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Coláiste na hOllscoile Corcaigh

Ollscoil na hÉireann, Corcaigh

National University of Ireland, Cork



Interactive EEG Visualisation in Virtual Reality: Design and Implementation

Adam Creed

A thesis submitted for the degree of

Master of Engineering in Electrical Engineering

School of Engineering,

University of College Cork

Head of School/Department: Prof. Jorge Oliveira/Prof. Peter Parbrook

Supervisors: Dr. Emanuel Popovici

Dr. Andreea Factor

Mr. David Murphy

8th March 2025

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List of Acronyms

EEG Electroencephalography

LTE Long Term Evolution

BCI Brain Computer Interface

fMRI Functional Magnetic Resonance Imaging

AI Artificial Intelligence

VR Virtual Reality

2D Two-Dimensional

3D Three-Dimensional

AR Augmented Reality

XR Extended Reality

6DoF Six Degrees of Freedom

GPU Graphics Processing Unit

CPU Central Processing Unit

LoD Level of Detail

API Application Programming Interface

fNIRS Functional Near Infrared Spectroscopy

ECG Electrocardiogram

HIE Hypoxic Ischemic Encephalopathy

NICU Neonatal Intensive Care Unit

EOG Electrooculogram

ICA Independent Component Analysis

SUS System Usability Scale

NASA-TLX NASA Task Load Index

UCC University College Cork

CT Computed Tomography

IED Interictal Epileptiform Discharges

DECLARATION

I, Adam Creed, hereby declare that the work presented in this thesis, titled *"Interactive EEG Visualisation in Virtual Reality: Design and Implementation"*, is entirely my own, except where explicitly stated otherwise. I have fully acknowledged and referenced all sources of information used in this document in accordance with academic and ethical guidelines.

I confirm that this work has not been submitted, either in part or whole, for any other academic degree or qualification at this or any other institution.

Adam Creed

8th March 2025

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Additionally, I am indebted to the participants and medical professionals who took the time to engage with the VR-based EEG visualisation platform and provide their feedback, ensuring that the tool is both user-friendly and clinically relevant.

On a personal note, I am profoundly grateful to my family and friends for their constant support and understanding during this time. Their encouragement kept me motivated, and their belief in my abilities has been a source of strength throughout this journey.

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ABSTRACT

Electroencephalography (EEG) has long been a cornerstone in both neuroscience research and clinical diagnostics, providing invaluable insights into the electrical activity of the brain. EEG is the gold standard to detect and analyse brain pathologies such as seizures. An early detection and diagnosis of seizures is key in an effective treatment and decrease in morbidity and mortality. However, neonatal seizures are difficult to detect through clinical signs and even through EEG. The standard method of analysis of neonatal EEG is through visualisation on conventional two dimensional (2D) displays. Despite its importance, interpreting the complex and often nuanced signals produced by EEG remains a significant challenge, particularly when viewed on conventional 2D displays. This limitation can be particularly evident for clinicians who may lack extensive experience in EEG analysis. As the demand for more accurate and accessible diagnostic tools grows, the need for more intuitive methods of data visualisation becomes increasingly apparent.

This thesis addresses these challenges by presenting the design, development, and comprehensive evaluation of an innovative neonatal EEG visualisation platform within a Virtual Reality (VR) environment, developed using Unity. The platform reimagines how EEG data can be presented, leveraging the immersive capabilities of VR to offer a fully three-dimensional (3D) space where users can interact with and explore brain activity data in real time. By moving beyond the constraints of 2D screens, this approach provides a more natural, immersive, and intuitive framework for both novice and expert clinicians alike.

Recently, another method of analysis through sonification of EEG was proposed to speed up analysis of EEG. This allows users to hear the brain's electrical activity as a dynamic auditory experience. This novel sonification technique not only provides an additional sensory modality for interpreting EEG data when used complementary with visualisation but also enhances the users' ability to detect patterns and anomalies in the brain's electrical signals that may be overlooked visually. Therefore, it was added to this platform. Furthermore, the platform integrates an AI-driven seizure detection algorithm. This feature maps detected seizure events onto a 3D brain model, offering clinicians a more spatially accurate representation of potential seizure zones. The ability to visualise these detections in a 3D context is expected to improve clinical decision-making.

To validate the effectiveness of this VR-based EEG platform, a series of user evaluations was conducted. Participants, including both clinicians with EEG knowledge and those without prior experience, interacted with the system and provided feedback on its usability and functionality. The results were overwhelmingly positive, with the platform achieving a high System Usability Scale (SUS) score of 83, indicating strong user satisfaction. Participants also completed the NASA Task Load Index (NASA-TLX), with an average score of 36.65, reflecting a low perceived cognitive workload during the interaction. This suggests that the platform not only offers a rich and engaging user experience but also minimises the mental effort required to interpret complex EEG data.

In addition to its intuitive user interface, the platform was rigorously tested across a range of hardware configurations, from high-end VR systems to more affordable, lower-end devices. It performed consistently well, demonstrating its potential for widespread adoption in diverse clinical environments, from cutting-edge research facilities to more resource-constrained healthcare settings.

1. INTRODUCTION

Electroencephalography (EEG) has long been a pivotal tool in the fields of neuroscience and clinical diagnostics, offering unparalleled insights into the brain's electrical activity. Since its birth in 1924, by German psychiatrist Hans Berger [1], EEG has been used to diagnose a range a neurological conditions such as Epilepsy [2], Alzheimer's disease [3] and sleep disorders [4]. The non-invasive nature and low cost make it an attractive option in a medical professional's toolbox.

Up to now, research in the area of EEG was concerned with the resolution of the signal [5], making portable devices [6] or the development of a Brain Computer Interface (BCI) [7]. However, the methods by which EEG signals are displayed and analysed through visualisation have received comparatively less attention. While some studies have explored the integration of EEG with medical imaging modalities, such as functional Magnetic Resonance Imaging (fMRI) [8], there remains a significant gap in the literature concerning the visualisation and interactive analysis of EEG data.

In light of recent advancements in VR technology, this thesis seeks to address this gap by designing and implementing an innovative, interactive neonatal EEG visualisation tool within a virtual environment. This tool will enable users to interact with EEG data in a three-dimensional (3D) space, providing a more intuitive and user-friendly experience compared to traditional two-dimensional (2D) displays. Additionally, the software will incorporate sonification techniques for EEG signals and employ an artificial intelligence (AI) algorithm to predict seizures. The predicted seizures will be visualised on a 3D brain model, thereby assigning a physical location to each EEG wave, which facilitates a more comprehensive understanding of the underlying neural activity—a process that is not feasible with conventional 2D screens. The VR headset used for this research was the PICO Neo 3 Pro which can be seen below in Figure 1.



Figure 1: Pico Neo 3 Headset used for VR visualisation and analysis

The integration of these methodologies is anticipated to enhance the accuracy and depth of EEG data interpretation, thereby supporting more informed clinical decision-making. This research not only contributes to the field of EEG visualisation but also exemplifies the potential of VR as a transformative tool in medical diagnostics and neuroscience research and medical training.

A. Background and Context

The study of bioelectricity traces its origins back to the late 18th century with the pioneering work of Luigi Galvani. The Italian physician and scientist observed in the 1790s that a frog's leg muscles would twitch in response to an electric spark; he called this phenomenon "animal electricity"[9]. This revolutionary discovery established the discipline of electrophysiology by proving, for the first time, that electrical forces are inherent in biological tissues. Galvani's research laid the foundation for later investigations into the electrical characteristics of the nervous system and eventually became the field of neurophysiology. Throughout the 19th century, the field of electrophysiology expanded with contributions from scientists like Emil du Bois-Reymond [10] and Hermann von Helmholtz [11], who further studied the nature of nerve impulses and the role of electricity in physiological processes. This period marked significant progress in understanding the electrical activity of the nervous system, culminating in the early 20th century with Hans Berger's invention of electroencephalography (EEG) in 1924. Berger's discovery that the brain generates electrical waves that can be recorded from

the scalp revolutionized neuroscience and clinical diagnostics, providing a non-invasive means to study brain function in real-time.

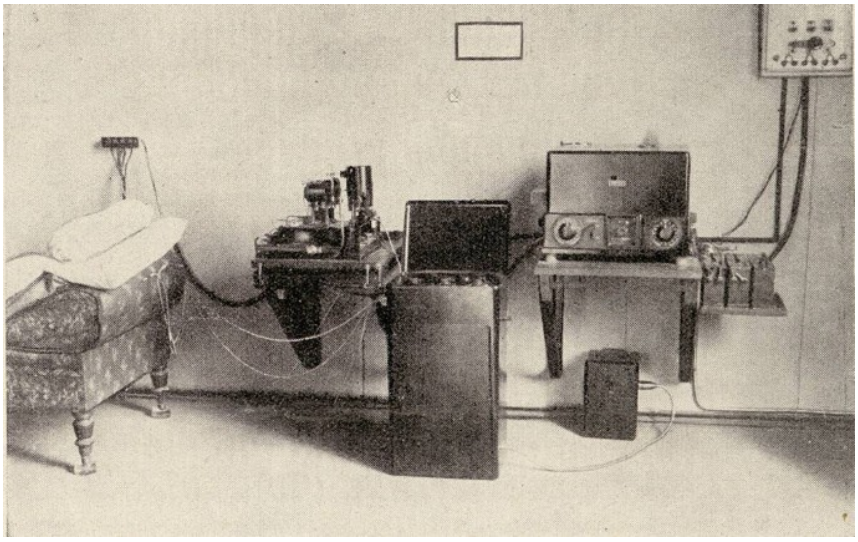


Figure 2: The first EEG machine developed by Hans Berger [12]

Berger used a technology that was exceedingly basic, by modern standards, to capture the first human electroencephalogram. The device used a string galvanometer, which converted the minute electrical impulses from the brain into observable waveforms on photographic paper, and silver wires that were placed under the scalp. This device can be seen in Figure 2. Recordings of this early EEG equipment were difficult to obtain since it was slow, cumbersome, and extremely sensitive to outside noise [1]. Notwithstanding these drawbacks, Berger's EEG apparatus represented a breakthrough in neuroscience by offering the first direct, non-invasive way to view brain activity in real time. Over the ensuing decades, advancements in electrode technology and amplifier technology led to a notable improvement in the sensitivity and dependability of EEG recordings [13].

Since its inception, EEG has become an indispensable tool in both clinical diagnostics and neuroscience research. EEG is a vital tool for identifying aberrant neural patterns that are indicative of various disorders since it can non-invasively record real-time brain activity, thereby aiding in timely and accurate diagnosis. In the context of addressing brain abnormalities in neonates, neonatal seizures represent one of the most prevalent neurological conditions. They are characterized by sudden and abnormal changes in the brain's electrical activity. They manifest in infants from the moment of birth until the transition out of the neonatal period, which typically ends at 28 days of life.

These seizures can present in various forms and may indicate underlying neurological conditions that require careful evaluation and management [14]. Neonatal seizures are frequently associated with several acute medical conditions, including strokes, hypoxic-ischemic encephalopathy (HIE), a severe injury to the brain due to insufficient oxygen and blood flow, and infections [15]. Neonatal seizures are often subtle and may be overlooked clinically. They differ from seizures in older children and adults due to the distinct organisation and connections of a newborn's developing brain, making them more challenging to identify [16]. In the clinical setting, EEG has proven to be particularly effective in diagnosing and monitoring a wide range of neurological conditions, including epilepsy [2], Alzheimer's disease [3], and various sleep disorders [4].

Beyond its clinical applications, EEG has played a central role in advancing the field of cognitive neuroscience, where it is used to study the neural underpinnings of cognitive processes such as attention, memory, and perception [17]. Additionally, EEG has been integral to the development of brain-computer interfaces (BCIs) [7], which aim to create direct communication pathways between the brain and external devices, offering promising applications for individuals with severe motor disabilities.

Research in this area has historically been focused on the signal resolution [5], the development of portable devices [6], and the creation of BCIs [7]. With the recent surge in AI research, there has been a growing interest in the study of EEG signals, with the aim of developing AI algorithms that can predict seizures [18]. The complex nature of the EEG signals, as well as large amounts of data gathered has spiked the interest of many aspiring AI researchers.

However, the methods by which EEG signals are displayed and analysed have received comparatively less attention. While some studies have explored the integration of EEG with medical imaging modalities, such as functional Magnetic Resonance Imaging (fMRI) [8] and Computed Tomography (CT) Scan [19], there remains a significant gap in the literature concerning the visualisation and interactive analysis of EEG data. VR has been successfully used in various medical fields, including the training of medical professionals in anatomy [20], surgical training [21], and patient rehabilitation [22], [23], [24]. However, the use of VR in EEG visualisation is still in its early stages.

B. Problem Statement

Even though EEG has been a vital tool for neuroscience research and clinical diagnostics [25], approaches for visualising and interpreting EEG data have not changed significantly in recent years. Traditionally, EEG data is represented using 2D displays—such as time-series plots, topographic scalp maps, and spectrograms—which have become standard tools in both research and clinical practice. Platforms like EEGLAB [26], [27], and FieldTrip [28] exemplify these techniques, providing clear, well-established methods for viewing the temporal dynamics and spatial distributions of EEG signals.

However, these 2D methods, while robust, inherently lack the capacity to convey the full three-dimensional structure of brain activity. When working with high-density EEG recordings or integrating multiple modalities, clinicians are often required to mentally reconstruct spatial relationships from flat images. This limitation can hinder the intuitive interpretation of complex neural data, potentially affecting diagnostic accuracy.

Thus, while current state-of-the-art 2D visualisation methods have served the field well, they underscore a significant gap: the need for interactive, 3D visualisation tools that can more naturally represent the intricate spatial and temporal dynamics of EEG signals. This gap forms the motivation for developing immersive VR-based solutions that promise enhanced usability and improved clinical insight.

Given the rapid advancements in VR technology, there is a substantial opportunity to bridge the gap by developing innovative tools that enable more intuitive and interactive EEG data analysis. These tools could transform how clinicians and researchers interact with complex neurological data, offering potential for faster diagnosis and more effective interventions. However, such tools have yet to be fully realized or systematically evaluated in the context of EEG visualisation and analysis. To date, only one published attempt has explored visualizing EEG in a novel way to help non-scientists understand brain activity [29]. This approach involved modifying a brain model based on the relationship between alpha and beta waves, showcasing the potential of creative methods while underscoring the need for clinically robust solutions that can meet real-world medical standards. This thesis focuses on neonatal EEG visualisation and analysis, as this subset of data is particularly challenging to interpret but has vast potential for improving early diagnosis and treatment of neurological conditions in newborns.

This work aims to address this critical gap by designing and implementing a VR-based EEG visualisation tool that enables clinical professionals to interact with EEG data in a 3D environment. By enhancing the visualisation and analysis capabilities of EEG data, this research seeks to support more informed clinical decision-making and advance the field of neuroscience research.

C. Research Objectives

The primary aim of this research is to develop and evaluate an innovative VR platform for the visualisation and analysis of EEG data. To achieve this, the following steps have been identified:

1) ***Development of a VR-Based EEG Visualisation and Analysis Platform:***
   Design and implement a VR environment specifically tailored for the visualisation and interactive analysis of neonatal EEG data. This objective focuses on creating a robust and user-friendly platform that leverages the immersive capabilities of VR technology.
2) ***Comparison of EEG Data Interpretation in VR vs. 2D Interfaces:***
   Evaluate the effectiveness and efficiency of EEG data interpretation when using the VR environment compared to traditional 2D screen-based interfaces. This objective aims to determine whether the VR platform offers significant advantages in understanding complex EEG data.
3) ***User Experience Assessment:***
   Assess user experience, including ease of use, immersion, and cognitive load, when analyzing EEG data in the VR environment compared to 2D platforms. This will involve gathering feedback from users to determine how the VR interface affects their interaction with EEG data.
4) ***Enhancement of Spatial Data Analysis:***
   Explore how the VR environment can enhance the understanding and interpretation of spatially complex EEG data, such as source localization or connectivity patterns. This objective seeks to identify the potential for VR to reveal new insights that are not easily discernible through 2D visualisation.
5) ***Feasibility and Scalability Study:***
   Investigate the feasibility of deploying the VR-based EEG analysis platform in

clinical, education and research settings, including considerations of hardware requirements, cost, and scalability. This objective addresses the practical aspects of implementing the VR platform in real-world scenarios.

By achieving these objectives, this research aims to advance the field of EEG data analysis, offering a more immersive and intuitive approach that has the potential to improve clinical decision-making and contribute to the broader understanding of brain activity.

D. Significance of the Study

This study aims to develop and evaluate a VR platform for the visualisation and analysis of neonatal EEG data, addressing a critical gap in the current methods of EEG interpretation.

The development of a VR-based EEG visualisation tool represents a significant advancement in how brain activity is analysed. By moving beyond traditional 2D displays, this study introduces a more immersive and interactive method for interpreting complex EEG data. This innovation has the potential to enhance the accuracy and depth of data interpretation, which is crucial for both clinical diagnostics and neuroscience research.

In clinical settings, adopting this VR platform could enhance decision-making by giving clinicians a clearer and more intuitive understanding of neonatal EEG data. This approach can also be expanded to older children and adults, potentially improving the diagnosis and management of neurological conditions such as epilepsy, Alzheimer's disease, and sleep disorders Additionally, the platform's potential to facilitate the analysis of spatially complex EEG data may lead to new insights into brain function, benefiting both clinical and research domains while also supporting medical education.

Beyond its immediate applications, this research has the potential to pave the way for future studies that integrate VR with functional neuroimaging modalities, such as Functional Magnetic Resonance Imaging (fMRI) [30] and Functional Near Infrared Spectroscopy (fNIRS) [31]. It can also help to interpret the Electrocardiogram (ECG), an important tool in diagnosing cardiac abnormalities [32]. The findings could also inspire further development of immersive technologies in the medical field, potentially leading to new standards for how brain activity is visualised and interpreted, in particular

with the continued growth of Augmented Reality (AR) [33] and Extended Reality (XR) [34]. Ultimately, this study contributes to the ongoing evolution of neurotechnology, with broad implications for healthcare, research, and education.

In summary, this study not only addresses a critical need in neonatal EEG data visualisation but also exemplifies the transformative potential of VR in advancing both clinical practices and scientific understanding.

E. Scope and Limitations

This study focuses on the development and evaluation of a VR platform specifically designed for the visualisation and analysis of neonatal EEG data. The scope of the research includes the following key aspects:

1) ***Development of the VR Platform:***

   The study involves the design and implementation of a VR environment tailored to visualise EEG data in a 3D space. The platform will incorporate features such as sonification of EEG signals and real-time interaction with a 3D brain model.

2) ***Comparative Analysis:***

   The research will compare the effectiveness of EEG data interpretation using the VR platform versus traditional 2D screen-based interfaces. This comparison will include measures of data interpretation accuracy, user experience, and cognitive load.

3) ***User Experience:***

   The study will assess the usability and user experience of the VR platform, focusing on factors such as ease of use, immersion, and user satisfaction when interacting with EEG data.

4) ***Feasibility and Scalability:***

   The research will explore the feasibility of deploying the VR-based EEG analysis platform in both clinical and research settings, including considerations of hardware requirements, cost, and scalability.

5) ***Participants:***

   The study will involve students and staff from University College Cork (UCC).

6) ***Time Frame:***

   The research will be conducted over a fifteen month period, allowing for the

development, testing, and evaluation phases of the VR platform.

While this study aims to make significant contributions to the field of EEG data visualisation, several limitations must be acknowledged:

1) ***Generalisability:***

   The findings from this study may be limited by the specific sample of neonatal EEG data used, which may not be fully representative of all EEG datasets or all neurological conditions. Consequently, the results may not be generalizable to broader populations or different clinical settings.

2) ***Technical Constraints:***

   The VR platform's performance may be affected by the hardware and software configurations available during the study. Differences in VR equipment or processing power could influence the user experience and data interpretation outcomes.

3) ***Learning Curve:***

   Users may require a period of adaptation to become proficient in navigating and interpreting EEG data within the VR environment. This learning curve could impact the initial assessments of user experience and data interpretation effectiveness.

4) ***Focus on Visualisation:***

   While the study focuses on the visualisation and interactive analysis of EEG data, it does not address other aspects of EEG analysis, such as advanced signal processing techniques or integration with neuroimaging modalities beyond the scope of VR.

5) ***Data Availability:***

   The study is contingent upon the availability of suitable EEG datasets. For the visualisation data a publicly available dataset was used [35].

These limitations, while inherent to the scope and nature of the research, will be considered in the analysis and interpretation of the study's results.

F. Structure of the Thesis

The remainder of this chapter provides an overview of the thesis structure. This thesis is organised into seven chapters, each of which builds upon the previous to develop a

comprehensive study on the interactive EEG visualisation in VR. The remaining chapters are structured as follows:

Chapter 2: Electroencephalography: Principles, Applications, and Signal Interpretation: This chapter discusses the fundamental principles of EEG signal generation, measurement, and interpretation. It provides an overview of the historical development of EEG technology and its applications in clinical diagnostics and neuroscience research.

Chapter 3: Technology Stack: This chapter discusses the technological tools and platforms used in the development of the VR-based EEG visualisation system. It includes an overview of the hardware and software components, and justifies the selection of these technologies.

Chapter 4: Design and Methodology: This chapter details the design process and research methodology employed in developing the VR visualisation tool. It explains the conceptual framework, the design principles followed, and the specific methods used for data collection and analysis.

Chapter 5: Implementation: This chapter describes the practical steps taken to implement the VR-based EEG visualisation system. It covers the development phases, including the integration of EEG data with the VR environment, the implementation of sonification, and the incorporation of AI algorithms for seizure prediction.

Chapter 6: Results and Discussion: This chapter presents the results obtained from the testing and validation of the VR platform. It provides a detailed analysis of the findings, comparing the effectiveness of VR-based EEG visualisation to traditional 2D methods, and discusses the implications of these results in the context of clinical diagnostics and neuroscience research.

Chapter 7: Conclusion: This chapter summarizes the key findings of the research, highlighting the contributions of the VR-based EEG visualisation tool to the field. It reflects on the research objectives and questions, confirming whether they were achieved and answered through the study.

2. Electroencephalography: Principles, Applications, and Signal Interpretation

ELECTROENCEPHALOGRAPHY (EEG) is a non-invasive technique for recording electrical activity generated by the brain [36]. It captures the brain's neural oscillations through electrodes placed on the scalp, providing valuable insights into the brain's functional state. EEG is widely used in clinical diagnostics [37], making it a powerful tool for understanding brain function in real-time.

A. EEG Signal Generation and Measurement

EEG is the process of recording electrical signals from the brain, which are generated by the collective activity of neurons, primarily within the cerebral cortex. The generation of these signals involves complex electrochemical processes that occur within the brain's neural networks. Specifically, EEG signals arise from the synchronized post-synaptic potentials of large populations of pyramidal neurons, which are oriented perpendicularly to the cortical surface. These neurons play a key role in the brain's information processing and communication pathways, and their electrical activity generates dipole fields that can be detected on the surface of the scalp.

1) Mechanisms of EEG Signal Generation: The brain's neurons communicate with one another via synaptic transmission, which involves the release and reception of neurotransmitters across synaptic gaps. This process leads to the generation of excitatory or inhibitory post-synaptic potentials, which can either depolarize or hyperpolarize the neuron. The EEG signal is not a direct measurement of action potentials (spikes), which are rapid, all-or-nothing events occurring within individual neurons. Instead, it captures the aggregate electrical activity of the vast network of neurons, primarily the slower, graded changes in membrane potential that are associated with synaptic activity [38].

Among the various types of neurons, pyramidal neurons are the key contributors to the EEG signal due to their size, number and alignment. They are organized in parallel within the cortical layers, and their dendrites (long tapering extensions) reach toward the cortical surface. This structural configuration allows for effective communication and synchronization among these neurons. When these neurons become active, their synchronous activity produces an electric field, with positive charges on the apical dendrites and negative charges at the soma (cell body). This configuration of changes

generates an open-field dipole, which can be detected as voltage changes on the scalp. EEG electrodes placed on the scalp measure these voltage fluctuations, representing the summation of the dipole fields across large areas of the cortex, thus providing valuable information about the underlying neural processes and overall brain activity[39]. A diagram explaining the mechanisms of EEG signal generation can be seen in Figure 3.

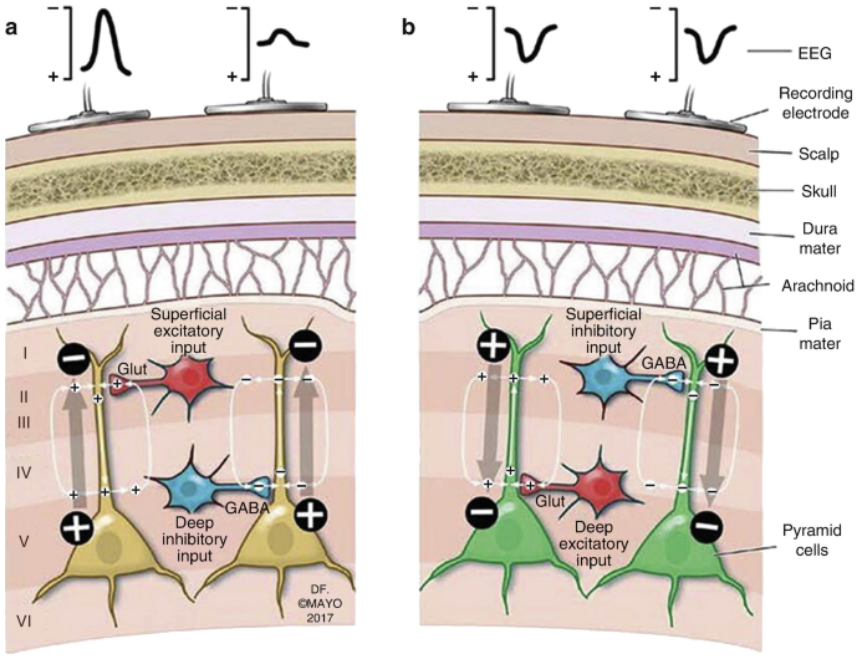


Figure 3: Mechanisms of EEG Signal Generation [40]

While the activity of individual neurons produces very small voltage fluctuations (on the order of microvolts), the collective activity of millions of neurons generates measurable electrical potentials. The resulting EEG signal is a combination of these potentials, influenced by the degree of synchrony among neurons and the depth and orientation of the sources within the brain.

B. The Role of Volume Conduction

One of the critical factors in understanding EEG signal generation is the concept of volume conduction. The brain is encased and protected by several important structures, including three delicate membranes known as the meninges, cranial bones that are part of the skull, and the scalp, composed of skin and underlying tissues. Furthermore, the brain is cushioned by cerebrospinal fluid (CSF), a clear liquid that fills the spaces within the brain. Together, these protective elements influence the transmission and propagation of electrical signals to the surface. When neurons generate electrical fields, these signals

must travel through the conductive brain tissue and other intervening layers prior to being detected by the electrodes [41]. This process, known as volume conduction, attenuates and smears the signal, making it difficult to localize the exact origin of electrical activity. As a result, the EEG signal recorded at the scalp represents a spatially diffuse mixture of electrical activity from multiple brain regions.

Volume conduction also means that EEG signals are subject to significant spatial overlap, where signals from different parts of the brain may sum together. This spatial smearing is a fundamental limitation of EEG, as it reduces the spatial resolution of the recorded data, making it challenging to isolate activity from specific cortical regions [42].

C. Electrode Placement and Measurement Configurations

EEG electrodes are typically placed on the scalp using standardized systems, such as the 10-20 International System, to ensure consistent and reproducible recordings across individuals and studies. In this system, electrodes are positioned at specific locations based on fixed percentages of the distance between key anatomical landmarks, such as the nasion (prominent protrusion at the posterior aspect of the skull) and the inion (the prominent bump at the back of the skull). This standardized system ensures that electrodes are positioned to cover major regions of the brain. These regions include the frontal lobe, responsible for higher cognitive functions; the central lobe, associated with sensory processing; the parietal lobe, involved in spatial awareness and navigation; the occipital lobe, responsible for visual processing; and the temporal lobe, associated with auditory processing and memory formation [43].

For neonatal EEG recordings, the 10-20 system is often adapted to accommodate the smaller head size and developmental differences in infant anatomy [44]. In this neonatal 10-20 placement, fewer electrodes are used, focusing on regions that are most likely to yield clinically relevant information. The variations in the 10-20 set-up can be seen in Figure 4, with Figure A showing the full 10-20 system and Figure C showing the neonatal electrode placement. Modified electrode positioning maintains the general principles of the 10-20 system but scales down to ensure secure and comfortable placement on a neonate's scalp, while still targeting essential brain areas. This adaptation

helps in recording accurate and meaningful EEG data from newborns, supporting both clinical monitoring and research on early brain development.

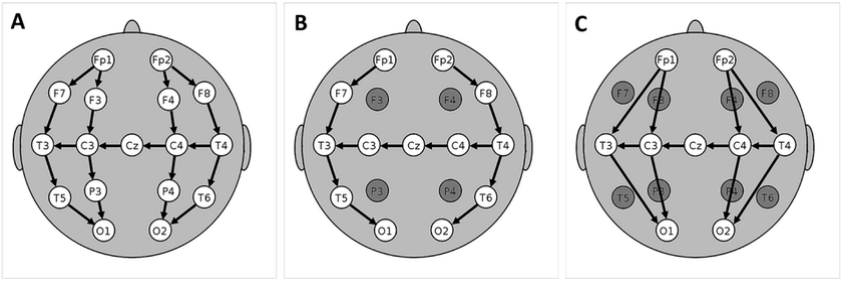


Figure 4: A: Full 10-20 system of electrode placement using 17 electrodes, B) A restricted 10-20 system using 13 electrodes, C) A restricted 10-20 system using 9 electrodes [44]

Electrodes in an EEG setup measure the voltage differences between pairs of sites on the scalp. There are two main types of measurement configurations: referential and bipolar.

- **Referential Montage:** In this configuration, each electrode is referenced to a common site, often located on a relatively neutral area such as the mastoid bone or the vertex of the scalp. This approach allows for comparisons of activity across different regions of the brain relative to the common reference [45].
- **Bipolar Montage:** In bipolar recordings, the voltage difference is measured between adjacent pairs of electrodes. This montage emphasizes local variations in the electrical field and is particularly useful for detecting focal events, such as epileptiform spikes [46].

The number of electrodes used in EEG can vary depending on the application, with clinical systems typically using 19 electrodes, and high-density EEG systems employing up to 256 electrodes for research purposes [47]. High-density EEG systems provide greater spatial resolution, making it possible to capture more detailed maps of brain activity. However, the trade-off is an increase in data complexity and the need for more sophisticated signal processing techniques to manage the large volumes of data generated [48]. In this thesis, the data comes from a publicly available dataset that used 16 electrodes to give 8 channels of neonatal EEG data [35].

D. Signal Amplification and Preprocessing

The electrical signals generated by the brain are extremely weak, typically ranging from 1 to 100 microvolts, which is several orders of magnitude smaller than the noise introduced by the surrounding environment or biological artifacts such as muscle movements [49]. As a result, raw EEG signals must undergo amplification before they can be recorded and analysed. EEG amplifiers increase the amplitude of the signal to a level suitable for digitization, while also minimizing noise and interference from external sources.

Once amplified, the EEG signal is digitized and stored as time-series data. However, the raw signal often contains various artifacts that can obscure the true brain activity. These artifacts may include:

- **Electromyogram (EMG):** Muscle activity, particularly from facial or scalp muscles, can introduce high-frequency noise into the EEG signal [50].
- **Electrooculogram (EOG):** Eye movements, blinks, and saccades [1] produce large, low-frequency artifacts that can distort the underlying EEG signal [51].
- **Electrocardiogram (ECG):** Cardiac activity can sometimes introduce rhythmic artifacts into the EEG signal, especially in recordings near the temporal region [52].
- **External Noise:** Environmental electromagnetic interference, such as power line noise at 50 or 60 Hz, can contaminate EEG recordings if proper shielding and grounding are not used.

To address these issues, preprocessing steps such as filtering, artifact rejection, and signal segmentation are applied to the raw EEG data. Common filters include low-pass filters to remove high-frequency noise, high-pass filters to eliminate slow drifts, and notch filters to remove specific frequencies, such as power line interference. Additionally, independent component analysis (ICA) [52] and other blind source separation techniques are employed to isolate and remove specific artifacts, such as eye movements, from the EEG signal.

[1]Quick eye movements that shift your gaze from one point to another

E. Temporal and Spatial Resolution of EEG

EEG is renowned for its high temporal resolution, allowing it to capture rapid changes in brain activity on the order of milliseconds. This makes EEG an ideal tool for studying dynamic processes such as sensory perception, motor control, and cognitive function, where precise timing of neural events is critical. The temporal resolution of EEG is determined by the sampling rate, with modern systems typically sampling at rates between 250 Hz and 1000 Hz or higher, depending on the specific research or clinical needs [53].

However, the spatial resolution of EEG is relatively low compared to other neuroimaging techniques, such as fMRI [54]. The spatial resolution is limited by the number of electrodes and the effects of volume conduction, which blurs the electrical signal as it travels through the brain and scalp. Advanced techniques, such as source localization and electrical source imaging (ESI), aim to improve the spatial resolution of EEG by estimating the underlying neural sources of the recorded signals [55]. These methods, which often incorporate anatomical data from MRI, attempt to reconstruct the location and extent of brain activity with greater precision.

The generation and measurement of EEG signals involves complex interactions between neural activity, the properties of the brain and scalp, and the technical characteristics of the recording system. While EEG provides unparalleled temporal resolution for tracking fast neural processes, its spatial resolution is limited by the physical constraints of the human head and the effects of volume conduction. By understanding the underlying principles of EEG signal generation and the techniques used for its measurement, researchers and clinicians can better interpret EEG data and deploy it in a wide range of applications, from basic neuroscience research to clinical diagnostics in neurology.

F. EEG Signal Characteristics

EEG signals exhibit distinct patterns that are categorised into different frequency bands, each associated with specific cognitive and physiological states. These frequency bands are vital for interpreting the brain's activity under various conditions, ranging from normal cognitive functions to pathological states. The EEG frequency bands are as follows:

- **Delta (0.5–4 Hz):** Delta waves are the slowest EEG frequencies, predominantly seen during deep stages of sleep, specifically non-REM stage 3 (also known as slow-wave sleep). Delta activity is crucial for restorative sleep processes and is associated with physical rejuvenation and memory consolidation [56]. In awake individuals, abnormal delta activity may indicate brain lesions, tumors, or other forms of structural damage, particularly in cases of traumatic brain injury or ischemic stroke. Increased delta activity is also observed in certain neurodegenerative diseases, such as Alzheimer's disease, where cortical atrophy is present [57].
- **Theta (4–8 Hz):** Theta waves are typically associated with drowsiness, early stages of sleep, and states of deep meditation [58]. Theta activity can also appear during periods of focused attention and memory encoding, such as during learning tasks. While theta waves are normal during sleep, excessive theta activity in awake adults may be linked to neurological disorders such as ADHD (Attention Deficit Hyperactivity Disorder) or other cognitive impairments. Abnormal theta rhythms can also indicate dysfunctions in the hippocampus, a brain structure integral to memory formation [59].
- **Alpha (8–13 Hz):** Alpha waves are most prominent when a person is in a relaxed, wakeful state with their eyes closed, often referred to as the "idling" state of the brain. Alpha activity is thought to represent a state of cortical inhibition, where brain regions reduce processing of external stimuli. Alpha rhythms are typically generated in the occipital and parietal regions of the brain, although they can also be observed in the frontal lobe during meditative or relaxed states. When eyes are opened or when attention is directed toward a cognitive task, alpha activity tends to decrease (a phenomenon known as alpha blocking or desynchronization) [60]. This suppression is an indicator of engagement with sensory input or active problem-solving. Abnormal alpha patterns, such as the absence or reduction of alpha activity, can be associated with cognitive decline, particularly in disorders like dementia.
- **Beta (13–30 Hz):** Beta waves are higher frequency patterns associated with active concentration, motor activity, and problem-solving. These waves are most evident in the frontal lobes during tasks requiring focused attention or during mental arith-

metic. Beta rhythms are also linked to motor control, often increasing in amplitude during voluntary movements. However, excessive beta activity, particularly in the form of high-amplitude, sustained beta rhythms, may indicate anxiety, agitation, or the use of stimulant drugs. In some cases, abnormal beta rhythms are observed in patients with conditions such as Parkinson's disease, where motor dysfunction leads to alterations in beta-band oscillations [61].

- **Gamma (>30 Hz):** Gamma waves represent the fastest brain rhythms and are involved in high-level cognitive processes such as attention, working memory, and the integration of sensory information. Gamma oscillations are believed to play a role in conscious perception and cognitive binding, where different features of a stimulus (e.g., color, shape, and motion) are integrated into a cohesive perceptual experience [62]. Abnormal gamma activity has been linked to various neurological and psychiatric disorders, such as schizophrenia, where reduced gamma-band synchronization may underlie disruptions in cognitive and perceptual processes [63]. Increased gamma activity is often observed during states of heightened awareness, such as during meditation or intense cognitive engagement.

EEG signals are transient and vary in amplitude and frequency depending on both internal and external stimuli. These signals are continuously influenced by sensory input, cognitive demands, emotional states, and even physiological processes such as breathing and heart rate. The dynamic nature of EEG patterns makes it an invaluable tool for real-time monitoring of brain states, especially in clinical environments.

G. Abnormal EEG Patterns and Clinical Significance

In addition to the characteristic frequency bands associated with normal brain function, EEG is also used to identify abnormal patterns that may indicate underlying neurological or psychiatric conditions. These abnormalities can manifest as deviations in frequency, amplitude, or synchronization of neural oscillations, providing important diagnostic information.

- **Sharp Waves and Spikes:** Sharp waves and spikes are brief, high-amplitude deflections in the EEG signal that are often associated with epileptic activity. These transient events, typically lasting less than 200 milliseconds, are indicative of abnormal, synchronous discharges in neural populations. Spikes are a hallmark

of Interictal Epileptiform Discharges (IEDs), which are observed between seizures in individuals with epilepsy. The presence of spikes and sharp waves in EEG recordings is a key diagnostic feature used to localise epileptogenic regions in the brain, especially during pre-surgical evaluations for epilepsy patients [64].

- **Slow Waves:** Abnormally slow EEG waves, particularly in the delta or theta range, can signal brain dysfunction. These slow waves are often seen in patients with encephalopathy (general brain dysfunction), brain lesions, or following traumatic brain injury. Diffuse slowing of the EEG, particularly in delta frequencies, can be a sign of metabolic disorders, toxic exposure, or global cerebral ischemia. Localized slowing, on the other hand, may indicate focal brain lesions, such as tumors, infarcts, or localized areas of inflammation [65].
- **Burst-Suppression Patterns:** Burst-suppression is a highly abnormal EEG pattern characterized by alternating periods of high-amplitude bursts of electrical activity and flat or low-amplitude suppression phases. This pattern is commonly observed in comatose patients or those undergoing deep sedation. Burst-suppression is associated with severe brain dysfunction and is often seen in conditions such as coma due to drug overdose, or in patients who are anesthetized with barbiturates. The pattern indicates a poor prognosis in many cases of severe brain injury [66].
- **Generalised and Focal Seizure Activity:** Seizure activity on EEG can present in various forms depending on the type of seizure and the regions of the brain involved. Generalized seizures, which involve the entire brain, often present with synchronous spike-and-wave discharges, characteristic of absence seizures. Focal seizures, which originate in a specific region of the brain, may show more localized abnormalities, such as rhythmic slowing or sharp waves, that spread to adjacent regions as the seizure progresses. The ability to detect and classify seizure activity through EEG is essential for the diagnosis and management of epilepsy [67].

Neonatal EEGs exhibit distinct characteristics due to the developmental stage of the brain. Common abnormal neonatal EEG patterns include *excessive discontinuity* (prolonged periods of low-voltage activity), which can signal brain immaturity or neurological impairment, especially if present in full-term infants. *Multifocal sharp waves* are another abnormal finding, often associated with brain injury or metabolic disorders in neonates. Unlike in adults, *burst-suppression* patterns in neonatal EEGs may suggest

severe hypoxic-ischemic encephalopathy (HIE) [68] or other serious conditions. Additionally, *age-inappropriate absence of expected neonatal patterns*, such as the trace alternant pattern during sleep, can indicate developmental abnormalities or brain injury. Recognizing these neonatal-specific abnormalities is essential for early diagnosis and intervention in neonates [69].

Dynamic Nature of EEG Signals

The transient nature of EEG signals means that they are constantly changing in response to a variety of internal and external factors. Even within a single recording, brain activity may shift between different frequency bands as the subject moves through various states of wakefulness, attention, and sleep. For example, during a typical sleep cycle, the EEG transitions from wakefulness (dominated by alpha and beta activity) to light sleep (theta waves) and finally into deep sleep (dominated by delta waves).

External stimuli, such as sensory input, cognitive tasks, or emotional stress, also affect EEG activity. For instance, visual stimuli can induce occipital alpha desynchronization, while mental arithmetic or problem-solving tasks may enhance beta-band activity in the frontal lobes. These shifts reflect the brain's adaptive response to different cognitive and environmental demands, making EEG a powerful tool for studying brain function in real time.

H. Applications of EEG in Clinical Diagnostics

EEG is a crucial tool in the diagnosis and monitoring of various neurological disorders:

- **Epilepsy:** EEG is the gold standard for detecting seizures, characterized by abnormal, synchronized electrical discharges in the brain. Specific patterns, such as spike-and-wave discharges, are highly indicative of seizure activity [70].
- **Sleep Disorders:** EEG is used to study sleep architecture, including sleep stages and their transitions, in the diagnosis of conditions like sleep apnea and narcolepsy [71].
- **Brain Injuries and Tumors:** EEG can detect abnormal slow waves or epileptiform discharges associated with brain lesions, tumors, or trauma [72].
- **Coma and Brain Death Assessment:** EEG is employed in the prognosis of comatose patients and in determining brain death by identifying the absence of

neural activity [73].

Beyond diagnostics, EEG is used in neurofeedback, cognitive neuroscience research [74], and BCIs [7], where real-time brain activity is leveraged for control systems or therapeutic applications.

I. Challenges and Limitations of EEG

While EEG is a powerful tool, it has several limitations that have been discussed:

- **Low Spatial Resolution:** EEG captures electrical activity from the scalp, making it difficult to pinpoint the exact location of neural activity deep within the brain [75].
- **Susceptibility to Artifacts:** EEG signals are prone to contamination from muscle movements, eye blinks, and other non-brain-related activity. Effective artifact removal is essential but can sometimes lead to the loss of valuable signal information [76].
- **Signal Complexity:** Interpreting EEG data requires expertise, as the signals can be complex and vary significantly between individuals, making automated analysis challenging [77].
- **Temporal Resolution Trade-off:** Although EEG has excellent temporal resolution, capturing rapid changes in brain activity, it often lacks the spatial accuracy needed for detailed brain mapping [78].

Despite these challenges, EEG remains an indispensable tool in both clinical and research environments, offering a real-time window into brain function.

In summary, this chapter has presented a detailed examination of the fundamental principles underlying electroencephalography, emphasizing the mechanisms of signal generation, the technical challenges associated with electrode placement and signal preprocessing, and the clinical relevance of EEG interpretations. The critical analysis of established 2D visualisation techniques has underscored their inherent limitations in capturing the multidimensional nature of neural activity, thereby highlighting the necessity for more sophisticated, interactive approaches. By integrating both theoretical insights and practical considerations, the discussion herein not only reinforces the pivotal role of EEG in neuroscience and clinical diagnostics but also establishes a robust foundation for the exploration of advanced visualisation methodologies in subsequent chapters.

3. TECHNOLOGY STACK

THE development of an innovative VR-based neonatal EEG visualisation platform necessitated a carefully selected technology stack that balances performance, usability, and compatibility. This section outlines the hardware and software tools that were integral to the project, including the VR headset, development platforms, and specialised libraries. Each component was chosen to optimise the integration of complex EEG data into an immersive VR environment, ensuring a user-friendly experience for clinicians and researchers. This section describes the hardware, software, and tool selections made for this project, as well as the reasoning behind each decision.

A. Hardware

There are several key hardware components that were essential for the development and testing of the VR-based EEG visualisation platform. These components are as follows:

1) Virtual Reality Hardware: The VR environment was developed using the ***Pico Neo 3 Pro*** headset. This device was selected for several key reasons:

a) High Resolution and Refresh Rate: The Pico Neo 3 Pro offers a resolution of 3664 x 1920 pixels (1832 x 1920 per eye) and a refresh rate of up to 90Hz when overclocked but typically operates at 72 Hz [79]. This high resolution and smooth refresh rate ensure that users experience a clear and immersive visualisation of EEG data, which is crucial for accurate data interpretation in a medical or research context. This device can be seen in Figure 1.

b) Stand-Alone Capabilities: Unlike tethered VR headsets, the Pico Neo 3 Pro is a stand-alone device with built-in processing power (powered by the Qualcomm Snapdragon XR2) [79], which allows for greater flexibility and mobility during user interactions. This is particularly beneficial in clinical settings where space and equipment mobility are often limited.

c) 6DoF Tracking: The headset supports six degrees of freedom (6DoF) tracking for both the headset and controllers, providing users with a highly interactive and engaging experience [79]. This is essential for accurately navigating and manipulating the 3D EEG data visualisation within the virtual environment.

d) Compatibility and Integration: The Pico Neo 3 Pro is compatible with the Unity 3D development platform [80], which was used to build the VR environment. Its compatibility with industry-standard VR development tools and its support for open APIs, such as OpenXR [81], made it an ideal choice for seamless integration into the existing technology stack while making it possible to use on other headsets in the future.

e) Comfort and Ergonomics: Given that users might spend extended periods analyzing data in the VR environment, the Pico Neo 3 Pro's lightweight design and ergonomic features ensure user comfort, reducing fatigue and enhancing the overall user experience.

The combination of these features makes the Pico Neo 3 Pro a robust and versatile choice for the development of a VR-based EEG visualisation platform, enabling high-quality, immersive experiences essential for accurate data analysis and interpretation.

2) Desktop Computing: Given the computational demands of real-time EEG data processing and VR rendering, a high-performance computer was used. The system was equipped with an *AMD Ryzen Threadripper PRO 3945WX* processor, *NVIDIA RTX A6000* GPU, and 128GB of RAM [82]. This setup ensured smooth operation and quick processing times during development and testing.

B. Software

Given the complexity of the VR-based EEG visualisation platform, a range of software tools and libraries were employed to facilitate development, data processing, and user interaction. The software components used in this project are as follows:

1) VR Development Platform: The *Unity 3D* engine was selected as the primary development platform due to its extensive support for VR applications, ease of use, and strong community support [83]. Unity's comprehensive built-in features, like physics and lightin, significantly streamlined the development process.

2) Programming Languages: The platform's development was primarily conducted in *C#*, which is natively supported by Unity. Additionally, *Python* was used for preprocessing EEG data and implementing AI algorithms, leveraging libraries such as *NumPy* [84]. This combination of languages allowed for seamless integration of EEG data processing and visualisation within the VR environment.

3) Libraries and Frameworks: Several libraries and frameworks were used to enhance the functionality and performance of the VR platform, the most notable of which OpenXR, which is an open standard for VR/AR development that allows multiple devices to run the same code [81]. The remainder are libraries that are standard in the C# [85] and Unity development environments.

4) Data Management Tools: All EEG data was managed using Pandas [86] to ensure efficient querying and retrieval. Version control was maintained using *GitHub* [87], allowing for collaborative development and robust tracking of code changes.

C. Integration Tools

1) Middleware: To test and debug the VR world as it was built it was necessary to utilise a middleware providing a seamless connection between the development computer, the Unity application and the VR headset. *Steam* [88], and *SteamVR* [89] were utilised for this interaction, enabling precise control over the virtual environment.

D. Testing and Development Environment

In order to ensure the system was robust and reliable, a comprehensive testing and development environment was required.

1) Development Environment: The development of the VR platform was conducted on a Windows 10 [90] workstation, utilizing the Unity 3D engine and Visual Studio [91] for coding. The Pico Neo 3 Pro headset was used for real-time testing and debugging, ensuring compatibility and performance optimisation.

2) Testing Tools: Unity's built-in testing tools were used to evaluate the performance and functionality of the VR environment, namely the Unity Profiler API [92]. Additionally, GPU profiling tools such as nvidia-Smi [93] were employed to identify and address performance bottlenecks during development.

E. Challenges and Considerations

There were significant challenges that arose during the development of this VR EEG visualisation platform, which required careful consideration and problem-solving. The primary challenges and considerations included:

1) Compatibility Issues: One significant challenge was ensuring compatibility between the Unity Environment and the VR headset. This required extensive testing and debugging to resolve issues related to rendering, tracking, and user interaction. The Pico Unity SDK [94] aided in this process. This platform was also built using OpenXR, which is a relatively new standard, and required additional configuration to ensure seamless integration with the Pico Neo 3 Pro headset. By using this standard, the platform is more likely to be compatible with other VR headsets in the future.

2) Performance Optimization: To maintain real-time performance, various optimisation techniques were employed, such as reducing the polygon count of 3D models and utilising Unity's built-in GPU profiling tools to identify and mitigate bottlenecks.

The technology stack chosen for this project provided a robust and flexible foundation for the development of a VR-based EEG visualisation platform. The integration of advanced hardware and software components ensured that the platform could meet the project's objectives, providing a powerful tool for both research and clinical applications.

4. Design and Methodology

As previously discussed in the problem statement and research objectives, this study seeks to address the limitations of traditional 2D EEG visualisation methods by developing and evaluating an innovative VR platform. This platform is designed to improve the interpretability of complex EEG signals through the immersive and interactive features of VR technology.

The research methodology outlined in this chapter is intended to ensure that the developed platform meets its intended objectives: creating a user-friendly system that provides a significant improvement over existing visualisation techniques. This section will detail the specific design processes, data collection methods, and analysis strategies that were employed to develop and validate the platform, thereby ensuring scientific rigour and practical applicability.

A. Research Design

Developmental Research Design [95], [96] is a methodological approach particularly well-suited for projects focused on the creation and refinement of new tools, technologies, or interventions. This approach is characterised by its iterative nature, where the development process is guided by continuous feedback and testing, allowing the product to evolve and improve throughout the research cycle.

In the context of this thesis, a developmental research design was chosen because it supports the systematic creation of a VR platform for EEG visualisation. The design process was structured around several key stages, each contributing to the platform's evolution and refinement:

1) ***Exploration and Problem Definition:***

   This stage involves identifying the research problem, defining the objectives, and exploring potential solutions. In this case, the problem was the limitations of 2D EEG visualisation and the objective was to develop a VR platform to address these limitations. This initial exploration helped to define the scope and direction of the research. There were four main problems identified in this stage:

   a) The physical constraints of the 2D screen, which limit the amount of data that can be displayed at one time.

   b) The time it takes medical professionals to interpret the EEG data.

c) The complexity of the data and the difficulty in interpreting it [97].
d) The experience, or lack thereof, of the medical professional in EEG analysis, in particular those who are new to the field.

The features of the VR system were defined, focusing on the development of a VR platform that addresses these challenges while providing a more intuitive and interactive method for EEG data analysis. The design of the VR platform was informed by the need to enhance data visualisation, improve user experience, and support more accurate and efficient interpretation of EEG signals. This was done by:

a) Creating a 3D environment that allows for the visualisation of EEG data in a spatial context, removing the limitations of the 2D screen.
b) Incorporating sonification techniques to represent EEG signals audibly, drastically reducing the time it takes to interpret the data.
c) Implementing an AI algorithm for seizure prediction and visualising the predicted seizures on a 3D brain model, helping the medical professional to understand the data.
d) Ensuring user-friendly interaction and intuitive navigation within the VR environment, so that even those with little experience can use the platform without additional training.

A VR system that incorporates these features was deemed to be a viable solution to the challenges identified in the exploration stage.

2) ***Design and Development:***

The design and development stage was pivotal in creating the VR platform, which incorporates key features such as the sonification of EEG signals, AI algorithms for seizure prediction, and interactive 3D visualisation. To ensure that the platform was both innovative and practical, an iterative prototyping approach was adopted. Initial versions of the platform were tested by a small group of users within the Embedded Systems Research Group at UCC. This early feedback was instrumental in identifying usability issues and functional gaps, allowing for rapid refinement and enhancement of the platform.

Once the initial cohort of users within the research group expressed satisfaction with the design and implementation, the testing phase was extended to include

external experts within University College Cork (UCC). Experienced professionals from the Department of Applied Psychology and the Department of Anatomy and Neuroscience were brought on board to evaluate the platform. Their extensive expertise in EEG analysis provided invaluable insights, contributing ideas for additional features that could enhance the platform and highlighting diverse use cases of EEG analysis across various disciplines. This collaborative approach ensured that the platform was robust, versatile, and applicable to a wide range of EEG analysis scenarios.

Throughout the development process, user-centered design principles were rigorously applied [98], [99], ensuring that the platform met the practical needs of both clinicians and researchers. The emphasis on user feedback at every stage of development helped create a tool that is both intuitive and effective in real-world applications. Additionally, significant challenges were addressed, such as optimising the VR environment for performance, ensuring seamless interaction within the 3D space, and effectively integrating advanced AI features for real-time analysis and seizure prediction. These challenges were met with innovative solutions, such as optimizing algorithms to run efficiently in the VR environment and refining the user interface to support a smooth and immersive experience.

3) ***Testing and Evaluation:***

The Testing and Refinement stage of this research was essential in ensuring that the VR platform for EEG visualisation was both effective and user-friendly. This process involved multiple phases, each focusing on different aspects of the platform's performance, usability, and overall functionality.

a) ***Internal Testing within the Research Group:***

The Embedded Systems Research Group initially focused on identifying and addressing significant technical issues at an early stage of development. Members engaged with the platform and provided essential feedback regarding its functionality, user interface, and overall usability. This feedback was crucial for implementing early refinements, such as enhancements to the user interface for improved navigation and the integration of EEG data within the VR environment. Following these improvements, the platform was presented to university staff with clinical and EEG knowledge who were not part of

the original group for further evaluation. These consultations aimed to:

i) Assess the platform's potential applications in clinical setting
ii) To identify additional features that could enhance its overall utility
iii) To evaluate the platform's ability to support accurate clinical diagnoses
iv) Offer recommendations for improving the predictive capabilities of the AI algorithm as well as the overall usability of the VR system.

b) ***Expert Consultation and Feedback:***

Following the internal testing phase, the platform was presented to external experts for further evaluation. These consultations focused on evaluating the platform's potential in clinical settings and identifying any additional features that could enhance its utility. The experts tested the platform's ability to facilitate accurate clinical diagnoses and offered suggestions for improving the AI algorithm's predictive capabilities and the overall usability of the VR environment.

c) ***Usability Testing and Questionnaires:***

To systematically assess the platform's usability, several questionnaires were administered to a broader group of users:

iPQ (iGroup Presence Questionnaire)

Over the past two decades, the iPQ has been utilised in numerous studies to quantify user immersion in VR settings. A comprehensive analysis of its application has led to refined methodologies for reporting presence scores, enhancing comparability across different VR studies [100]. This extensive use underscores the iPQ's reliability and validity in assessing presence across a range of VR applications.

In the context of medical and scientific visualisation, the iPQ has been employed to evaluate the effectiveness of VR-based training and assessment tools. For instance, research investigating emergency medicine training in 360-degree VR environments found that higher iPQ scores correlated with greater user engagement and knowledge retention, suggesting that presence enhances interaction with complex datasets [101]. Given that EEG interpretation requires a high level of cognitive engagement and spatial reasoning, ensuring a strong sense of presence is essential for optimising user

interaction with the VR-based visualisation platform. The selection of the iPQ in this study is further justified by its widespread adoption in evaluating VR-based analytical tools. By utilising a well-established presence metric, this research provides a robust assessment of how immersion impacts EEG data interpretation in a 3D virtual environment. The full questionnaire can be found in Appendix G.

NASA-TLX (Task Load Index)

The NASA Task Load Index (NASA-TLX) was employed to assess the cognitive workload imposed on users while interacting with the VR-based EEG visualisation platform. Cognitive load is a critical factor in determining the usability and efficiency of interactive systems, particularly in medical and analytical applications where users must process complex data under time constraints. The NASA-TLX is one of the most widely used and validated subjective workload assessment tools, providing a multidimensional measure of cognitive demand across six factors: mental, physical, and temporal demand, effort, frustration, and performance [102].

The NASA-TLX has been extensively applied in human-computer interaction (HCI) and virtual reality research to evaluate the usability of novel technologies. Studies have demonstrated its effectiveness in measuring cognitive load across various domains, including laparoscopic surgery, anesthesia, and patient controlled analgesia [2] [103].

The selection of the NASA-TLX for this study is justified by its proven reliability in assessing workload [104] and its frequent use in evaluating cognitive demand in medical technology. By integrating this metric, the study provides a robust assessment of how the VR platform impacts cognitive effort in EEG data interpretation. The full questionnaire is included in Appendix H.

System Usability Scale:

The System Usability Scale (SUS) is a widely recognised tool for evaluating the usability of various systems, including digital health applications and

[2] the loss of sensation of pain that results from an interruption in the nervous system pathway between sense organ and brain

virtual reality platforms. Developed by John Brooke in 1986, SUS offers a reliable and quick method to assess user satisfaction and system usability across diverse contexts [105].

In the context of VR, SUS has been effectively utilised to gauge user experience and interface intuitiveness. For instance, a study evaluating a VR smartphone application employed SUS to measure usability, revealing its applicability in immersive environments [106]. The SUS questionnaire comprises ten items that cover various aspects of system usability, such as ease of use, integration of functions, and the need for support. Participants rate each item on a Likert scale, and the cumulative score provides an overall measure of usability. This standardized approach facilitates the identification of usability issues and supports the iterative improvement of system interfaces. In this study, the SUS was employed to gather comprehensive feedback on the platform's usability, focusing on elements like navigation ease, interface intuitiveness, and overall user satisfaction. Additionally, users were encouraged to provide qualitative insights, highlighting any challenges encountered and suggesting potential enhancements. The complete questionnaire and detailed results are presented in Appendix I.

General Feedback Form

This general questionnaire gathered broader feedback on the platform's usability, including aspects such as ease of navigation, intuitiveness of the interface, and overall user satisfaction. Users were also asked to provide qualitative feedback, highlighting any difficulties encountered and suggesting potential improvements. This can be seen in Appendix K.

Clinical Diagnosis Accuracy:

Users' ability to make accurate clinical diagnoses within the software was also tested. This involved scenarios where users interpreted neonatal EEG data to detect seizures. The accuracy of these diagnoses was compared to those made using traditional 2D methods to assess whether the VR platform provided any significant advantages.

d) ***Performance Testing:*** Performance testing was a critical aspect of the testing phase, focusing on the technical capabilities of the platform. Key perform-

ance metrics included:

Frames Per Second (FPS)

The FPS was monitored to ensure that the VR environment ran smoothly without lag, which is crucial for maintaining a high level of immersion and preventing user discomfort [107].

Latency and Responsiveness

The platform's responsiveness to user inputs and the time it took to load and visualise EEG data were also tested. These factors are essential for creating a seamless user experience, especially when dealing with large datasets [108].

System Resource Usage

The platform's impact on system resources, such as CPU and GPU usage, was assessed to ensure that it could run efficiently on typical hardware setups used in clinical and research settings [109].

By systematically evaluating these performance metrics, the platform's technical robustness and scalability were assessed, providing valuable insights for further refinement and the feasibility of deployment in real-world scenarios.

4) ***Implementation and Deployment:***

The final stage involves implementing the VR platform in real-world settings, such as clinical or research environments, to assess its feasibility and scalability. This stage may involve further refinement based on user feedback and practical considerations. Given the time frame of the research, the implementation and deployment stage was limited to a feasibility study, with the potential for future expansion and integration into clinical practice.

By following this developmental research design, the study aims to create a robust and user-friendly VR platform for EEG visualisation that meets the needs of clinicians and researchers. The iterative nature of the design process ensures that the platform evolves based on user feedback and testing, resulting in a tool that is both innovative and practical in real-world applications.

Here's a revised version that organizes the content into clearly delineated subsections, making it easier to follow and emphasizing each data type:

B. Data Collection Methods

To comprehensively evaluate the VR-based EEG visualisation platform, data were collected from three main sources: EEG signals, user feedback, and technical performance metrics. Each source was gathered using targeted methods designed to support the development, testing, and validation of the platform.

1) EEG Data: EEG data used in this study were obtained from a publicly accessible dataset [35], which comprises recordings from neonatal patients. This dataset was chosen for its diversity—it includes both normal brain activity and seizure events—making it ideal for evaluating the platform's seizure analysis capabilities. The raw EEG data were preprocessed and converted into a Comma Separated Value (CSV) format to ensure seamless integration into the Unity environment.

2) User Feedback: User feedback was collected using a multi-pronged approach:

- **Questionnaires:** Both quantitative and qualitative questionnaires were administered to assess usability, user experience, and overall effectiveness.
- **Discussions:** Informal discussions provided deeper insights into user perceptions, suggestions, and concerns.
- **Usability Testing Sessions:** Observations of users interacting with the VR environment were conducted to identify any issues or difficulties.

Detailed documentation of these methods is provided in Appendices G through O.

3) Technical Performance Metrics: The platform's technical performance was evaluated using the Unity Profiler, which measured key performance indicators such as frames per second (FPS), latency, and system resource usage. This data was analyzed to identify performance bottlenecks and to guide subsequent optimisations and refinements of the platform.

This structured approach ensured that both the qualitative and quantitative aspects of the platform's performance and usability were thoroughly examined, thereby supporting a robust evaluation of the VR-based EEG visualisation tool.

C. Ethical Considerations

The ethical considerations of this research were carefully addressed to ensure that all data collection and user interaction processes adhered to the highest standards of ethical practice. Given the involvement of human participants and the use of sensitive

EEG data, several steps were taken to protect the rights, privacy, and well-being of all participants involved in the study.

Prior to commencing the study, ethical approval was obtained from the Social Research Ethics Committee (SREC) at University College Cork (UCC) (LogNo: 2024-123). The approval process involved a thorough review of the research proposal, including the methods for data collection, the handling of sensitive EEG data, and the procedures for obtaining informed consent from participants. The consent form can be seen in Appendix E. The SREC's approval ensured that the study met all necessary ethical standards and complied with institutional and legal requirements.

Informed consent was a critical component of the research process. All participants involved in the user testing phases of the study were fully informed about the nature of the research, the purpose of the VR platform, and the specific activities they would be asked to perform. Participants were provided with detailed information sheets that outlined the study's objectives, the data that would be collected, and how this data would be used.

Participants were given the opportunity to ask questions and clarify any concerns before agreeing to participate. Consent forms were signed by each participant prior to their involvement in the study. Participants were also informed of their right to withdraw from the study at any time without penalty, ensuring that their participation was entirely voluntary.

The privacy and confidentiality of participants were maintained throughout the study. All EEG data and user feedback were anonymized to prevent the identification of individual participants. Data was stored securely on the UCC One Drive platform, with access restricted to authorized members of the research team.

The study was designed to minimise any potential risks to participants [110]. The VR platform was thoroughly tested to ensure it did not cause discomfort or adverse effects, such as motion sickness or cognitive overload. Participants were monitored during their interaction with the platform, and they were encouraged to take breaks if needed. In the unlikely event that a participant experienced discomfort, they were instructed to stop using the platform immediately, and appropriate support was provided.

The study was conducted in a manner that ensured equal access and non-discrimination among participants. All individuals were invited to participate in the study regardless

of physical or cognitive ability, or their level of familiarity with VR technology. The platform was designed to be user-friendly and accessible to a broad range of users, with features that accommodated different levels of experience and expertise.

All findings and results from the study will be reported transparently and accurately, adhering to ethical guidelines for research reporting. Any limitations or challenges encountered during the research will be disclosed to ensure the integrity of the research process.

The participants' rights were paramount throughout the study. They were informed of their right to withdraw from the study at any time without penalty or consequence. Participants were assured that their decision to withdraw would not affect their relationship with the research team or the institution. Additionally, participants were informed of their right to access their data and request its deletion at any time, in accordance with data protection regulations.

D. Limitations of the Methodology

Despite the strengths of this study, a few limitations must be acknowledged, that may impact the generalisability and application of the findings:

The study relies on a specific sample of neonatal EEG data, which may not be fully representative of all EEG datasets or the wide range of neurological conditions. As a result, the findings may not be directly applicable to broader populations or varied clinical settings, limiting the generalisability of the research outcomes.

The performance of the VR platform is subject to the hardware and software configurations used during the study. Variations in VR equipment, processing power, and system configurations could influence user experience and the effectiveness of the EEG data interpretation. Future implementations may need to account for these differences in technical setup to ensure consistency across diverse environments.

The adoption of the VR platform for EEG visualisation introduces a learning curve, particularly for users who are less familiar with VR or EEG data analysis. Initial assessments of user experience and platform effectiveness may be impacted as users become proficient in navigating and interpreting data within the VR environment.

While the study emphasizes the development and evaluation of a visualisation platform, it does not address other critical aspects of EEG analysis, such as advanced

signal processing techniques or integration with other neuroimaging modalities beyond VR. This focus on visualisation restricts the scope of analysis, potentially overlooking opportunities for deeper insights into the EEG data.

This methodology offers an organised and methodical approach to the creation, testing, and assessment of the VR-based EEG visualisation platform. The project uses a developmental research strategy with the goal of developing a novel and intuitive tool that overcomes the drawbacks of conventional EEG visualisation techniques. This study's data collection techniques and analytic approaches are intended to provide a thorough assessment of the platform's functionality, efficacy, and technical performance. In order to safeguard the rights and privacy of each study participant, ethical storage of the data was paramount. Although the methodology has many advantages, it must be acknowledged that it has drawbacks that could affect how the research findings are used and how broadly they can be applied. Acknowledging these constraints, the study attempts to offer an open method for creating and assessing the VR platform, guaranteeing that the study's conclusions are correct, and suitable for practical situations.

5. IMPLEMENTATION

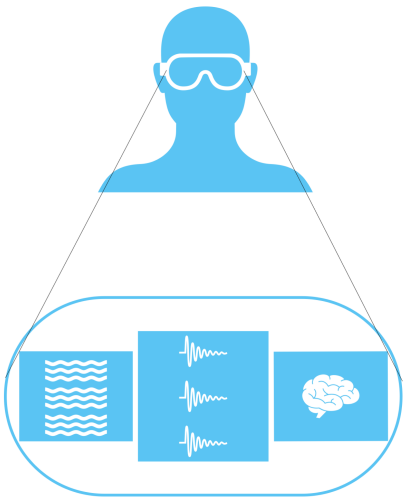
THis section deals with the steps taken to develop the VR platform. Building on the design and methodologies discussed in earlier chapters, this section details how the key components of the system were brought together to create an immersive and intuitive environment for analysing EEG data.

The implementation process involved several phases, including data preprocessing, the integration of EEG signals into the 3D environment, the development of real-time visualisation and interaction features, and the incorporation of additional functionalities such as sonification and AI-based seizure detection. Each of these phases was tailored to meet the objectives of creating a user-friendly and clinically relevant tool, ensuring that the platform was both efficient and reliable for end users.

The chapter, first discusses the development environment and tools used, followed by a detailed explanation of how the core features were implemented. The chapter also addresses key challenges encountered during the development process and the solutions employed to optimise the performance of the VR environment. This implementation lays the foundation for the subsequent testing and validation, which evaluates the system's effectiveness and usability.

A. Physcial Design of the VR World

The design of the VR world was a critical aspect of the implementation process, as it determined the visual and interactive elements of the platform. Before any steps were taken in the 3D VR world, the design process began on the 2D screen with wireframe mock-up designs of how the world was envisaged to look. This step was crucial as it allowed for early stage feedback from different members within the research group and allowed for quick and easy iteration of the design. There were a few iterations of the design before the final design was agreed upon. A simplistic version of this final design can be seen below in Figure 5a. For a more detailed version of the design please see the appendices, from Appendix A to Appendix C. These designs were done using Figma [111], a web-based design tool.



(a) Wireframe Design of the VR World



(b) Real Implementation of the VR World

Figure 5: Comparison of Wireframe Design and Real Implementation of the VR World

The final design of the physical VR World was divided into three sections.

Left Screen:

This screen was very similar to the main screen, with the main differences being that the EEG data was presented in a 3D format with the graphs were coming into and out of the screen, and the data is the frequency breakdown of a chosen channel. This screen was designed to be used in conjunction with the main screen, with the user being able to see the EEG data in a 3D format, while also being able to see the data in a 2D format. This allows the user to see the data in a new light, while also being able to see the data in a familiar setting. This was done to encourage the user to use of the 3D world, while also providing them with a safety net of the 2D world. The frequency bands of the EEG are used in particular by medical professionals to help diagnose different conditions, such as psychiatric disorders [112] and Parkinsons disease [113]. The wire diagram for this screen can be seen in Appendix A.

Main Screen:

This main screen was the largest and was where the EEG data was visualised. The main objective of this screen was to make the user feel familiar with the data and to provide a clear and concise visualisation of the EEG data. The screen was designed to be as simple as possible, with the EEG data being the main focus. At a glance, the screen would look very similar to what would typically be expected in a 2D version of the software, with the user being able to see the EEG in its standard waveform format, while having the ability to manipulate the data as they see fit. This included, but was

not limited to, changing the scale of both the x and y axe, the speed at which the data was being presented to them and the ability to scrub the data back and forth, similar to that of a video player. This allowed the user to focus on specific parts of the data that they felt were important, while not changing the way the data was being presented to them from the 2D world, thereby lowering the learning curve for the user, while also providing them with a familiar setting to encourage them to use the software. The screen size was fully customisable, with the user being able to change the size of the screen to fit their needs, thereby removing the physical constraint of the typical 2D screen. All of these features would be typical of an EEG analysis software in the 2D environment like Natus [114], with the main difference being that the user was in a 3D environment. This was done to provide the user with a safety net, while also providing them with the ability to explore the 3D world at their own pace. The wire diagram for this screen can be seen in Appendix B.

Right Screen:

The initial design for this screen was to have the same waveform data as the main screen, but with one key difference, the graphs would change colour based on the detection of seizures. This was inspired by other attempts to do something like this in the 2D world [115], [116]. It was decided to use a traffic light system to provide the user with lots of information at just a glance, with green meaning there was no seizure detected, yellow meaning that there was a possible seizure detected and red meaning that a seizure was detected. This screen's goal was to help inform the user, in particular those with less experience with complex EEG data in the hope to improving the accuracy of the diagnosis. The final design was slightly different, with the screen being replaced with a 3D brain object that changed colours in different areas, based off the same traffic light system. This was done to provide the user with a more visual visualisation of the data, to help deepen their spatial representation of the data, while also providing them with the same information as the original design. This 3D brain object can be picked up by the user, allowing them to rotate and move the object around the world, providing them with a more interactive experience and increasing the immersion of the user in the world. The wire diagram for this screen can be seen in Appendix C.

This initial design stage was crucial in establishing the foundation for the VR platform, providing a clear vision of the user interface and the interactive elements that

would be incorporated into the 3D environment. The wireframe designs served as a foundational reference throughout the development process, guiding implementation to ensure alignment with both the project objectives and user requirements. Actual screenshots of the final designs and how they were implemented can be seen in subsequent sections of this chapter.

B. Pre-Processing and Data Integration

Before the EEG data could be visualised in the VR environment, it had to be pre-processed and integrated into the platform. This involved several steps, including data cleaning, and formatting, before they could be loaded into the Unity environment for accurate representation. The data was pre-processed using Python, with the final data being saved in a Comma Separated Value (CSV) format. This format was chosen as it is easily readable by Unity and can be easily manipulated to fit the needs of the user.

1) ***Pre-Processing of EEG Data:***

The data for this project was taken from an open source data set [35]. This dataset contained unfiltered data taken from neonatal patients. Therefore, it was necessary to first clean the data before it could be used in the VR world. The first step of this was to remove any noise from the data. This was done by using a bandpass filter to remove any frequencies that were not within the range of 0.5Hz to 100Hz. These ranges were of note as Delta waves are typically 0.5-4Hz and Gamma waves are typically 30-100Hz [117]. For context, the frequency bands can be seen below in Table I.

Table I: Frequency Bands of EEG Signals [117]

Frequency Band	**Frequency Range (Hz)**
Delta	0.5 - 4
Theta	4 - 8
Alpha	8 - 13
Beta	13 - 30
Gamma	30 - 100

2) ***Formatting of Data:***

While the data is now cleaned, it is still not in a format that can be used by the Unity environment. The Unity environment is expecting the data to be in a

specific CSV format. This format is a 2D array where each row is a different channel and each column is a different time stamp. This method allowed the use of a global index variable that ensured the three visualisation methods were at the same time stamp. This was crucial as the data was being visualised in a 3D environment and the data needed to be synchronised to ensure that the user was seeing the same data across all three screens. The rows of the CSV corresponded to different parts of the visualisation. A simplified version of the CSV format can be seen in Table II, a more detailed version of which can be seen in Appendix D.

Table II: Description of rows in the CSV format

Row Number(s)	Data Type
1-8	Normal EEG Data
9-16	Seizure Probabilities
17	Amplitude EEG
18-25	Delta Waves
26-33	Theta Waves
34-41	Alpha Waves
42-49	Beta Waves
50-57	Gamma Waves

As can be seen from this table, the data was split into different sections, with each section corresponding to a different part of the visualisation. To get the data ready to be passed in this CSV format there are still three missing ingredients, namely, the seizure probabilites, the Amplitude EEG (aEEG) and the frequency bands.

Seizure Probabilities:

The eight channels of neonatal EEG are also analysed by using a CNN architecture, also presented also in Gomez et al. [118]. The CNN architecture was designed to automatically learn features associated with seizure patterns, removing the need for manual feature extraction. After processing the data through multiple convolutional layers, the final layer utilised a softmax activation function to generate a probability distribution over the possible classes, such as seizure or non-seizure. The softmax layer assigns probabilities to each class by normalizing the network's output, providing a probabilistic estimate of whether a seizure is occurring in the EEG signal. This probability estimation method offers an effective

and scalable approach to real-time seizure detection, with higher accuracy and sensitivity compared to traditional techniques. Through this model, the detection of seizures is not only automated but also presented as a probability, helping clinicians interpret the likelihood of seizure events in continuous EEG monitoring [119]. It is these probabilities that are used in the VR environment to change the colour of the 3D brain model.Each section of the 3D brain model is colored Green, Yellow or Red based upon the probability value. With Green indicates a low chance of seizure ($< 10\%$), Yellow indicates possible seizure ($10\% - 50\%$) and Red shows a high chance of seizure ($> \%50$). It is important to note that the algorithm outputs seizure probabilities at a rate of 1 Hz, meaning that probabilities are generated once every second. To match the EEG data, which is sampled at 256 Hz, each probability is replicated across the corresponding EEG samples, ensuring that the probabilities are synchronised with the EEG data.

Amplitude EEG (aEEG):

Amplitude Integrated EEG (aEEG) is a method of monitoring the EEG signal that is commonly used in neonatal intensive care units (NICUs) [120], [121], [122]. It involves compressing the EEG signal into a single trace, providing a simplified representation of brain activity that can be easily interpreted by clinicians and researchers. This simplification allows users to quickly assess overall brain function and detect abnormalities or seizure patterns with minimal expertise required in EEG interpretation. aEEG is particularly valuable in NICUs for monitoring the brain activity of newborns, especially those at risk of hypoxic-ischemic encephalopathy (HIE) [123], seizures [124], and other neurological conditions. Its ease of use and continuous monitoring capabilities make it an essential tool in early detection of brain dysfunctions, which is critical for timely interventions [125].

The aEEG process works by taking the raw, multi-channel EEG data and applying several transformations to convert it to a more readable format. In this thesis, the aEEG channel was calculated by using a rolling average window across all eight channels of the EEG data. This smoothing technique allowed the system to condense the data into a form that highlights the overall amplitude of the brain's electrical activity, while maintaining critical information about significant events like seizures. By applying this rolling average, the system could simplify the data

for faster interpretation, which is essential in both clinical applications and in the VR environment. This calculated aEEG data was then added to the CSV format used for EEG visualisation in the VR platform, thus enabling real-time analysis and exploration of the brain's activity in a 3D space.

Additionally, integrating aEEG into the VR environment offered several key advantages. Firstly, it allowed clinicians and researchers to visualise the spatial distribution of brain activity, making it easier to localise abnormalities or focus on specific time periods of interest. Secondly, the combination of traditional aEEG data with immersive 3D visualisation enhanced the ability to detect subtle patterns in the brain's electrical signals that might be otherwise missed in standard 2D monitoring. The incorporation of aEEG into the VR interface also facilitated intuitive interaction with the data, making it accessible for both expert and novice users alike.

This integration of aEEG data into the VR platform not only simplifies the interpretation of EEG signals but also provides another dimension for understanding complex brain activity. This increases the potential for early detection of neurological conditions. By presenting this data in an interactive format, the VR environment can support clinical decision-making, aid in educational applications, and potentially lead to new insights in both research and diagnostics.

Frequency Bands:

The final way in which the data was presented to the user involved splitting the EEG data up into its frequency bands. The bands and their corresponding characteristics can be seen earlier in Chapter 2, page 28.

The process for splitting the EEG signal into its respective frequency bands involved applying a series of digital filters:

a) ***Delta Waves (0.5-4Hz):***

   A low-pass filter with a cutoff frequency of 4 Hz was applied to extract the slowest brainwave activity, corresponding to Delta waves. This filter allowed only frequencies below 4 Hz to pass through, effectively isolating the Delta waves.

b) ***Theta Waves (4-8Hz):***

   A bandpass filter was applied to allow only frequencies between 4 and 8 Hz.

This filter eliminated both lower and higher frequency components, leaving only Theta wave activity.

c) ***Alpha Waves (8-13Hz):***

Another bandpass filter was applied to isolate Alpha waves, capturing neural activity in the 8 to 13 Hz range.

d) ***Beta Waves (13-30Hz):***

To extract Beta waves, a bandpass filter was applied to allow frequencies between 13 and 30 Hz. This band is particularly useful in detecting brain activity related to cognitive tasks and motor control.

e) ***Gamma Waves (30-100Hz):***

The Gamma band required a high-pass filter with a lower cutoff at 30 Hz and an upper cutoff at 100 Hz to capture the fast, high-frequency activity associated with higher cognitive functions and potential seizure activity.

Once the EEG data was decomposed into its corresponding frequency bands, each band was stored in a separate row in the CSV format to facilitate easy loading into the VR environment. Each channel of the EEG data was processed separately, with the filtered data for each frequency band corresponding to specific rows in the CSV file. This organization allowed for clear separation of the frequency bands when visualised in the VR platform. Again, the breakdown of the table format can be seen in Table II with a more detailed view in Appendix D.

By visualising the data into its frequency bands in the VR environment, users can explore the brain's activity at different levels of granularity, gaining insights into the neural processes underlying various cognitive states and conditions. This multi-dimensional representation of EEG signals enhances the platform's utility for both clinical and research applications, providing a comprehensive view of brain activity in an immersive 3D space.

3) ***Integration with Unity:***

Once the data was transformed into the CSV format, it was then ready to be imported and processed within the Unity environment. Given the large number of rows and the complexity of the EEG data, efficiently loading and managing this data presented a significant challenge. The volume of data required to represent

multiple EEG channels across various time points is memory-intensive, and attempting to load all the data at once could lead to performance bottlenecks or even crashes within the Unity environment.

In order to solve this, a Coroutine [126] was put in place to load the data more quickly and efficiently using less memory. Unity's Coroutines allow operations to be dispersed over several frames, preventing the system from becoming overloaded by processing too much information at once. Rather than loading all the data in one run, which would use up too much memory, the Coroutine divides the operation into smaller, more practical portions. This guarantees that the data loads gradually, minimising memory utilisation and preserving fluid VR environment performance. By using this method, the data from each EEG channel is loaded sequentially, and each frequency band or time segment is processed one step at a time. The Coroutine pauses after loading a portion of the data, allowing the Unity engine to continue rendering frames and processing other tasks, preventing any interruptions to user interaction or visualisations.

This approach not only optimises memory management but also allows for more complex and larger datasets to be integrated into the system without degrading the user experience. Clinicians or researchers can then smoothly navigate through the EEG data in real-time, ensuring that the VR environment remains responsive and immersive throughout the interaction.

In summary, the use of a Coroutine was crucial for balancing the need to handle large volumes of EEG data while maintaining system performance and responsiveness in the VR visualisation tool. A summary of the data integration process can be seen in Figure 6.

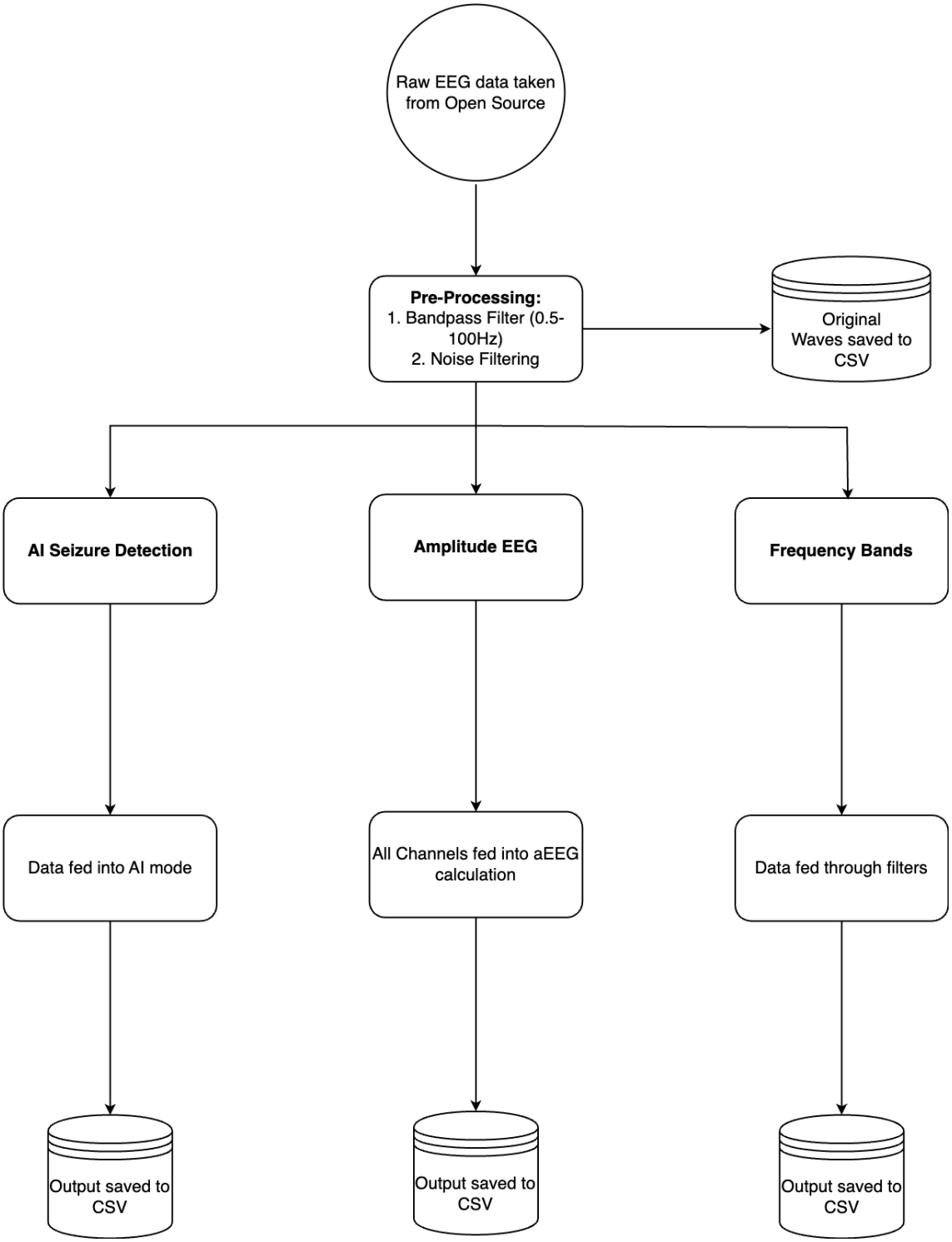


Figure 6: Data Integration Process

C. Core Implementation

With the data now pre-processed and integrated into the Unity environment, the core features of the VR platform could be implemented. This section details the development of the main screen, the 3D graph screen, and the 3D brain model, highlighting the key functionalities and interactions that were incorporated into each component.

The core implementation phase was driven by the need to provide users with an intuitive and interactive way to explore EEG data in a virtual environment. Each screen and model was designed to offer a unique perspective on the data, facilitating deeper analysis and easier identification of critical patterns, such as seizure activity. By combining traditional data visualisation methods with the immersive capabilities of VR, the platform enhances user engagement while also improving the clarity of EEG signal interpretation.

During the development process, a trial-and-error approach was employed, where various design elements and optimisations were tested iteratively. This was crucial for achieving the necessary frame rate (FPS) for smooth VR performance. The initial versions of the platform often fell short of the required 72 FPS for VR, causing stuttering or lag, which disrupted the user experience. To address this, there were experimentations with different rendering techniques, model optimisations, and data processing strategies, adjusting these elements until the design achieved the desired performance.

This trial-and-error methodology was crucial not only for optimising performance but also for refining the overall design. By repeatedly testing and modifying the implementation, it was possible to balance visual quality with performance, creating a platform that is both functional and responsive within the constraints of VR technology.

1) Traditional 2D Screen: The Main Screen of the VR platform was designed to closely resemble the traditional 2D EEG analysis interface. The primary goal of this screen was to offer users a familiar environment, encouraging them to engage with the software while also introducing innovative ways to interact with the data. By maintaining a familiar layout, users experienced minimal disruption when transitioning from conventional tools to this VR-based platform.

While the conceptual design of the screen has been discussed in the ”Physical Design of the VR World” section, this part focuses on how the design was implemented in Unity. The screen’s development involved translating the familiar 2D elements of EEG analysis

into a 3D space while retaining essential functionalities, such as waveform navigation and data scaling. This allowed users to benefit from the immersive nature of VR without losing the essential characteristics of standard EEG displays.

The final implementation of the main screen can be seen in Figure 7, where the user interface and interaction tools are fully realised.

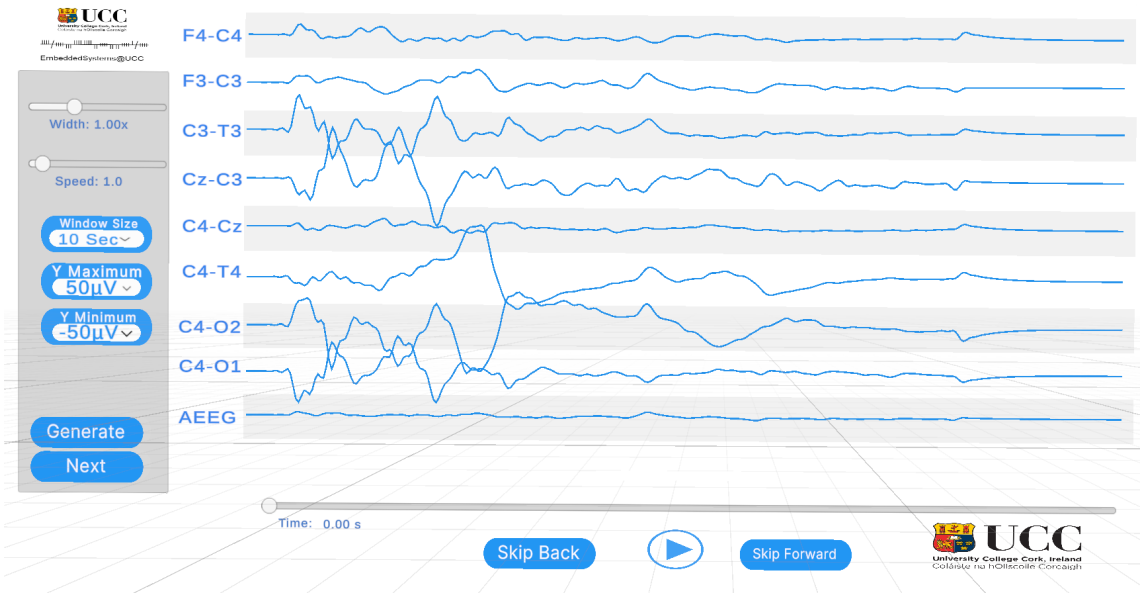


Figure 7: Traditional Screen of the VR World

To reach the final design, numerous iterations were conducted, with continuous refinement at each step. However, three key design attempts shaped the final version of the platform:

1) *Algorithm 1: Manually Plotting the EEG Data*

   At first glance, developing a plotting solution may seem straightforward given the wide array of tools available to modern programmers. However, in the context of this project, the task proved to be far more complex. Unity's native toolset lacked dedicated plotting algorithms, and the unique requirements of EEG data visualisation in a 3D VR environment were not fully addressed by existing solutions. To overcome this, a custom plotting library was developed specifically for Unity. This library was optimized to efficiently process large datasets, like EEG signals, and to display them interactively within the VR environment, providing a seamless and responsive user experience.

   The main goal of the plotting library was to create a flexible and efficient system that could render EEG data in real-time, allowing users to interact with the data

as they navigate through the VR environment. Several key considerations guided the development of this custom solution:

a) **Performance Optimisation:**

EEG datasets are large, often comprising thousands of data points per second across multiple channels. To ensure smooth performance, the library was built to handle these datasets in a way that minimised memory usage and computational load. Unity's LineRenderer [127] component was used to render data points efficiently.

b) **Customisation:**

The plotting library needed to be highly customisable. This flexibility allowed for dynamic scaling of both axes, real-time updates, and multiple visualisations (e.g., standard waveforms, 3D graph screens). Users can control the scaling and adjust the viewing angles to get a more detailed or broader perspective of the data.

c) **Real-Time Interaction:**

A crucial feature of the library was the ability to interact with the plots in real-time. Users can manipulate the plotted data through intuitive controls, such as zooming in on specific time segments, panning across different EEG channels, and adjusting visual elements like colours and transparency to focus on particular data features.

d) **3D Data Representation:**

Unlike traditional 2D plotting libraries, this custom solution was designed for a 3D space. EEG signals were plotted not only in a traditional 2D waveform but also extended into 3D space, where data could be explored spatially. For example, users could observe the amplitude of signals coming in and out of the screen, adding a layer of depth to the data visualisation.

As previously mentioned, this data was loaded into the unity environment using Coroutine to minimise the memory it required. Each row of the CSV was read by Unity as an array that corresponded to a channel in the EEG. The first few attempts to implement this plotting algorithm were unsuccessful, with the FPS dropping as low as $<$10 FPS as the system tried to display the data. The algorithm was simple, with manual calculations to determine the x and y position of each data

point. Plotting a data point as a gameObject, then plotting a line between the data points to give the impression of a line graph. A simplified version of the algorithm can be seen in Figure 8.

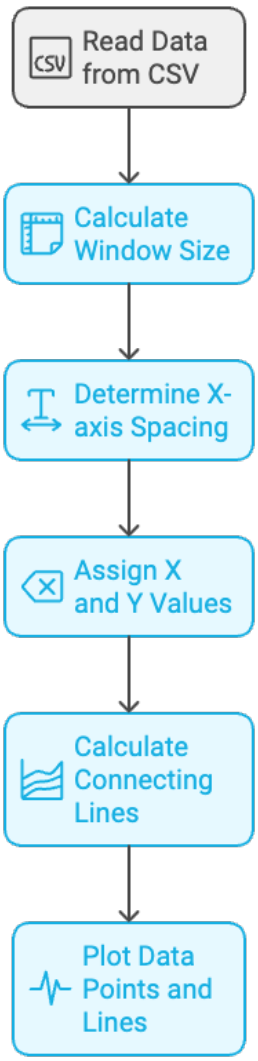


Figure 8: First Attempt at Plotting Algorithm

This algorithm was not efficient enough to handle the vast amount of data. While it could plot accurate data, once an attempt was made to make the data update in real-time, the system would slow to less than 10FPS. This was due to the system trying to plot all the data at once, rather than plotting the data in smaller chunks. The shear number of gameObjects (approximately 122,880) that were being created was causing the system to slow down. This was a crucial learning point for the project, with the attention changing to find ways to minimise the number of gameObjects that were being created. The breakdown of the number of gameObjects that were being created and the performance of this algorithm

can be seen in Table III.

2) Algorithm 2: Reducing GameObjects

In an effort to reduce the computational load, a second algorithm was developed. Instead of plotting both the individual data points and the connecting lines, only the lines were plotted. Given the density of the data, this still resulted in a visual output resembling a line graph. This modification led to a notable improvement, reducing the number of gameObjects by 50%. However, the system remained unable to handle real-time data visualisation over extended periods, specifically when trying to display more than 30 seconds of continuous data. Performance data for this method is also provided in Table III, and the flowchart of this algorithm is shown in Figure 9.

It became evident that this methodology was not scalable for the real-time processing demands of the project. The inefficiencies inherent in plotting individual data points and lines, combined with the large number of gameObjects being generated, caused significant performance degradation, particularly during attempts to handle continuous streams of data. Consequently, it was necessary to re-evaluate the approach entirely, focusing on more optimized solutions capable of handling the real-time visualisation of extensive datasets.

3) Algorithm 3: Pre-Rendering with masking

While earlier methods successfully plotted EEG data for a single 30-second interval, they failed to achieve the speed necessary for providing users with a seamless real-time experience. The subsequent approach sought to address this by plotting the entire dataset in one go, while only displaying a 30-second segment at any given time. This was achieved using a ”mask” technique within the Unity environment. The mask functioned by making only the data that passed within its bounds visible to the user, effectively hiding data outside the mask.

This approach allowed the system to handle all the data simultaneously, yet display it incrementally, providing a more dynamic and responsive visualisation. Notably, this method significantly improved performance, with the system achieving an update rate of nearly 30 FPS. This was a marked improvement over earlier techniques, which struggled to keep up with real-time demands.

However, despite the performance gains, the system still fell short of the desired

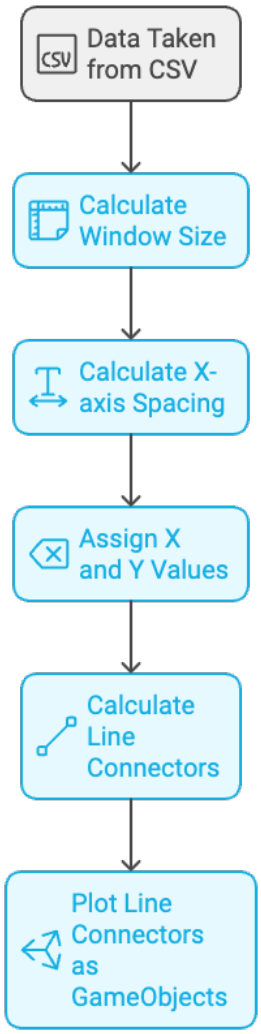


Figure 9: Second Attempt at Plotting Algorithm

72 FPS needed to ensure a positive user experience. The primary bottleneck was the need to move a large number of individual game objects within a single frame, which created inefficiencies. This issue is illustrated through a detailed performance breakdown in Table III, highlighting the trade-offs between the number of game objects and system performance. A flowchart outlining this plotting algorithm can be seen in Figure 10, which provides a clearer understanding of its operational structure.

Although the method brought substantial improvements, further optimisation is necessary to achieve the target frame rate and ensure a truly real-time experience for users. By reducing the computational load per frame, either through object pooling, batch rendering, or more efficient data structures, it may be possible to push the system closer to its performance goals.

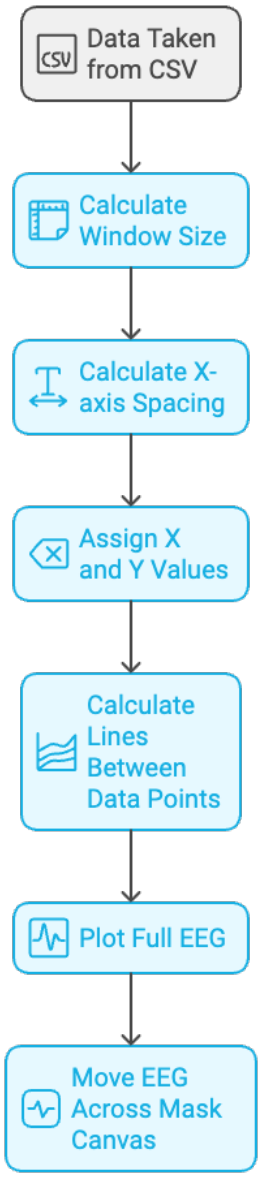


Figure 10: Third Attempt at Plotting Algorithm

4) Algorithm 4: Continuous rendering with LineRenderer

The final iteration of the EEG data visualisation algorithm focused on optimising the rendering process to achieve the target frame rate. This required a comprehensive redesign of the plotting method, shifting away from the use of individual game objects in favour of a more efficient and streamlined approach.

In this version, the algorithm leveraged Unity's LineRenderer component to plot the EEG data as a continuous line, effectively eliminating the need to manage numerous separate game objects. This change significantly reduced the computational overhead, as the LineRenderer component allowed for smooth, real-time rendering without the performance penalties associated with updating many discrete objects. By treating the EEG data as a continuous graphical entity, the system was able to reduce the strain on both CPU and GPU resources, enabling higher frame rates and more responsive interactions. This approach not only simplified the rendering process but also allowed for smoother, more fluid visualisations, bringing the system closer to the desired frame rate performance.

This final optimisation proved to be a critical advancement, as it streamlined the data visualisation pipeline and enabled the system to operate more efficiently within Unity's graphical framework. While additional refinements may still be necessary to fully maximize performance, the transition to using the LineRenderer component represented a major leap forward in delivering a real-time EEG data visualisation experience. The flowchart of this algorithm can be seen in Figure 11, which illustrates the improved efficiency and performance gains achieved through this method. A comparison of the performance metrics for each algorithm is provided in Table III, highlighting the significant improvements made in frame rate and computational efficiency.

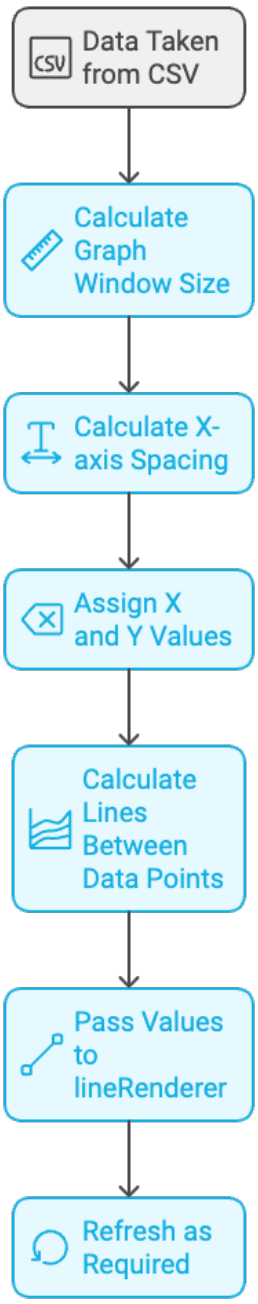


Figure 11: Final Attempt at Plotting Algorithm

The final algorithm was able to achieve the desired frame rate of over 72 FPS, providing users with a smooth and responsive EEG data visualisation experience. By leveraging Unity's LineRenderer component and optimising the rendering process, the system was able to efficiently plot large datasets in real-time, enabling users to explore EEG signals interactively within the VR environment. This optimisation was a critical step in enhancing the platform's performance and usability, ensuring that users could engage with the data seamlessly and intuitively.

Table III: Performance Comparison of Plotting Algorithms for 30 seconds of 8 Channel EEG data

Method	GameObjects Count	Frame Rate
Algorithm 1	122,880	<10 FPS
Algorithm 2	61,440	<20 FPS
Algorithm 3	61,440	<30 FPS
Algorithm 4	8	>72 FPS

2) 3D Graph Screen: The development of the 3D Graph section commenced once the desired frame rate for the 2D display was successfully achieved. Building on the same framework and utilizing Unity's LineRenderer component, this extension was designed to further enhance the user's ability to visualise EEG data. The 3D Graph Screen provided a unique perspective, allowing users to explore brain activity in a spatial context that the traditional 2D waveform display could not offer.

In this 3D environment, the data displayed consisted of the brain's frequency bands, such as delta, theta, alpha, beta, and gamma—at a given time for a specific EEG channel. By introducing a third dimension, this visualisation enabled users to gain deeper insights into the spatial and temporal distribution of these frequency bands across the brain. Unlike the 2D display, where line graphs were limited to the x and y axes, the 3D Graph depicted these frequency bands extending into and out of the viewing space, effectively mapping the changes in frequency over time in a more immersive way. This additional dimension offered a valuable enhancement to understanding neural activity. By interacting with the data—rotating, zooming, and navigating through the 3D space—users could better explore the dynamics of brain activity, making it easier to identify patterns and anomalies in frequency distributions that might not be as apparent in a 2D format.

The ability to view EEG frequency bands in this spatial environment provided new opportunities for analysing multi-channel data, where comparing the frequency responses across different brain regions becomes crucial. The 3D visualisation made it possible to see how the brain's frequency bands evolved simultaneously across multiple dimensions, offering a clearer representation of both localised and distributed brain activity.

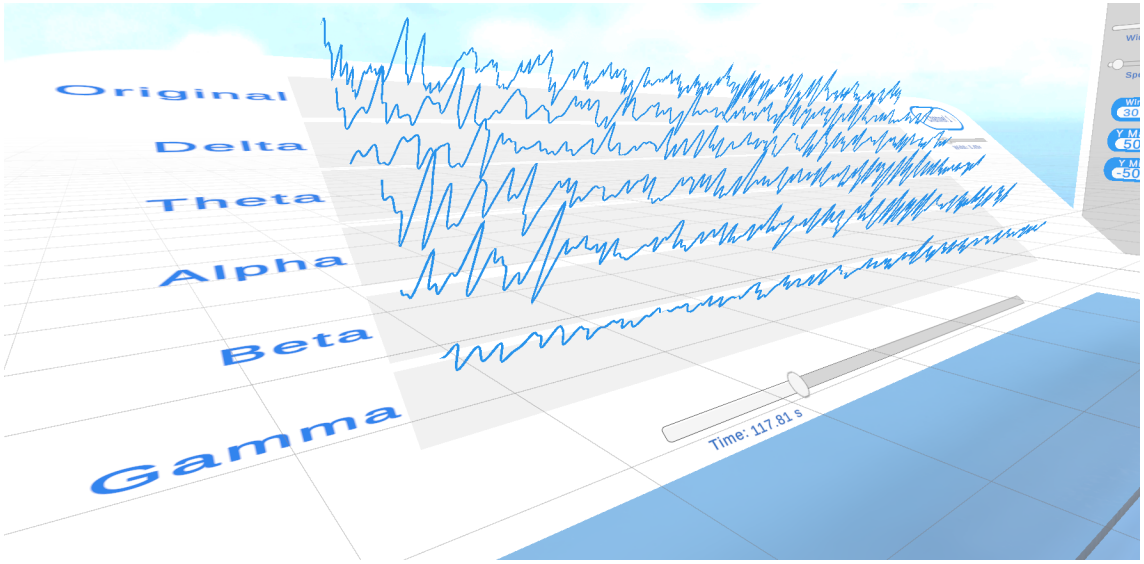


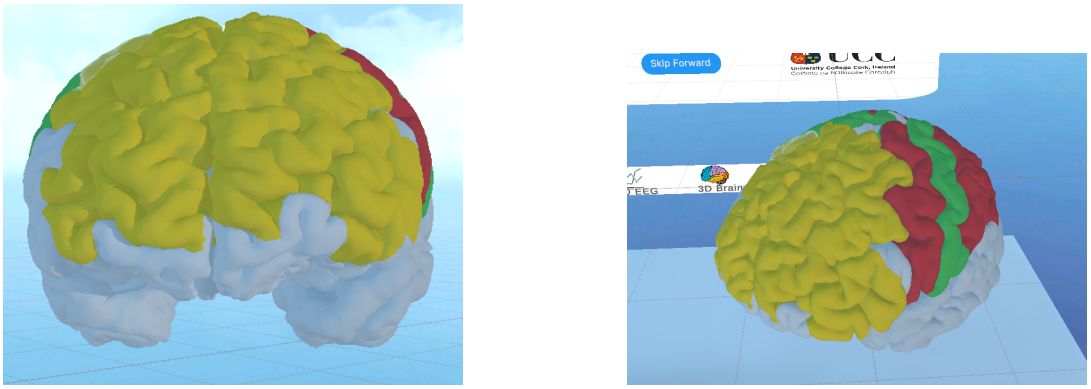
Figure 12: 3D Graph Screen of the VR World

In summary, the 3D Graph Screen was not just an aesthetic enhancement but a functional improvement, allowing for more robust analysis of EEG data by visualising the brain's frequency bands in a dynamic and spatially rich context. A screenshot of the 3D Graph Screen can be seen in Figure 12. This screen was a critical addition to the VR platform, providing users with a novel way to explore and interpret EEG data that was not possible with traditional 2D displays.

3) 3D Brain Model: The final component of the system was the 3D brain model, which dynamically changed colours based on an AI-driven algorithm that detected seizure activity in real time. This model provided a visual representation of brain activity, with colour changes indicating the likelihood of a seizure event. The colour-coding followed a traffic light system: green indicated normal brain activity, yellow signified a warning of potential seizure onset, and red represented the detection of a seizure event. This intuitive system allowed users to quickly identify critical events in the EEG data, facilitating a more focused analysis of specific time segments or channels that warranted closer attention.

To implement this feature, the majority of the computational load occurred during the initial data load into the virtual environment. The input data, stored in a CSV file, contained rows of probability values corresponding to different brain regions. These values ranged from zero to one, where zero indicated no risk of a seizure and one represented the occurrence of a seizure. The system processed these values and mapped them to the appropriate colours, effectively transforming the brain model's appearance in

real time based on the seizure probability data. The colour changes were implemented using Unity's material system, wherein the material applied to the brain model was updated to reflect the probability of a seizure. By keeping the system design as simple and efficient as possible, the model was able to handle the large volume of data being processed without compromising performance. This ensured that users could seamlessly interact with the 3D brain model while receiving real-time updates on seizure activity, enhancing both the usability and effectiveness of the visualisation.



(a) Front-On View of the 3D Brain Model (b) Side View of the 3D Brain Model

Figure 13: Captures of the 3D Brain Model colored by AI probabilities

The final implementation of the 3D Brain Model can be seen in Figure 13. This model not only added a critical layer of interactivity to the visualisation system but also provided an accessible means for users to monitor seizure risks, making it a vital tool for both research and clinical applications.

D. User Interaction

The user interaction component of the VR-based EEG visualisation platform is central to its design, emphasizing the ability to manipulate and explore complex EEG data in real-time within a 3D virtual environment. The interactive features of the platform are intended to enhance the user's capacity to engage with, interpret, and analyse EEG data more effectively compared to traditional 2D interfaces. The interaction design was guided by user-centered design principles and refined through iterative testing, ensuring both intuitive usability and advanced data manipulation capabilities.

Dynamic Control of Visualisation Parameters:

One of the core functionalities of the platform is the ability to manipulate the EEG data display dynamically. This was done using the VR controllers that came with the Pico

headset. Programming the buttons on the controllers was done through the OpenVR library in Unity [128]. Users are granted full control over temporal and amplitude scaling, allowing for detailed analysis of specific data segments:

- *Temporal Scaling (X-Axis):* Users can modify the time window displayed by expanding or contracting the time scale, enabling them to either focus on brief, high-resolution time frames or survey larger periods of brain activity. This functionality allows users to detect rapid events, such as seizure onsets, or analyse long-term trends in brain activity by adjusting the temporal resolution. The user can set the time to as short as 10 seconds to as high as a minute. This is twice the length of the time window that is displayed on the 2D screen.
- *Amplitude Scaling (Y-Axis):* The platform allows users to adjust the vertical scaling of EEG waveforms, enhancing the visibility of subtle signal fluctuations. This feature is particularly useful when examining specific EEG events that require a closer inspection of waveform amplitude, such as epileptic discharges, which may be less discernible at standard scales. The user can scale the axis anywhere from -60 μV to -10 μV as the bottom limit and 10μV to 60 μV as the top limit.

Temporal Navigation and Data Scrubbing:

The platform incorporates advanced temporal navigation tools, allowing users to scrub through EEG recordings with precision. By utilising hand controllers, users can scroll through the EEG data timeline, move forwards or backwards in time, and pause at critical moments for detailed inspection. The scrubbing functionality synchronises across all visualisations, ensuring that the EEG data displayed on multiple screens remains temporally aligned. This facilitates the examination of data from different perspectives and modalities without losing temporal coherence.

Frequency Domain Analysis in Three Dimensions:

The platform provides a novel approach to frequency domain analysis through 3D representations of EEG data. This 3D frequency breakdown enables users to interact with the EEG signals in a spatial context, facilitating a deeper understanding of frequency components. EEG signals are decomposed into standard frequency bands (Delta, Theta, Alpha, Beta, Gamma), and each band is visualised as a depth plot within the virtual environment. Users can rotate and navigate these 3D plots, examining how frequency components evolve over time. This level of interaction enhances the user's ability to

identify patterns and anomalies that may not be apparent in traditional 2D visualisations.

Seizure Detection and Spatial Visualisation

An integral feature of the platform is its AI-driven seizure detection system, which provides real-time probability estimates of seizure events. The platform spatially visualises this information on a 3D brain model, offering users an interactive and intuitive means of exploring seizure activity within the brain. The seizure probability data is mapped onto a colour-coded 3D brain model, with regions of the brain affected by potential seizures highlighted based on probability thresholds. Users can interact with the brain model by rotating it, zooming in on specific regions, and exploring the spatial distribution of seizure activity across different cortical areas.

Sonification of EEG Signals

The platform introduces the sonification of EEG signals as an alternative modality for data interpretation. This feature translates EEG waveforms into sound, providing users with auditory feedback in real-time. Different frequencies and amplitudes are mapped to specific audio tones, allowing users to identify rhythmic patterns or abnormalities through sound. This auditory mode is particularly useful in detecting periodic patterns, such as rhythmic seizure discharges or slow evolution of frequency in time, which may be less apparent in visual data. By combining visual and auditory feedback, the platform enhances the user's ability to detect subtle EEG features and patterns, providing a multi-sensory approach to data exploration [118]. The sonification algorithm that is implemented is the work of Gomez-Quintana et al. [118]. The flow of this algorithm can be seen in Figure 14.

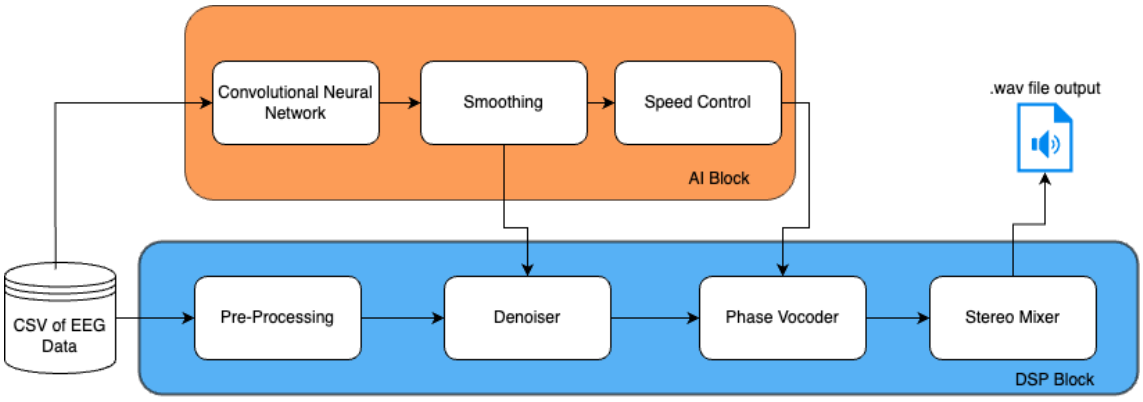


Figure 14: Sonification Algorithm Flowchart

The signal pre-processing stage prepares EEG signals for the sonification algorithm

by reducing noise outside the target frequency band and removing artifacts, particularly ECG interference. A denoising block highlights unusual EEG activity, applying spectral subtraction (commonly used in speech processing) to reduce non-seizure-related activity. The phase vocoder is used to shift EEG frequencies into the audible range, transforming EEG data into sound. Originally developed for speech, this technique is adapted here with a time-variable stretching factor, compressing EEG segments differently based on signal properties. A deep learning AI model detects seizure events in the EEG, informing the dynamic stretching factor. Finally, a stereo mixer combines multiple EEG channels into a stereo output, positioning each channel in a 2D space around an imaginary listener based on interaural time delay, enhancing spatial perception of the audio [118]. An important finding of the work, suggests that AI-assisted sonification that is listened to by humans is more accurate than using AI alone. Once the data is sonified, it is then played through the VR headset's earphones, allowing the user to hear the EEG data in real-time. In the audio domain, the seizures can be heard as a pitch-evolving sound (like a chirp) with tonal variations. Seizures evolve in time and this is perceivable by the human ear. The process for generating the sound file occurs at the same time as the EEG data is inferred by the AI model for probabilites [129].

Customisation of Interaction and Display Settings

The VR platform supports a high degree of customization, enabling users to tailor the display and interaction settings to their specific needs. Users can modify the size, orientation, and positioning of the virtual screens within the environment. This flexibility allows users to create a personalised workspace, adjusting the layout to accommodate their preferred workflow or analysis requirements.

Haptic Feedback Integration

The platform also incorporates haptic feedback to further enhance the immersive experience and provide tactile reinforcement during data exploration. Through the use of haptic-enabled hand controllers, users receive physical feedback when interacting with key features of the system, such as rotating the 3D brain model or adjusting the time and amplitude scales. This tactile feedback reinforces user actions, improving the precision and intuitiveness of interactions, particularly in tasks requiring fine control, while also increasing the immersion of the experience.

The platform provides real-time feedback in response to user actions, ensuring a

seamless and interactive experience. Whether manipulating the time scale, adjusting amplitude, or navigating the 3D brain model, the system is perceived to respond instantaneously to user inputs. This immediate feedback allows for uninterrupted data exploration and analysis, maintaining user immersion and focus on the task at hand.

E. Performance Optimisation

The VR-based EEG visualisation platform requires significant computational resources due to the real-time rendering of complex EEG data and interactive 3D visualisations. To ensure that the platform operates efficiently, several performance optimisation strategies were implemented, to address potential bottlenecks related to rendering, data processing, and resource management.

1) **Data Streamlining and Caching:**

   A key challenge was managing the large volume of EEG data in real-time without sacrificing performance. To address this, the platform utilised data caching and pre-processing techniques to minimize the overhead during active use. EEG data was pre-processed to reduce memory usage while maintaining the essential features needed for clinical analysis.

   Caching frequently accessed data, such as EEG segments during temporal scrubbing and seizure probability updates, further reduced delays in rendering. This caching system also supported asynchronous data loading, allowing the VR environment to remain responsive while new data was being fetched and processed.

2) **Level of Detail Optimisation:**

   To improve performance in ”visual-heavy” sections of the platform, particularly when interacting with the 3D brain model, a Level of Detail (LOD) [130] system was implemented. This system dynamically adjusts the complexity of rendered objects based on the user’s proximity and interaction with them. For example, when the user is viewing the 3D brain model from a distance, the system uses a simplified version of the model with fewer polygons. As the user zooms in, higher-resolution versions of the model are loaded, ensuring both visual fidelity and performance efficiency.

   This dynamic LOD adjustment significantly reduced the GPU load during periods of low interaction, allowing the platform to maintain a high frame rate while

delivering detailed visualisations when necessary.

3) **Object Pooling:**

Memory management was optimized through careful monitoring of object instantiation and destruction within the Unity environment. Frequent object creation and deletion, particularly for EEG waveforms and graphical elements, can result in spikes in garbage collection and degrade performance over time. To address this, object pooling [131] was introduced for frequently used objects such as EEG waveform segments. By reusing objects instead of creating and destroying them repeatedly, memory overhead was reduced, and garbage collection events were minimised.

Additionally, large objects such as the 3D brain model were split into smaller, more manageable segments, allowing for more efficient loading and unloading during interaction. This segmentation reduced memory consumption and improved the responsiveness of the VR environment.

In conclusion, Chapter 5 has delineated the comprehensive implementation of the VR-based EEG visualisation platform, bridging theoretical insights with practical system design. The chapter detailed the sequential development stages—from the architectural planning of the VR environment and the integration of pre-processed EEG data, to the iterative refinement of visualisation algorithms and performance optimisations. Notably, the transition to a continuous rendering approach using Unity's LineRenderer component, alongside the integration of sonification and AI-driven seizure detection, underscores the innovative strategies employed to address real-time performance challenges. These implementation strategies not only validate the system's technical viability but also lay a robust foundation for subsequent evaluations of user experience and clinical applicability in the following chapters.

6. Results and Discussion

To test the performance of the platform, a series of user studies ($N = 20$) were conducted, evaluating the system's usability, functionality, and overall user experience. The results of these studies provided valuable insights into the platform's effectiveness and potential areas for improvement. The studies can be split into three sections: User Experience Testing, Clinical Diagnosis Testing, and Hardware Performance Testing.

A. User Experience Testing

This section focused on evaluating the user experience of the VR platform, assessing the ease of use, interactivity, and overall engagement of the system. Participants were asked to perform a series of tasks within the VR environment, such as navigating EEG data, adjusting visualisation parameters, and interacting with the 3D brain model. To get a comprehensive understanding of the user experience, the participants were asked to fill out standardised questionnaires after completing the tasks, namely the System Usability Scale (SUS) [132], the NASA Task Load Index [102], the I-Group Presence Questionnaire (iPQ) [100] and a general feedback questionnaire, as previously discussed in the Methodology section of this thesis. These questionnaires provided quantitative and qualitative feedback on the platform's usability, cognitive load, and immersive qualities, helping to identify areas of strength and areas for improvement. The results are organised into the following categories: descriptive statistics, comparative analysis, correlation analysis, and qualitative feedback.

1) Descriptive Statistics: Table IV provides an overview of the descriptive statistics for the NASA-TLX, SUS, and iPQ scores. These metrics were used to quantify participants' workload, usability perception, and sense of presence within the VR environment.

- **NASA-TLX Mental Rating**

  The mean mental rating was 8.9, with a standard deviation (σ) [133] of 5.2. This relatively high mean suggests that the task was mentally demanding for participants. The wide range (min = 1.0, max = 15.5) indicates variability in how participants perceived the cognitive demands of the VR environment. This mental rating was

Table IV: Descriptive Statistics for NASA TLX, SUS, and iPQ Measures

Measure	Mean	Standard Deviation	Min	Max
Nasa TLX Mental Rating	8.90	5.20	1.5	15.5
Nasa TLX Physical Rating	4.85	3.77	1.0	14.5
Nasa TLX Temporal Rating	3.95	3.36	1.0	12.5
Nasa TLX Performance Rating	6.20	3.93	2.0	16.5
Nasa TLX Effort Rating	7.83	3.69	2.5	14.5
Nasa TLX Frustration Rating	3.92	3.56	0.0	12.0
SUS Score	83.00	11.14	60.0	100.0
iPQ SP Score	13.25	1.62	10.0	15.0
iPQ INV Score	17.40	2.84	13.0	21.0
iPQ Real Score	16.40	4.36	9.0	23.0
iPQ GP Score	1.90	1.02	1.0	5.0

on par with simple tasks like visual tracking or simple arithmetic, suggesting that the cognitive load was manageable for most participants [134].

- **NASA-TLX Physical Rating**

  The mean physical demand was 4.85, which is relatively low, indicating that participants did not perceive the task as physically strenuous. This is expected, as interactions in the VR environment were primarily through head and hand movements rather than extensive physical activity. This is on par with other patient monitoring tasks [135].

- **NASA-TLX Temporal Rating**

  The mean temporal demand was 3.95, reflecting low stress levels related to time constraints during the task. This suggests that participants were not rushed and could navigate the VR environment at their own pace.

- **NASA-TLX Performance Rating**

  A mean score of 6.2 suggests that participants generally felt they performed well on the tasks, achieving high levels of accuracy or effectiveness. In other words, they likely believed they were successful in completing the assigned tasks and meeting the task requirements. This score falls on the lower end of the NASA-TLX performance scale, indicating a positive self-assessment of performance.

- **NASA-TLX Effort and Frustration Ratings**

  The effort and frustration ratings provide insights into the overall user experience. The effort rating of 7.83 suggests a moderate level of exertion was required to complete the tasks, while the frustration rating of 3.92 indicates that, although the

task was mentally demanding, it did not lead to high levels of frustration.

In Figure 15 shows the distribution of the NASA-TLX mean scores for each category. The results are split between experts and non-experts. This comparison will be discussed later in this section. For now, it is worth looking at how each category was rated by the participants. Overall there is no category that stands out as being particularly difficult or easy. The mean scores are all relatively close to each other.

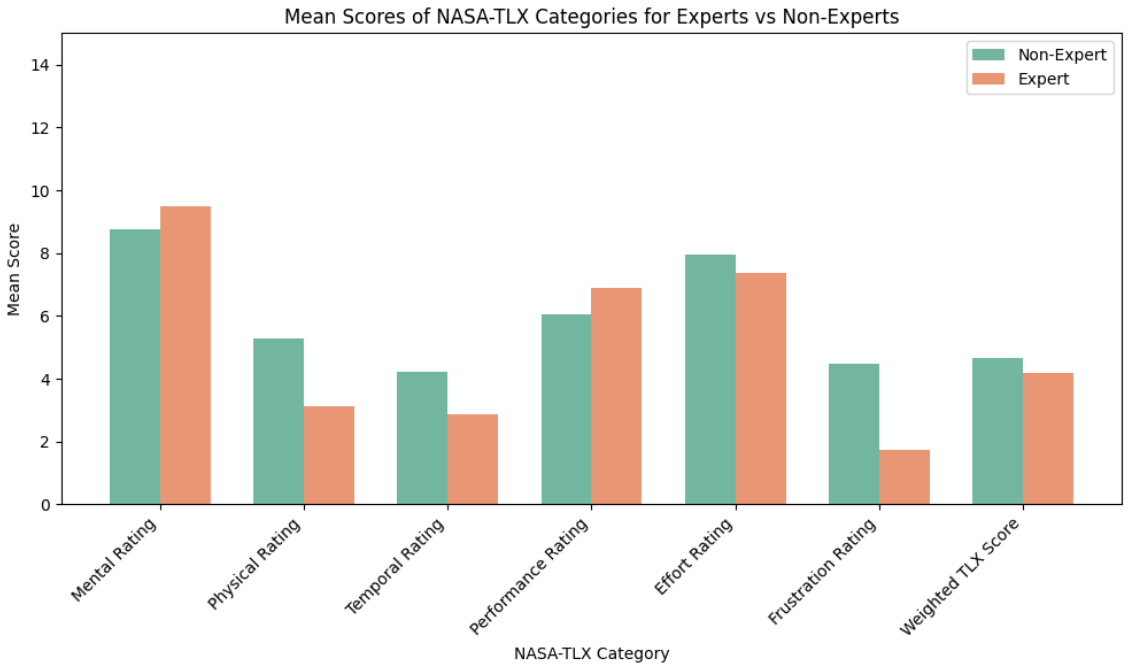


Figure 15: NASA-TLX Mean Scores Comparison

- **System Usability Score**

  SUS provides a quick and reliable way to measure usability, and its scores can be interpreted to understand how users perceive a product's ease of use. SUS scores range from 0 to 100, with higher scores indicating better usability. In the context of the VR-based EEG visualisation platform, the mean [136] SUS score was 83, with a standard deviation of 11.14. A mean SUS score of 83 is considered above average and falls into the "excellent" range on the SUS scale [137]. Scores of above 68 but less than 80 are considered to be above average, while scores above 80 indicate excellent usability. This suggests that participants found the VR platform to be highly usable and user-friendly, with a positive overall experience. This result is particularly encouraging given the complex and difficult nature of the task the participants were asked to complete. For a system that visualises complex

data in a 3D environment, achieving such a high usability score indicates that the interface design, interaction methods, and overall user experience were effective in making complex tasks manageable for users. The positive usability perception is a key success factor for the VR platform because it ensures that both novice and experienced users can comfortably use the system without extensive training. This is crucial for practical adoption in clinical or research settings, where ease of use can significantly impact the effectiveness of the tool. Benchmarking this against other software, a SUS score of 83 typically corresponds to an ”A” rating, placing it in the top 10-20 percent of systems in terms of usability [138]. Such a score indicates that the VR platform has usability comparable to well-designed commercial software and is likely to be well-received by users in clinical and research contexts.

- **iPQ**

  The *Spatial Presence* subscale measures how much participants felt they were physically situated within the VR environment. A mean score of 13.25 ($\sigma = 1.62$) indicates that participants experienced a moderate to high level of spatial presence. This suggests that they felt immersed in the VR world and could effectively perceive the spatial arrangement of EEG data and other visual elements. This level of spatial presence is crucial for complex data visualisation tasks, as it ensures that users can leverage the additional space and depth provided by the VR environment to better understand and interpret EEG signals. Higher spatial presence generally leads to better engagement with the content and a more intuitive understanding of spatially complex data, which is a core objective of this VR-based visualisation platform [139] A mean score of 13.25 (out of a typical range of 0-20) indicates that participants experienced a moderate to high level of spatial presence [140]. This suggests that they felt immersed in the VR world and could effectively perceive the spatial arrangement of EEG data and other visual elements. This level of spatial presence is crucial for complex data visualisation tasks, as it ensures that users can leverage the additional space and depth provided by the VR environment to better understand and interpret EEG signals. Higher spatial presence generally leads to better engagement with the content and a more intuitive understanding of spatially complex data, which is a core objective of this VR-based visualisation platform.

Involvement measures the degree to which participants felt engaged and focused while interacting with the VR environment. A mean score of 17.4 ($\sigma = 2.84$) indicates a high level of involvement [100]. This suggests that participants were deeply engaged with the task of EEG data interpretation and were not easily distracted. High involvement is an important factor in determining the effectiveness of a VR-based learning or analysis tool, as it shows that participants were actively concentrating on the task without being hindered by the complexity or unfamiliarity of the environment. The VR platform's design successfully maintained users' attention and facilitated engagement, which is essential for performing complex analytical tasks such as identifying patterns in EEG data.

Realism evaluates how realistic and credible participants found the virtual environment. A score of 16.4 ($\sigma = 4.36$) suggests that participants perceived the VR environment as quite realistic [100], which is particularly important for a platform intended to visualise medical data. This realism is especially beneficial for expert users (e.g., clinicians and researchers) as it enhances their ability to make informed decisions based on visualised EEG data.

- **Pre and Post-VR Ranking**

  The Pre-VR Rank and Post-VR Rank are subjective ratings provided by participants to express their initial expectations before using the VR platform and their final evaluation after completing the tasks in the VR environment. It is a rating out of 10. The mean Pre-VR Rank score is 5.75 ($\sigma = 1.45$), indicating that participants had moderate expectations before using the VR platform. With a minimum score of 3.0 and a maximum score of 8.0, participants' initial expectations ranged from low to relatively high. The mean Post-VR Rank score increased to 7.90 ($\sigma = 1.02$), which shows that participants' evaluations of the VR platform were significantly higher after using it. The increase in scores reflects a positive change in perception and a strong endorsement of the VR platform's effectiveness. The mean change in rank from Pre-VR to Post-VR is 2.15 points ($\sigma = 0.90$), showing a substantial improvement in participants' perceptions after using the VR platform. The positive shift across all participants (min = 0.5, max = 4.0) indicates that the VR platform exceeded initial expectations for most users. The results for this can be seen in Table V.

Table V: Descriptive Statistics of Pre-VR and Post-VR Rank Scores

Measure	Mean	Std. Dev	Min	Max
Pre-VR Rank	5.75	1.45	3.0	8.0
Post-VR Rank	7.90	1.02	5.5	9.5
Change	2.15	-0.43	+2.5	-1.5

The results of the user experience testing demonstrate that the VR platform successfully provided an effective and user-friendly environment for interacting with complex EEG data. The analysis of the NASA-TLX, SUS, and iPQ scores reveals that participants perceived the system as having an excellent level of usability, manageable cognitive load, and a high sense of presence and involvement. The NASA-TLX results indicated that while the VR platform required a moderate level of mental effort, it did not lead to excessive physical strain or frustration, enabling participants to focus on the task without significant distractions.

Furthermore, the high SUS score of 81.3 suggests that users found the platform intuitive and well-designed, placing it on par with established commercial software. The iPQ scores also highlight a strong sense of spatial presence and realism, which are essential for effective data interpretation in a VR setting. The positive shift from pre-VR to post-VR rankings indicates that participants' expectations were exceeded, with users expressing greater satisfaction after completing the tasks.

2) Comparative Analysis: Experts vs. Non-Experts: One of the research objectives was to evaluate the impact of expertise on user performance and experience within the VR platform. The study classified participants into two groups: experts (those with professional experience in EEG analysis, n=4) and non-experts (individuals without such experience n=16). This section of the analysis will look at the differences between experts and non-experts in terms of their experience within the VR platform, this is important to ensure that the experience of the platform is consistent across all users. A summary of the comparative analysis is provided in the Table VI with the results of the t-test and p-values showing the significance of the differences between the two groups.

- ***NASA-TLX Scores:***

  Mental Demand: Experts ($\bar{x} = 8.5$) [141] reported slightly lower mental workload compared to non-experts ($\bar{x} = 9.3$), but the difference was not statistically significant (p = 0.66) [142]. This suggests that both groups found the VR-based

Table VI: Comparative Analysis of NASA-TLX, SUS, and iPQ Scores between Experts and Non-Experts

Measure	Experts (Mean ± SD)	Non-Experts (Mean ± SD)	T-Statistic	P-Value
NASA-TLX (Mental)	8.5 ± 4.8	9.3 ± 5.5	-0.45	0.66
NASA-TLX (Physical)	4.2 ± 1.3	4.5 ± 1.0	-0.58	0.57
NASA-TLX (Temporal)	1.0 ± 1.2	1.3 ± 1.4	-0.68	0.50
NASA-TLX (Effort)	7.5 ± 3.4	8.1 ± 4.0	-0.45	0.66
NASA-TLX (Frustration)	3.8 ± 3.0	4.1 ± 3.6	-0.24	0.81
SUS Score	82.5 ± 7.8	80.0 ± 9.5	0.83	0.41
iPQ Spatial Presence	14.6 ± 4.8	14.1 ± 5.2	0.25	0.81
iPQ Involvement	16.5 ± 2.7	17.6 ± 3.2	-0.93	0.36
iPQ Realism	19.0 ± 4.5	15.75 ± 4.0	1.97	0.05

EEG analysis tasks to be mentally challenging but manageable. The slightly lower scores for experts could indicate their familiarity with the subject matter, making the cognitive load less intense.

Physical Demand: The physical demand scores were low for both groups (Experts: $\bar{x} = 4.2$; Non-Experts: $\bar{x} = 4.5$), indicating that the platform did not require significant physical exertion. This finding is consistent with the nature of the tasks, which involved minimal physical interaction.

Effort and Frustration Ratings: The effort and frustration ratings were comparable between the groups. Experts rated the effort slightly lower ($\bar{x} = 7.5$) compared to non-experts ($\bar{x} = 8.1$), indicating that they found the tasks to require less effort. Frustration levels were also low across both groups, suggesting that the platform was generally easy to use. The results of the NASA-TLX scores and how the experts and non experts scored are illustrated in Figure 15.

- ***System Usability Scores:***

  The SUS scores provide an overall assessment of usability. Experts reported a slightly higher mean SUS score ($\bar{x} = 82.5$) compared to non-experts ($\bar{x} = 80.0$) , but this difference was not statistically significant (p = 0.41).This result indicates that both groups found the platform highly usable and easy to interact with. The slightly higher SUS scores for experts may reflect their prior experience with similar systems or a better understanding of the visualised data, making the VR environment more intuitive for them. A box plot of the SUS scores for experts and non-experts is shown in Figure 16.

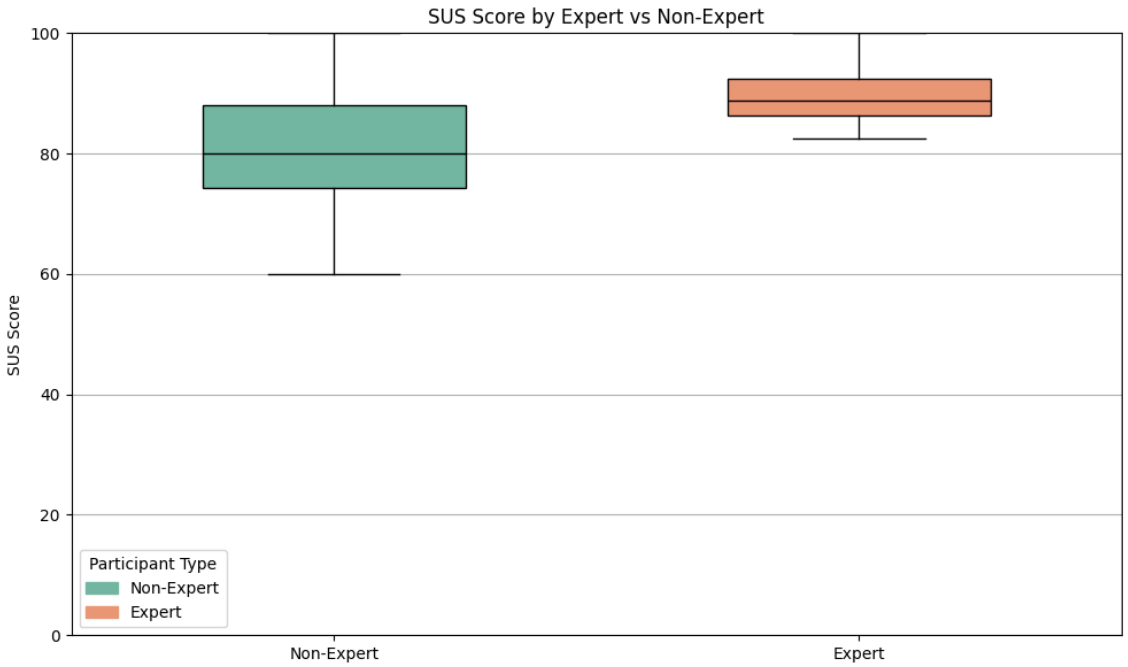


Figure 16: SUS Scores Comparison

- ***iPQ Scores:***

  Spatial Presence: Both experts ($\bar{x} = 14.6$) and non-experts ($\bar{x} = 14.1$) reported similar levels of spatial presence, indicating that the VR platform successfully immersed all participants in the virtual environment.

  Involvement: Non-experts had a slightly higher involvement score ($\bar{x} = 17.6$) compared to experts ($\bar{x} = 16.5$), but this difference was not statistically significant (p = 0.36). This may suggest that non-experts were more absorbed by the novelty of the VR environment, whereas experts might have been more focused on the analytical aspects of the task.

  Realism: The realism score was significantly higher for experts ($\bar{x} = 19.0$) compared to non-experts ($\bar{x} = 15.75$) with a p-value of 0.05. This suggests that experts found the VR environment more realistic and credible, possibly because they were better able to evaluate the fidelity and accuracy of the EEG visualisations based on their prior knowledge. A visual representation of the iPQ scores for experts and non-experts is shown in Figure 17.

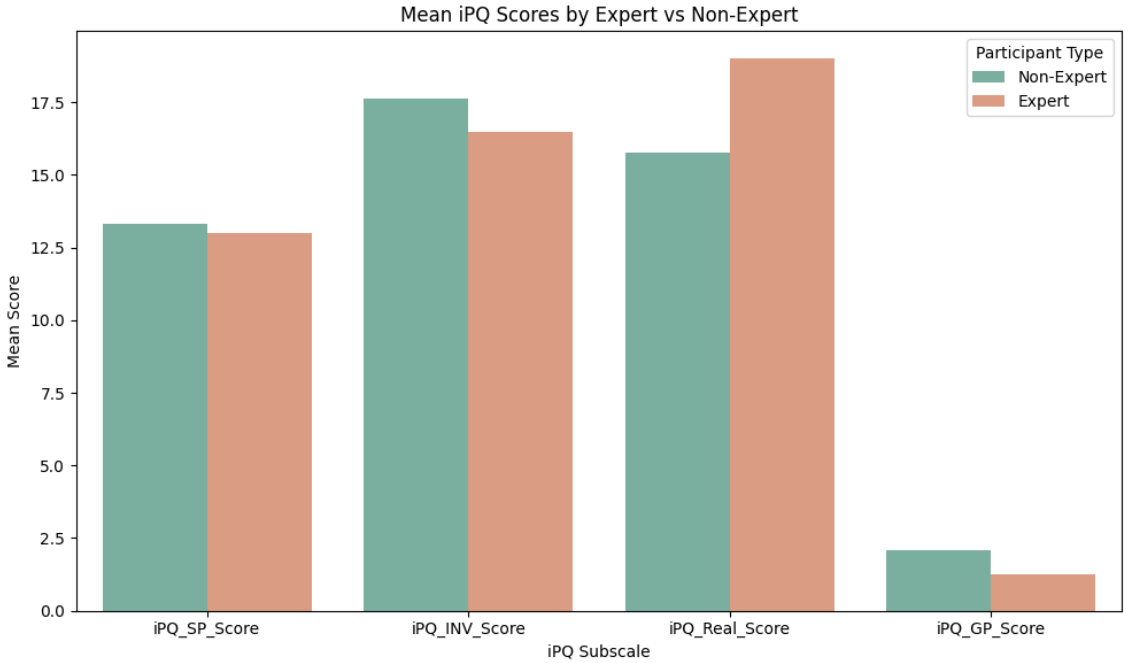


Figure 17: iPQ Scores Comparison

- ***Pre-VR and Post-VR Rank Scores:***

  The Pre-VR and Post-VR Rank scores for both experts and non-experts were analysed to assess any differences in expectations and final evaluations of the VR platform. Comparing these scores helps identify whether the platform had a more substantial impact on one group over the other and if their initial expectations were aligned with the final experience. Table VII shows the results of the Pre-VR and Post-VR Rank scores for experts and non-experts.

Table VII: Descriptive Statistics of Pre-VR and Post-VR Rank Scores for Experts and Non-Experts

Group	**Measure**	**Mean**	**Std. Dev**	**Min**	**Max**
Experts	Pre-VR Rank	5.8	1.5	4.0	8.0
	Post-VR Rank	8.2	0.8	6.5	9.5
Non-Experts	Pre-VR Rank	5.7	1.4	3.0	7.5
	Post-VR Rank	7.7	1.1	5.5	9.0
All Participants	Pre-VR Rank	5.75	1.45	3.0	8.0
	Post-VR Rank	7.90	1.02	5.5	9.5

When examining the Pre-VR and Post-VR Rank scores separately for experts and non-experts, the data reveal that both groups entered the study with similar expectations, as indicated by the Pre-VR Rank scores of experts ($\bar{x} = 5.8$, $\sigma = 1.5$) and non-experts ($\bar{x} = 5.7$, $\sigma = 1.4$). This similarity was confirmed by an inde-

pendent samples t-test, which yielded a p-value of 0.78, indicating no significant difference between the initial expectations of the two groups. After using the VR platform, however, experts rated the Post-VR Rank significantly higher ($\bar{x} = 8.2$, $\sigma = 0.8$) than non-experts ($\bar{x} = 7.7$, $\sigma = 1.1$), with a p-value of 0.03. This statistically significant difference suggests that experts perceived more value in the VR environment's ability to present EEG data in a realistic and meaningful way, which could be attributed to their familiarity with EEG data and their ability to better appreciate the platform's advanced visualisation capabilities. While non-experts also showed a positive shift in their evaluations, their slightly lower Post-VR Rank suggests that they may have found the VR environment beneficial but required additional support or guidance to fully utilise its features. This significant difference highlights the need for further refinement of the platform to enhance its accessibility and ease of use for non-experts, ensuring a universally positive experience across user groups. A visual representation of the Pre-VR and Post-VR Rank scores for experts and non-experts is shown in Figure 18.

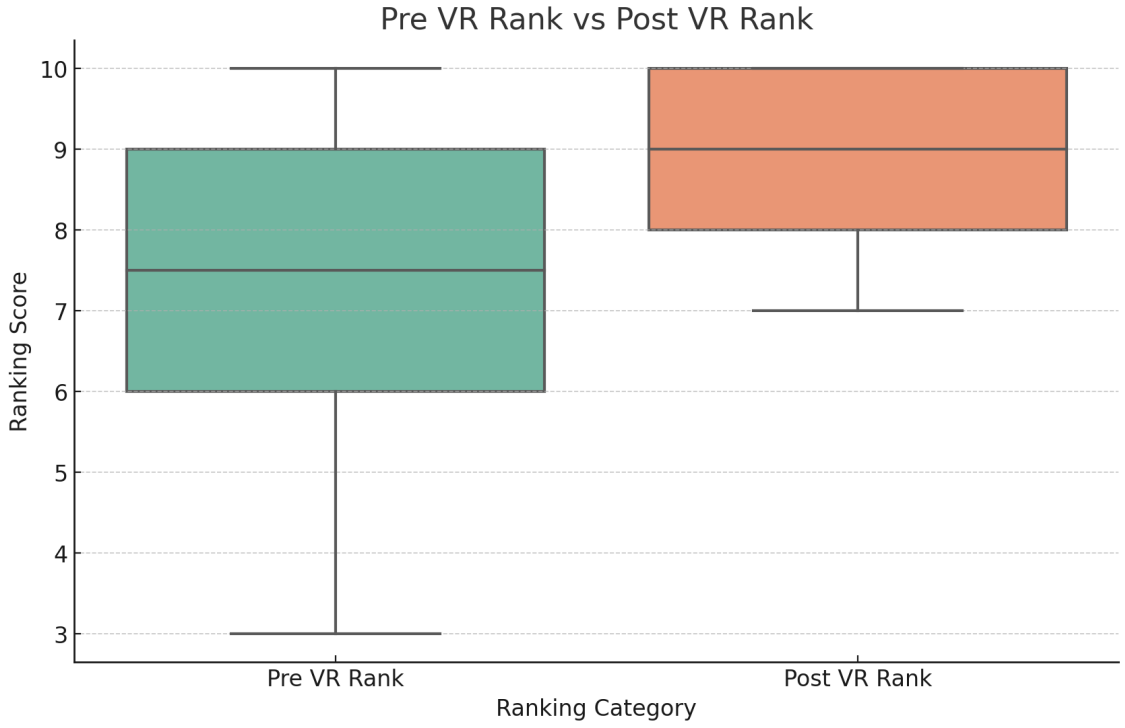


Figure 18: Pre-VR and Post-VR Rank Scores Comparison

Overall, the NASA-TLX, iPQ, and SUS scores show that both experts and non-experts perceived the VR-based EEG visualisation platform positively, with high usability, moderate mental workload, and a strong sense of immersion. The platform successfully

supports users of different expertise levels, with no major usability or workload barriers. However, the differences in perceived realism suggest that future iterations of the platform could include additional features to enhance visual fidelity and interactivity, ensuring that both novice and expert users find the environment equally realistic and engaging. Similarly, the Pre-VR and Post-VR Rank analysis further reinforces these findings by demonstrating a significant positive shift in participants' evaluations after using the VR platform. While both groups entered the study with similar expectations, as reflected in comparable Pre-VR Rank scores, experts reported a significantly higher Post-VR Rank than non-experts after experiencing the platform. This indicates that experts were able to better leverage the VR environment's advanced features for analysing EEG data, likely due to their prior familiarity with the subject matter. Non-experts, while also showing a positive shift in their evaluations, may have needed additional guidance to fully grasp the potential of the VR platform. These findings highlight the importance of making further refinements to the platform, such as incorporating more tutorials or interactive elements, to ensure that the VR experience is accessible and beneficial for users of all expertise levels.

3) Correlation Analysis: A correlation analysis was conducted to explore the relationships between different user experience measures and identify potential patterns or associations [143]. The analysis focused on examining the correlations between the NASA-TLX, SUS, and iPQ scores to understand how different aspects of the user experience interact and influence each other. The results of the correlation analysis are presented in Table VIII.

The correlation analysis of factors affecting the *Post-VR Rank* reveals that several variables significantly influence a participant's rank after the VR experience. Notably, the SUS Score has the strongest positive correlation at 0.755, indicating that participants who found the VR experience more usable tended to achieve higher post-VR rankings. This suggests that usability is a critical factor in determining user performance and satisfaction in VR environments. Additionally, the Pre VR Rank shows a substantial positive correlation of 0.595, indicating that participants with higher pre-VR ranks generally maintain their performance levels post-VR. This highlights the influence of prior experience and skill on post-VR outcomes. The iPQ Real Score also shows a positive correlation of 0.424, suggesting that participants who perceived the VR

Table VIII: Correlation Analysis of Factors Affecting Post-VR Rank

Variable	**Correlation with Post-VR Rank**
SUS_Score	0.755
Pre VR Rank	0.595
iPQ_Real_Score	0.424
Temporal Weight	0.358
Effort Weight	0.337
iPQ_SP_Score	0.318
iPQ_INV_Score	0.234
Effort Rating	0.170
VR Experience	0.167
Mental Weight	0.147
Expert	0.111
Performance Weight	-0.003
30+	-0.097
Physical Rating	-0.120
Physical Weight	-0.178
Temporal Rating	-0.350
Video Game Experience	-0.386
Mental Rating	-0.393
Performance Rating	-0.410
Participant	-0.425
Frustration Weight	-0.443
iPQ_GP_Score	-0.471
Weighted TLX Score	-0.476
RAW TLX Score	-0.529
Frustration Rating	-0.799

environment as more realistic tended to perform better post-VR. This underscores the importance of creating immersive and engaging VR experiences to enhance user performance and satisfaction.

On the other hand, Frustration Rating shows a strong negative correlation (-0.799) with post-VR rank, signifying that increased frustration levels drastically reduce post-VR performance. Other negative correlations, such as RAW TLX Score (-0.529) and Weighted TLX Score (-0.476), further support the notion that higher perceived workload impedes performance. This suggests that minimizing task load and frustration during the VR experience could lead to better post-VR outcomes.

In conclusion, ensuring high usability and reducing frustration and workload are key to improving post-VR performance. Pre-existing skills and the ability to accurately interpret visual information also play crucial roles in determining post-VR success. By addressing these factors, the VR platform can enhance user experience, engagement, and performance, leading to more effective EEG data analysis and interpretation.

4) Qualitative Feedback: The qualitative feedback provided by participants was gathered through open-ended questions included in the post-experiment questionnaire. This section aims to present the key themes identified from the feedback, offering deeper insights into the user experience and potential areas for improvement in the VR-based EEG visualisation platform.

Participants were asked to provide comments on their experience with the VR environment, focusing on usability, immersion, and any challenges they encountered. Feedback was gathered from all participants, including both experts and non-experts, to ensure a diverse range of perspectives.

Key Themes: Several themes emerged from the qualitative feedback, highlighting both positive aspects of the VR platform and areas for improvement. The key themes identified are as follows:

- **Usability and Interaction:** Participants appreciated the intuitive design of the VR interface, noting that the ability to manipulate EEG data in a 3D space was particularly beneficial for understanding complex patterns. In particular, amongst the experts, one stated their most liked aspect was, *"Moving different elements each filling their own field of view and being able to move between them easily."* Another expert noted that while they liked all the features but they would like to see *"the screens more condensed so that I could read both the raw EEG and the frequency bands at the same time."* This feedback suggests lack of explanation at the start as the user can already move around the screens and condense them to suit their own needs. This highlights the need for a more in-depth walk through in the future.
- **Immersiveness and Engagement:** The immersive nature of the VR environment was frequently mentioned as a positive aspect. Participants felt that the VR setting enhanced their focus and engagement with the data. One related point of note is that one participant noted that the VR environment was *"too bright and hurt my eyes"* while another said that their least favourite aspect was the fact that they *"couldn't see what was going on around them"*. Both of these highlight the need to move the platform into the Augmented Reality or Mixed Reality sphere. This would allow the user to see their surroundings while still being able to interact with the data and have less bright light in the users' eyes.

- **Suggestions for Improvement:** While the feedback was positive, the participants offered some valuable suggestions for improvement. The most consistent feedback was with regards to the buttons being inconsistent. This was noticeable when watching the users interact with the dropdown menus in the environment. The target clickable area for these was too small for the size of the button, with some users requiring guidance to click on the correct area. This was also noted in the feedback with one participant stating that *"A larger button would be useful to grab onto for the slider and the dropdown menu, sometimes it was hard to point the controller at the exact spot"*.

The qualitative feedback provides valuable insights into participants' experiences with the VR platform, highlighting the strengths and weaknesses of the system. The positive feedback on usability and immersion underscores the platform's potential for enhancing EEG data analysis and interpretation. However, the suggestions for improvement, particularly regarding button consistency and size, point to areas that require further refinement to enhance user experience and accessibility. By addressing these feedback points, the VR platform can be optimised to better meet users' needs and expectations, ensuring a more effective and engaging environment for EEG data visualisation.

B. Clinical Diagnosis Testing

The clinical diagnosis testing aimed to evaluate the platform's effectiveness in supporting accurate and efficient EEG data interpretation for clinical purposes. Participants were presented with a series of EEG recordings and asked to diagnose each recording as either seizure or non-seizure data. The EEG recordings were selected from the Helsinki dataset [35] and had been previously labelled by three expert neurologists. The participants' diagnoses were compared to the expert labels to assess the accuracy of their clinical judgments. The results of the clinical diagnosis testing are presented below.

1) Descriptive Statistics: Table IX presents the descriptive statistics for three different performance measures: Sound, Visualisation, and Combined. Each measure captures the participants' performance across different modalities used to detect seizures in the VR environment. The mean scores indicate that participants performed best when using

both sound and visualisation (Combined $\bar{x} = 7.60$), followed by the visualisation alone (Visualisation $\bar{x} = 6.10$) and sound alone (Sound $\bar{x} = 5.50$).

The standard deviation is relatively consistent across the three measures, ranging from 1.23 for the Combined to 1.28 for the Sound, suggesting that there was similar variability in participants' performance across all conditions. The minimum and maximum values show that participants scored between 3 and 8 for the Sound, between 4 and 8 for the visualisation, and between 5 and 10 for the Combined. This indicates a wider range of performance when both modalities are combined.

Table IX: Descriptive Statistics for Sound, Visualisation, and Combined Scores

Statistic	**Sound**	**Visualisation**	**Combined**
Mean	5.50	6.10	7.60
Std. Dev.	1.28	1.25	1.23
Minimum	3.00	4.00	5.00
Maximum	8.00	8.00	10.00

The results are consistent with the hypothesis that combining sound and visualisation would lead to better performance in detecting seizures. The higher mean score for the Combined condition suggests that the multi-modal presentation of EEG data enhances participants' ability to identify seizure patterns accurately.

2) Comparative Analysis: Experts vs. Non-Experts: The comparative analysis of clinical diagnosis performance between experts and non-experts aimed to identify any differences in diagnostic accuracy based on participants' expertise levels. The results are presented in Table X. The table shows the mean scores for experts and non-experts across the Sound, Visualisation, and Combined measures, along with the standard deviations, t-statistics, and p-values. The t-statistics indicate the significance of the differences between the two groups, while the p-values show the probability of observing these differences by chance.

Table X: Comparison of Expert and Non-Expert Performance Across Measures

Category	**Expert Mean**	**Expert StdDev**	**NonExpert Mean**	**NonExpert StdDev**	**T-Statistic**	**P-Value**
Sound	5.5	0.577	5.5	1.41	0	1
Visualisation	6.25	0.957	6.06	1.34	0.261	0.796
Combined	8	1.154	7.5	1.26	0.72	0.48

The comparative analysis between expert and non-expert participants shows that there is little variation in performance across the three scores of: Sound, Visualisation, and

Combined. For the Sound measure, both experts and non-experts scored an average of 5.5, indicating no difference in performance (t-statistic = 0, p-value = 1). This suggests that participants, regardless of expertise, performed equally well in tasks based solely on sound information.

For the Visualisation measure, experts scored slightly higher ($\bar{x} = 6.25$) compared to non-experts ($\bar{x} = 6.06$), but the difference was not statistically significant (t-statistic = 0.261, p-value = 0.796). This lack of a significant difference indicates that visual-based tasks did not greatly differentiate participants based on expertise.

The Combined measure, which evaluates performance when using both sound and visual information, showed a slight increase in scores for experts ($\bar{x}$ = 8) compared to non-experts ($\bar{x}$= 7.5). Although experts had a higher average score, the difference was still not significant (t-statistic = 0.72, p-value = 0.48). This suggests that the combination of modalities did not result in a meaningful performance gap between the two groups. This is an interesting finding, given the difficult and complex nature of the task. Accurate EEG analysis takes years of training and experience, and the fact that non-experts were able to perform similarly to experts in this task is a promising result for the VR platform's usability and effectiveness. Below is a visual representation of the comparison between experts and non-experts in the clinical diagnosis testing.

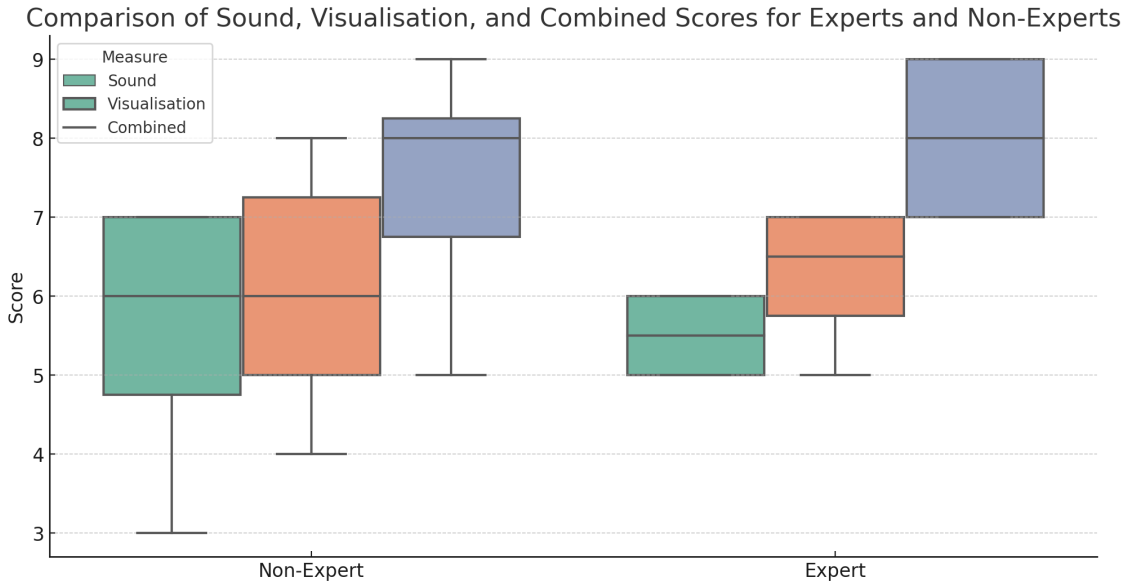


Figure 19: Clinical Diagnosis Comparison Between Experts and Non-Experts

3) Correlation Analysis: The correlation matrix illustrated in Figure 20 presents the relationships between performance measures, participant characteristics 30+, and Video

Game Experience. As expected, a moderate positive correlation is observed between the Sound and Combined scores (0.50), as well as between the Visualisation and Combined scores (0.51). This is no surprise as the outcome of the Combined score is a combination of the Sound and Visualisation scores.

Interestingly, Video Game Experience demonstrates a negative correlation with all performance measures: -0.23 with Sound, -0.14 with Visualisation, and -0.38 with Combined. This implies that participants with more video game experience did not necessarily perform better in the context of these tasks. The negative correlation with the Combined score is particularly notable, indicating that video game experience might even detract from overall performance when sound and visualisation are combined. This result could be attributed to the specific nature of the experimental tasks, which might not leverage skills typically developed through video gaming, such as quick reflexes or hand-eye coordination.

The 30+ variable, representing older participants, shows a weak correlation with performance scores. There is a slight positive correlation with the Sound (0.18) and Combined scores (0.13), suggesting that older participants performed slightly better in these areas, although the relationship is not strong. This is expected given the time required to become an expert in EEG analysis.

Overall, the correlation analysis suggests that while individual modality performance is strongly linked to combined performance, participant characteristics such as age and video game experience do not have a substantial positive impact on task performance. This finding could imply that the tasks used in the study do not align well with the skills typically associated with video game experience or that additional factors, such as task complexity and familiarity, might play a more critical role in influencing participant performance. This strengthens the argument that the VR platform's effectiveness in supporting EEG data interpretation is not significantly influenced by participants' age or video game experience, highlighting the platform's accessibility and usability across different user groups.

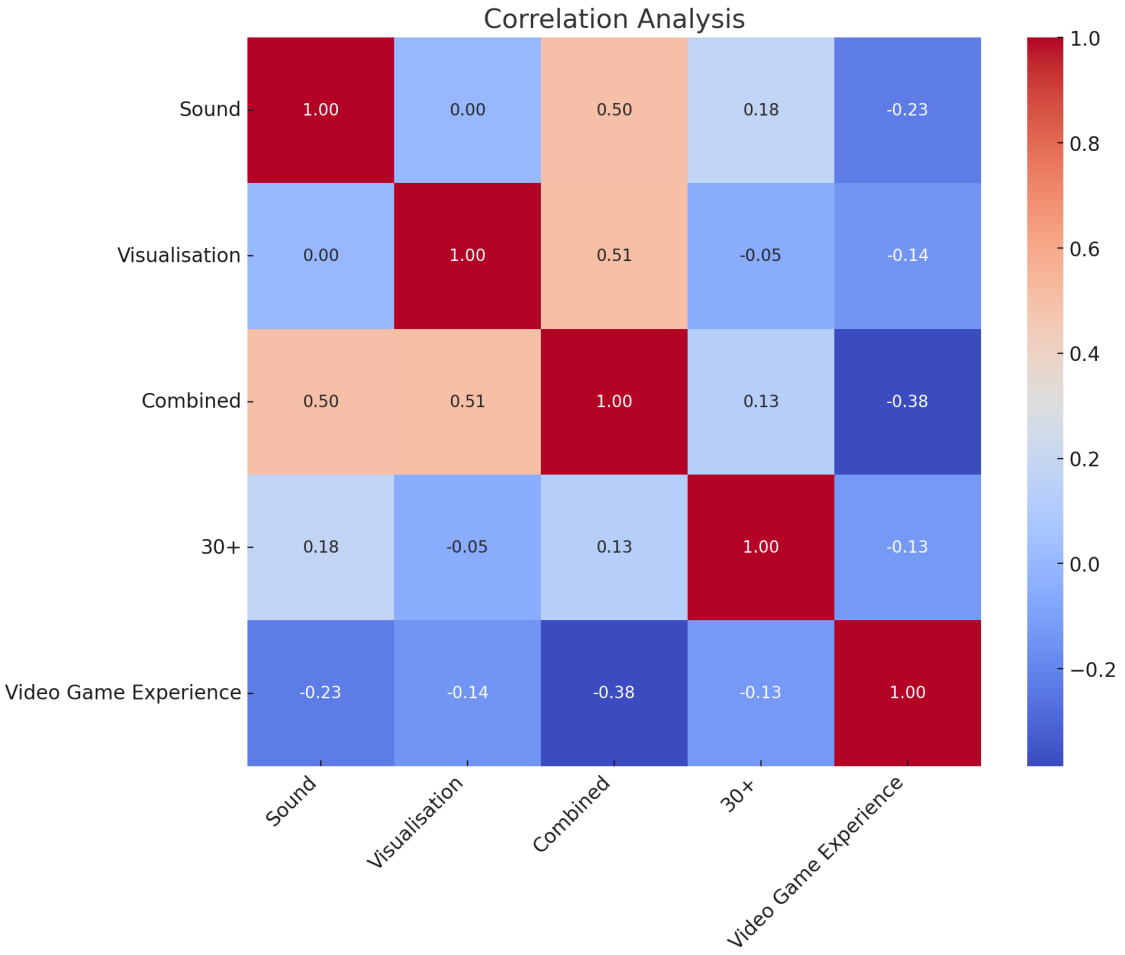


Figure 20: Correlation Analysis of Clinical Diagnosis Performance

C. Hardware Performance Testing

The hardware used in this research played a crucial role in determining the performance and feasibility of the VR-based EEG visualisation platform. Given the computational demands of rendering complex EEG data in real-time within an immersive 3D environment, the choice of hardware significantly impacted the responsiveness and usability of the system. This section provides an analysis of the hardware performance across different devices, including high-end and low-end computing systems as well as standalone VR headsets. To ensure that the testing was fair on all platforms, the same tasks and datasets were used across all devices. This was the VR questionnaire that the participants filled out when testing the clinical accuracy of the platform. The results of the hardware performance testing are presented below. It is worth noting that the PICO NEO 3 Pro is capped at 72 FPS but this can be over clocked to 90 FPS in the developer settings.

1) Testing on High End Computer: The high-end computing system used in this research was equipped with an AMD Ryzen Threadripper PRO 3945WX processor, an NVIDIA RTX A6000 GPU, and 128GB of RAM. This setup provided ample computational power for handling the real-time processing and rendering requirements of the EEG data. This computer would not be the typical setup for a clinical environment, but it was used to test the upper limits of the VR platform's performance capabilities and during the development of the platform. This PC scored a benchmark of 98% from an open source PC Benchmark Test. The full results can be seen in the Appendix P [144]. The results of the hardware performance testing on the high-end computer are presented in Table XI.

Table XI: Hardware Performance Testing on High-End Computer

Metric	**Mean**
Frame Rate (FPS)	70.27
Latency (ms)	0.01
GPU Usage (GB)	8.07
Power Draw (W)	121.03

- *Frame Rate (FPS):* The high-end computer achieved an average frame rate of 70.27 FPS, indicating smooth and responsive performance during the VR tasks. The high frame rate ensured that EEG data visualisations were rendered in real-time without lag or stuttering, enhancing the overall user experience. The high frame rate is essential for maintaining immersion and reducing motion sickness in VR environments, making the platform more comfortable and engaging for users. A frame rate above 60 FPS is generally considered optimal for VR applications, and the high-end computer exceeded this threshold, providing a seamless and immersive experience for participants. A visual representation of the frame rate performance is shown in Figure 21. The following average for this graph and the following graphs are all windows of 10 seconds.

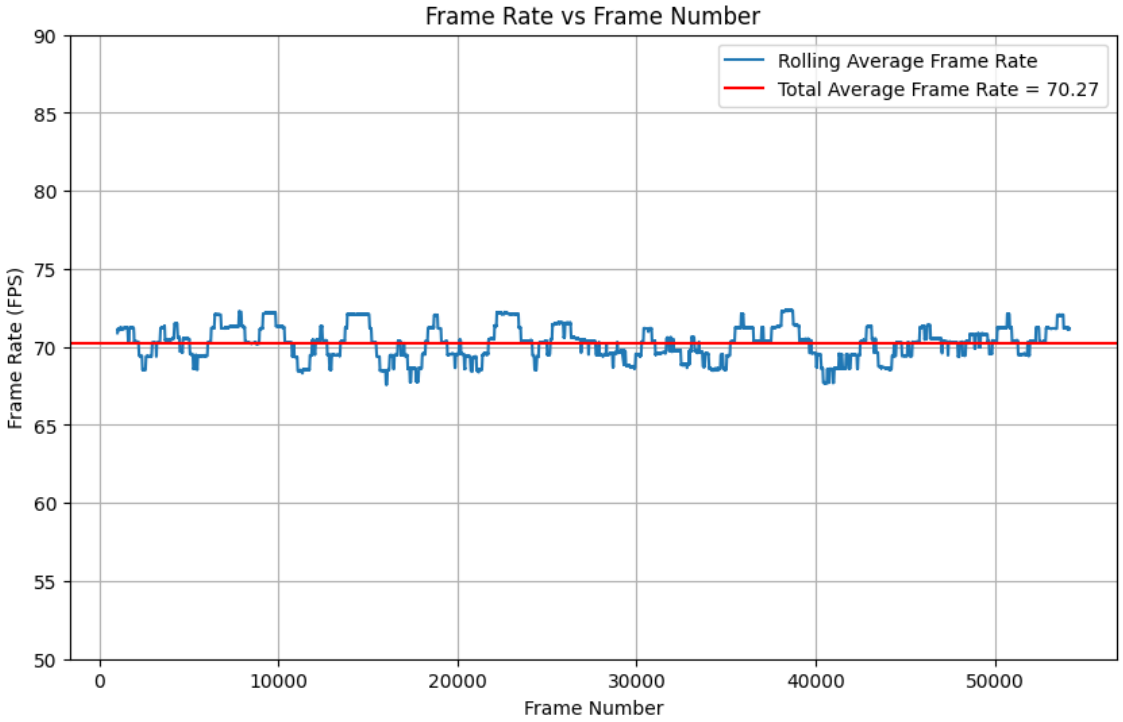


Figure 21: Frame Rate Performance on High-End Computer

- *Latency (ms):* The latency of 0.01 ms was negligible, indicating minimal delay between user input and system response. Low latency is critical for VR applications to ensure that interactions feel natural and responsive, preventing motion sickness and enhancing user engagement. The low latency on the high-end computer contributed to a seamless and immersive VR experience, allowing participants to interact with EEG data in real-time without noticeable delays. In Figure 22 illustrates a visual representation of the latency performance on the high-end computer. The peaks and troughs in the graph are due to the nature of the tasks that the participants were completing. The more challenging the task, the higher the latency. Latency was highest when the participants were asked to move the EEG data around the environment or else when they interacted with the 3D Brain model. However, the latency was still very low and did not impact the participants' experience.

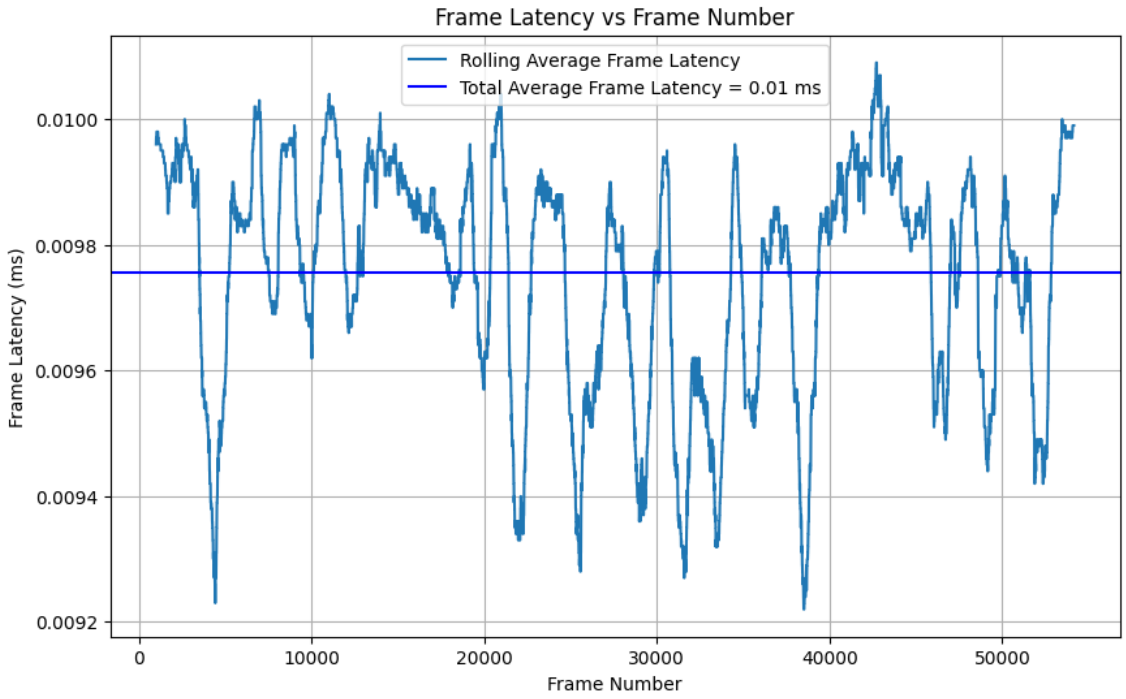


Figure 22: Latency Performance on High-End Computer

- *GPU Usage (GB):* The GPU usage of 8.07 GB indicated that the platform efficiently utilised the GPU resources to render complex EEG visualisations. The high GPU usage reflects the computational demands of processing and displaying EEG data in a 3D environment, highlighting the importance of powerful graphics hardware for optimal performance. The efficient GPU usage on the high-end computer ensured that EEG data was visualised accurately and in high detail, enhancing the platform's usability and effectiveness for EEG analysis. As shown in Figure 23, the GPU usage remained stable throughout the testing period, indicating consistent performance and resource management.

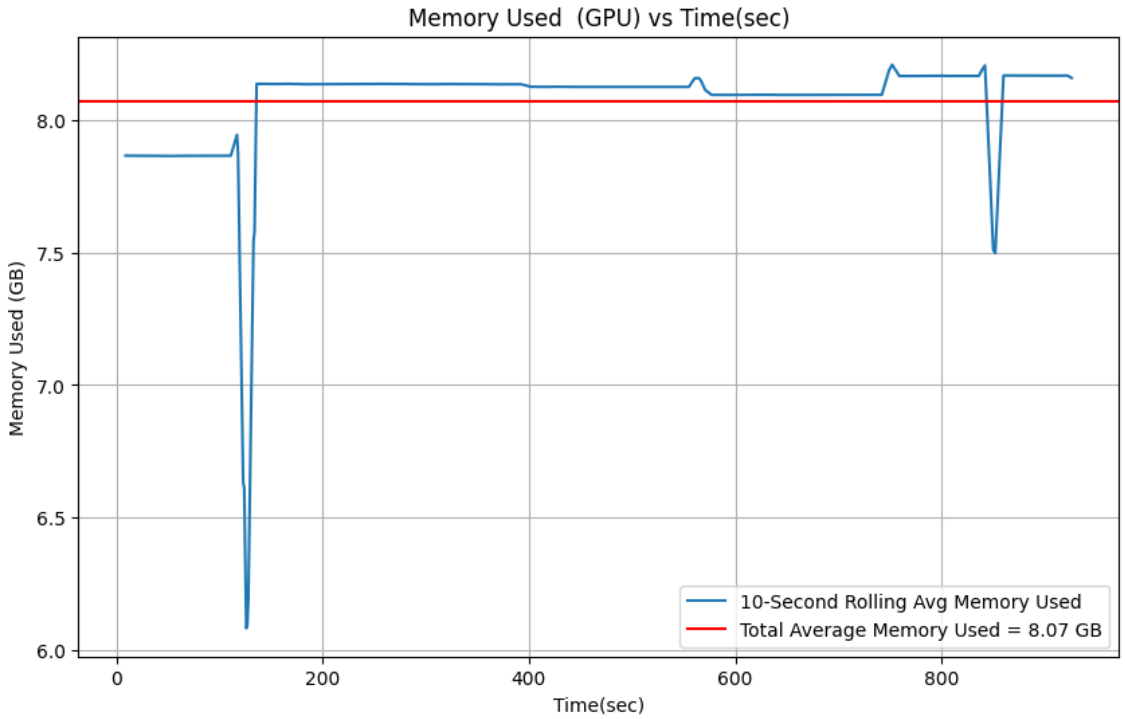


Figure 23: GPU Usage Performance on High-End Computer

- *Power Draw (W):* The power draw of 121.03 W was within the expected range for a high-end computing system with a powerful CPU and GPU. The power draw reflects the system's energy consumption during intensive VR tasks, such as rendering complex 3D visualisations and processing real-time EEG data. While high power draw is typical for high-performance computing systems, it is essential to consider energy efficiency and cooling requirements to maintain system stability and longevity. The power draw of 121.03 W on the high-end computer was manageable and did not impact the system's performance or reliability during testing. Similar to the other metrics, the power draw remained reltively stable throughout the testing period, as shown in Figure 24.

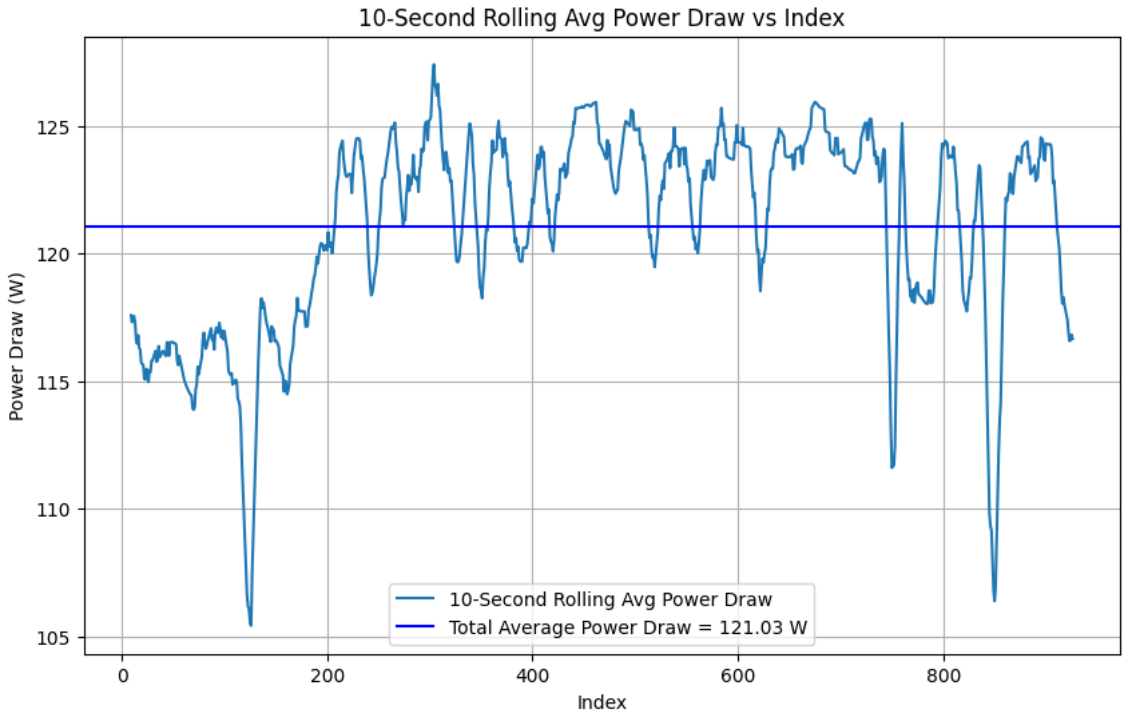


Figure 24: Power Draw Performance on High-End Computer

As expected with a computer of this calibre, there were no significant performance issues during the testing. The high frame rate, low latency, efficient GPU usage, and manageable power draw demonstrated the high-end computer's capability to support real-time EEG visualisation in a VR environment. The system's powerful hardware ensured smooth and responsive performance, enabling participants to interact with EEG data accurately and effectively. The results of the hardware performance testing on the high-end computer validate the platform's potential for clinical applications but do not make the platform accessible to a wider audience due to the high cost of the hardware. Therefore, further testing on low-end computers and standalone VR headsets was conducted to evaluate the platform's performance on more affordable and accessible devices.

2) Testing on Low End Computer: The low-end computer system consisted of Intel Core i7-10700, a NVIDA T1000 Graphics card and just 16GB of RAM. This is the standard computer that is available to researchers in our research lab. While a relatively new computer, it is designed for everyday computing and not VR Gaming. This PC scored just 50% in the PC Benchmark Test. The full results can be seen in Appendix Q [144]. The results of the hardware performance testing on the low-end computer are presented in Table XII.

Table XII: Hardware Performance Testing on Low-End Computer

Metric	Mean
Frame Rate (FPS)	70.07
Latency (ms)	0.01
GPU Usage (GB)	6.4
Power Draw (W)	123.01

- *Frame Rate (FPS):* The low-end computer achieved an average frame rate of 70.27 FPS, matching the performance of the high-end computer. This result indicates that the low-end computer was able to render EEG visualisations in real-time without lag or stuttering, providing a smooth and responsive user experience. The consistent frame rate ensured that participants could interact with EEG data accurately and effectively, enhancing the platform's usability and accessibility. The frame rate performance on the low-end computer is shown in Figure 25.

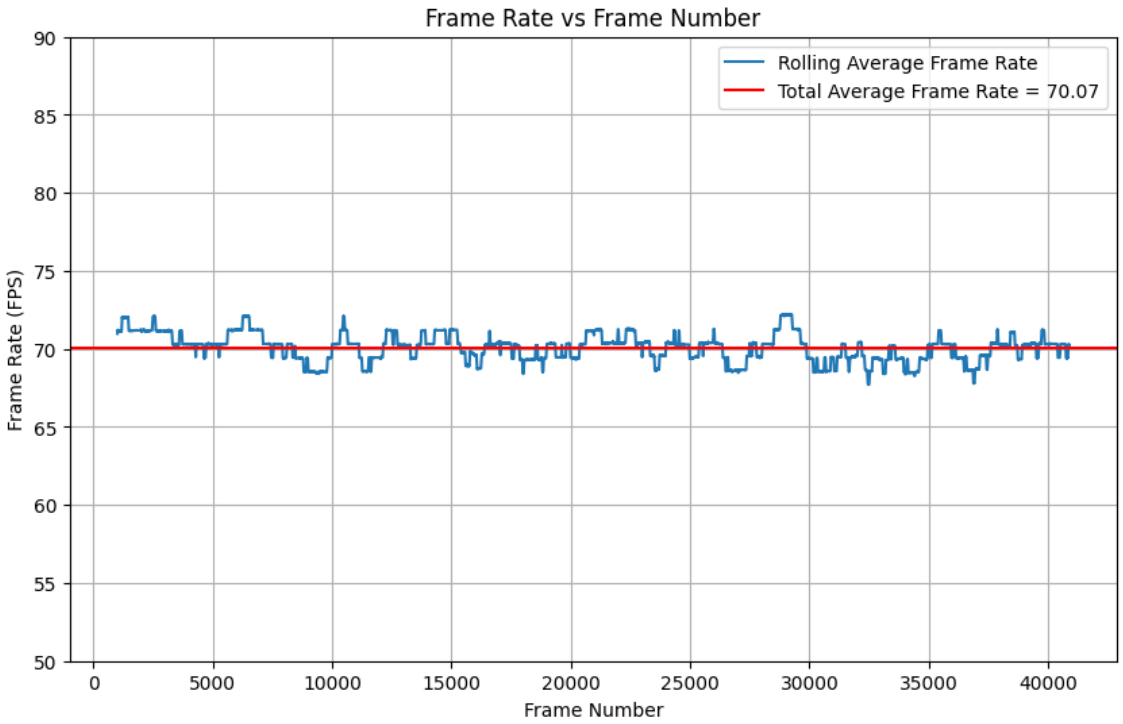


Figure 25: Frame Rate Performance on Low-End Computer

- *Latency (ms):* The latency of 0.01 ms on the low-end computer was identical to that of the high-end computer, indicating minimal delay between user input and system response. The low latency ensured that interactions with EEG data were natural and responsive, enhancing the overall user experience. The low-end computer's ability to maintain low latency during VR tasks demonstrates its suitability for real-time

EEG visualisation and analysis. The latency performance on the low-end computer is shown in Figure 26.

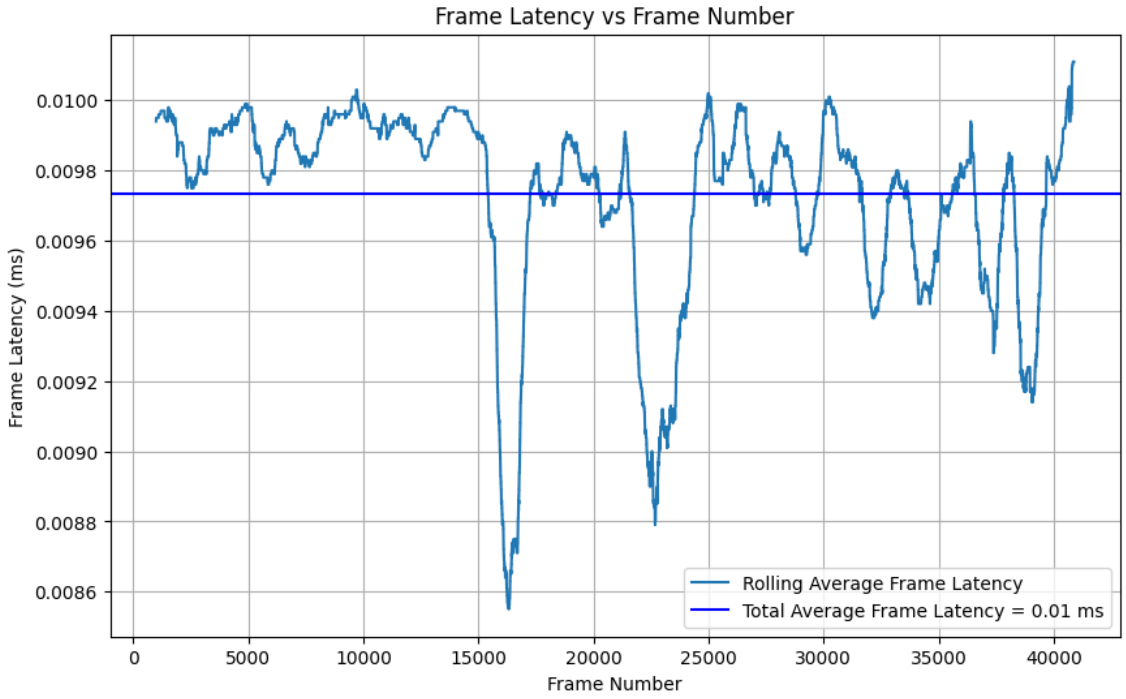


Figure 26: Latency Performance on Low-End Computer

- *GPU Usage (GB):* The GPU usage of 6.4 GB on the low-end computer was slightly lower than that of the high-end computer, but still within an acceptable range for rendering complex EEG visualisations. The efficient GPU usage indicates that the low-end computer effectively utilised its graphics resources to process and display EEG data in a 3D environment. The stable GPU usage throughout the testing period demonstrates the system's ability to manage resources efficiently and maintain consistent performance. The GPU usage performance on the low-end computer is shown in Figure 27.

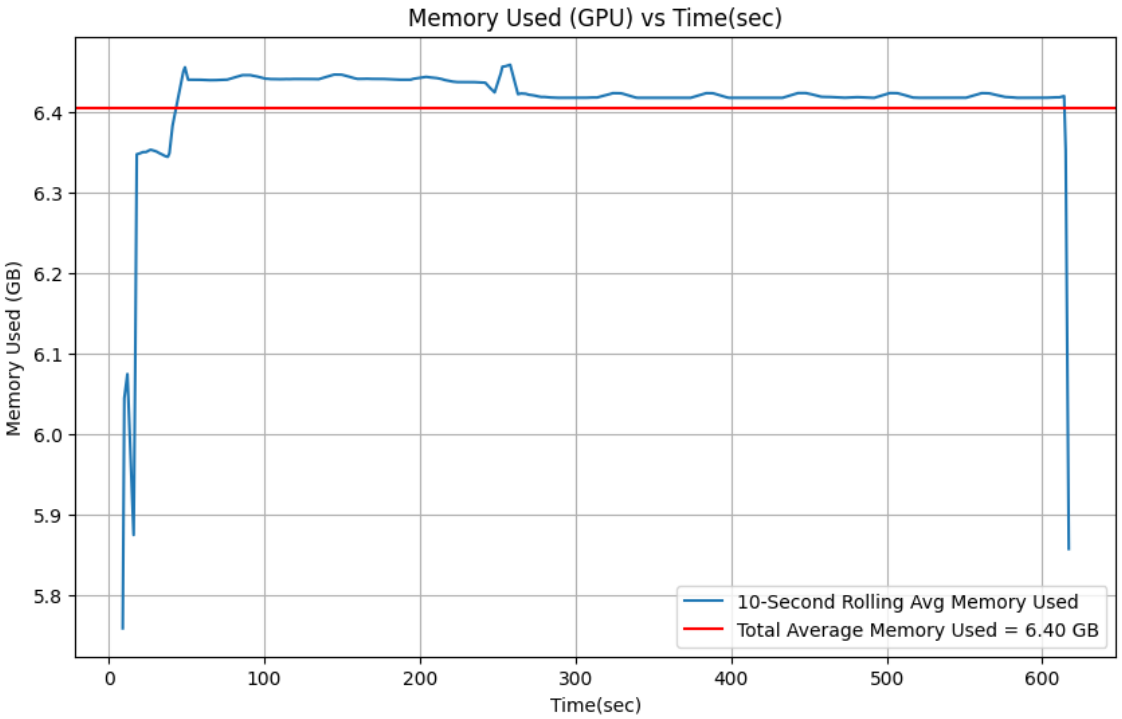


Figure 27: GPU Usage Performance on Low-End Computer

- *Power Draw (W):* The power draw of 123.01 W on the low-end computer was slightly higher than that of the high-end computer but still within an acceptable range for everyday computing systems. The power draw reflects the system's energy consumption during VR tasks and highlights the importance of energy efficiency and cooling management. The manageable power draw on the low-end computer ensured that the system remained stable and reliable during testing, providing a consistent user experience. The power draw performance on the low-end computer is shown in Figure 28.

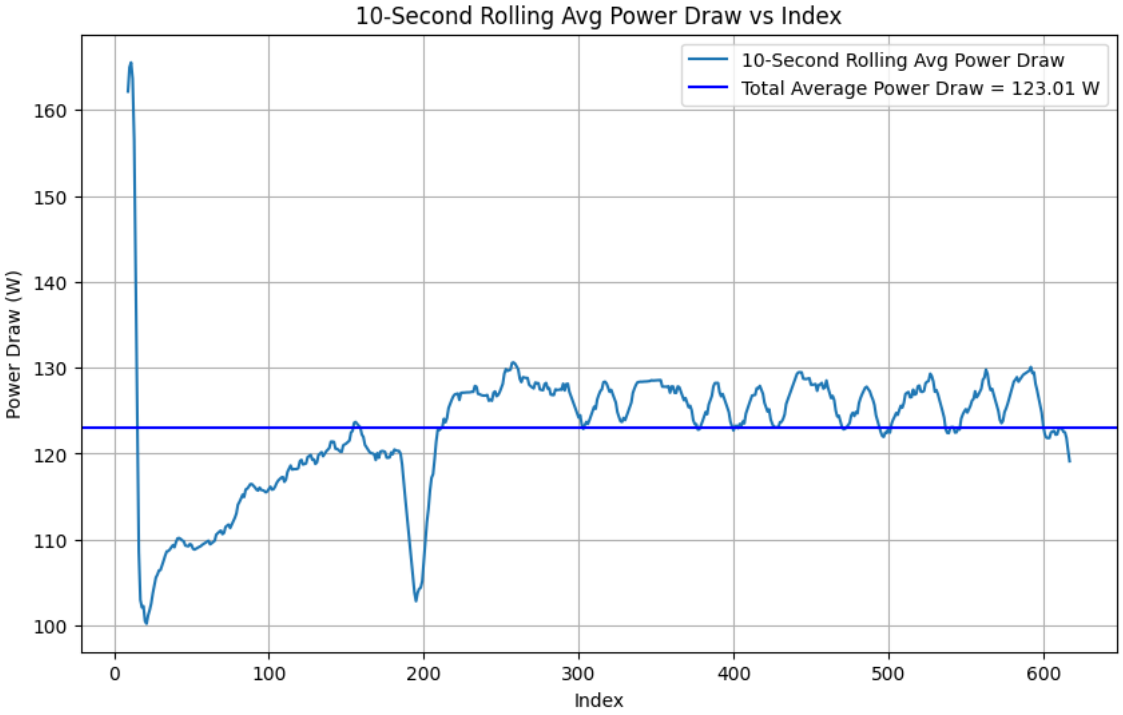


Figure 28: Power Draw Performance on Low-End Computer

The low end system had a surprising performance that was on par with the high end system. The frame rate, latency, GPU usage, and power draw were all within acceptable ranges for VR applications, demonstrating the low-end computer's capability to support real-time EEG visualisation. The results of the hardware performance testing on the low-end computer validate the platform's potential for use on more affordable and accessible devices, making it suitable for a wider range of users and settings. It is worth noting that the low-end computer was able to run the VR platform without any issues, but the high-end computer was able to run the platform with more ease and less strain on the system. This can be seen in both the GPU usage and power draw. In both sets of graphs there are 10 peaks which are visible. These are the moments when the EEG that was being visualised was changed. This caused a spike in the GPU usage and power draw. Despite the increase in GPU usage and power draw, the FPS did not experience a significant drop at these points. This is a positive sign as it shows that the system is able to handle the increased load without any issues. It is also worth noting that the total GB of GPU power used in the high end computer (8.07GB) was higher than the low end computer (6.4GB). The high end PC even has a higher clock speed (1860 MHz) compared to the low end PC (1065 MHz). It is believed that the level of detail optimisation

in the VR platform is the reason for this decrease in GPU power.

3) Testing on Pico Neo 3 Pro: Finally, the most important test was to run this software on, a wireless standalone VR headset. The Pico Neo 3 Pro was used for this test. This headset is a standalone VR headset that is designed for enterprise use. It is powered by a Qualcomm Snapdragon XR2 processor and has 6GB of RAM. The same test that was carried out on the computers was carried out on the Pico Neo 3 Pro. Android Debug Bridge [145] was used to communicate with the device to pull data from it at a low level. These tests were able to read Frame Rate, GPU Memory, GPU Frequency and GPU Temperature. The results of which are presented in Table XIII. The GPU Temperature is important given the compact nature of the Pico Neo 3 Pro to ensure that the device does not overheat or begin to throttle performance due to the heat issues.

Table XIII: Hardware Performance Testing on Pico Neo 3 Pro

Metric	**Mean**
Frame Rate (FPS)	78
GPU Memory (GB)	3.72
GPU Frequency (MHz)	471.64
GPU Temperature (C)	56.38

- *Frame Rate (FPS):* The Pico Neo 3 Pro achieved an average frame rate of 78 FPS, which is higher than the high-end and low-end computers. This result indicates that the standalone VR headset was able to render EEG visualisations in real-time with a smooth and responsive performance. While in standard mode the PICO headset is capped at 72FPS. However, with overclock, a maximum FPS of 90 FPS can be achieved. This does not work when tethered to the computer, which may have capped the FPS for the PC tethered tests of the High End and Low End PC. The frame rate performance on the Pico Neo 3 Pro is shown in Figure 29.

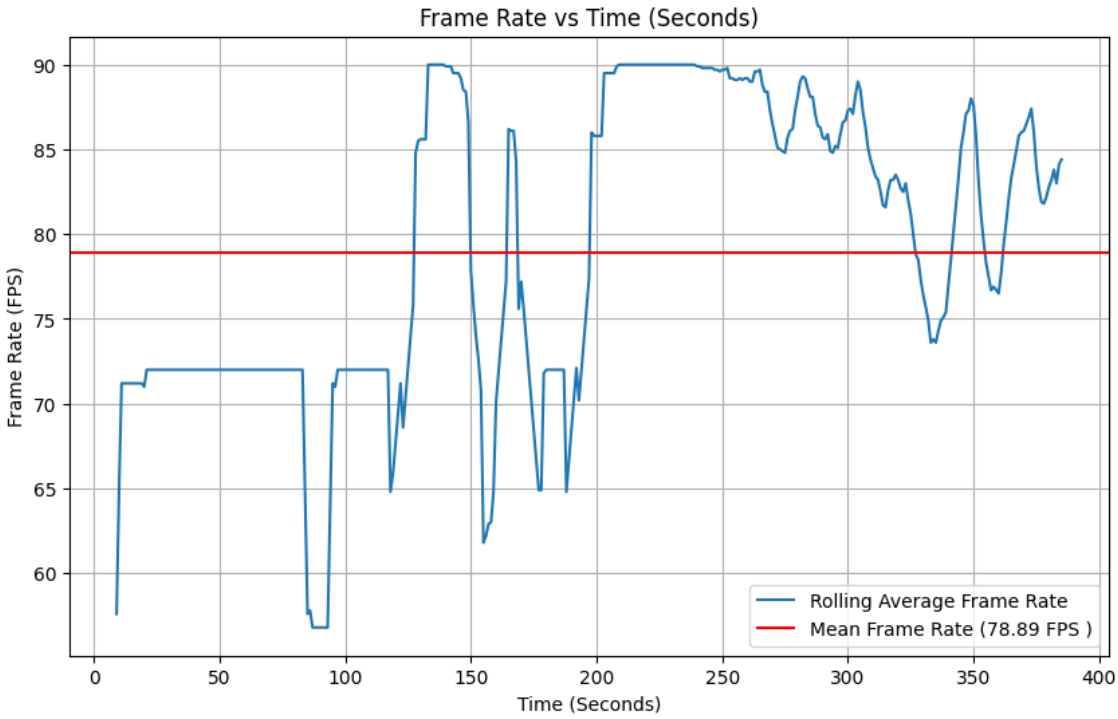


Figure 29: Frame Rate Performance on Pico Neo 3 Pro

- *GPU Memory (GB):* The GPU memory usage of 3.72 GB on the Pico Neo 3 Pro was lower than that of the high-end and low-end computers. This result indicates that the standalone VR headset efficiently utilised its graphics resources to process and display EEG data in a 3D environment. The stable GPU memory usage throughout the testing period demonstrates the system's ability to manage resources efficiently and maintain consistent performance. The GPU memory usage performance on the Pico Neo 3 Pro is shown in Figure 30.

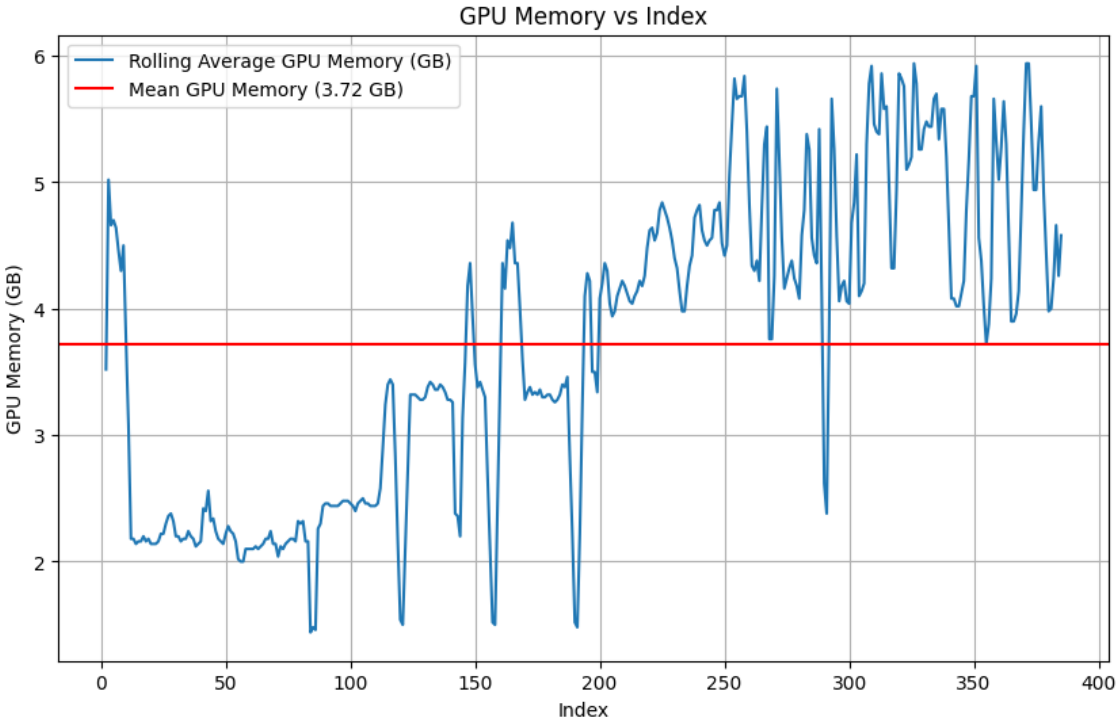


Figure 30: GPU Memory Performance on Pico Neo 3 Pro

- *GPU Frequency (MHz):* The GPU frequency of 471.64 MHz on the Pico Neo 3 Pro was lower than those of the high-end and low-end computers. This result indicates that the standalone VR headset operated at a lower clock speed to conserve power and maintain performance. The stable GPU frequency throughout the testing period demonstrates the system's ability to manage resources efficiently and optimise performance for VR applications. The GPU frequency performance on the Pico Neo 3 Pro is shown in Figure 31.
- *GPU Temperature (C):* The GPU temperature of 56.38°C on the Pico Neo 3 Pro was within an acceptable range for a standalone VR headset. This result indicates that the device maintained a stable temperature during intensive VR tasks, ensuring optimal performance and reliability. The stable GPU temperature throughout the testing period demonstrates the system's ability to manage heat efficiently and prevent overheating. The GPU temperature performance on the Pico Neo 3 Pro is shown in Figure 32.

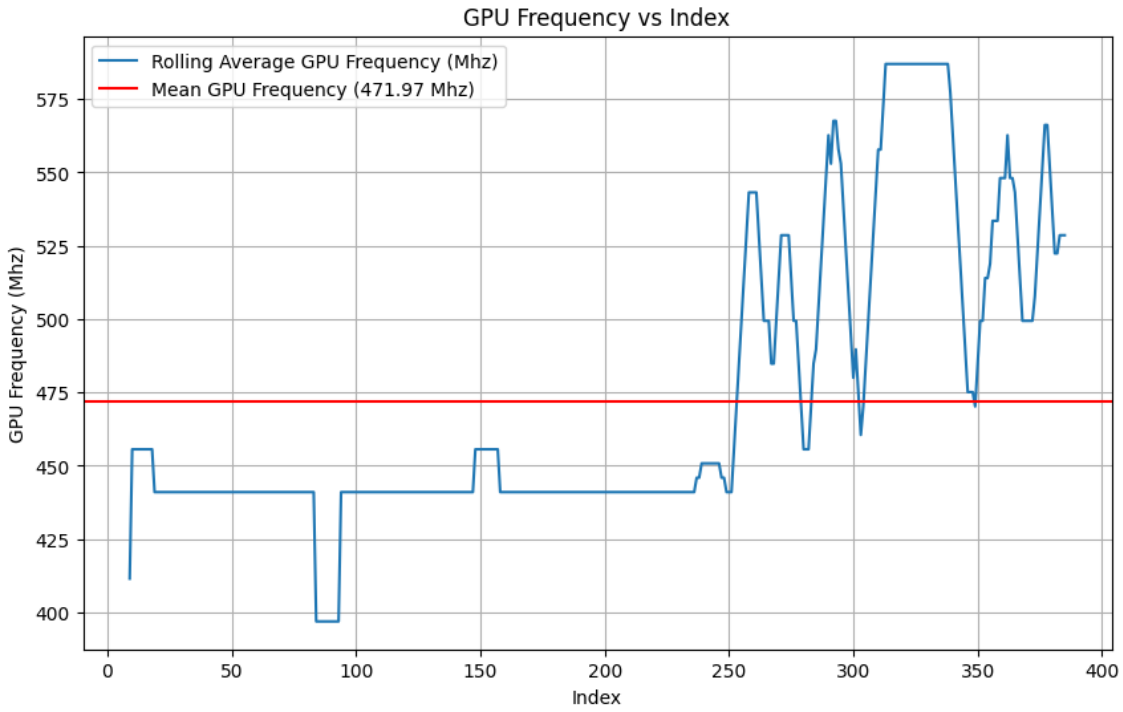


Figure 31: GPU Frequency Performance on Pico Neo 3 Pro

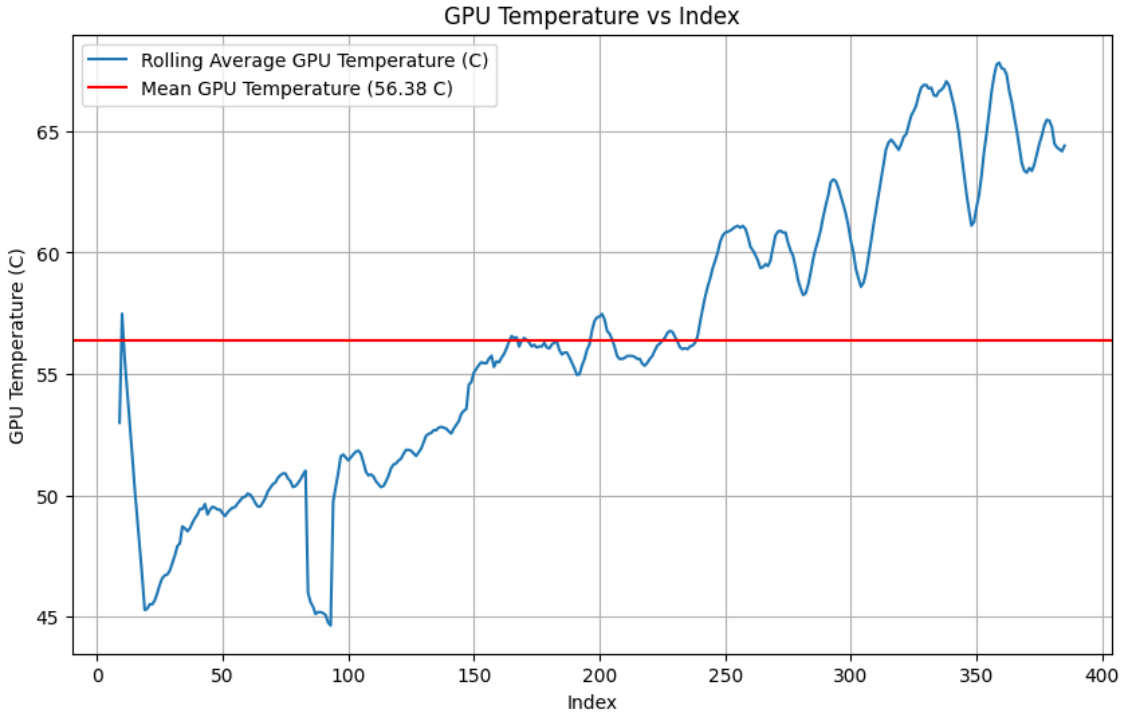


Figure 32: GPU Temperature Performance on Pico Neo 3 Pro

The Pico headset was able to run the VR platform without any issues. The frame rate, GPU memory, GPU frequency, and GPU temperature were all within acceptable ranges for VR applications, demonstrating the Pico Neo 3 Pro's capability to support real-time EEG visualisation. The results of the hardware performance testing on the Pico Neo

3 Pro validate the platform's potential for use on standalone VR headsets, making it suitable for a wider range of users and settings. This allows for more freedom as to where and when the platform could be used by removing the need to be tethered to a computer.

Overall, throughout the User Experience Testing, Clinical Diagnosis Testing, and Hardware Performance Testing, the VR platform demonstrated its effectiveness in supporting EEG data interpretation for clinical and research purposes. The platform's usability, accuracy, and performance were evaluated across different tasks, user groups, and hardware devices, providing valuable insights into its capabilities and limitations. The results of the testing indicate that the VR platform offers a promising solution for visualising and analysing EEG data in an immersive 3D environment, enhancing user engagement, performance, and satisfaction. By addressing key factors such as usability, task load, and hardware performance, the platform can provide a valuable tool for EEG data interpretation and support a wide range of applications in clinical, research, and educational settings.

4) Feasibility Study: The feasibility study aimed to assess the practicality and viability of implementing the VR-based EEG visualisation platform in clinical and research settings. The study evaluated the platform's usability, effectiveness, and performance across different user groups and tasks, providing insights into its potential applications and benefits. The Usability, Clinical Diagnosis Accuracy and Hardware Performance have already been discussed in the previous sections. These results show that it is feasible to implement such a system from a technical perspective. However, the cost and accessibility, ethical considerations and limitations of the system must also be considered.

Cost and Accessibility:

The feasibility study also considered the cost and accessibility of implementing the VR-based EEG visualisation platform. The platform's compatibility with a wide range of hardware devices, including high-end computers, low-end computers, and standalone VR headsets, demonstrated its flexibility and scalability for different budgets and requirements. The low cost of the platform, combined with its ease of use and effectiveness, makes it an attractive solution for clinical, research, and educational settings. Given that the platform was built on the OpenXR platform, this platform can run on many

other headsets that support this standard. The platform's ability to run on affordable and accessible devices, further enhances its accessibility and usability, enabling a wider range of users to benefit from its features.

Ethical Considerations:

The feasibility study also addressed ethical considerations related to the use of the VR-based EEG visualisation platform. The platform was designed to ensure user privacy and data security, with the data being kept on device and not in the cloud. However, this data was pre-processed off device. The way in which patient data can be gathered, processed and stored for visualisation is a key consideration for future work on this platform to ensure its compliance with data protection regulations.

Scalability:

The system is designed to seamlessly visualise data in the VR platform once it is formatted correctly. However, the primary challenge lies in preparing the data for visualisation, particularly when it comes to acquiring EEG data from existing hardware in an ethical and compliant manner. To increase accessibility and scalability, the platform will now be made open source, allowing users to freely download, install, and contribute to its development. Future work should focus on enabling multi-user access and ensuring the platform supports concurrent collaboration, paving the way for broader adoption within research and educational communities.

Limitations:

While the feasibility study provided valuable insights into the platform's usability, effectiveness, and performance, several limitations should be considered. The study was conducted with a small sample size of participants, which may limit the generalisability of the results. Additionally, the study focused on specific tasks and user groups, which may not fully represent the diverse range of applications and users that could benefit from the platform. Future research should include a larger and more diverse sample of participants to validate the platform's effectiveness across different settings and user groups. Furthermore, the study did not address the long-term usability and sustainability of the platform, which will be critical for its adoption and integration into clinical and research workflows. Future work should focus on addressing these limitations to ensure that the platform meets the needs and requirements of its users.

Overall, the feasibility study demonstrated that the VR-based EEG visualisation

platform offers a promising solution for enhancing EEG data interpretation in clinical and research settings. The platform's usability, effectiveness, and performance were evaluated across different tasks, user groups, and hardware devices, providing valuable insights into its potential applications and benefits. The results of the feasibility study suggest that the platform is well-suited for supporting EEG data analysis, providing an intuitive, engaging, and effective tool for visualising brain activity in a spatially rich 3D environment. By addressing key factors such as usability, clinical accuracy, hardware performance, and ethical considerations, the platform has the potential to transform EEG data interpretation and support a wide range of applications in healthcare, research, and education. The feasibility study has laid a strong foundation for future work on the platform, highlighting its scalability, accessibility, and potential impact on EEG analysis and clinical decision-making.

7. CONCLUSION

This study successfully demonstrated the potential of using a VR-based platform to enhance EEG data visualisation and analysis. The interactive environment provided by the VR setup allows users to interact with EEG signals in a spatially rich 3D context, significantly overcoming the limitations imposed by traditional 2D visualisations.

This thesis explored the design, development, and evaluation of a novel VR-based platform for EEG data visualisation and analysis. The research addressed a critical gap in existing EEG visualisation techniques, which primarily rely on 2D displays, by introducing an interactive, 3D environment that offers a more intuitive and spatially comprehensive view of brain activity. The integration of sonification and AI-based seizure detection further enhanced the capabilities of the platform, making it a robust tool for clinical and research applications.

Summary of Contributions

1) Development of a VR-Based EEG Visualisation Platform:

   This research presents a novel VR-based EEG visualisation platform that enables users to interact with EEG signals within a fully immersive 3D environment. Unlike traditional 2D visualisation methods, this platform integrates real-time spatial mapping of brain activity, seizure probability estimation, and dynamic EEG signal exploration. By leveraging VR's interactive capabilities, it enhances user engagement and provides a more intuitive understanding of complex EEG data, facilitating improved analysis and decision-making

2) Integration of Sonification and AI-Based Seizure Detection:

   The incorporation of sonification techniques enabled users to interpret EEG signals audibly, reducing cognitive load and increasing the speed of data interpretation. Additionally, the AI-based seizure detection algorithm accurately identified seizure events and visualised them on a 3D brain model, thereby offering a clearer understanding of the spatial distribution of neural activity. These aids enabled participants with no prior EEG knowledge to achieve an accuracy comparable than that of the experts, and this discrepancy was found to be not statistically significant.

3) Evaluation of the Platform's Usability and Effectiveness:

   Usability testing through the iPQ, NASA-TLX, and SUS questionnaires confirmed

that users found the platform intuitive, engaging, and effective in supporting their analysis of EEG data. The results indicated that the VR environment provided a strong sense of presence, low cognitive load, and high overall user satisfaction, highlighting its potential as a viable tool for both clinical and research use.

4) Contribution to Clinical Decision-Making and Medical Education:

   The platform's ability to provide real-time visualisation and intuitive interaction with EEG data has the potential to improve clinical decision-making. The 3D environment enables a more accurate spatial understanding of brain activity, which can be particularly beneficial for diagnosing and treating complex neurological conditions, such as epilepsy and sleep disorders. Given the platform's accessibility and ease of use, it also holds promise for medical education and training, allowing students and clinicians to learn about EEG interpretation in an immersive and engaging manner. This is shown in how those with no experience in EEG analysis were able to perform comparably to experts in the clinical diagnosis testing. The VR environment can be an integrator in the medical setting, allowing EEG analysis to be more accessible to clinicians

The research presented in this thesis opens up several avenues for future work and development. Some of the key areas for further exploration include:

1) Data Acquisition and Integration:

   As previously discussed in the feasibility study, there is a need to bridge the gap from the standard EEG acquisition hardware to the VR platform. This would involve developing a system that can acquire, process, and transmit EEG data in real-time to the VR platform. Additionally, integrating the platform with existing EEG data repositories and databases would enable users to access and analyse large datasets for research and clinical applications. It is also important to consider the ethical implications of data acquisition and storage, ensuring that patient data is handled securely and in compliance with data protection regulations.

2) Large Scale Clinical Testing:

   While the testing conducted in this research provided valuable insights into the platform's effectiveness, further testing with a larger and more diverse sample of participants would be beneficial. This would help validate the platform's performance across different user groups and settings, providing a more comprehensive

understanding of its clinical utility. Additionally, longitudinal studies could be conducted to assess the platform's long-term impact on clinical decision-making and patient outcomes.

3) Large Language Models:

   Basic testing has been conducted on deploying a Local Large Language Model (LLM) within the VR environment, aimed at educating users about the EEG data they are viewing. However, a key challenge encountered was the lack of context provided to the model. For the LLM to deliver meaningful insights, a method needs to be developed that enables the model to understand and interpret the specific features of the EEG being analysed. By incorporating such a mechanism, the model would be able to offer more accurate and contextually relevant information to the user. Given the sensitivity of the data being analysed, it is essential to ensure that the LLM runs locally on the user's device and does not transmit any data to external servers. This would help maintain data privacy and security while providing valuable insights and educational content to users.

4) Multi-User Support and Collaboration:

   As mentioned in the scalability section of the feasibility study, making this platform open source would be a key step in increasing accessibility to a wider audience. By releasing the platform as open source, it would allow for greater collaboration and contributions from the community. Additionally, enabling real-time collaboration and communication features would enhance the platform's utility for research and educational purposes, allowing users to interact and share insights in a shared virtual environment.

5) Other Applications and User Groups:

   While this research focused on EEG data visualisation and analysis, the platform has the potential to support a wide range of applications and user groups. Future work could explore the platform's utility for other types of neuroimaging data, such as fMRI and MEG, as well as its applications in educational settings for teaching neuroscience and brain anatomy.

6) Augmented Reality Integration:

   The integration of augmented reality (AR) technology could further enhance the platform's capabilities by overlaying EEG data on the user's physical environment.

This would provide a more seamless and intuitive way to interact with brain activity, enabling users to visualise EEG signals in real-world contexts and scenarios. AR integration could also support remote collaboration and telemedicine applications, allowing clinicians and researchers to share and discuss EEG data in real-time. With the release of the latest set of Augmented Reality glasses by Meta, their smaller form factor allows for much more potential with this technology. A professional could carry the small pair of glasses inside their pocket and use them when needed. This would allow for a more seamless integration of the technology into the workplace.

In conclusion, the VR-based EEG visualisation platform developed in this research marks a significant advancement in EEG data interpretation by offering an immersive, interactive, and intuitive tool for visualising brain activity. Key innovations, such as sonification, AI-driven seizure detection, and 3D brain modelling, provide a powerful solution for both clinical and research applications. Built on the OpenXR framework, the platform is compatible with a wide range of devices, enhancing its accessibility and usability.

Extensive evaluations, including user experience testing, clinical accuracy assessments, and hardware performance benchmarking, underscore its potential to transform EEG analysis and support diverse neurological applications. By addressing essential factors such as user accessibility, clinical reliability, technical efficiency, and ethical considerations, this platform has the capacity to revolutionise EEG data interpretation and significantly improve clinical decision-making in neurology and neuroscience.

This research establishes a strong foundation for future development, highlighting the platform's scalability, accessibility, and potential impact on EEG analysis and clinical practice.

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APPENDIX A

DETAILED WIRE DIAGRAM DESIGN - LEFT SCREEN

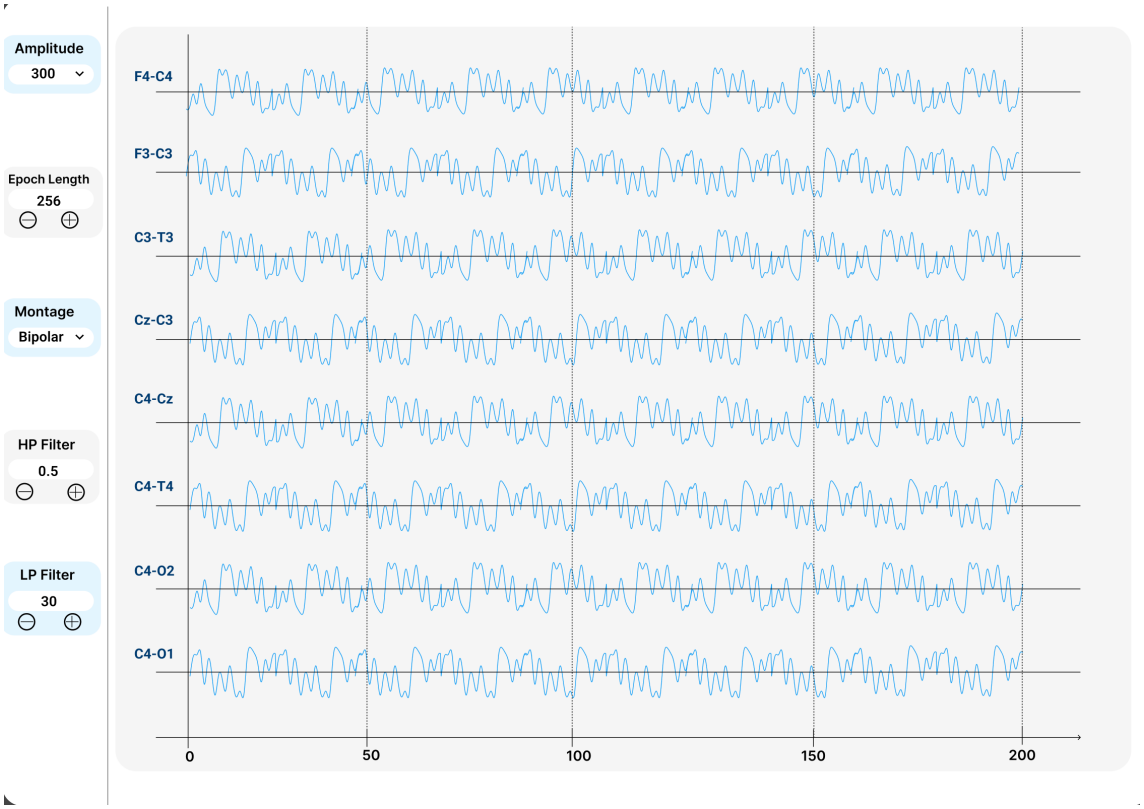


Figure 33: The Left Screen of the VR World

APPENDIX B

DETAILED WIRE DIAGRAM DESIGN - MIDDLE SCREEN

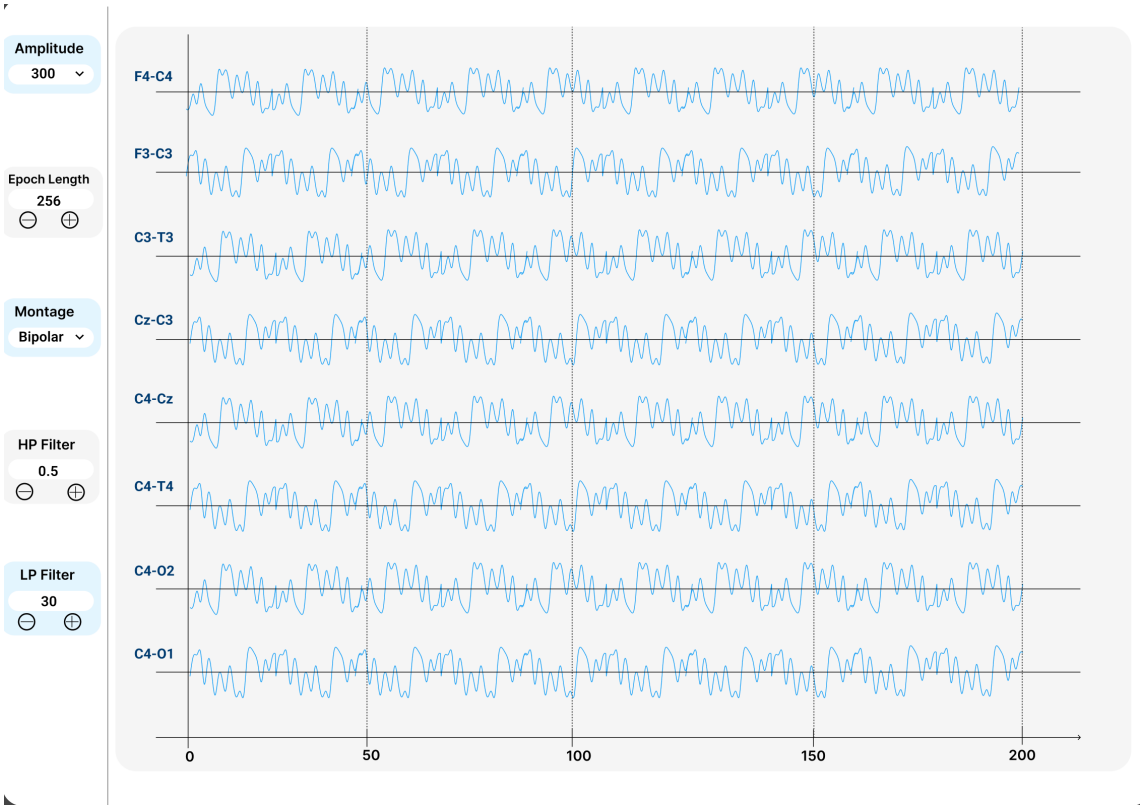


Figure 34: The Middle Screen of the VR World

APPENDIX C

DETAILED WIRE DIAGRAM DESIGN - RIGHT SCREEN

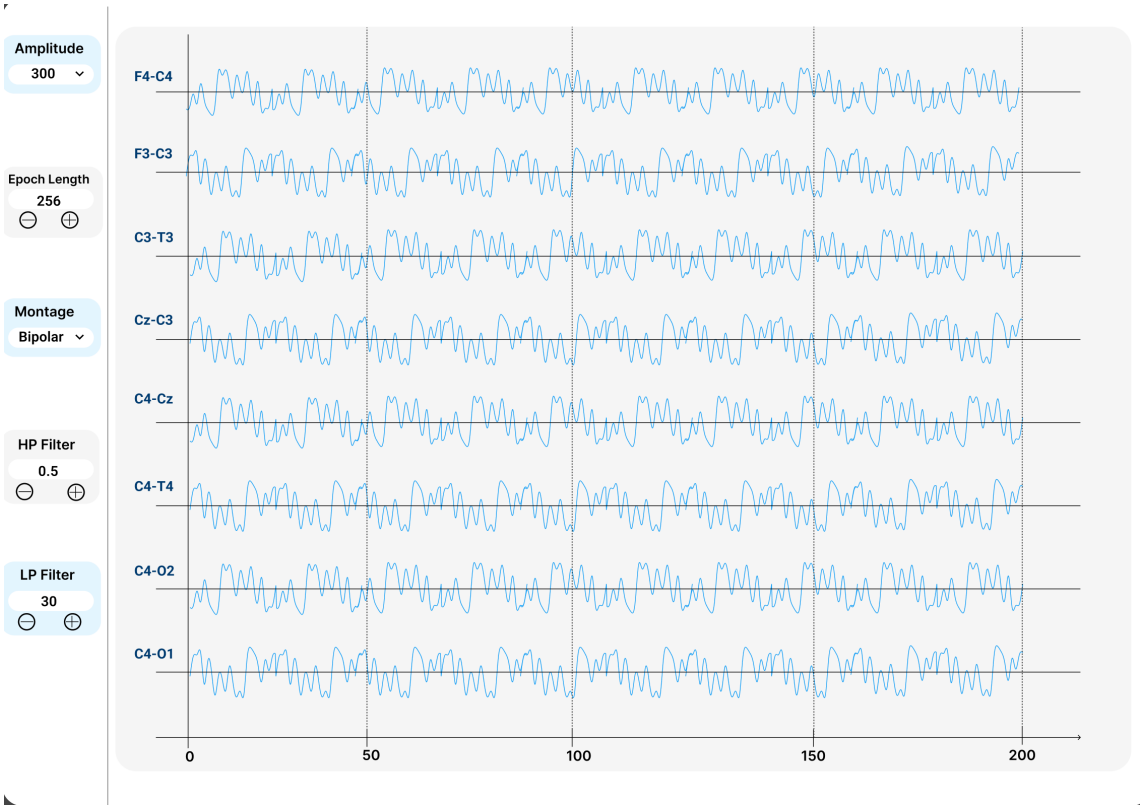


Figure 35: The Right Screen of the VR World

APPENDIX D

DETAILED CSV FORMAT

Row Number	**Description**
1	Normal EEG Data Channel 1
2	Normal EEG Data Channel 2
3	Normal EEG Data Channel 3
4	Normal EEG Data Channel 4
5	Normal EEG Data Channel 5
6	Normal EEG Data Channel 6
7	Normal EEG Data Channel 7
8	Normal EEG Data Channel 8
—	—
9	Seizure Probabilities Channel 1
10	Seizure Probabilities Channel 2
11	Seizure Probabilities Channel 3
12	Seizure Probabilities Channel 4
13	Seizure Probabilities Channel 5
14	Seizure Probabilities Channel 6
15	Seizure Probabilities Channel 7
16	Seizure Probabilities Channel 8
—	—
17	Amplitude EEG (aEEG)
—	—
18	Delta Waves Channel 1
19	Delta Waves Channel 2
20	Delta Waves Channel 3
21	Delta Waves Channel 4
22	Delta Waves Channel 5
23	Delta Waves Channel 6
24	Delta Waves Channel 7
25	Delta Waves Channel 8

Row Number	Description
—	—
26	Theta Waves Channel 1
27	Theta Waves Channel 2
28	Theta Waves Channel 3
29	Theta Waves Channel 4
30	Theta Waves Channel 5
31	Theta Waves Channel 6
32	Theta Waves Channel 7
33	Theta Waves Channel 8
—	—
34	Alpha Waves Channel 1
35	Alpha Waves Channel 2
36	Alpha Waves Channel 3
37	Alpha Waves Channel 4
38	Alpha Waves Channel 5
39	Alpha Waves Channel 6
40	Alpha Waves Channel 7
41	Alpha Waves Channel 8
—	—
42	Beta Waves Channel 1
43	Beta Waves Channel 2
44	Beta Waves Channel 3
45	Beta Waves Channel 4
46	Beta Waves Channel 5
47	Beta Waves Channel 6
48	Beta Waves Channel 7
49	Beta Waves Channel 8
—	—
50	Gamma Waves Channel 1
51	Gamma Waves Channel 2

Row Number	Description
52	Gamma Waves Channel 3
53	Gamma Waves Channel 4
54	Gamma Waves Channel 5
55	Gamma Waves Channel 6
56	Gamma Waves Channel 7
57	Gamma Waves Channel 8

APPENDIX E

APPENDIX: STUDY PARTICIPANT CONSENT FORM

Consent Form for Participation in Research Study

Title of the Study: Evaluating Visualisation and Sonification of EEG Data on a VR Platform
Principal Investigator: Dr. Emanuel Popovici
Affiliation: School of Electrical Engineering, University College Cork (UCC)
Contact Information: e.popovici@ucc.ie

Introduction

You are invited to participate in a research study conducted by the School of Computer Science & Information Technology at University College Cork. Before you decide whether to participate, it is important for you to understand why the research is being done and what it will involve. Please read the following information carefully and discuss it with others if you wish.

Purpose of the Study

This pilot study aims to collect data from UCC third-level students and staff to evaluate the visualisation of data series associated with openly available ElectroEncephalogram (EEG) data implemented on a virtual reality (VR) platform. The application uses sounds and visual effects of these data series to enhance the user experience and aid in detecting seizure activity.

Study Procedures

If you agree to participate in this study, you will be asked to:

1. Immerse yourself in a seated 3D environment using a VR headset.
2. Experience the EEG application, which includes both visual and AI-driven sonification components.
3. Complete three standardised questionnaires (SUS, NASA-TLX, and iPQ) to evaluate the effectiveness and usability of the VR EEG application.
4. Provide feedback on any challenges or issues encountered during the use of the VR application.
5. The entire study session will take approximately 60-90 minutes to complete.

Voluntary Participation

Participation in this study is voluntary. You have the right to withdraw from the study at any time up to the point of data anonymisation without giving any reason and without any penalty.

Confidentiality

All data collected will be anonymised to ensure your privacy. The anonymised data will be stored securely in the department's filing cabinets and on a password-protected computer in a limited-access room. The data will be used for research purposes only and will be destroyed after data analysis is complete.

Potential Risks and Discomforts

There is a remote possibility that some users of VR may experience mild discomfort. Established protocols for dealing with mild discomfort and health and safety considerations will be followed. The research team has the necessary expertise to handle such situations.

APPENDIX F

APPENDIX: STUDY PARTICIPANT CONSENT FORM

Potential Benefits

While there may be no direct benefits to you for participating in this study, your participation will contribute to the development and improvement of VR applications for EEG data visualisation and sonification, which may benefit future users in clinical and research settings.

Contact Information

If you have any questions or concerns about the study, please contact the principal investigator at [Your Email Address]. If you have any concerns about your rights as a research participant, you may contact the UCC Ethics Committee at [Ethics Committee Contact Information].

Consent Statement

I have read and understood the information provided above.
I have had the opportunity to ask questions and have had them answered to my satisfaction.
I understand that my participation is voluntary and that I can withdraw at any time up to the point of data anonymisation without any penalty.
I agree to participate in this study.

Participant's Name: _____

Participant's Signature: _____

Date: _____

Thank you for considering participation in this study.

APPENDIX G

APPENDIX: IGROUP PRESENCE QUESTIONNAIRE (IPQ)

Please enter your participant number: _____

igroup Presence Questionnaire (iPQ)

The igroup Presence Questionnaire (iPQ) is a tool used to measure the sense of presence experienced by users in virtual environments. Presence, in this context, refers to the feeling of being "there" in the virtual environment, as if it is a real place. The iPQ helps researchers and developers understand how immersive and convincing their virtual reality (VR) environments are from the perspective of the user. Please select the answer that best expresses how you feel about each statement after using system today.

	Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
1. In the computer-generated world, I had a sense of "being there."	☐	☐	☐	☐	☐
2. Somehow I felt that the virtual world surrounded me.	☐	☐	☐	☐	☐
3. I felt present in the virtual space.	☐	☐	☐	☐	☐
4. I was aware of the real environment surrounding me	☐	☐	☐	☐	☐
5. I had a sense of acting in the virtual space, rather than operating something from outside.	☐	☐	☐	☐	☐
6. How much did your experiences in the virtual environment seem consistent with your real-world experiences?	☐	☐	☐	☐	☐
7. The virtual world seemed more realistic than the real world	☐	☐	☐	☐	☐
8. I was not aware of my real environment	☐	☐	☐	☐	☐
9. I still paid attention to the real environment.	☐	☐	☐	☐	☐
10. I was completely captivated by the virtual world.	☐	☐	☐	☐	☐
11. The virtual world seemed real to me.	☐	☐	☐	☐	☐
12. How much did you experience in the virtual environment seem consistent with you real world experience.	☐	☐	☐	☐	☐
13. The virtual world seems more realistic than the real world	☐	☐	☐	☐	☐
14. I needed to learn a lot of things before I could get going with this system.	☐	☐	☐	☐	☐

APPENDIX H

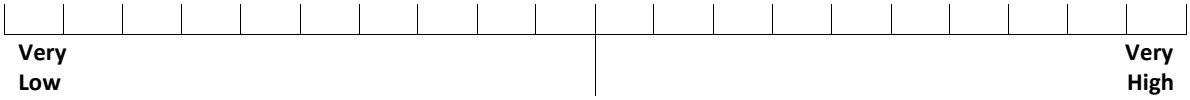
Rating Task APPENDIX: NASA TASK LOAD INDEX (NASA-TLX) **ID_____-1**

Participant ID:_____ Date:_____

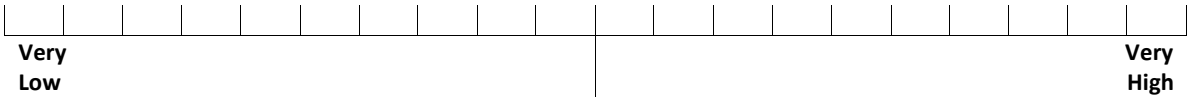
NASA Task Load Index (2 pages)

We are interested in the workload you experienced while completing this task. As workload can be caused by several different factors, we ask you to rate several of the factors individually on the scales provided.
Note: Performance goes from good on the left to bad on the right.

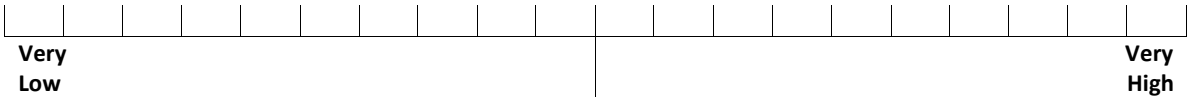
Mental Demand: How mentally demanding was the task?



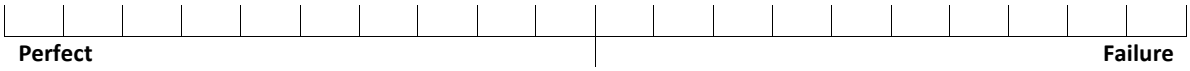
Physical Demand: How physically demanding was the task?



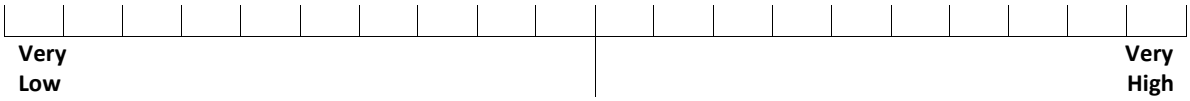
Temporal Demand: How hurried or rushed was the pace of the task?



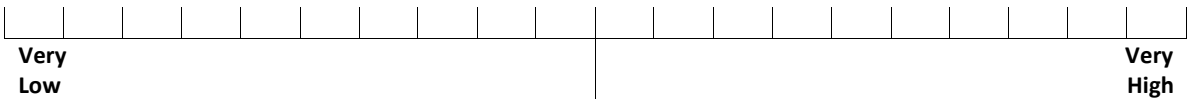
Performance: How successful were you in accomplishing what you were asked to do?



Effort: How hard did you have to work to accomplish your level of performance?



Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you?



APPENDIX I

Pairing Task APPENDIX: NASA TASK LOAD INDEX (NASA-TLX) **ID_____-2**

For each of the following pairs, please circle the scale title that contributed more to your experience of workload during this run.
In other words, which of the pair made the task *harder*?

1	Mental Demand	Physical Demand
2	Temporal Demand	Performance
3	Effort	Frustration
4	Mental Demand	Temporal Demand
5	Effort	Physical Demand
6	Performance	Frustration
7	Effort	Mental Demand
8	Temporal Demand	Frustration
9	Physical Demand	Performance
10	Mental Demand	Performance
11	Temporal Demand	Effort
12	Frustration	Physical Demand
13	Frustration	Mental Demand
14	Physical Demand	Temporal Demand
15	Performance	Effort

Hart, S. G. & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock and N. Meshkati (Eds.) *Human Mental Workload*. Amsterdam: North Holland Press.

APPENDIX J

APPENDIX: SYSTEM USABILITY SCALE (SUS)

Please enter your participant number: _____

System Usability Scale (SUS)

This is a standard questionnaire that measures the overall usability of a system. Please select the answer that best expresses how you feel about each statement after using the website today.

		Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
1.	I think I would like to use this system frequently.	☐	☐	☐	☐	☐
2.	I found the system unnecessarily complex.	☐	☐	☐	☐	☐
3.	I thought the system was easy to use.	☐	☐	☐	☐	☐
4.	I think that I would need the support of a technical person to be able to use this system.	☐	☐	☐	☐	☐
5.	I found the various functions in this system were well integrated.	☐	☐	☐	☐	☐
6.	I thought there was too much inconsistency in this system.	☐	☐	☐	☐	☐
7.	I would imagine that most people would learn to use this system l very quickly.	☐	☐	☐	☐	☐
8.	I found the system very cumbersome to use.	☐	☐	☐	☐	☐
9.	I felt very confident using the system.	☐	☐	☐	☐	☐
10.	I needed to learn a lot of things before I could get going with this tool.	☐	☐	☐	☐	☐

How likely are you to recommend this website to others? (please circle your answer)

Not at all likely 0 1 2 3 4 5 6 7 8 9 10 Extremely likely

APPENDIX K

APPENDIX: PRE-QUESTIONNAIRE SURVEY

We would be very grateful if you could complete this questionnaire, which can take up to 10 minutes. The questionnaire addresses your background, use of VR and understating of seizures. Participation is entirely voluntary. There is no obligation to participate, and should you choose to do so you can refuse to answer specific questions or decide to withdraw from the study prior to completing the survey. All information you provide will be confidential and your anonymity will be protected throughout the study. All responses will be treated as strictly confidential and the information you provide will be used for a MSc thesis, research, publications and or conference presentations.

☐ I have read the provided information and agree to participate in this research.
☐ I am above the age of 20.
☐ I do not have had epilepsy

Pre-questionnare

Please tell us about yourself by answering the following questions

1. Please state your age bracket (20-29, 30-39, 40-49, 50-51, >60)

2. Do you have any knowledge of what electroencephalogram (EEG) is?
☐ Yes
☐ No

APPENDIX L

APPENDIX: PRE-QUESTIONNAIRE SURVEY

3. If yes, briefly describe

4. Do you have any knowledge of how to recognise seizures on EEG?

☐ Yes
☐ No

5. If yes, briefly describe

6. Do you have any experience with video games?

☐ Yes
☐ No

7. If yes, please specify the length of your video game experience.

8. Do you have any experience with Virtual Reality? (Virtual reality is simulated experience using head-mounted display that fully immerses the user's senses in a 3D environment that mimics real-world properties)

☐ Yes
☐ No

9. If yes, please specify the length of your VR experience.

APPENDIX M

APPENDIX: PRE-QUESTIONNAIRE SURVEY

10. Where have you utilised VR in the past?

☐ Video games
☐ At a museum
☐ At an educational conference
☐ In a classroom
☐ Other. Please specify_____
☐ Not applicable

11. How would you describe your experience with VR?

☐ Positive
☐ Neutral
☐ Negative
☐ Not applicable

12. On a scale from 1-10 (with 1 being the lowest, and 10 the highest), how would you rate your VR experience?

1	2	3	4	5	6	7	8	9	10

13. Would you be interested in using VR to detect seizures?

☐ Yes
☐ No
☐ Unsure

14. Have you been diagnosed with any of the following?

A. Learning disabilities ☐ Yes. Please specify_____ No ☐
B. Vision problems ☐ Yes. Please specify_____ No ☐
C. Loss of balance/equilibrium ☐ Yes. Please specify_____ No ☐

APPENDIX N

APPENDIX: PRE-QUESTIONNAIRE SURVEY

18. If you previously used a VR headset, did you experience any physical discomfort while using it? Please choose all that apply.

- ☐ Headache
- ☐ Nausea
- ☐ Double vision
- ☐ Blurred vision
- ☐ Dizziness
- ☐ Motion sickness
- ☐ Loss of balance
- ☐ Other. Please specify_____
- ☐ Not applicable

Thank you for completing this questionnaire!

APPENDIX O

APPENDIX: POST-QUESTIONNAIRE SURVEY

Post-Questionnaire

1. Which aspect of the VR EEG software did you like the most and why?

2. Which aspect of the VR EEG software did you like the least and why?

3. On a scale from 1-10 (with 1 being the lowest, and 10 the highest), how would you rate your VR EEG experience?

1	2	3	4	5	6	7	8	9	10

4. Would you be interested in using VR to detect seizures?

☐ Yes
☐ No
☐ Unsure

Thank you for completing this questionnaire!

APPENDIX P

HIGH END COMPUTER BENCHMARK TEST RESULTS

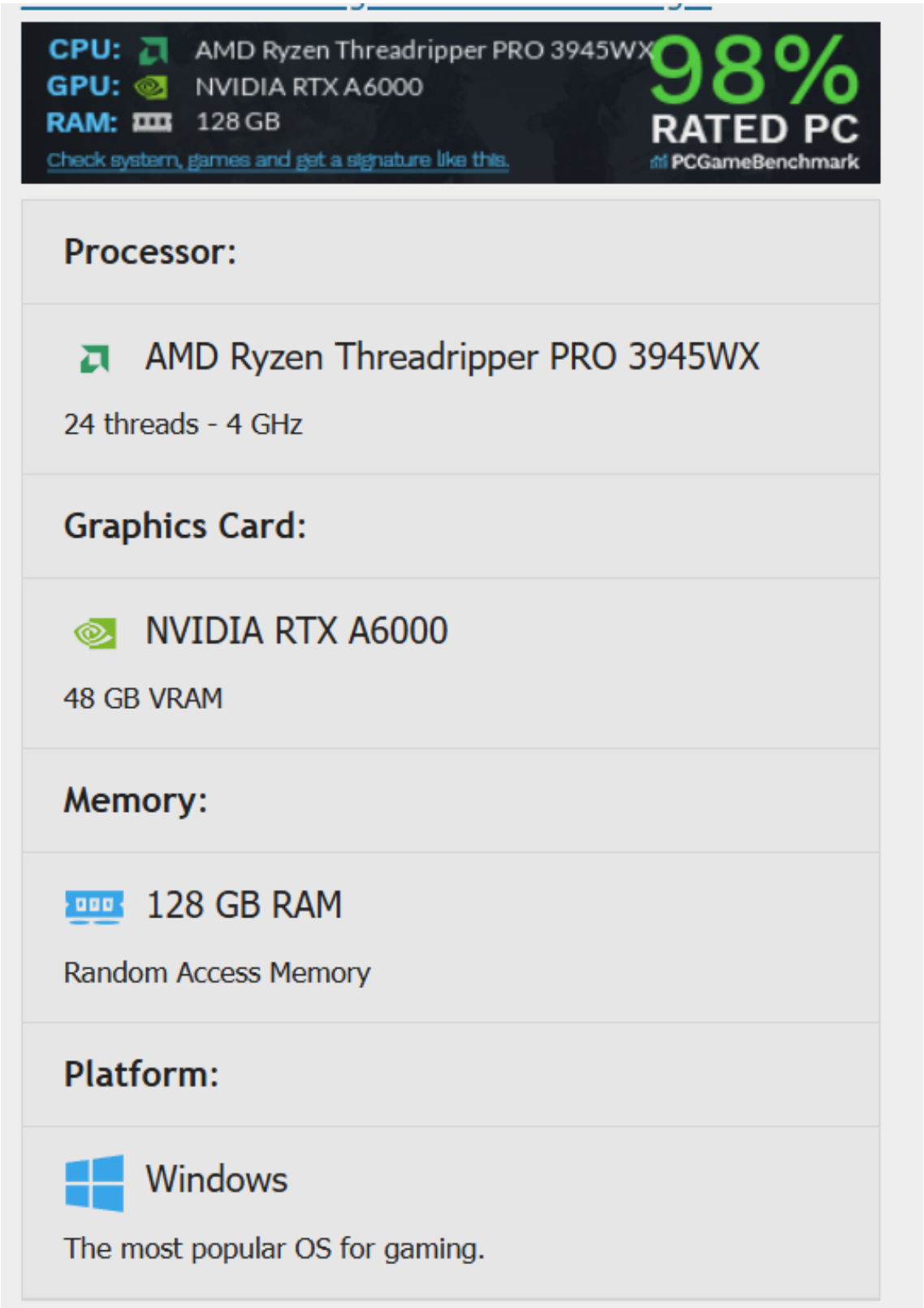


Figure 36: High End Computer Benchmark Test Results

APPENDIX Q

LOW END COMPUTER BENCHMARK TEST RESULTS

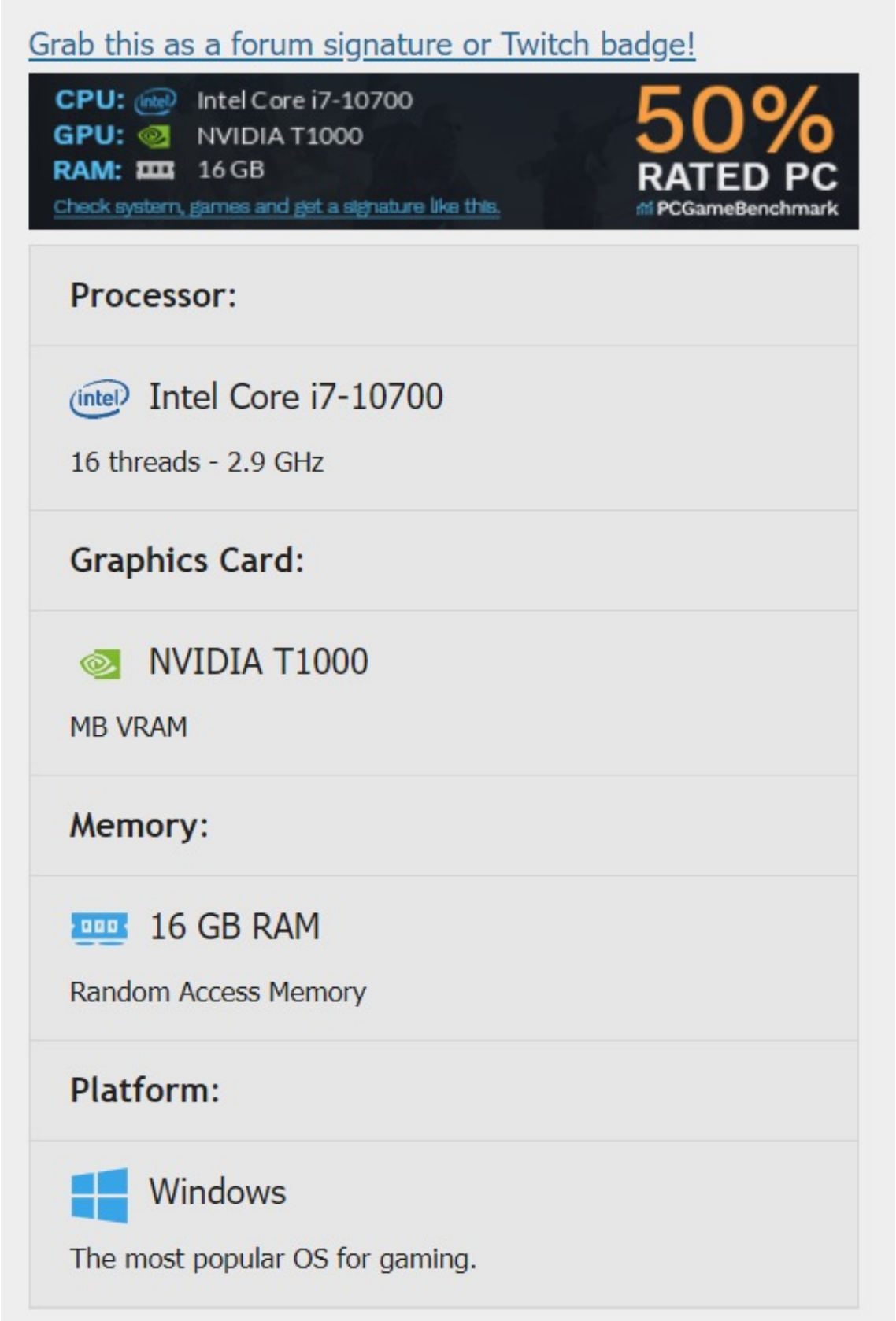


Figure 37: Low End Computer Benchmark Test Results