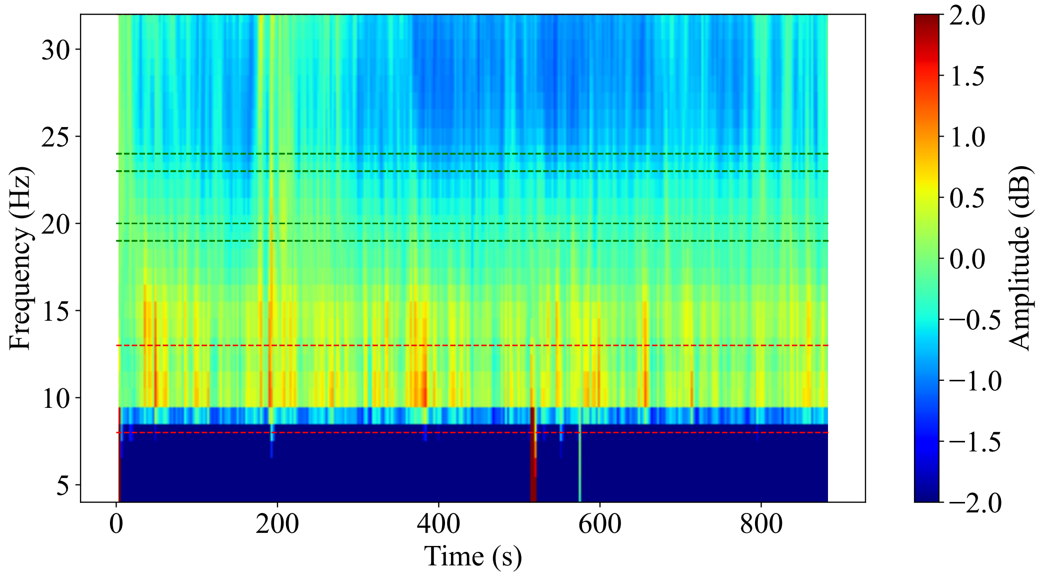


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.8: Spectrogram of TP region for a test participant that was exposed to the Beta entrainment stimulus

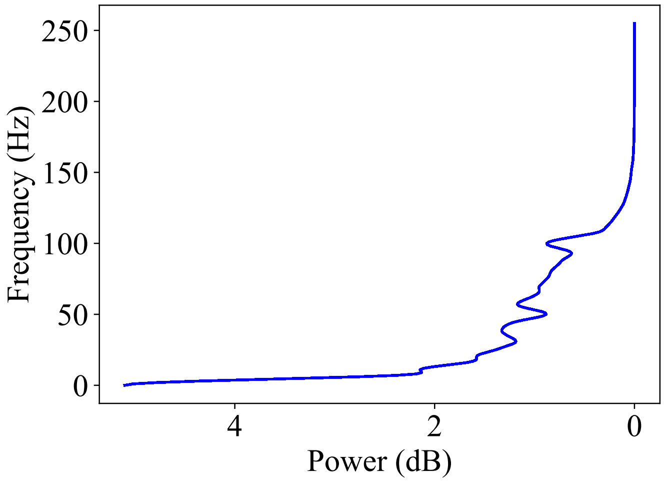


(a) Baseline power spectrum

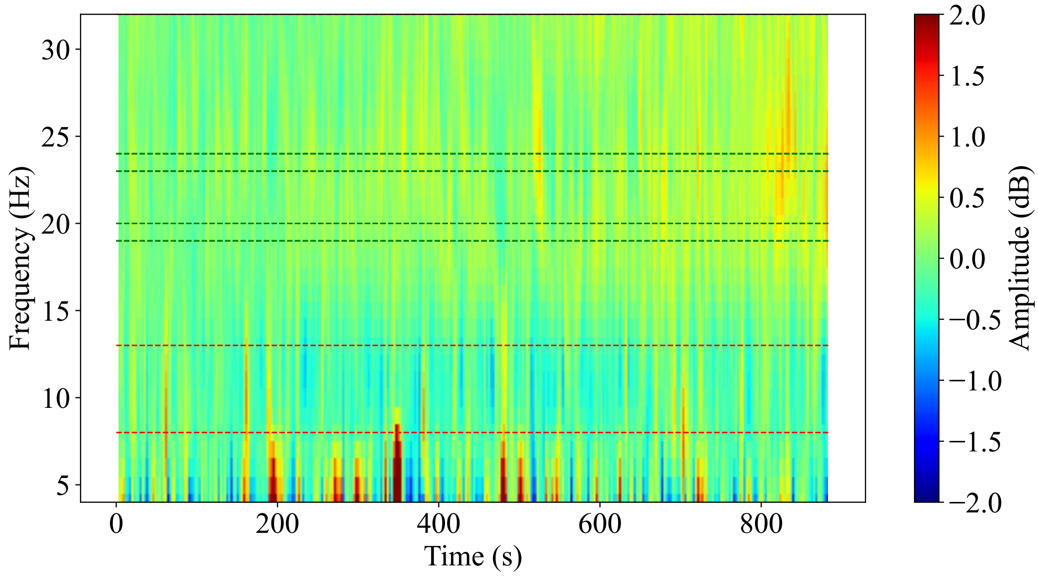


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.9: Spectrogram of FT region for a test participant that was exposed to the Beta entrainment stimulus

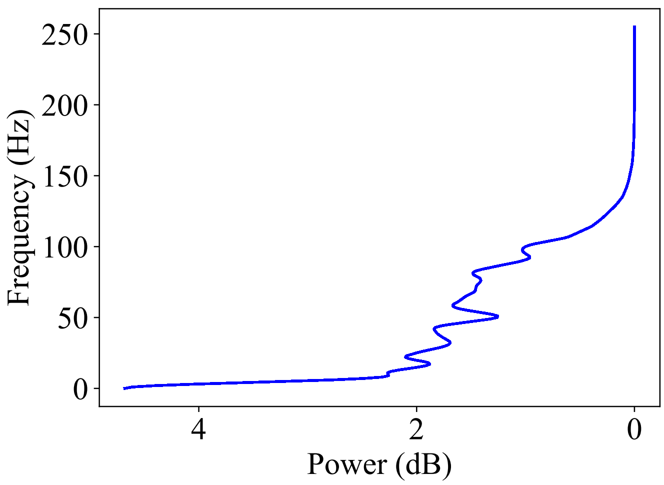


(a) Baseline power spectrum

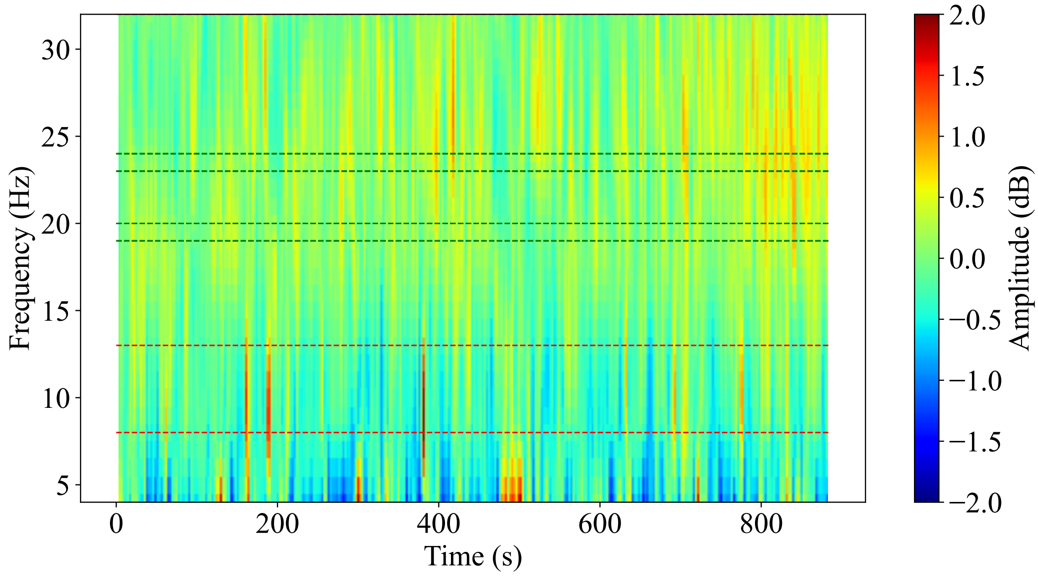


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.10: Spectrogram of T region for a test participant that was exposed to the Q-Learning (QL) driven entrainment stimulus

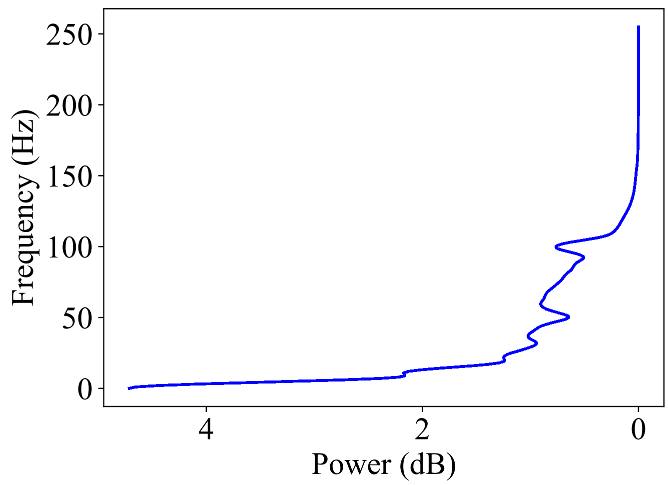


(a) Baseline power spectrum

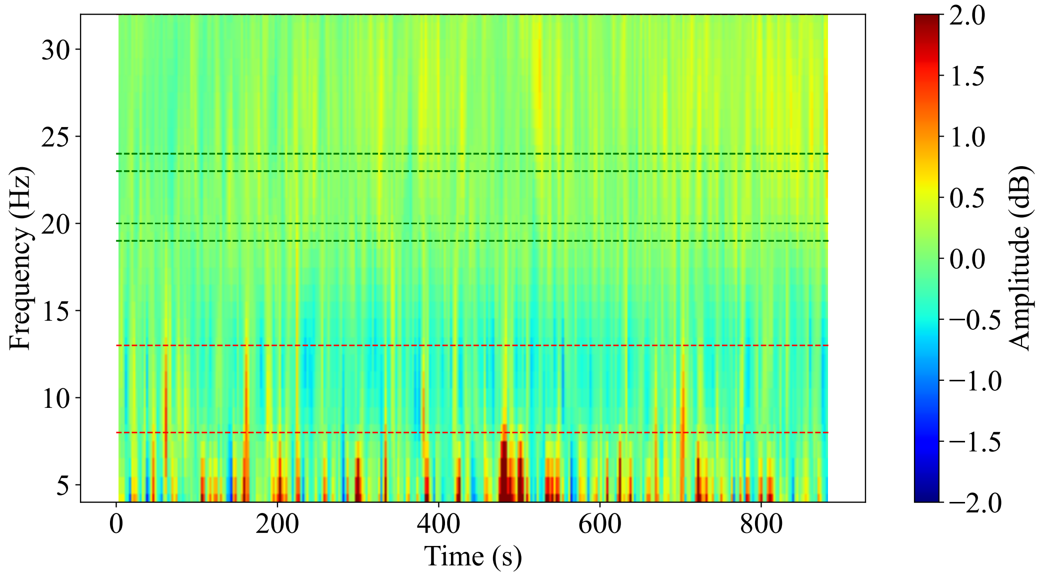


(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.11: Spectrogram of TP region for a test participant that was exposed to the QL driven entrainment stimulus



(a) Baseline power spectrum



(b) Spectrogram for the Alpha, Theta, and Beta band frequency range

Figure B.12: Spectrogram of FT region for a test participant that was exposed to the QL driven entrainment stimulus

Appendix C

Ethics Approval

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)

13 April 2022

Mr MR Cassim
School of Electrical and Information Engineering
University of the Witwatersrand

Sent by email to: rashcassim@gmail.com

Dear Mr Cassim,

Re: **Protocol Ref No:** M211146
Protocol Title: *Optimising learning of a novel motor skill in a virtual environment using brain state manipulation*
Principal Investigator/s: Mr MR Cassim and Professor D Rubin
Protocol Amendments

This letter serves to confirm that the Chairman of the Human Research Ethics Committee (Medical) has approved the amendments for the abovementioned protocol, as detailed in your letter, received 06 April 2022.

The following documents were received:

- Summary letter
- Information forms
- Consent forms
- Advertisement message
- Ethics clearance certificate

Thank you for keeping us informed.

Yours Sincerely,

UNIVERSITY OF THE WITWATERSRAND
OFFICE OF THE DEPUTY VICE CHANCELLOR RESEARCH
1 3 APR 2022
RESEARCH OFFICE
HREC (Medical)
JOHANNESBURG

Ms MV Ramaila
Administrative Officer
Human Research Ethics Committee (Medical)

Research Office: Faculty of Health Sciences, Phillip Tobias Building, 3rd Floor, Office 302, Corner York Road and 29 Princess of Wales Terrace, Parktown, 2193 Private Bag 3, Wits 2050 I T+27 (0)11-717-1234/2656/2700/1252I **Office E** HREC-Medical.ResearchOffice@wits.ac.za IWebsite: www.wits.ac.za/research/about-our-research/ethics-and-research-integrity/

Figure C.1: Ethics clearance certificate

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG	HUMAN RESEARCH ETHICS COMMITTEE (MEDICAL)

Office of the Deputy Vice-Chancellor (Research and Innovation)

TO: Mr MR Cassim and Professor D Rubin
School of Electrical and Information Engineering
University

E-mail: rashcassim@gmail.com

CC: Supervisor: Mr A Pantanowitz
<Adam.Pantanowitz@wits.ac.za>
and <HREC-Medical Research Office@wits.ac.za>

FROM: Mr Iain Burns
Human Research Ethics Committee (Medical)
Tel: 011 717 1252

E-mail: Iain.Burns@wits.ac.za

DATE: 2022/03/24

REF: R14/49

PROTOCOL NO: **M211146** (This is your ethics application reference number. Please quote it in all enquiries, oral or written, relating to this study.)

PROJECT TITLE: *Optimising learning of a novel motor skill in a virtual environment using brain state manipulation*

Please find attached the Clearance Certificate for the above project. I hope it goes well and that an article in a recognized publication comes out of it. This will reflect well on your professional standing and contribute to Government funding of the University.

MSWorks2000/Iain0007/Clearscan.wps

Figure C.2: Approved ethics amendments certificate

CONSENT FORM FOR RECORDING OF SCORE AND EEG DATA BY PARTICIPATING IN THE STUDY TITLED: Optimising learning of a novel motor skill in a virtual environment using brain state manipulation

I agree to participate in this research study and that:

1. I have been given a Participant Information Sheet which explains the nature and processes involved in this study, which is attached hereto;
2. I was given time to read it, or had it read to me, in the language I best understand;
3. I was given time to ask any questions I wanted to and found any answers given to me to be reasonable and satisfactory;
4. I understand that I cannot participate in this study if I have a history of photosensitive epilepsy and that I should disclose this prior to participation;
5. I believe I fully understand why the study is being conducted and what the intended outcomes will be;
6. I understand that there will be no immediate benefit to me, should I agree to participate, nor will I receive any payment; conversely, participation will not cost me anything but my time;
7. I understand that, even if I initially consent to take part in the study, I may subsequently withdraw at any time and would not be required to give any reasons; if that happened, any data collected about me for the purposes of the study would immediately be destroyed, unless I give consent for it to be retained
8. I have been given a range of contact details, listed below. If I require further information or become concerned about any aspect of this study I am free to speak to any of these contacts.
9. I will contact the Principal Investigator, contact details listed below, should I exhibit any symptoms for or test positive for Covid-19 in the next 14 days.

Contact details:

Muhammed Rashaad Cassim, Principal Investigator, telephone no. +27712766585, or by e-mail at 1099797@students.wits.ac.za,

Adam Pantanowitz, Supervisor, on telephone no. +27829666001 , or by e-mail at adam.pantanowitz@wits.ac.za

I hereby consent to the usage of flashing lights and sounds to alter my brain's state in a virtual environment and the storage of EEG recordings of my brain before, during and after playing on a keyboard (piano) while in an Augmented Virtual Reality game along with any scores I obtain while playing the game.

I understand that:

- The EEG and score data stored will not have any link to my personal information such as my name or contact information such that it could be used to identify me.
- The EEG and score data may be published after the study has concluded. This published data will contain no information relating to my personal information and no field will be able to identify me.
- Full participation will include a second recording session where I will play the game again. However, I am under no obligation to return for the second session if I do not want to or am unable to do so.
- I might be exposed to flashing lights.
- I might be exposed to sounds played through a pair of headphones.

Figure C.3: Consent form used for participants (page 1 of 2)

- The recordings will be securely stored in a Database that has strict permissions for access.
- I will be playing a piece of piano music on a keyboard while in an augmented virtual reality environment. This may require me to move my body.
- I will be required to wear/use an EEG cap, a pair of headphones, a VR headset and a pair of controllers. All apparatus used will be sanitized before and after every use.
- My data collected or specific statistical analysis of it may be cited in the research report or other write-ups of research without any information that could identify me.

Name of Participant: ______________________________

Date: ______________________________

Place: ______________________________

Signature or mark ______________________________

Witnessed by:

Name of Witness: ______________________________

Signature: ______________________________

Date: ______________________________

Figure C.4: Consent form used for participants (page 2 of 2)

WITS UNIVERSITY

Optimising learning of a novel motor skill in a virtual environment using brain state manipulation

Good day

My name is Rashaad and I am doing research attempting to optimize how we learn a novel/new motor skill in a virtual environment by manipulating brain states. In this study we want to learn if we can help people learn how to better acquire new skills.

I am inviting you to take part in my research study and will give you more details about what this will involve through this info sheet.

Please note that participation is voluntary: refusal to participate will involve no penalty or loss of benefits to you. In the case that you no longer wish to be a part of the study, all data collected from you will be destroyed.

What are brain states?

Brain states are naturally occurring states in your brain that are constantly changing throughout the day. They are characterized by distinctive EEG readings that we can measure. Largely, they are dominant in different regions of the brain during specific activities, feelings and parts of our day. By changing brain states, we are not doing anything your brain does not do constantly. We are attempting to prime the brain to allow it to jump into an activity easier using what it already does.

What will you experience if you take part?

During this study we will perform two recording sessions. Session 1 can be divided into five phases and Session 2 can be divided into four. The second session will be run one day after the first. We will measure your brain activity during all phases. Before we start you will put on an EEG cap, Oculus Quest 2 headset, a pair of noise cancelling headphones and you will hold two controllers. All of the equipment that you will interact with will be sanitised before and after use. Additionally, both myself and you will keep our masks on for the duration of the session to ensure safe protocols are followed in the context of Covid-19.

The first two phases will require relatively low effort from your side and will be the same in Sessions 1 and 2. Initially, during the first phase, you will sit while looking at a background image. During the second phase you might be exposed to some flashing lights and audio

Figure C.5: Information sheet used for participants (page 1 of 2) stimulation while looking at a different background image. These two phases will take around 20 minutes to complete and you might see a graphic of your brain state during these phases.

The third phase of Session 1 will involve playing a piece of piano music on a keyboard while in an Augmented Virtual Reality environment, using the VR game Magic Keys. The VR environment will teach you how to play a specific piece of piano music. The game will require you to play a piece of piano music while being aided by the VR game indicating which keys you should press and when to do so.

During the fourth phase of Session 1 you will again look at a background image. Lastly, phase five of Session 1 will involve you playing the piece of piano music from memory without the VR game.

Session 2 will run one day after Session 1. As previously mentioned, phase one and two of Session 2 will be identical to that of Session 1. During phase three of Session 2 you will play the same piece of piano that you did in Session 1 from memory, as you did during the last phase of Session 1. Lastly, during the fourth phase of Session 2, you will again use the VR game to play a new piece of piano music on a keyboard as you did during Session 1. This will conclude any participation from your side in the study.

Ask me any further questions if you have any regarding what playing the game will look like, I am also able to show you a video of someone playing the game. Additionally, you can visit the game's website using the QR code below to see videos and get more details.

Magic keys website:

How long will it take?

In total each recording session will take around 1 hr and 30 minutes, including time to fill out Covid-19 screening forms and setting up. We will block off some time and send a calendar note to ensure that we can find a time that works for both of us.

Figure C.6: Information sheet used for participants (page 2 of 2)

WITS UNIVERSITY

Covid-19 Screening form for Optimising Learning of a Novel Motor skill in a virtual environment using brain state manipulation participation

Personal details:

Full name:	
Phone number:	
Email:	
Alternate contact details:	
Temperature:	
Date:	

Screening Questions:

In the last 30 days have you:	Indicate Yes or No with a Y or N respectively	Comments:
Tested positive for Covid-19?		
Been exposed to someone who is positive for Covid-19?		
Traveling outside of the country?		
Been exposed to someone who has Covid-19 symptoms?		

Figure C.7: COVID-19 screening form used for participants (page 1 of 2)

In the last 2 - 14 days have you had:	Indicate Yes or No with a Y or N respectively.	Comments:
A fever or chills?		
A loss of smell?		
Excessive/unexplained tiredness?		
A loss of taste?		
Headaches?		
A sore throat?		
Aches and pains?		
Nausea or digestive system related symptoms?		
Difficulty breathing?		
Shortness of breath?		

I affirm and certify that the information and answers to questions herein are complete, true, and correct to the best of my knowledge. I understand that the answers to these questions are used purely to screen participants in the study and will not be used in any other capacity. Additionally, I acknowledge that if I develop any Covid-19 symptoms in the next 14 days that I will contact the Principal investigator of the study, Muhammed Rashaad Cassim, via email, 1099797@students.wits.ac.za, as soon as possible.

Signature:	
Print full name:	

Figure C.8: COVID-19 screening form used for participants (page 2 of 2)