STUDIES ON THE INFLUENCE OF MUSIC ON EMOTIONS AND COGNITIVE-BASED TASKS

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STATEMENT OF CANDIDATE

I, Rajiv Mehta, declare that this report, submitted as part of the requirement for the award of Bachelor of Engineering in the School of Engineering, Macquarie University, is entirely my own work unless otherwise referenced or acknowledged. This document has not been submitted for qualification or assessment an any academic institution.

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ABSTRACT

Throughout, human history music has played a very important role in preserving culture, history and is overall a testament to the creativity of mankind. With the advancements in technology through the 20th and 21st centuries, music has become increasingly available to everyone at a moment's notice. Though the ability to access music has changed, the purpose of music has not and as Plato described in his quote above, the use of music for learning has remained a constant in history. This thesis explores the effect of different genres of music on the performance of university students in complex cognitive-based tasks to assess if music does in fact improve the learning ability of students. Participants are subjected to different genres of music while playing 'Dr Kawashima's Brain Training - Nintendo Switch'. This study collects EEG data, survey, and test result which is analysed using machine learning algorithms to determine if different genres of music positively or negatively influence cognitive performance.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

“I would teach children music, physics, and philosophy; but most importantly music, for the patterns in music and all the arts are the keys to learning” – Plato [1].

Music is an integral part of human culture and society, captivating the human spirit and invoking powerful emotions through its roles in entertainment, education, and history. In reality, the purpose of music has not changed but rather the ever-increasing ease-of-access. This is evident by looking at the growth of streaming company ‘Spotify’ listener base over the past 7 years, seen in Figure 1.1. This exponential growth in listeners evidently points to music being consumed at a larger rate and studies show that adults between the ages of 18-34 tend to consume the most music [2].

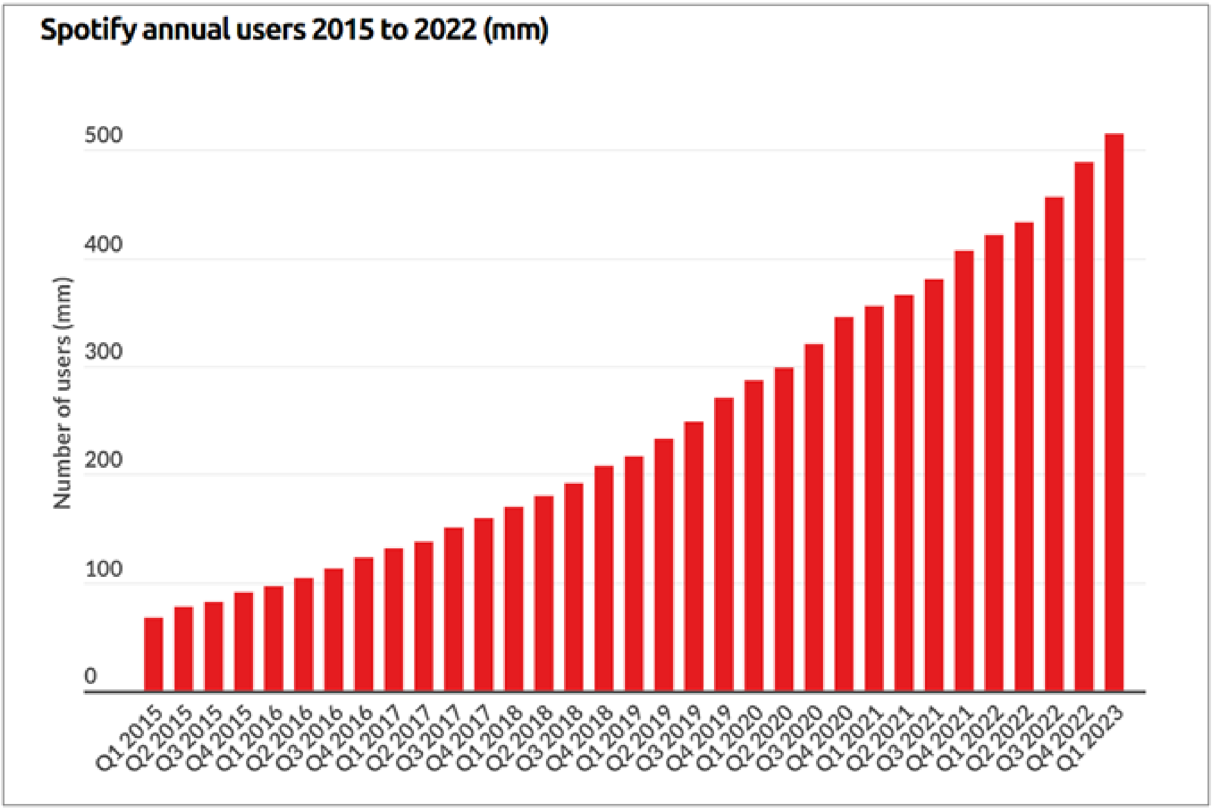

Figure 1.1: Spotify listener base over the past 7 years [3].

According to Universities Australia, as of Oct 2022, there were currently 1,108,662 students enrolled into a university course program [4]. When walking around any university campus, such as Macquarie University, it is plain to see many students, staff or visitors study while listening to various forms of music, each from different genres or eras of music. Many of the studies performed on the effects of music on cognitive performance are quite outdated and with the constant innovation of technology, the need for updated data and analysis is required to determine if music can positively influence performance in cognitive tasks and what genres of music have the greatest impact.

1.1 Project Scope and Deliverables

The innovations in technology and the constant growth in both listeners and the music industry indicate that there is a need to conclusively determine if listening to music while performing complex cognitive based activities will positively or negatively affect performance.

The scope of this study is to examine how different genres of music affect the emotions and in turn, determine how music affects performance in complex cognitive based tasks. To achieve this, the project aims to deliver the following:

1. Use software engineering methods to collect data using EEG sensors through wireless communications on study participants.
2. Using software engineering design and methodologies to develop an emotion recognition model that can accurately predict emotions of a participant at 90% accuracy.
3. Examine if music has a positive or negative influence on complex cognitive based tasks.
4. Determine if emotions influence performance in complex cognitive based tasks.
5. Determine if any, which genre of music is optimal to listen to when studying.

1.2 Assumptions

To come up with conclusive results on how different genres of music affect emotions and performance of young adults, the following assumptions are made within this study:

1. External distractions that could influence performance are completely removed. To do this the study aims to have all participants perform the tests in isolated environments, though due to the data collection, variations time, weather and location may vary.
2. Emotion classification algorithm does correctly identify and differentiate emotions based on the influence of different genres of music.
3. Participants age and gender will be diverse and showcase an approximate equal distribution for an accurate population representation.
4. The devices used to collect the data are accurate and representative of what the paper aims to deliver. Participants will be able to correctly identify the emotion that the music made them feel.
5. Participants will be able to perform the cognitive-based tasks at an approximately equal level so that intelligence does not play a factor on what the paper aims to deliver.

Chapter 2

Literature Review

This chapter focuses on researching the previous contributions made to music can influence emotions and cognitive performance. By looking at previous studies, the author aims to combine previous works and ideas to optimise the experimentation and data collection process to explore the potential benefits of different genres of music.

2.1 Background

The topic of how music affects performance has had much debate in the field of Psychology. Though in recent years, not many papers have been published outlining this topic and almost all papers contradict each other in one form or another. Therefore, it is important to first analyse recent studies to check how other academics have approached the problem and the results they obtained.

The paper 'Facing the Music: Performance Implications of Working with Music in the Background' by Claudia Moise and Rachel Adler published in 2019, analysed how music can affect the mental arithmetic, memory, reading comprehension, concentration, and spatial abilities of participants through a mobile application they built [5]. To do this, the methodology was to divide the app created into various sections that would check the above-mentioned test cases while only using one rock song and one classical piece of music. The app asked questions to test, and subjects were subjected to sitting the tests with music and without music. An ANOVA test was used to differentiate the results and found that in silent conditions, participants scored better in most modules except in the reading module, where no difference was shown.

In 2019, Manuel Gonzalez and John Aiello also released a paper trying to showcase how music affects cognitive task performance in their paper 'More Than Meets the Ear: Investigating How Music Affects Cognitive Task Performance.[6]' In their paper, they based their experimental framework on the 'Distraction-Conflict Theory' by Robert S. Baron, an alternative to the earlier work of Robert Zajnoc's theory of social facilitation, the study tries to explain how the introduction of music can act as a non-social distraction when trying to complete cognitive tasks[6][7]. To test this, they devised complex and simple tasks and asked participants to complete the Boredom Proneness Scale by Farmers and Sundberg, test scores of participants and task difficulty ranking responses [6][8]. By using this data, they applied a general linear model hypothesis test to analyse the data and found that music negatively impacted complex tasks when compared to no music. With simpler questions, the impact of music was not as strong, but they found music that was classified as complex had a greater negative impact on performance.

Another study in 1997 tried to explain the effect of background music on the cognitive performance of introverts and extroverts[9]. This paper 'Music while you work: The Differential Distraction of Background Music on the Cognitive Test Performance of Introverts and Extroverts' by Adrian Furnham and Anna Bradley used pop music on 10 extroverts and 10 introverts and made them sit three tests, a comprehension test, a math test (not analysed against) and a memory test. By using an analysis of variance test they found that performance was marginally lowered in the presence of music for only one out of three studies, but due to the method, the study could not identify which cognitive task was affected by music.

'The Influence of Different Genres of Music on the Performance of Medical Students on Standardized Laparoscopic Exercises' by Nees et.al analysed the effects of different genres of music on medical students when performing laprasodic exercises [10]. The study consisted of 82 students from Heidelberg University Medical School in 2018. Students were divided into four groups each exposed to a different genre of music as they completed these exercises. Using statistical analysis, they found that classical music appeared to highly increase performance when compared hip hop and radio with the worst being rock. It also finds that when the sound pressure level of 70 decibels, hip hop and classical appear to have a larger positive performance.

Jeong-hwa Lee and Chongnak in their recent study 'The Effect of negative emotion on concentration through emotional regulation: mediated moderation of Metacognitive Awareness' found that among adolescents, those who were experience negative emotions such as sadness would perform a lot worse in cognitive-based exams [11]. They found this by testing 409 high school students and collected data through four measurement scales, 'Emotional Regulation Checklist', 'Metacognitive awareness scale', 'Negative emotions scale' and 'Concentration scale'. Using hierarchical regression analysis, it was found that there was a direct linkage between negative emotions and concentration levels which resulted in lower cognitive performance in adolescence.

Comparing the previous study, another study 'Enhancement of Movement Intention Detection Using EEG Signals Responsive to Emotional Music Stimulus' by Hasan, et.al found that when analysing EEG data, happy emotional stimulation outputted better results than when sad music stimuli was played [12]. In the study, they tested to see if they could create a movement detection system by having a 10/20 system of nodes placed on the brain. These nodes cover the frontal lobes where cognitive ability and motor control are controlled in the brain. Using EEGlab they pre-processed the data and found support vector machines and pseudo-online testing schemes to be the best models for predicting sad, happy or neutral motor control in the brain.

2.2 Emotion

Looking at the studies outlined in section 2.1, it is clear that the field of music affecting performance and music affecting emotions has been studied multiple times in recent history. Though the studies produce accurate results, they do not explain the causality of why music affects emotions and cognitive-based tasks. To fix this, it is first paramount to define what an emotion is and how they are formed.

2.2.1 Definition

The book "The Science of Emotion" by Randolph R. Cornelius describes the view of how emotion is defined in literature as similar to the 'Sufi Story: The Elephant and the blind men. [13]' The story describes the encounter of an elephant by a blind village and how when four blind men went to touch the elephant, they all touched different parts and when it came to describing the elephant, they all contracted each other and argued over who was correct. Similarly, in literature there is no clear definition of emotion and often the definitions posed by various studies and articles are based on the portion of research they are covering.

Therefore, to decide the appropriate model of emotions that should be used to prove the effect of music on emotions, it is important to first look at the history of modelling and decide which model best suits the thesis criteria.

2.2.2 James-Lange Theory of Emotions

In the late 19th century William James and Carl George Lange independently worked on models to describe how emotions are experienced by people, which were then later combined to become the James-Lange Theory[14].

In James' paper 'What is an Emotion', he hypothesizes that "the bodily changes follow directly the perception of the exciting fact, and that our feeling of the same changes as they occur is the emotion."[15] What this means is that the emotions felt by a person are just the bodily reaction to an external stimulus. In his paper for example, he describes the flight or fight response to seeing a bear. If the body decides to run and use its flight response, does the person feel fear or if they choose to fight, does the person feel angry? The answer in this theory is no, as it just depends on how the body reacts which is the emotion.

In his paper, he goes on to explain this by referencing the work done by Darwin in his book ‘Expression of the emotions in man and animals’, where he explains the evolutionary theory and how animals and humans have adapted to solve problems based on their environment[15][16]. For example, when someone is worried, the contraction of eyes and brows may be displayed which would make the person or animal feel worried. This leads to the major point of his paper as he states “If we fancy some strong emotion, and then try to abstract from our consciousness of it all the feelings of its characteristic bodily symptoms, we find we have nothing left behind, no ” mind-stuff” out of which the emotion can be constituted, and that a cold and neutral state of intellectual perception is all that remain.”[15]

Carl George Lange in his paper that came out one year later with his book that expressed a similar idea but with noticeable differences to James’ paper. Lange’s paper was very similar to the James’ theory on emotions with the key difference being that Lange’s model tried to consider not just the primary emotions but also other states of being, making it not as generalized as James’ theory [14]. Though they had the same fundamental idea, Lange’s model differences were overlooked by most academics and both theories got combined into the James-Lange Theory, described in Figure 2.1.

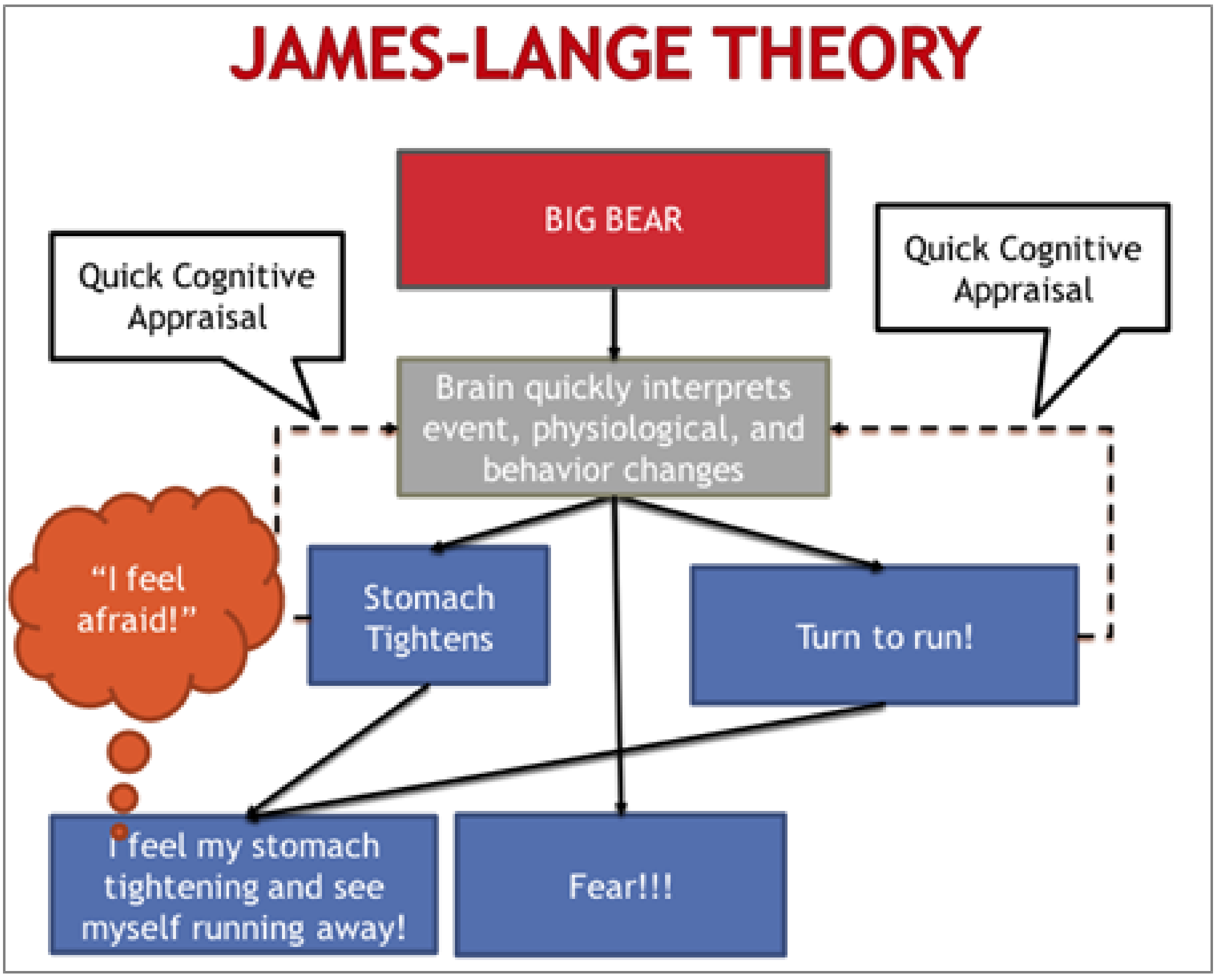

Figure 2.1: An eliciting event of seeing a bear explained using James-Lange Theory [17].

2.2.3 Cannon-Bard Theory

Though the James-Lange theory was the core accepted theory during the time, Walter Cannon and Phillip Bard created the Cannon-Bard theory due to the various weaknesses that Cannon had identified in his analysis and recreation of James' experiments [17][18]. He identified in his animal testing that the conscious feeling of emotion could occur faster than the bodily response from the stimuli and that bodily responses such as stomach tightening could be experienced with various emotions and not be allocated to a specific one.

This led to the Cannon-Bard Theory which as shown in Figure 2.2, indicates the bodily response does not occur before the feeling of emotion but rather they happen concurrently. The study indicated that emotion itself was a thalamic process and the strength of the emotion was due to the amount of brain activity and the division of thalamocortical neurons for motor information and cognitive responses, which resulted in bodily changes and emotions to stimuli [18]. This theory though does have its weaknesses similar to the James-Lange Theory, sudden stimuli can cause the body to react first long before cognitive recognition of the emotion occurs [17].

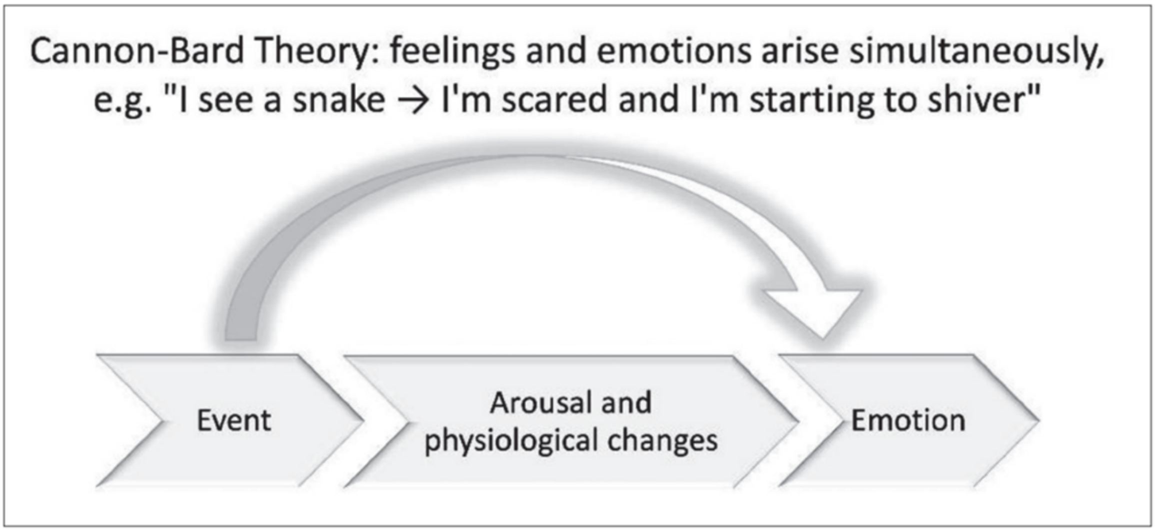

Figure 2.2: Cannon-Bard's Theory of Emotion [18].

2.2.4 Schachter-Singer Two-Factor Theory

Contrary to the theories hypothesised by the James-Lange theory and Cannon-Bard theory, the model hypothesised by Stanley Schachter and Jerome Singer in 1962 included an extra factor into the model, 'Appraisal', as shown in Figure 4 [19].

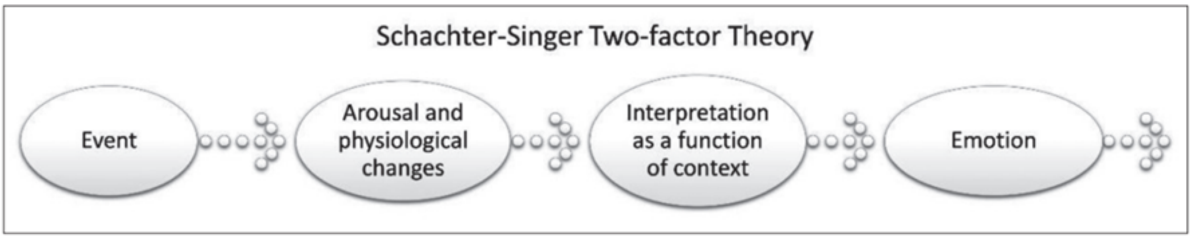

Figure 2.3: Schacter-Singer Two Factor Theory [18].

They hypothesised that like the James-Lange theory, there was a process to feeling an emotion. An event would stimulate a physiological change, but they introduce the idea that the person makes an appraisal of the situation first before experiencing the said emotion. For example, in the bear situation showed in Figure 2.1, the person would first see the bear, then the brain would quickly do some physiological changes such as tightening the stomach, but now an appraisal of the situation occurs where it notices the bear coming towards the person, causing fear.

The addition of an appraisal feature to the model does fix many of the weaknesses with the James-Lange model. Though one major problem with the model is that with an appraisal feature, the person will potentially pick the wrong emotion with the wrong event as there could be multiple events causing multiple physical changes and appraisals [17].

2.2.5 Lazarus's Cognitive Appraisal Theory

Richard Lazarus's Cognitive Appraisal theory differs heavily from the previous three models [20][21]. Instead of basing emotion on the physiological side where bodily reactions create emotion, this model suggests that emotions are determined by the cognitive decision of the person, as seen in Figure 2.4.

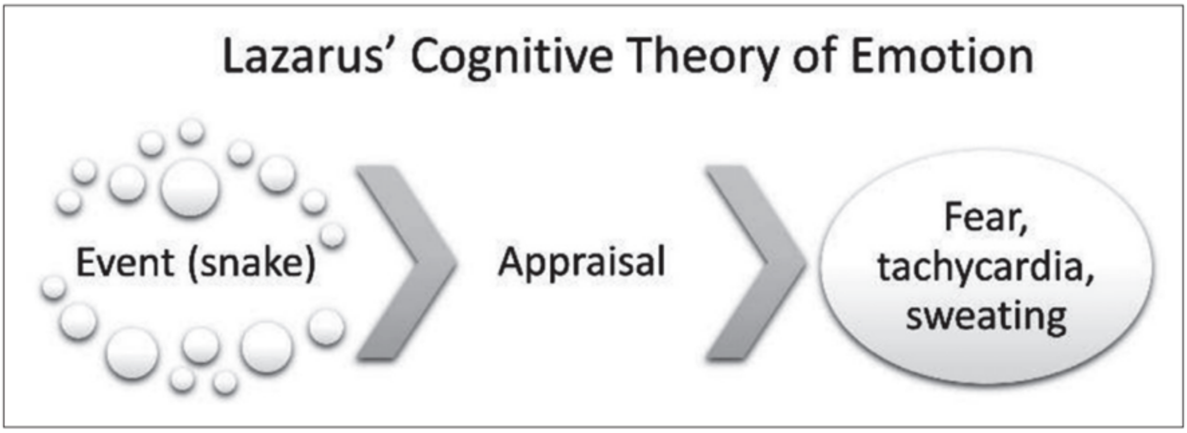

Figure 2.4: Lazarus' Cognitive Appraisal Theory [18].

What this means is that when an event occurs, such as seeing a bear, the person first assesses the situation. If they see a bear but it's really far away, then they might see the risk as lower which could change the physical changes and emotions felt by then if the bear was closer. This shows that the model is robust as it is not limited to category emotions like the previous models while also explaining how different emotions can have the same physiological changes.

2.3 Emotion Classification

As the previous models in section 2.2 explored the different methodologies on how emotions occur, it is important to showcase how previous studies have classified these emotions. To start with common classification models to analyse, it was important to first check the most common models being used to link music and emotions. 'A review of music and emotion studies: Approaches, emotion models, and stimuli' by T. Eerola and

J. K. Vuoskoski indicated that 70% of models are ‘categorical’ or ‘dimensional’ from the late 1980s to 2008 [22].

2.3.1 Categorical Model

Categorical models of emotions also known as the basic emotion theory has been developed considerably adopted and developed by many notable figures such as William James and Carl Lange [23]. The model postulates that all emotions are independent of each other and that only of the emotion could be felt at any given moment and that there is no scale to those emotions.

For example, ‘Ekman’s Six Basic Emotions’ model by Paul Ekman stipulated that there are six primary emotions that are universally recognized including joy, anger, disgust, surprise, sadness, and fear [24]. In his theory a person no matter their cultural identity can only experience one of these emotions at any given time. To prove this, Ekman travelled to Papa New Guinea and told stories to the native village to showcase a type of emotion. Then each participant were given 3 photos and were told to choose the correct emotion. The results can be seen in Figure 2.5, which prove that overall participants were able to choose the correct emotion expressed the majority of the time, apart from where fear was the expected result.

Adult Results

Emotion described in the story	Emotions shown in the two incorrect photographs	No. *Ss*	% choosing correct face
Happiness	Surprise, disgust	62	90**
	Surprise, sadness	57	93**
	Fear, anger	65	86**
	Disgust, anger	36	100**
Anger	Sadness, surprise	66	82**
	Disgust, surprise	31	87**
	Fear, sadness	31	87**
Sadness	Anger, fear	64	81**
	Anger, surprise	26	81**
	Anger, happiness	31	87**
	Anger, disgust	35	69*
	Disgust, surprise	35	77**
Disgust (smell story)	Sadness, surprise	65	77**
Disgust (dislike story)	Sadness, surprise	36	89**
Surprise	Fear, disgust	31	71*
	Happiness, anger	31	65*
Fear	Anger, disgust	92	64**
	Sadness, disgust	31	87**
	Anger, happiness	35	86**
	Disgust, happiness	26	85**
	Surprise, happiness	65	48
	Surprise, disgust	31	52
	Surprise, sadness	57	28[a]

Figure 2.5: Table of Adult Results of Ekman's Emotion Classification Test [24].

Since Ekman's original theory, many changes have been made to the categorical method of classification such as introducing new emotions and how they are showcased by the human body [25]. Particularly, looking at Darwin's description, the original six proposed by Ekman became thirteen introducing emotions such as 'astonishment' and 'contemplation' as well as a few others [26]. Unlike Ekman's model, it started to show more overlap between these emotions as 'tears' would be represented in both 'laughter' and 'sympathy.'

These leads to a few problems with categorical classification model. Firstly, as there can be common signs between each emotion, there is a chance of confusion between trying to correctly characterize how a person is feeling as the results show in Figure 2.5 whereas the percentages are high for choosing the correct expression, they are not all 100%. Also due to the choice for emotions are categories, it implies that only one emotion can be felt at a time and that the person would experience the full emotion with no levels to it, meaning that a person will feel the same level of sadness for if someone close has passed away to an experience where they fail a school examination. Though, due to the simplicity of the modelling and definitive results it is quite a reliable method for emotion classification.

2.3.2 Dimensional Model

Unlike the categorical model for emotion classification, the dimensional model looks at emotion classification as a scale of emotions [23]. This brings in the idea that instead of a person being only able to experience one emotion at its fullest extent, emotions are not entirely independent and therefore, a person can feel the emotion at different levels.

A popular theory of this emotion classification model was developed in the late 1970s by Robert Plutchik called the 'Circumplex Model' in his paper 'Emotion: A Psychevolutionary Synthesis.[27][28]' In this study, Plutchik proposed that emotions could be set on a two-dimensional scale, like a colour wheel. The structure of the wheel took the work of Ekman's six basic emotions model as the 6 main primary emotions but also introduced a combination of secondary emotions as seen in Figure 2.6.

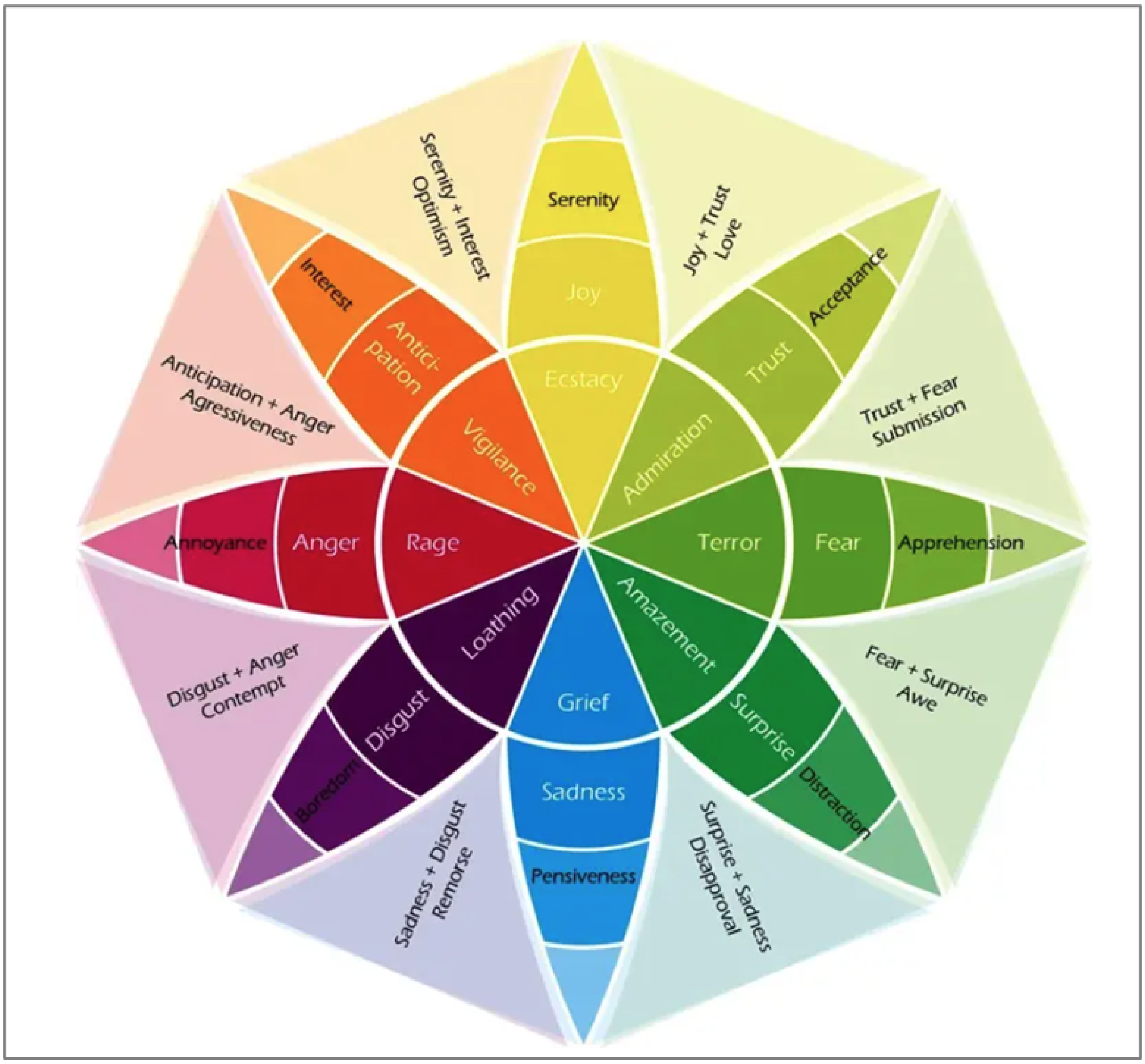

Figure 2.6: Robert Plutchik's model of emotions [19].

Following this model, James Russell also introduced a two-dimensional circumplex model which used 'Valence' and 'Arousal' values as axis on the plane and has his main emotion categories on the outer plane with no in between emotion categories to describe the level of the feeling [23][30]. Russel described the space in between as emotions that have a 'Fuzzy Membership.' Russel describes this region as the degree of the categorical emotion. For instance, when describing a glass of water, a glass can be considered full if it's filled 90% as people tend to round. Though, what if the glass was over three quarters full but not exactly 90% full? This leads to the idea that cases exist where things cannot be categorised, hence indicating that by only having the core emotions, that the space in between can indicate the level of intensity of those emotions, showcased in Figure 2.7.

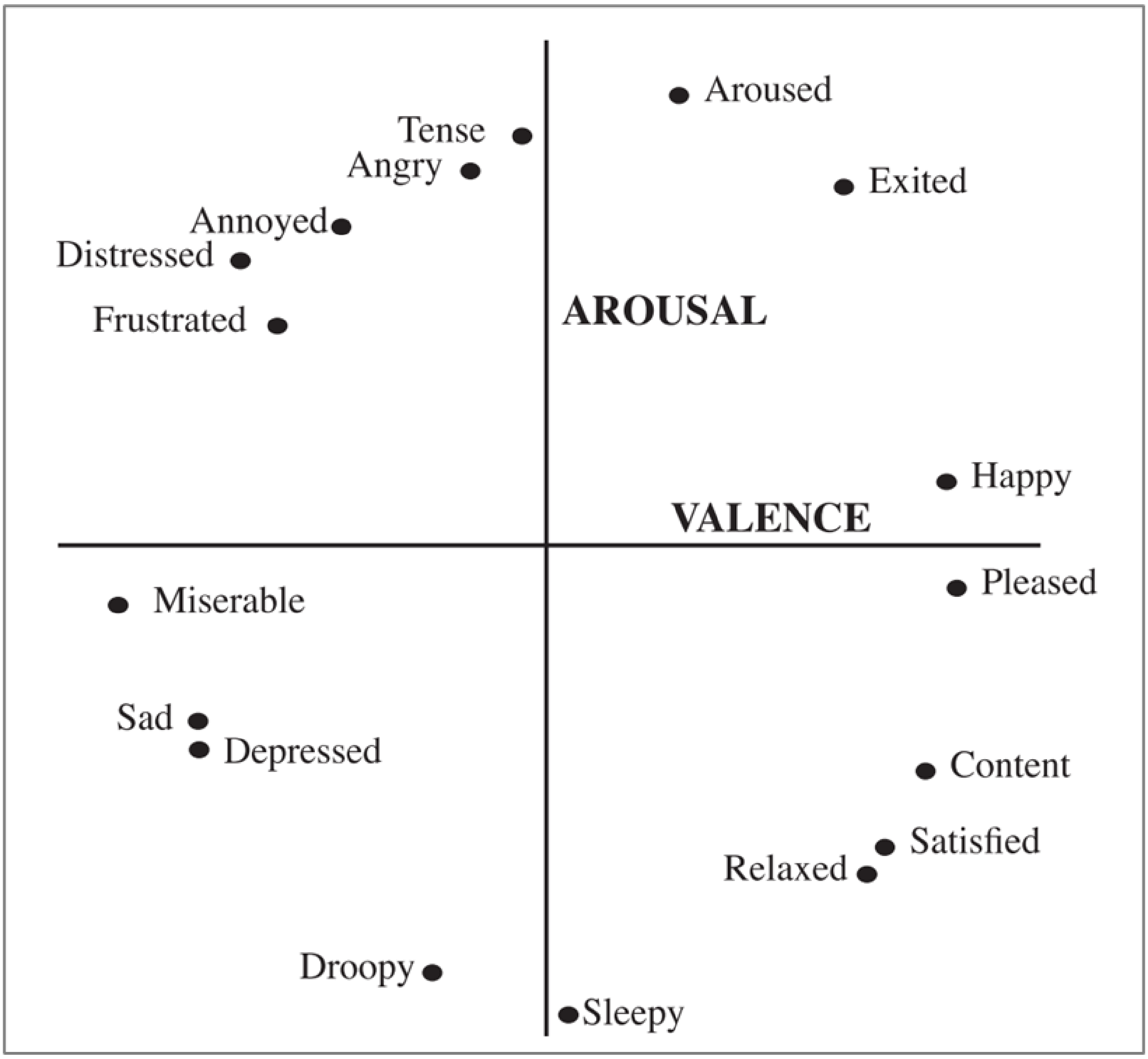

Figure 2.7: Russel's adapted emotion classification model [23].

With the idea of taking emotion classification as a range, there are a few problems that arise when using these models. The first predominant issue, is that often it is hard for a person to rate the level of emotion they are feeling and as Russel described in his study, a person cannot feel the same emotion twice to the same level as there are many different factors that cause the emotion in the first place [30]. Also, as classifying emotions can vary among people, the category placement for each emotion can shift person to person, meaning that it becomes very hard to come up with conclusive results. Though, the main benefit to the dimensional model is that it does showcase how not all emotions are the felt to a full extent and that there are levels that can be felt.

2.4 Emotion Classification Modelling

Looking at historical studies on this emotion classification such as Ekman's original study on categorical emotion classification, there was a reliance on classic statistical approaches to analysing the data. For instance, Ekman's paper used binomial t-test to calculate a significance between emotion recognition [24]. Though as technology has further developed, there has been a change in how analysis is done with newer studies opting for machine learning techniques to best classify emotions. A common approach to classifying emotions is through the analysis of electroencephalogram (EEG) data.

A study performed in 2021 'Predicting Exact Valence and Arousal Values from EEG' by Galvao et.al found that when comparing multiple machine learning algorithms for regression, 'K-nearest neighbours Regressor' and 'Random Forest Regressor' had the best accuracy for detecting arousal and valence values when compared to the 'Autoregressive', 'Linear Regression', 'Decision Trees' and 'Support Vector Machines' models [31]. In their study, they obtained data from multiple established datasets such as DEAP and analysed the 'Alpha', 'Beta' and 'Gamma' brain waves and found that K-nearest neighbours regressor had an 89.84% accuracy for predicting arousal values and 89.83% accuracy for predicting valence values.

Similar results were also found in a conference paper 'Music Emotion Recognition Using K-Nearest Neighbours Algorithm' by Ualibekova et.al [32]. In their paper they decided to use Plutchik's wheel of emotions with Russell's two-dimensional model to then try and classify emotions. What the study found was that a support vector machine was the least accurate with a 32.73% accuracy. This was followed by a k-nearest neighbours with a 53.7% accuracy with support vector regressor being the best algorithm with a 63.03% accuracy. Though, what the paper found was that when compared to the results the k-nearest neighbours algorithm produced the best results.

Contrary to the results above, another study 'Automatic ECG-Based Emotion Recognition in Music Listening' by Hsu et al. used a mix of machine learning and statistical analysis to find the most efficient analysis [33]. In their study they performed a generalized discriminant analysis to identify the features that were significantly affecting the electrocardiogram (ECG) waves for dimension reduction. Then by implementing a least squares support vector machine, they were able to correctly classify emotions at an 82.78%, 72.9% and 61.52% accuracy for the classification tasks that were set up.

Unlike the previous studies mentioned, 'Emotion classification using a CNN-LSTM based model for smooth emotional synchronization of the humanoid robot RENXIN' by Ning Liu and Fuji Ren decided to implement an algorithm that consisted of both a convolutional neural network and a long-short-term memory neural network to determine and classify emotions [34]. Though, as the other studies focused on analysing EEG or ECG data, the data they use are photos of someone showing said emotions. They then by using this data they would train an avatar robot and analyse the best model based on time spent training and accuracy. They found that the CNN-LSTM was the best model compared to a normal CNN or LSTM model.

Chapter 3

Methodology

This chapter will look at the findings of the literature review and define the process and reasoning of the proposed testing method to determine how different genres of music can affect the emotions of participants and in turn, affect the cognitive performance of young adults. The chapter outlines the technology requirements for the experiment, plus the methods for data collection, cleaning, preliminary testing and modelling methods for both short and long-term cognitive performance tests.

3.1 Discussion

To answer the question of whether different genres of music can influence the emotions and cognitive performance of people, it was first important to do preliminary research into the field of study. It was found that, although many of the papers did come up with accurate results when looking into emotion recognition and cognitive performance separately, no study showed a direct correlation between the two or tried to use the change of emotion as the reasoning for a decrease or increase in performance. Therefore, to first prove if there is a linkage, it is important to first define what an emotion is.

Looking at the literature discussed in Chapter 2.2, Lazarus' cognitive appraisal theory is the optimal choice. Lazarus' theory states that an emotion will occur after an appraisal of the situation by the person, which will then cause bodily changes. As participants will be aware of the study and the test process before the experiment it makes sense that the situation will be appraised before any emotion is felt. This means that it is unlikely that emotions like fear or sadness will occur at the start of the experiment, resulting in Lazarus' cognitive appraisal theory being the optimal choice for this study.

Now that what causes emotion has been defined, it is important to choose a classification method for this study. Looking at previous literature, both the dimensional and categorical approach have their positives and negatives. To overcome the shortcomings of both models, a combination of both classification techniques is the optimal choice. To achieve this, the study will use Paul Ekman's six basic emotions theory to simplify the number of categories while also using machine learning models to analyse arousal and valence values proposed by James Russel for accuracy on the level of emotion felt. Combining these two approaches, in theory, will be optimal as the answers required from participants will be simpler and more accurate.

Therefore, for this study, the following emotion classification has been proposed to simplify the dimensionality of emotion while integrating a mix of categorical and dimensional approaches. The model will be 4 dimensions with a 5-point scale:

- Scale 1: Sad to Happy (1-5)
- Scale 2: Angry to Relaxed (1-5)
- Scale 3: Droopy to Excited (1-5)
- Scale 4: Sleepy to Tense (1-5)

When looking at how the previous studies have tested their participants, it appears that there has been quite a large mix of surveys such as emotion scales and EEG data. This mixture appears to be a perfect mix as classification models in the past are producing accurate results for their models. Therefore, the study will use a Muse 2 headset device for collecting accurate EEG data as well as survey forms for categorical emotion collection and quiz results.
To determine the modelling techniques that should be used, previous literature indicates that using K-nearest neighbour clustering and Random Forest Classifiers/Regressors will give the most accurate results. Though as the data being analysed will have different parameters and results, these models are a good starting point as they point towards 'supervised learning' models but will be subject to change in this study.

3.2 Technology Requirement

3.2.1 Muse 2 Headband and Mind Monitor Phone Application

The Muse 2 Headband is a wearable device designed to provide real time feedback on brainwave activity, heart-rate, body, and breath mediation[35]. It uses seven highly calibrated EEG sensors to record alpha, beta, delta, and gamma waves in the brain and produce graphs within the companion device. The device is lightweight and sits comfortably on the forehead, which when turned on, transmits the data via Bluetooth onto the phone application. The main advertised features of the Muse 2 can be seen in Figure 3.1.

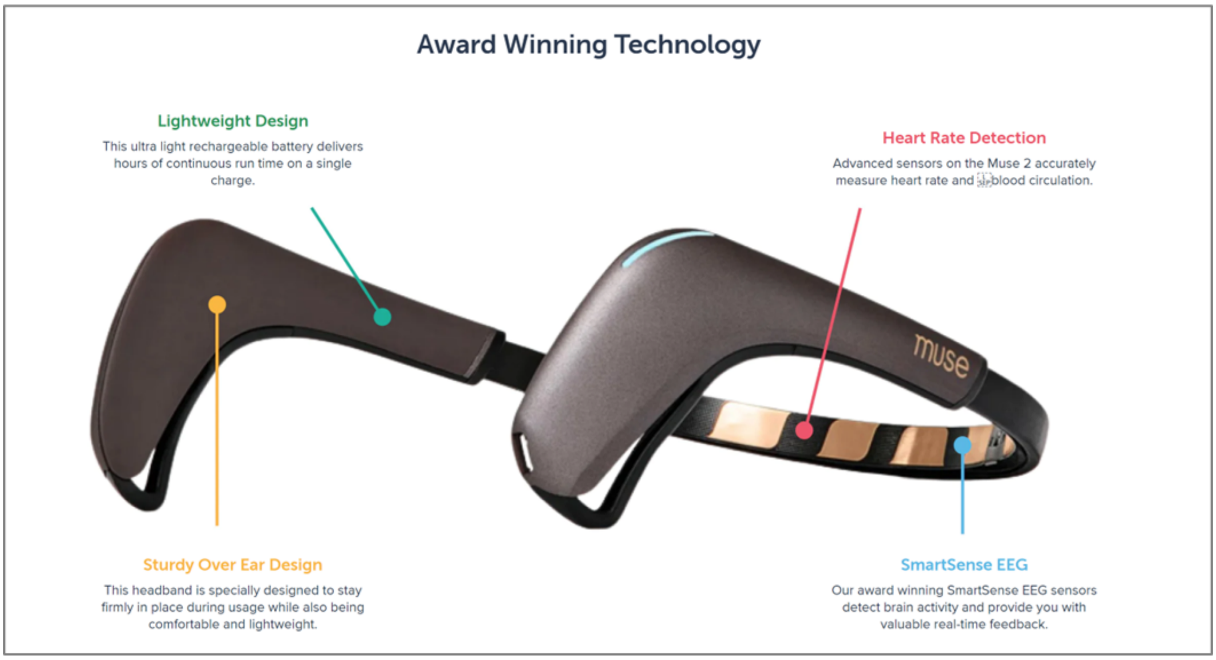

Figure 3.1: Muse 2 Headband [35].

When choosing the phone application to receive the data, it was important to choose an application that would allow the raw EEG data to be extracted and used for machine learning. Unfortunately, the official application from Muse does not offer that feature and only shows graphs within its application. To get over this hurdle, the choice was made to use the Mind Monitor application by James Clutterbuck which allows the raw EEG data to be exported into a CSV file and uploaded to Google Drive[36]. The app also has a few features that make it better over the official application such as the ability to change the frequency of data collection and have a small display to show if all the sensors are correctly fitted.

As there are only seven EEG sensors, the entire brain is not analysed for brain waves but only waves from the frontal portion of the brain. For a study on cognitive performance, this device works to the benefit of the study as studies show that frontal portion of the brain such as the frontal lobes, cerebellum and basal ganglia are directly linked with cognitive thinking and motor control.
When the data is extracted from the Muse 2, the following categories are outputted:[36]

1. Frequency Spectrum and Hertz Range:
   - Delta = 1-4Hz
   - Theta = 4-8Hz
   - Alpha = 7.5-13Hz

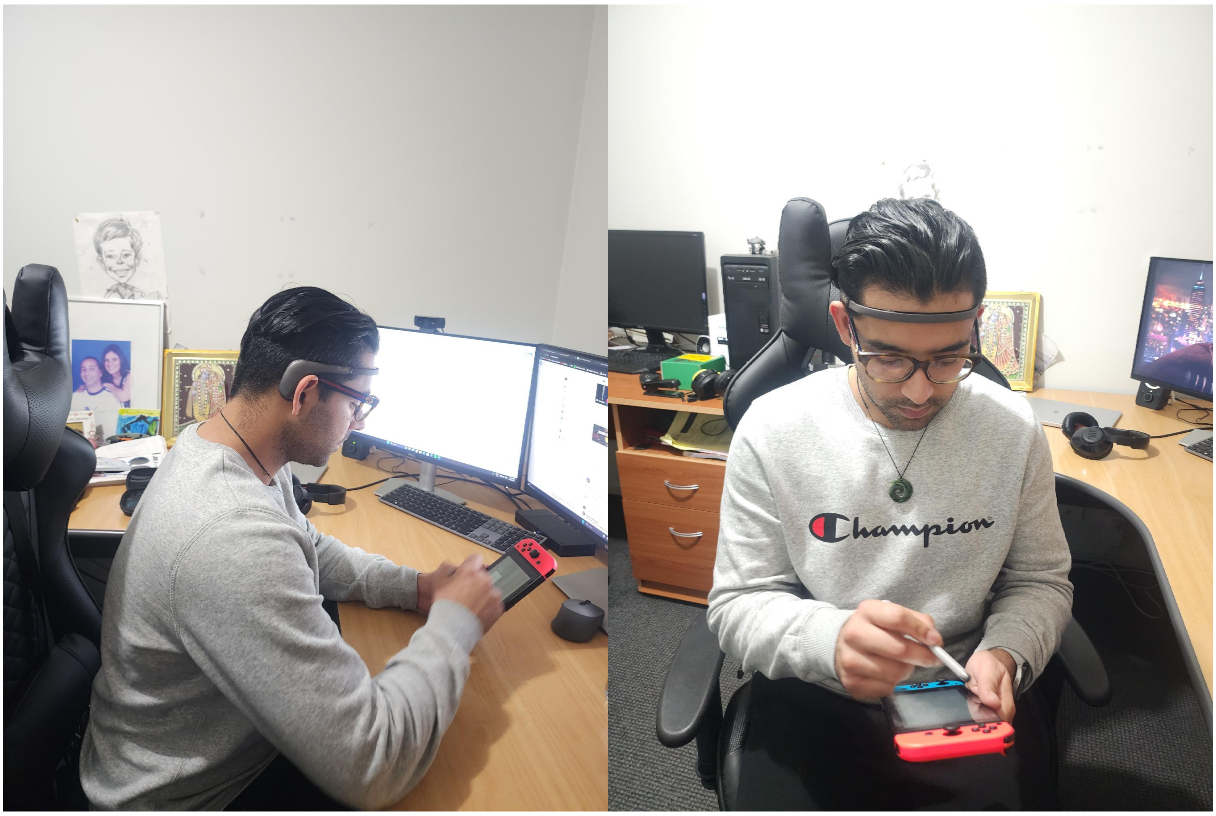

Figure 3.2: Muse 2 Headband Setup

- Beta = 13-30Hz
- Gamma = 30-44Hz

2. Raw Sensor data from location:
   - P9 - Left ear
   - AF7 - Left forehead
   - AF8 - Right forehead
   - TP10 - Right ear
   - AUXR - Right Auxiliary
   - AUXL - Left Auxiliary (MS-01/MS-02 only)
3. Gyroscope data of headband movement:
   - Gyro-X
   - Gyro-Y
   - Gyro-Z

In terms of reliability of the Muse 2, a study done by Limin Zhang and Hong Cui tested the reliability of the Muse 2 and Tobii Pro Nano for capturing mobile application user's real time cognitive workload changes [37]. Though, the Muse 2 device did not yield as effective results as the Tobii in this study, the authors did note that the device was producing reliable results and would show promise for detecting cognitive workload in future works, indicating that the device would reliably transfer correct EEG signal data for this study.

3.2.2 Nintendo Switch and Dr Kawashima's Brain Training for Nintendo Switch

For the examinations that the participants will undertake, it is essential that a range of cognitive based activities are tested to truly see the impact of different genres of music on cognitive abilities particularly, 'processing speed', 'short-term memory' and 'self-control'. Instead of creating a set of tests where they participants would have to physically write answers on paper and in turn, be hand marked by the author to determine results and timings, the author has opted to use the video game 'Dr Kawashima's Brain Training for Nintendo Switch' (Brain Training)[38].

The game developed by Nintendo is built for the 'Nintendo Switch' a handheld console designed for both household and portable gaming. Originally released in March 2017, the console has a 6.2-inch LCD touchscreen, detachable Joy-Con controllers, wireless connectivity and offers a wide range of games for all ages.

The study by Rui Nouchi et al. 'Brain Training Game Boosts Executive Functions, Working Memory and Processing Speed in the Young Adults: A Randomized Controlled Trial' based its findings on whether brain training games can improve cognitive performance of a period to time[38]. It did this by comparing Dr Kawashima's original Brain Training game for the Nintendo DS with Tetris and found that the mini games on Brain Training showed an overall beneficial affect on participant cognitive function. As the mini games tested on executive functions, working memory and processing speed the main area of the brain being activated are the frontal lobes, cerebellum and basal ganglia which tie perfectly to the brain wave activity measured by the Muse 2 Headband mentioned in section 3.2.1 [39].

3.2.3 XBOX Series X and Electronic Arts Formula 1 2022

To examine the learning/improvement rate over a period, it is important to be able to simplify the test to something that could concurrently test the three focused cognitive functions of multi-tasking, memory, and cognitive processing. In this case, the author has chosen to measure the improvement of race-time over three different grand prix in Electronic Arts (EA) Formula 1 2022 on Microsoft's XBOX Series X to see under which music or non-music condition would indicate a greater improvement in race time from the start to the end date.

The game designed by EA, involves 20 formula 1 cars race around a race weekend such as the São Paulo Grand Prix, recording different data points such as sector times from each lap, start and finish positions, lap times and overall race time. It also simulates the rules and car performance to simulate the real performance of formula 1 drivers. Previous studies such as 'Video games as a means to reduce age-related cognitive decline: attitudes, compliance, and effectiveness' by Walter. R Boot, et all... have tested racing games such Mario Kart for the DS as a means for cognitive ability enhancement. In their study they saw positive and negative changes in processing speed, memory, and attention as seen in Figure 3.2 below [40]. This indicates that the racing games and in particular F1 2022 are a viable option for testing due to the amount of data points available and the cognitive skills that are being tested in this experiment.

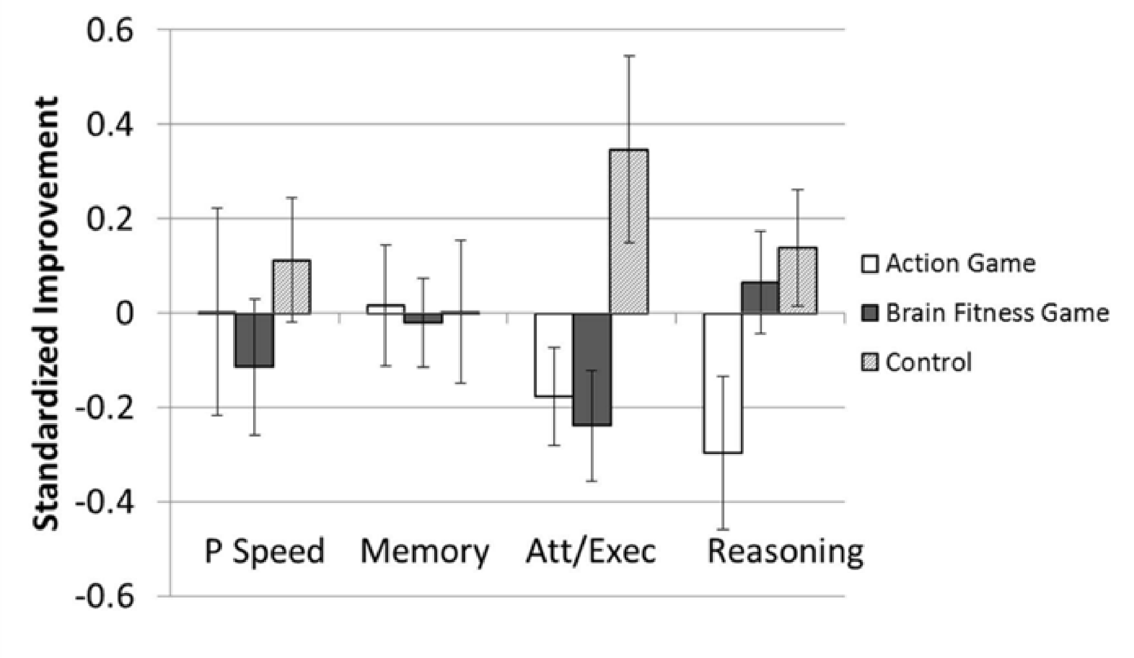

FIGURE 1 | Standardized (*Z*-score) composite improvement scores as a function or task type and group. Error bars represent ± SEM.

Figure 3.3: Performance in Mario Kart vs Brain Age 2 [40]

3.2.4 Computer/Laptop Specification

To create an emotion classification algorithm the author uses the specifications found in Table 3.1 but notes that this is the minimum specification requirement and that better specifications could improve efficiency in training models.

Table 3.1: Author's Laptop Specifications

System	Specification
System Model	Surface Laptop 4
Processor	AMD Ryzen 7 Microsoft Surface (R) Edition 2.00 GHz
Installed RAM	8.00 GB (7.45 GB usable)
System type	64-bit operating system, x64-based processor
Pen and touch	Pen and touch support with 10 touch points
Edition	Windows 11 Home
Version	22H2
Installed on	24/09/2022
OS build	22621.1702
Experience	Windows Feature Experience Pack 1000.22641.1000.0

3.2.5 Earphones/Headphones

In terms of the music device, the optimal choice would be for each participant to use their preferred headphones or earbud device. This is because participants will be able to better simulate how they study with their preferred volume settings without having to fiddle around at the start and reduce the effect of the distraction-conflict theory[40]. If the participant does not have access to a personal music listening device, then the participant will be able to use a pair of JBL Quantum 350 Wireless Over Ear Gaming Headset provided by the author.

3.3 Experiment 1 - Short-Term Cognitive Performance Analysis in Response to Video Game Intervention

3.3.1 Participants

For this experiment 26 participants took part between the ages of 16 and 27. The study was diverse and included 16 males and 10 females. To reduce the bias in the data, 23/27 of the participants in the study were current university students studying their respective bachelor's degrees at various universities in Sydney. Looking at the histogram in Figure 3.4, the participant 16 years of age is an outlier in the data. Though due to the limitations of time and number of participants, the outlier has been retained for this study.

3.3.2 Dr Kawashima's Brain Training Tests

To test the cognitive abilities of each participant, it was important to be able to isolate the three core skills of brain processing, memory and multi-tasking and collect data on how

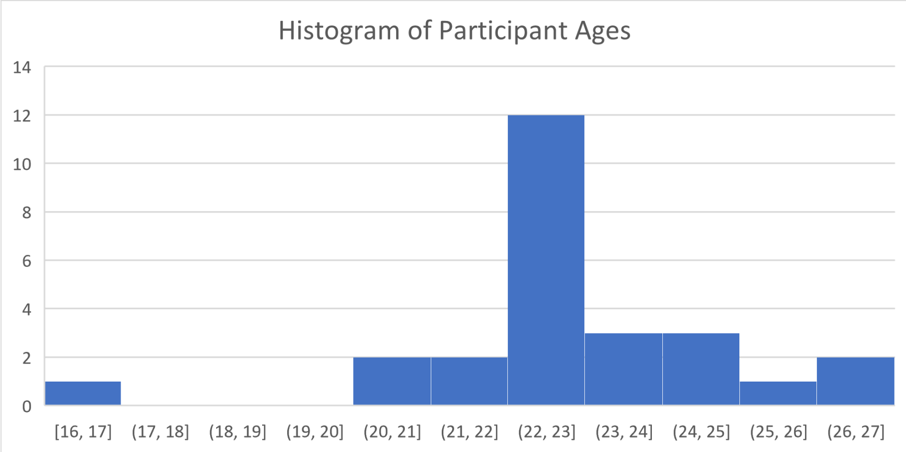

Figure 3.4: Histogram of Participant Ages

different genres of music would affect these core skills. To analyse these changes, three different games were selected: 25x – Calculations, Short-Term Memory, and Dual-Task, showcased in Figure 3.5.

The first test '25x – Calculations' is designed to test the brain processing skills of the participant. In this game the user is presented with 25 basic mathematics questions including addition, subtraction, and multiplication. Participants are tasked to complete the questions as fast as they can with as little mistakes they can make. The data collected is completion time, number of mistakes and total time where each mistake adds 5 seconds to the completed time.

The second test 'Short-Term Memory' is designed to test the short-term memory of participants by asking participants to remember the previous shown image and then select that photo while being shown a new one. Participants are then asked to repeat with the latest shown image. Like the previous test, the goal is to complete the number of questions at the lowest possible time with the least number of mistakes. The data collected is completion time, number of mistakes and total time where each mistake adds 5 seconds to the completed time.

The third test 'Dual-Task' is designed to test the multi-tasking ability of participants by asking participants to select the largest valued numbers at the bottom of the screen while tapping the top of the screen to make the stick man jump over hurdles. The goal is to select the highest values as fast as possible without selecting incorrect values and hitting the hurdles. The data collected is completion time, number of mistakes and total time where each mistake adds 5 seconds to the completed time.

3.3.3 Testing Method

1. The participant will first go through a setup process where they would be explained how to navigate to each of the games, been shown what the games look like and be setup with the MUSE 2 device. The participant would then throw a six-sided

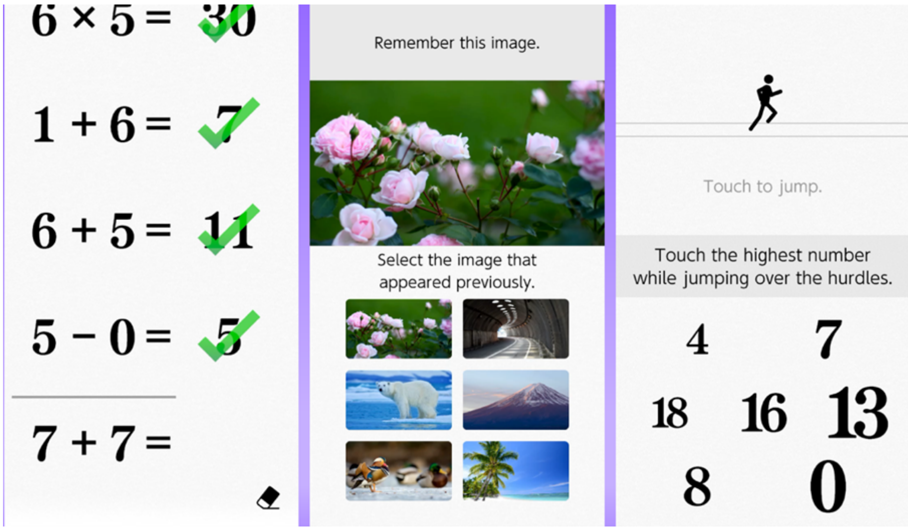

Figure 3.5: Dr Kawashima's Brain Training Mini Games

dice and would randomly be allocated a starting genre as seen below. The music selection can be found in Appendix 6.2

Music List:

(a) No Music – Genre 1

(b) Film-Score – Genre 2

(c) Hip-Hop – Genre 3

(d) Rhythm and Blues – Genre 4

(e) Rock – Genre 5

(f) Re-Roll the dice

2. The participant will then be asked to sit for five minutes listening to the genre of music that they rolled on the dice, to get them synchronised and comfortable with the change in music.

3. Once the five minutes is up, they will then play the three games mentioned in the section 3.3.2. At the end of each quiz, they will fill in a survey on Microsoft Forms on how they will think they performed and the emotions they felt when undertaking the quizzes. At the end of each quiz, stop the recording of EEG data to separate the brain wave activity.

4. Once the third game is played, the participant will listen to the next genre for five minutes and then repeat step 3 until all genres are completed.

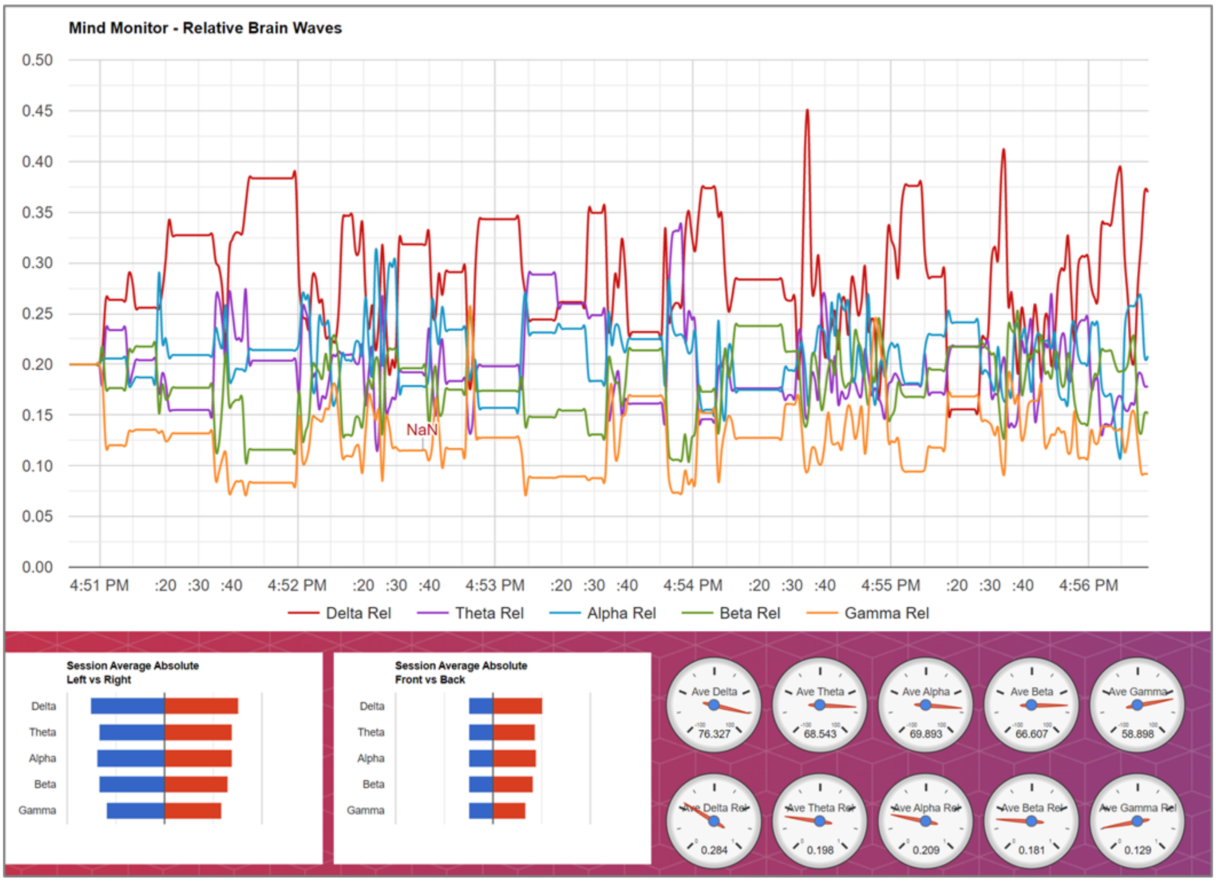

Figure 3.6: *'No Music' wait period preliminary test*

3.3.4 Preliminary Testing

No Music Test

As indicated in the chapter 3.3.3, after allocating first choosing 'no music', the participant wore the Muse 2 EEG device for five minutes without undertaking any activity. Using the Mind Monitor's website to generate the graph seen in Figure 3.6, when doing the relative brainwaves check, the delta wave appeared to be comparatively the highest by a large margin when compared to the alpha, beta and theta waves which were approximately the same and the gamma waves being very low comparatively. It is also worth noting that the device itself seemed to have moved around when the participant was waiting.

After the five-minute waiting period, the participant was then asked to try two of the three brain training tests, 'Calculations x 25' and 'Dual Task' The graph in Figure 3.7, showcases the relative brainwaves results.

Comparing the brain wave activity of cognitive tasks, it appears that the average wave values are considerably higher when the participants was attempting the cognitive skills

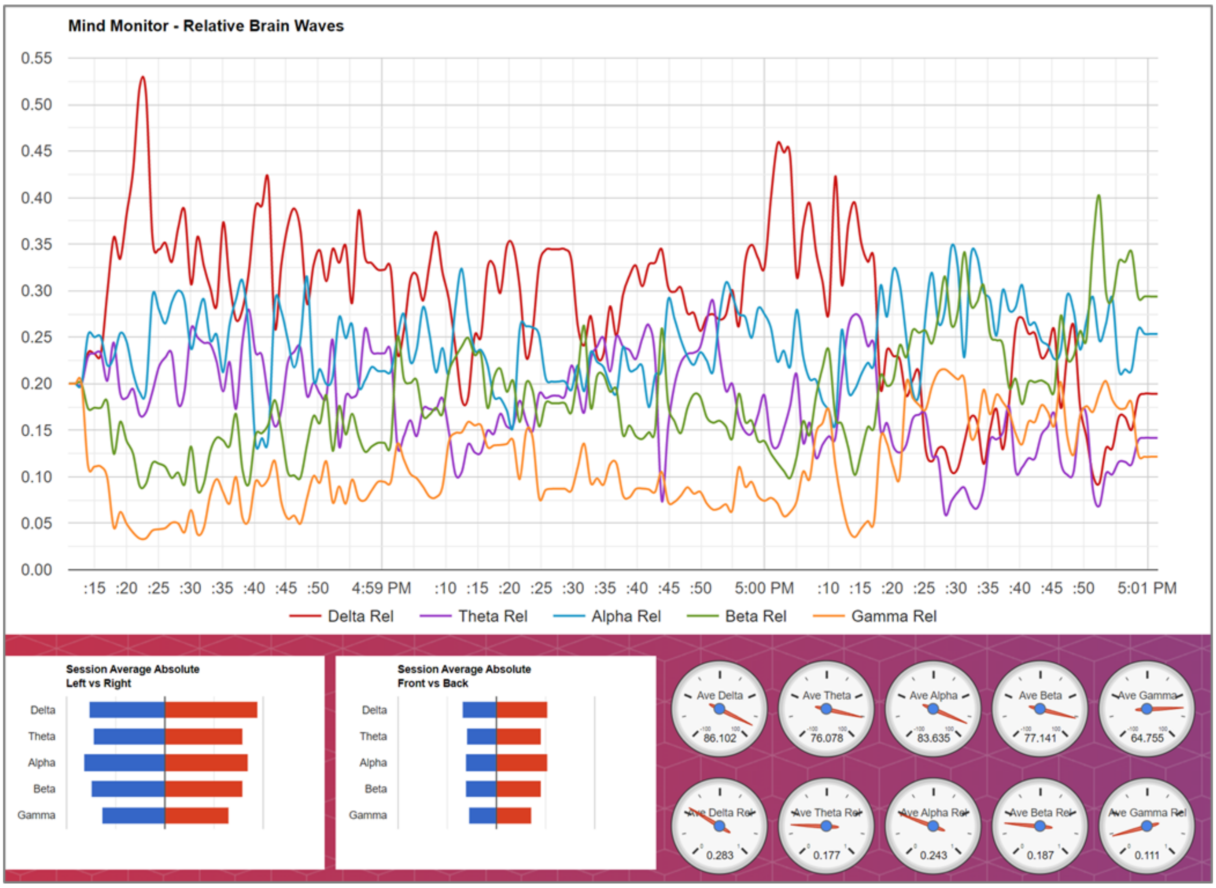

Figure 3.7: 'No Music cognitive task preliminary test

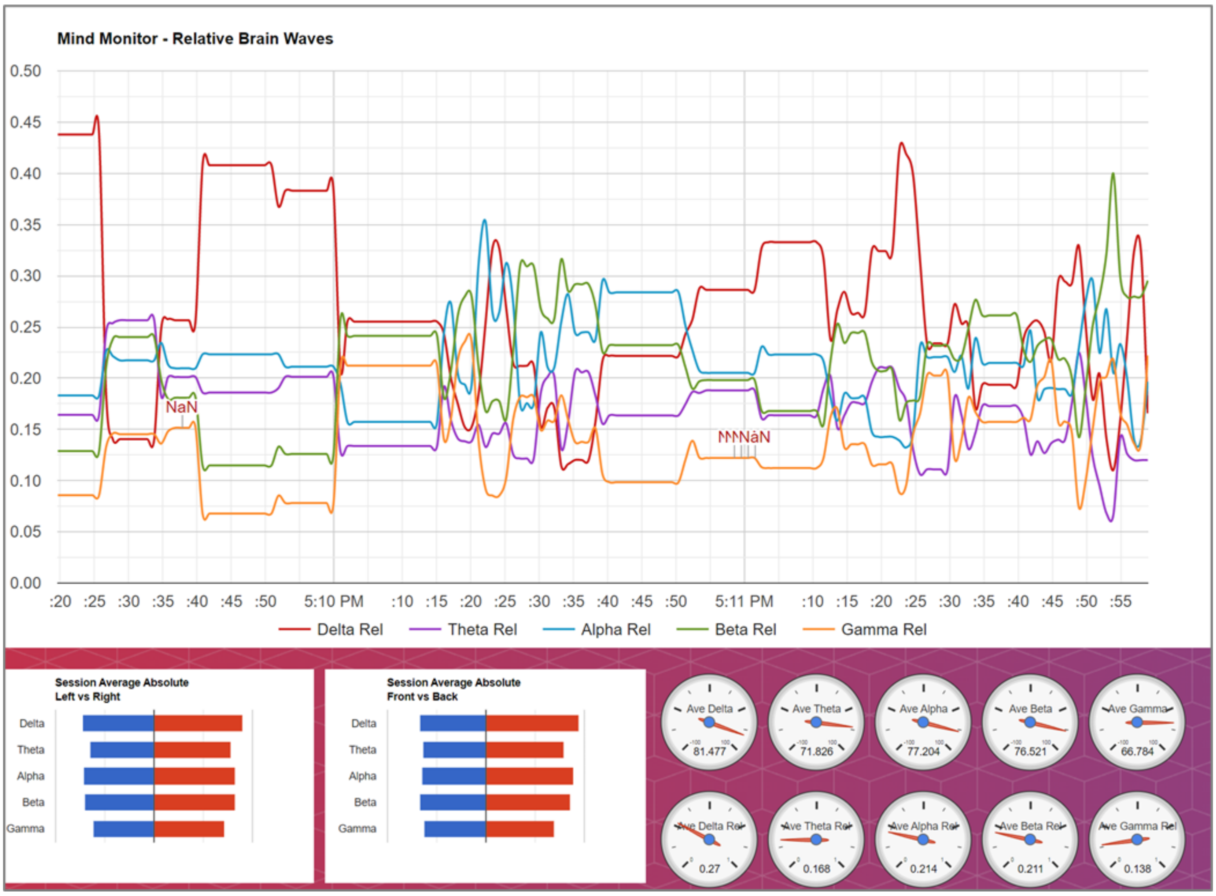

Figure 3.8: . *'Film Score' wait period preliminary test*

test. Noticeable difference is in the ordering of the wave as on average in the cognitive test, the waves apart from gamma, seem to be closer on average to each other, indicating that the other waves seem to intensify when a task is being completed.

Film Music Test

The second choice that the participant selected was to attempt the experiment listening to 'Film-Score'. As before, the participant was first asked to sit for five minutes listening to the film-score playlist. The initial results can be seen in Figure 3.8. The results show that similar to the no-music wait test, the delta waves appear to be significantly higher than the other waves., with gamma waves still being considerably lower on average.

Following the wait period, the participant sat the cognitive tasks while listening to the music. Looking at Figure 3.9, there is a direct increase in all brain wave activity, with the average delta frequency reaching an average of 92.228. All the other brain waves though, when compared to no music were also on average higher and closer together indicating that the brain was working harder when music was being played.

On top of the quiz results shown in Table 3, the participant was also asked to comment

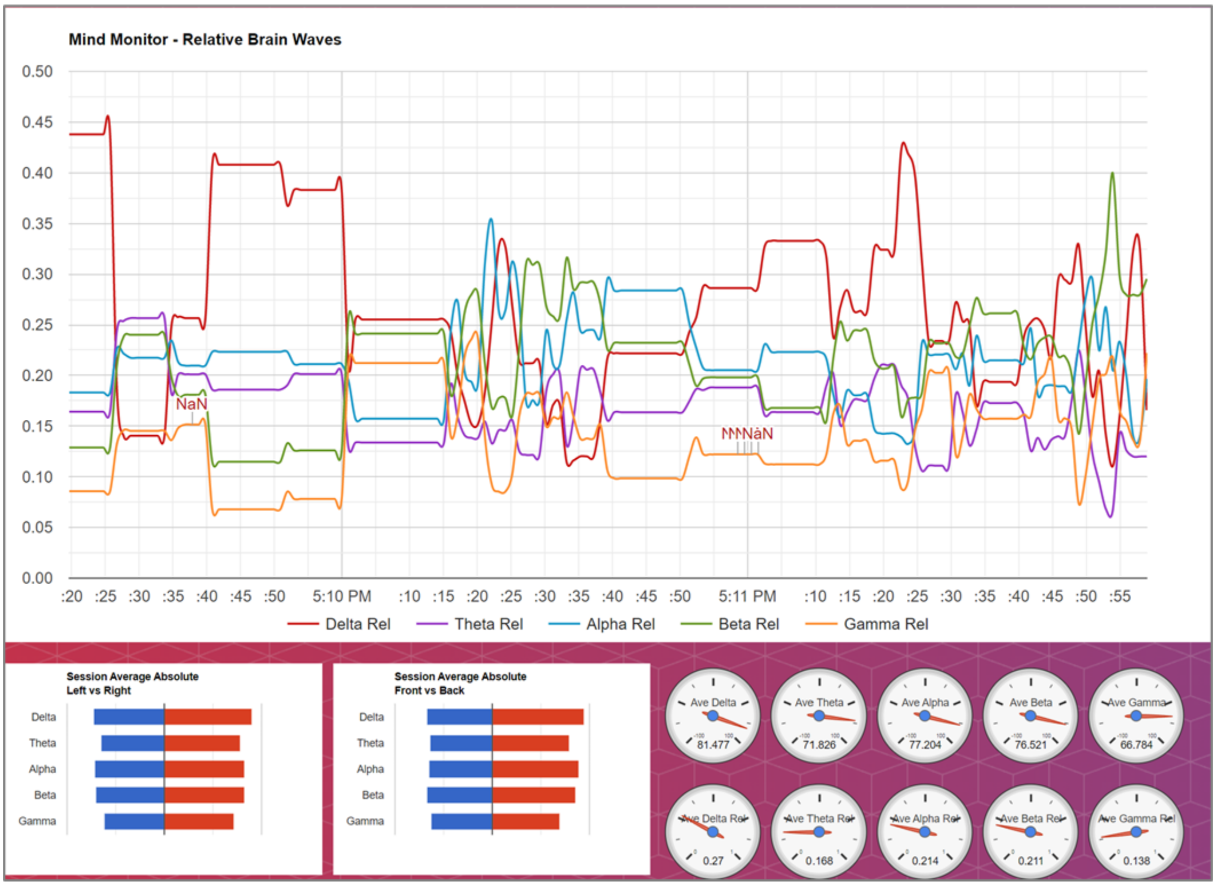

Figure 3.9: *'Film Score' cognitive tasks preliminary test*

Table 3.2: Preliminary Test Results

Test	**Genre**	**Time**	**Incorrect answers**	**Total Time**
Calculations – x 25	No Music	37.93 seconds	0	37.93 seconds
Dual Task	No Music	44.24 seconds	4 – 20 second time penalty	64.24 seconds
Calculations – x 25	Film Score	60.07 seconds	0	60.07 seconds
Dual Task	Film Score	34.0 seconds	0	34.0 seconds

on the quizzes and the music as seen below:

· No music: "*2^{nd} task made me feel slightly panicked otherwise I felt calm during the first task. Failures ensured a hint of annoyance. Emotionally calm, then slightly annoyed.*"

· Movie score: *"Expectant at second task due to familiarity. First task music distracted calculations in head causing some issues. Emotionally distracted, then was in the zone."*

Looking at Table 3, there is quite a difference in results for both tasks when listening and not listening to music. The 'Calculations x 25' test for 'no music' was able to be completed in almost half the time when music was being played, but in 'Dual Task' when no music was played the participant made 4 mistakes and took a total time is 64.24 seconds. Then when the participant played it with music, their time almost halved to 34.0 seconds with zero music. This indicates that music could act as a distraction for processing skills but also aid in concentration and multi-tasking.

3.3.5 Data Cleaning and Processing

For this experiment, due to how the results were recorded by both participants and the muse device, it was necessary to adjust the data to make it appropriate for machine learning and analysis. The first problem was with how participants recorded their test scores on Microsoft Forms. Due to not specifying how to record the time, participants recorded their times with different units of measurement for example some participants wrote '90 seconds' while others wrote '1min30sec'. To fix this, the time of each participant was converted into seconds and then was changed to be a difference of time from the 'No-Music' scores to standardise the time and reduce potential outliers. For instance, a participant scored '53.78 seconds' in 'no music' and '31.40 seconds' in 'Rock' for the calculations the data was changed to 0 seconds and '-22.38 seconds' respectively.

It was then important to check for outliers in the data sets, when doing an initial check of each test, a few outliers were noticed and 2 participants were excluded from the '25x – Calculations', and 3 participants were excluded from the 'Short-Term Memory' and 'Dual-Task' tests. The histograms for time are approximately normally distributed indicating the data will be usable for machine learning as seen in Figures 3.10, 3.11 and 3.12 below.

The second component to the data cleaning process was to clean the EEG data collected by the muse device. To achieve this, MATLAB's EEGLAB library was used to first remove all rows with missing data points, calculate the sampling rate and apply a band-pass filter using Nyquist formula as seen below:

Nyquist=1/2 ×Sampling Rate[41]

Normally in EEG processing, artifact rejection is also performed on the brain waves for better analysis, though as the data collected per test per participant was less than 5 minutes artifact rejection was not performed as the data loss would be too high for analysis. Instead, an average of each wave was taken from each test and then an average of averages was applied to combine the waves from each node to get one singular value average for Alpha, Beta, Theta and Gamma waves. The pseudo algorithm works as seen below:

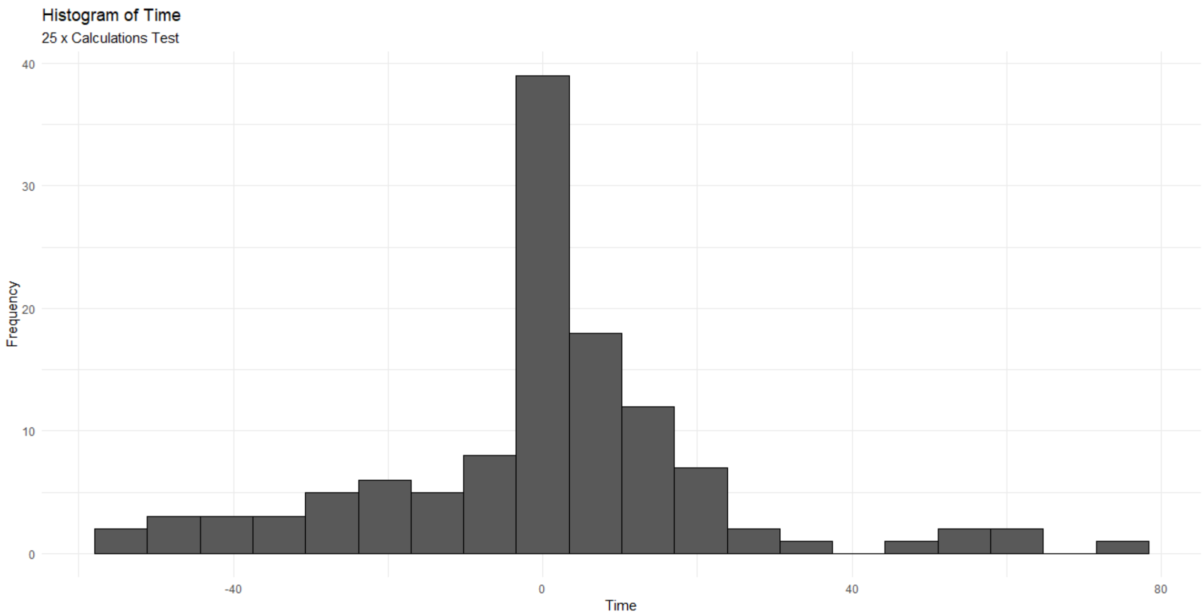

Figure 3.10: Histogram of Time for '25x- Calculations' Test

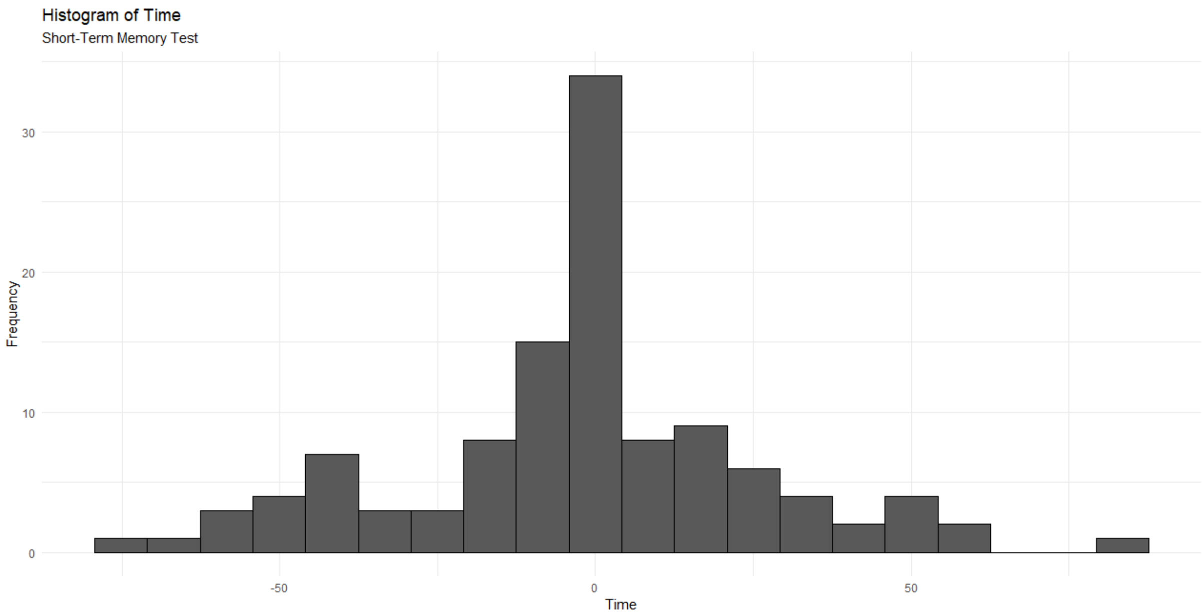

Figure 3.11: Histogram of Time for 'Short-Term Memory' Test

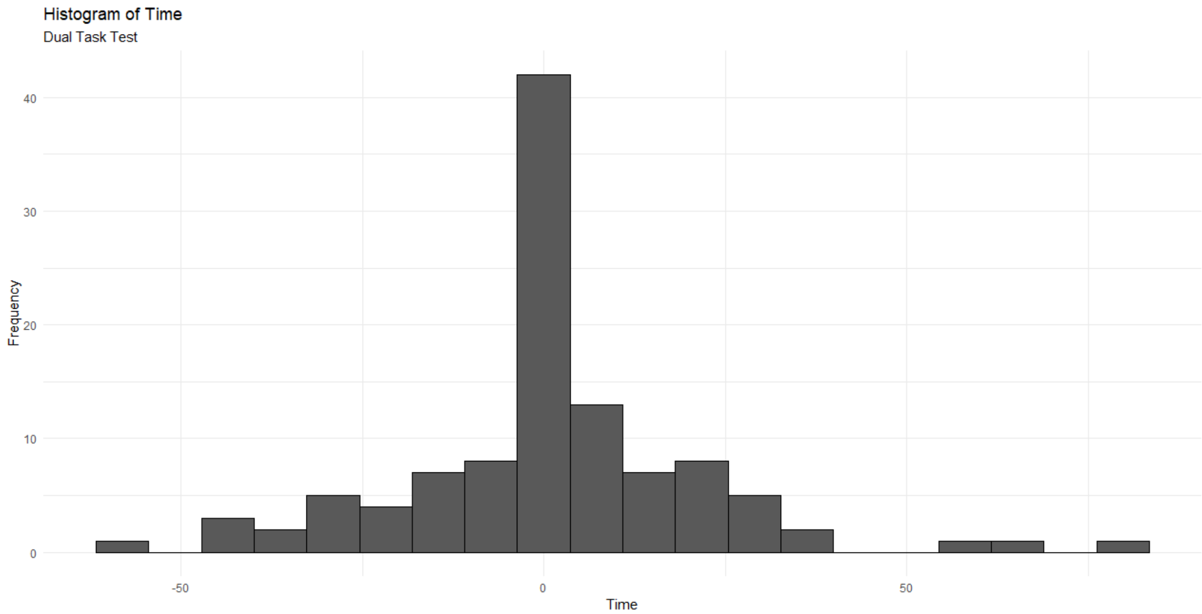

Figure 3.12: Histogram of Time for 'Dual-Task' Test

1. Define the directory where EEG datasets (CSV files) are located
2. List XLSX files in the data directory.
3. Create an array to store EEG tables.
4. Loop through each XLSX file.
5. Extract the dataset name from the file.
6. Read and store EEG data from the XLSX file.
7. Debug: Print the EEG data for the current dataset.
8. Save each EEG table as MAT files.
9. Load the EEG data from the MAT file.
10. Launch EEGLab.
11. Process each EEG table.
    (a) Extract EEG data from the cell array.
    (b) Set the sample rate and calculate the high-pass cutoff.
    (c) Create an EEG structure for EEGLab.
    (d) Apply a high-pass filter and update the EEG data.
    (e) Print the filtered EEG data.

3.3.6 Modelling Techniques

To find how cognitive ability, emotions and genres of music influence each other, two models were chosen to look at prediction testing and the effect of emotions and genres on Time.

For the prediction models, section 2.4 indicated that K-Nearest Neighbours (KNN) in past studies had predicted the most accurate results. Therefore, for prediction a KNN regression algorithm was implemented with a multiple linear regression to test how accurate the data collected could be used to predict emotions.

The pseudo code for this algorithm is explained below:

1. Import the dataset.
2. Define the target variables as the four scales of emotions.
3. Split the data to training and testing – 80% and 20%
4. Apply Principal Component Analysis (PCA) to reduce the dimension of the data to 2D as it allows for the variances to remain and becomes easier to analyse.
5. For each value of K in a range of K values:
6. Create a K-Nearest Neighbours (KNN) regressor.
7. Apply cross-validation to estimate model performance using K-fold cross-validation.
8. Store the mean squared error (MSE) for the KNN model.
9. Select the optimal K by choosing the value with the lowest cross validation error.
10. Train a KNN model with the previous value of K and make predictions on the four scales of emotions.
11. Create a Multiple Linear Regression model.
12. Apply cross-validation to estimate the model performance.
13. Store the Mean Standard Error
14. Make predictions on the four scales of emotion.
15. Create scatter plots to compare the predicted and actual values.
16. Output the descriptive statistics and MSE for KNN and Linear Regression.

To determine the effect of genres on emotions and cognitive ability, a linear mixed model was chosen as the model allows for the multiple linear regression lines based on random effect groupings and fixed effects.

1. The pseudo code for this algorithm is explained below:
2. Load the data from the file directory.
3. Define the model equation:

$$\begin{aligned} sTime = &\text{Mistakes} + \text{Favourite} + \text{DeltaWaveAverage} \\ &+ \text{ThetaWaveAverage} + \text{AlphaWaveAverage} + \text{BetaWaveAverage} \\ &+ \text{GammaWaveAverage} + \text{Scale1} + \text{Scale2} \\ &+ \text{Scale3} + \text{Scale4} + \text{Gyro\_X} \\ &+ \text{Gyro\_Y} + \text{Gyro\_Z} + (1|\text{Name}) + (1|\text{Genre}) \end{aligned} \tag{3.1}$$

4. Generate a liner mixed effects (LME) model from this model.
5. Generate a model summary.
6. Generate a Residual plot.
7. Generate line plots for each emotion by time with for each genre.
8. Generate random effects summary.
9. Generate descriptive statistics.

3.4 Experiment 2 – Long-Term Cognitive Performance Analysis in Response to Video Game Intervention

3.4.1 Participants

For this experiment, two participants both male ages 17 and 24, played EA's F1 2022 for a one-week period against each other with 18 AI drivers. The experience level of each participant greatly varied, with the older participant having zero knowledge on the game and racetracks and the younger participant having 6 years of experience playing the previous titles.

3.4.2 EA Formula 1 2022

For this experiment, three tracks were selected to showcase the performance and emotional change over a week period under three different music stimuli. The tracks selected were selected at random from the 'Easy' difficulty filter, resulting in the Bahrain Grand Prix, Brazil Grand Prix and Mexico Grand Prix being selected for testing. For each of these races, the settings were always set to clear-dry weather conditions and each race was run in their realistic race time, i.e., Bahrian was run at night, Brazil and Mexico were run in the day.

To equal out the testing, the games was set to a difficulty rating of 40, with each participant having to use an Xbox controller and the same settings for setup. The participants were able to modify their fuel load and race strategy/tyre selection for each race. To also even out the testing, participants both raced for the McLaren F1 team, which at the time was a midfield team resulting in all races starts being from approximately the middle of the pack and as we had car performance set to equal it could mean it was possible for participants to finish in any position on the grid. To standardise the race distance as each racetrack is different in length, all races were set to 25% of their total distance, resulting in Bahrian being 14 laps, Brazil and Mexico being 18 laps in total. EA F1 2022 also outputs various data points per race, including the sector times from each lap, penalties, lap-times, and total race time which were all collected for analysis, apart from all sector times as only the fastest sectors were recorded, plus fastest and slowest total lap time.

3.4.3 Testing Method

1. Both participants will be setup with their respective MUSE 2 headbands as described in section 3.2.1 and open up F1 2022 on the XBOX series X. Navigate to the split screen and add Bahrain, Brazil, and Mexico to the race calendar. Then set the simulation settings to AI level 40, clear weather, and the race rules to normal. Also, set the car performance to equal, select McLaren, and the race length to 'Medium 25%'

2. Start the Bahrain Grand Prix as the first race with no music and complete the race while recording with EEG data. Record the fastest sector times, fastest lap time, slowest lap time, start and finish position. Also using the emotion model as described in the section 3.1, record the emotion rating for each participant.

3. Open the lyrical music playlist (as seen in Appendix 6.3) through a speaker and wait 15 minutes to start the Brazil Grand Prix. Run the race and then record the same data as described in step 2.

4. Open the instrumental music playlist (as seen in Appendix 6.1) through a speaker and wait 15 minutes to start the Mexico Grand Prix. Run the race and then record the same data as described in step 2.

5. Repeat these steps over a seven-day period.

3.4.4 Preliminary Testing

For the preliminary testing of this setup, an initial test was conducted using the Canadian Grand Prix on the short setting (6 laps) and the British Grand Prix on the medium (25

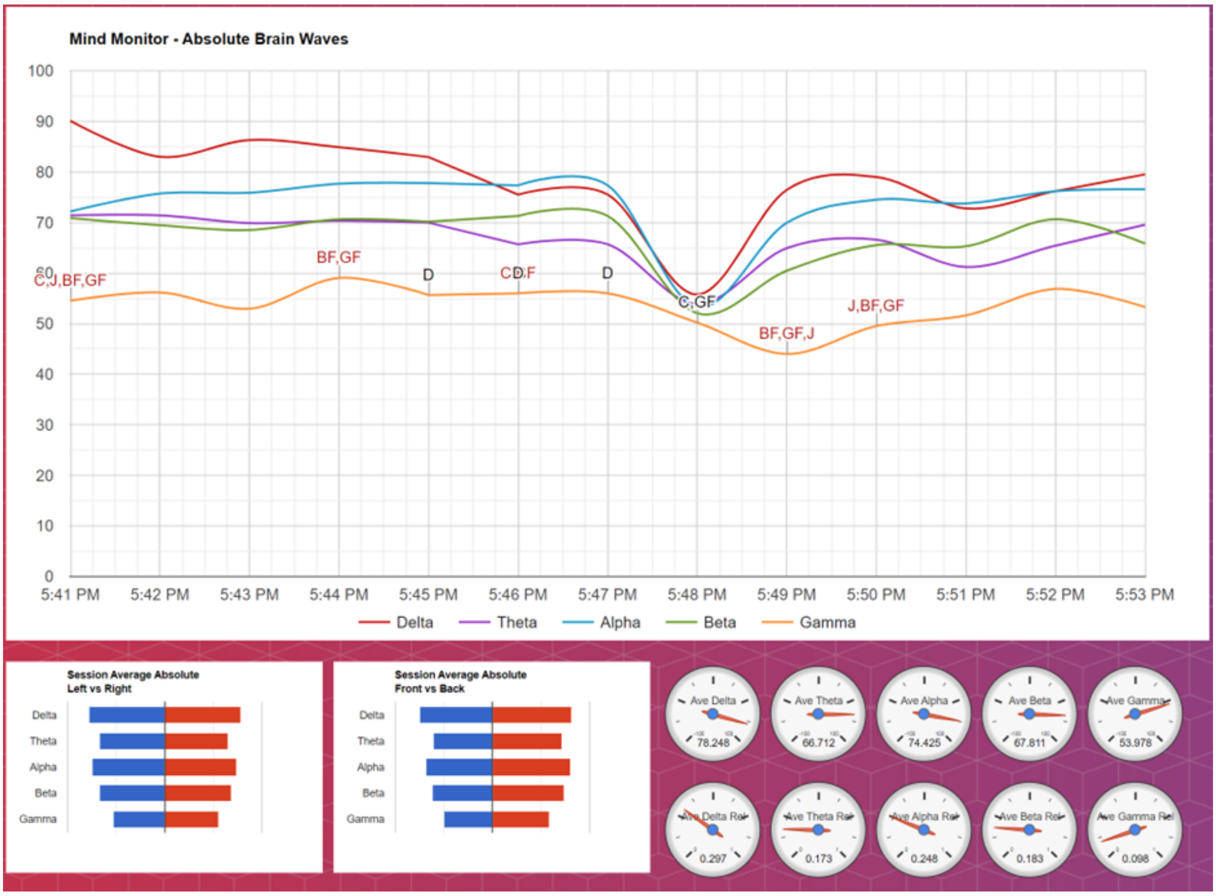

Figure 3.13: Preliminary testing for Canadian Grand Prix

laps) to test the muse device, game difficulty and music audio before testing on the three racetracks for the experiment. In this preliminary test stage, it was discovered that racing on the game difficulty of 40 and adjusting the sound level to 60%:40% ratio from music sound to game sound respectively was the optimal for both participants as the difficulty was not easy for the experienced driver but also not too difficult for the inexperienced. For the British Grand Prix, the participants tested with having 'music with lyrics' in the audio to see the overall comparison to the Canadian Grand Prix where 'music without lyrics' was played. Figure 3.13 and 3.14 below, showcase the Muse Device output data when graphed on the mind-monitor website.

Looking at these figures, unlike experiment 1, the Muse Device is susceptible to dropping out for periods over a lengthy period. It also worth noting that the from an initial observation from these figures it appears that even though the race was 11 minutes longer the average delta, theta and alpha brain waves were consistently higher than the Canadian Grand Prix, except for the gamma wave being approximately the same due to bad fits.

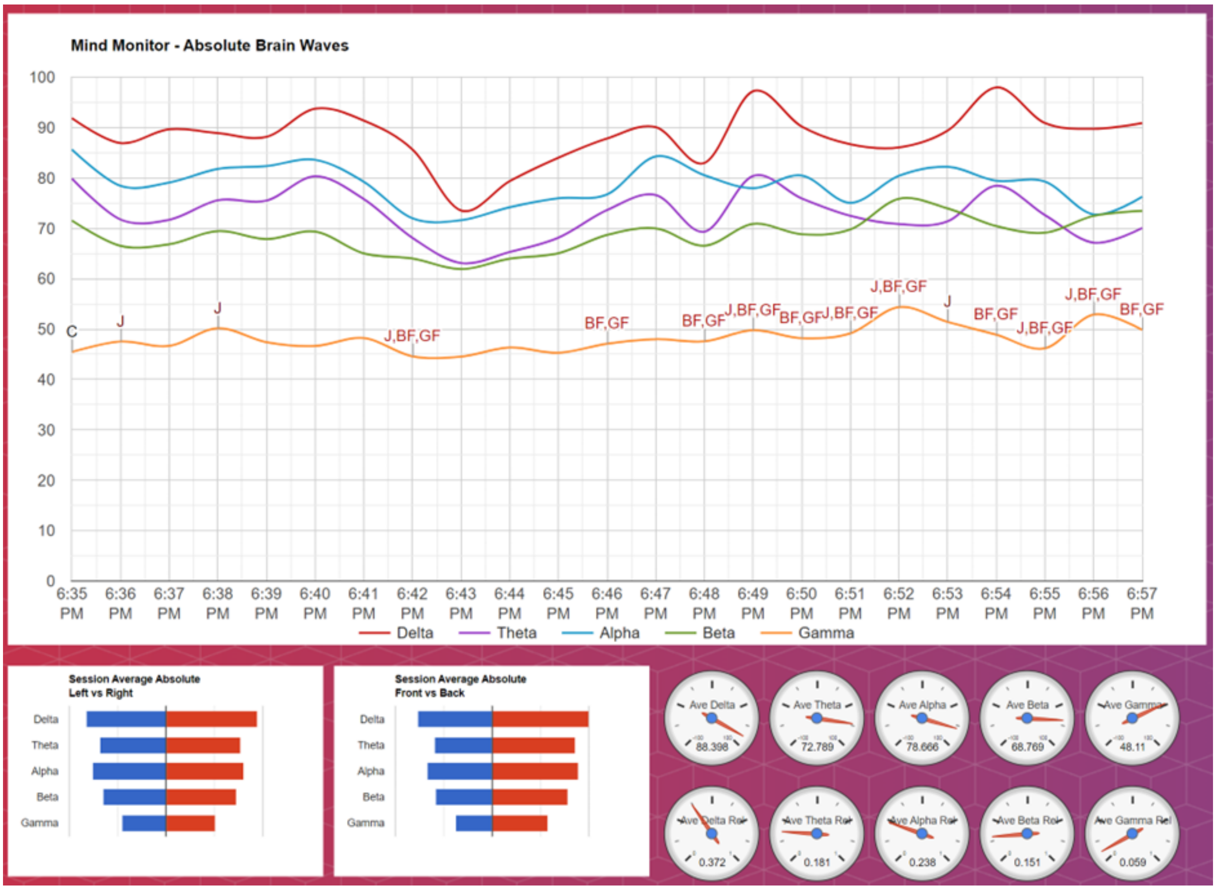

Figure 3.14: Preliminary Testing for British Grand Prix

3.4.5 Data Cleaning and Processing

For the second experiment, the data cleaning process was quite similar to the process in experiment 1. Starting with the cleaning of EEG data for the participants. EEGLAB was used and a similar process was used where a high-band pass filter was used calculated by the Nyquist formula and a low-pass filter was used to keep remove any major spikes in the data for each participant [41]. The average value of each wave from the nodes was then taken and an average of averages was performed to get the create a singular average for Alpha, Beta, Delta, Gamma and Theta waves.

The pseduo can be seen below:

1. Define the directory where EEG datasets (CSV files) are located.
2. List all XLSX files in the data directory.
3. Create a storage array for EEG tables.
4. Loop through each XLSX file.
   (a) Get the dataset name from the filename.
   (b) Read and store EEG data from XLSX file.
   (c) Debug: Print the EEG data.
5. Save each EEG table as MAT files.
6. Launch EEGLAB.
7. Create a table for storing averages.
8. Process each EEG table.
   (a) Extract EEG data.
   (b) Apply high-pass filter.
   (c) Update the EEG table with filtered data.
   (d) Debug: Print the filtered EEG data.
   (e) Calculate averages for each variable.
   (f) Create a new row for the average table.
   (g) Add file name and average values to the new row.
   (h) Append the new row to the average table.
9. Display the average table.
10. Define the output CSV file path.
11. Save the average table as a CSV file.

The second process of cleaning the data was to fix the values recorded from the races. For instance, in races where a participant did not finish the race they were given a completion time of 3000 seconds when the approximate race time was between 1300 to 1500 seconds. Then from these times, a difference was calculated for each day which would be used for predictions in the modelling process.

3.4.6 Modelling

To model the time series data and find the effects of music on cognitive performance, past literature had indicated that the algorithm that gave the highest accuracy was 'Random Forest' as discussed in section 2.4. Therefore, for each race track and participant a random forest regression model was trained and used for comparison amongst race tracks to see under which conditions optimal development occurred.

The pseudo algorithm below cycles through each participant and track and trains the model. The algorithm at the end calculates a mean standard error and outputs time series and feature importance graphs for analysis. Import necessary libraries.

1. Define the list of participants and tracks.
2. Iterate over tracks.
    (a) Create a new figure for the current track.
3. Iterate through participants.
    (a) Load data for the current participant and track.
    (b) Data Preparation and Preprocessing.
    (c) Split the data into training and testing sets.
    (d) Train the Random Forest Regressor.
    (e) Model Evaluation.
    (f) Plot predicted and real values.
4. Create subplots for feature importances.
    (a) Load data for the current participant and track.
    (b) Data Preparation and Preprocessing for feature importances.
    (c) Train the Random Forest Regressor for feature importances.
    (d) Plot feature importances.
5. Save and show the plot.

Chapter 4

Results and Discussion

This chapter discusses and analyses the results from the two experiments by drawing conclusions from the three cognitive tests and long-term performance test. This chapter will discuss the limitations of these experiments and suggest future work to be conducted from this study.

4.1 Experiment 1 – Short-Term Cognitive Performance Analysis in Response to Video Game Intervention

4.1.1 '25x Calculations Test' – Processing Ability

As mentioned in the methodology, the 25x Calculations test was chosen to test the brain processing ability of participants as outlined in Dr Kawashima's paper. Looking at the K-Nearest Neighbour Regressor (KNN) and Linear Regression model (LR) the accuracy of the models was very high with Mean Squared Error (MSE) being 0.93 for the KNN and 0.87 with the optimum number of clusters for analysis being 11.

Figure 4.1 showcases the predictions for each emotion scale as described in Chapter 3 section 3.1. When analysing the graphs further, it is interesting to note the distribution of emotions across that the model predicted. From the predictions, Scale 1 and Scale 2 indicated that most participants were happy and relaxed when undertaking the math questions while Scale 3 showed that participants were overall droopier then excited with approximately a third of the predictions leaning to being excited. Scale 4 is interesting to note as the models predicted many of the participants to feel tense when performing this task. These factors could indicate that most participants felt that they were overall happy with their performance but due to the nature of the test where it was all about speed, they competed with themselves to try and achieve the best results possible.

Looking at the results of the Linear Mixed Models (LMM) seen in Figure 4.2, it is important to note that the fit of the data was quite high with mean absolute error having a value of 7.97 and root mean squared error having a value of 0.704.

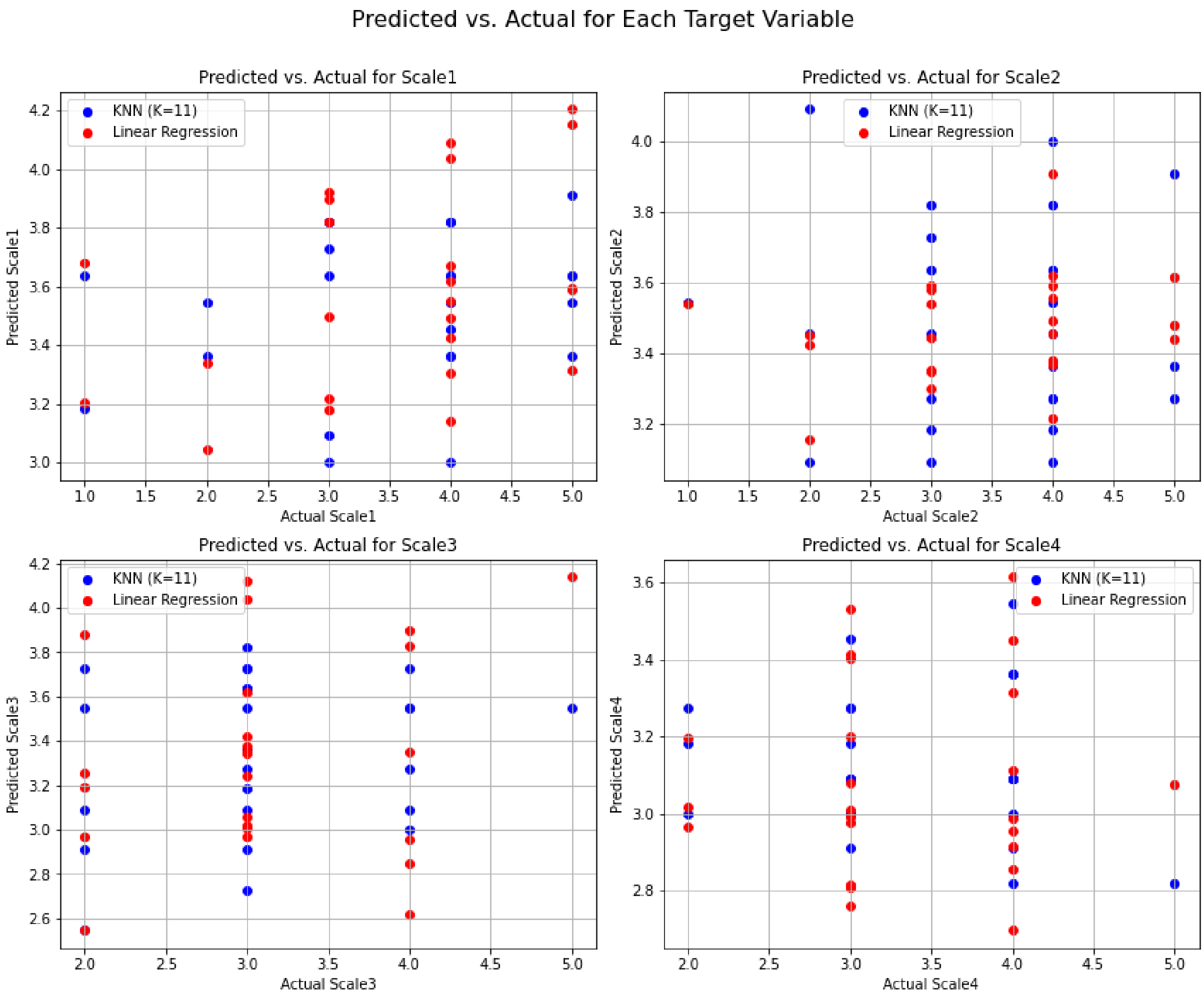

Figure 4.1: Emotion Prediction from 25x-Calculations Test

```
Linear mixed model fit by REML ['lmerMod']
Formula: sTime ~ Mistakes + Favourite + DeltaWaveAverage + ThetaWaveAverage +
    AlphaWaveAverage + BetaWaveAverage + GammaWaveAverage + Scale1 +
    Scale2 + Scale3 + Scale4 + Gyro_X + Gyro_Y + Gyro_Z + (1 |      Name) + (1 | Genre)
   Data: filtered_data

REML criterion at convergence: 893

Scaled residuals:
     Min       1Q   Median       3Q      Max
-1.93216 -0.48788  0.00492  0.36571  2.81365

Random effects:
 Groups   Name        Variance Std.Dev.
 Name     (Intercept) 359.290  18.955
 Genre    (Intercept)   2.952   1.718
 Residual             174.992  13.228
Number of obs: 115, groups:  Name, 23; Genre, 5

Fixed effects:
                 Estimate Std. Error t value
(Intercept)        7.8340    18.3494   0.427
Mistakes           8.9087     2.0963   4.250
Favourite         -0.8438     3.1786  -0.265
DeltaWaveAverage   9.7071    13.1752   0.737
ThetaWaveAverage -20.3859    20.1110  -1.014
AlphaWaveAverage  14.6916    20.5110   0.716
BetaWaveAverage  -17.3969    31.4219  -0.554
GammaWaveAverage  13.9876    21.9674   0.637
Scale1            -0.2776     2.0221  -0.137
Scale2            -2.6961     1.7601  -1.532
Scale3             0.6191     1.9415   0.319
Scale4             0.1545     2.3360   0.066
Gyro_X            -0.8104     3.0199  -0.268
Gyro_Y             0.6558     2.4239   0.271
Gyro_Z            -1.6200     2.1510  -0.753

$Genre
  (Intercept)
1   0.1971741
2  -0.4621115
3   1.0030860
4   0.4941645
5  -1.2323131
```

Figure 4.2: Results from 25x – Calculations Linear Mixed Model

The fixed effects that were being analysed such as the brain waves indicates that the higher average frequencies of Theta and Beta waves have a large impact on the reducing the time taken to complete tasks, whereas the other brain waves increase the overall time. Also analysing the emotion scales, being happier and relaxed will lead to a decrease in time taken while being excited and tense can lead to an increase in overall completion time.

Figures 4.3 showcases the effect of different genres on emotions and time. Looking at these figures, rock music appears to make participants sadder, angrier, tenser, and excited then the other genres. The random effects value in the model output also indicates that rock music is the optimal choice for speed processing tasks as on average it reduces the time on average by 1.2 seconds. On the other end, hip-hop appears to cause an increase in time taken to complete the questions on average by 1 second.

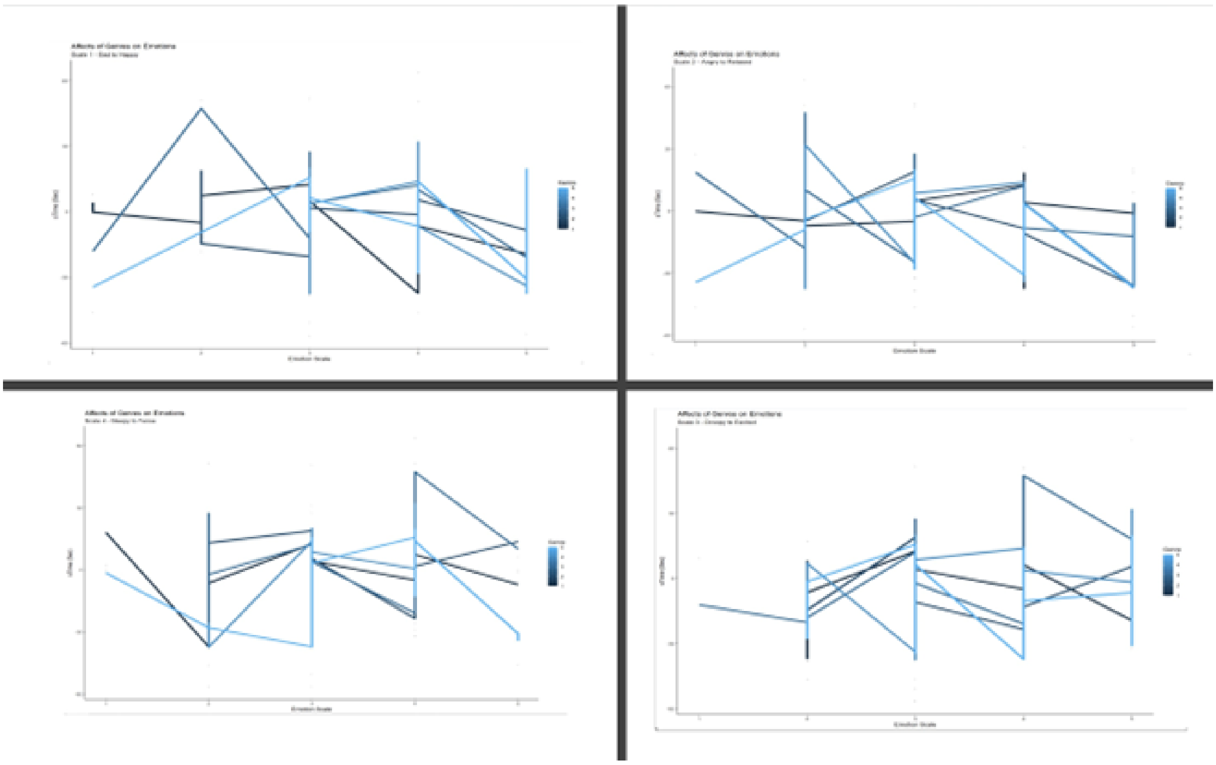

Figure 4.3: Effect of Genre on Emotions and Time

4.1.2 'Short-Term Memory Test' - Memory Ability

The 'Short-Term Memory Test' as mentioned in the methodology was designed to test the memory of participants by asking them to select previous images while remembering a new one as described in the methodology. When looking at the emotion classification machine learning algorithms, the KNN and LR overall give a higher accuracy percentage with values of 0.82 and 0.81 respectively.

Looking at Figure 4.4 below, the prediction scales are a lot further spread out when compared to the brain processing test from section 4.1.1. Scale 1,2 and 3 have an almost equal number of predictions across the scale range. Though when looking at Scale 4, it appears apart from a few outliers that the model predicted that most people would be either very tense or neutral, indicating that participants either found it super difficult or lost interest and became indifferent.

Looking at the results of the Linear Mixed Models (LMM) seen in Figure 4.5, it is important to note that the fit of the data was quite high with mean absolute error having a value of 8.315 and root mean squared error having a value of 0.834 confirming that the data for the short-term memory test was an overall better fit then the data collected in the brain processing test.

The fixed effects in this data indicate that like in the brain processing test, a higher frequency average for the Theta brain wave has a strong correlation with a reduction in time taken to complete the task. Though unlike the previous, the model indicates that a

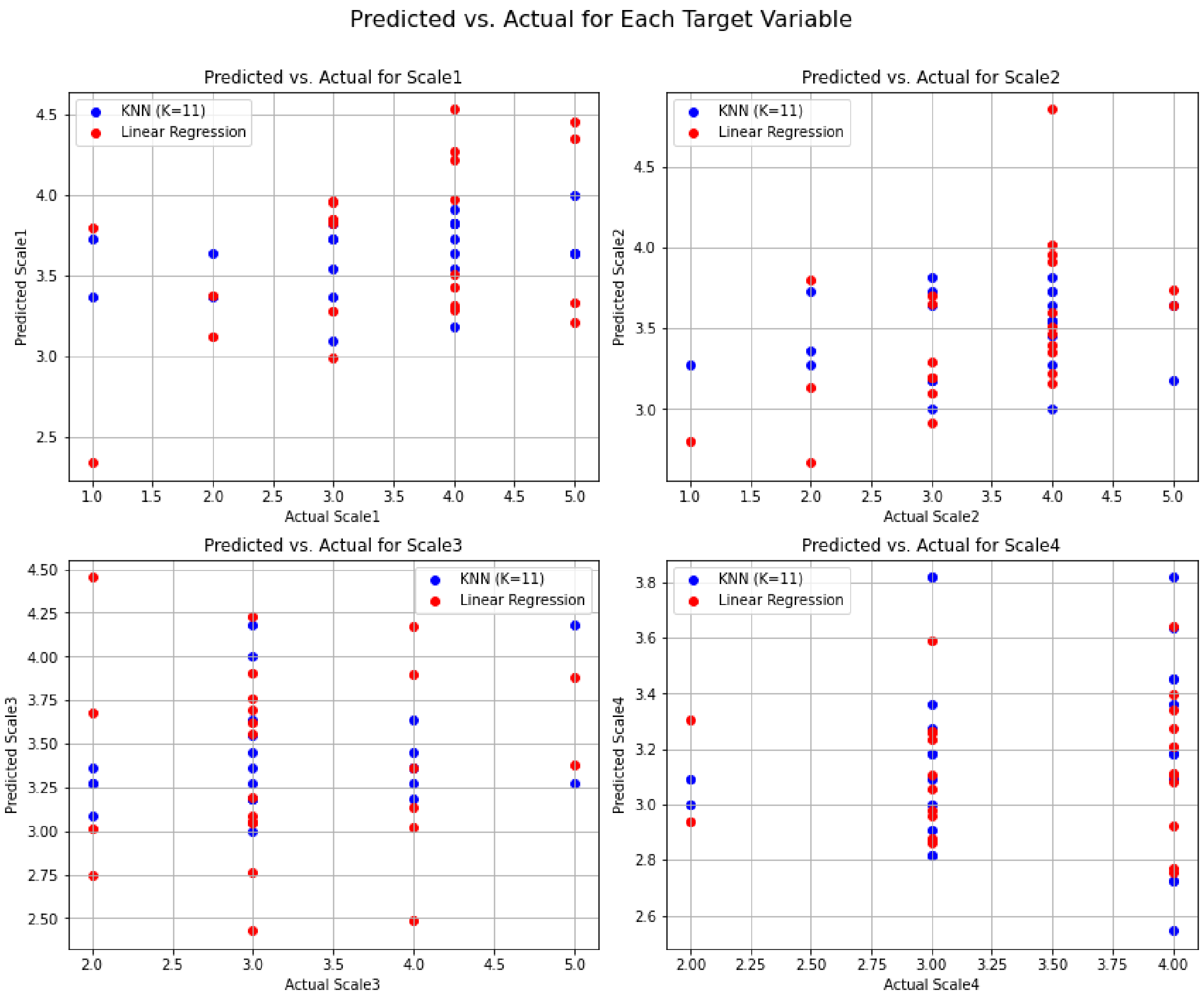

Figure 4.4: Emotion Prediction from 'Short-Term Memory' Test

```
Linear mixed model fit by REML ['lmerMod']
Formula: sTime ~ Mistakes + Favourite + DeltaWaveAverage + ThetaWaveAverage +
    AlphaWaveAverage + BetaWaveAverage + GammaWaveAverage + Scale1 +
    Scale2 + Scale3 + Scale4 + Gyro_X + Gyro_Y + Gyro_Z + (1 |      Name) + (1 | Genre)
   Data: filtered_data

REML criterion at convergence: 921.4

Scaled residuals:
     Min       1Q   Median       3Q      Max
-2.93810 -0.42617  0.02884  0.39344  2.33592

Random effects:
 Groups   Name        Variance Std.Dev.
 Name     (Intercept) 1199.0   34.63
 Genre    (Intercept)    0.0    0.00
 Residual              187.7   13.70
Number of obs: 115, groups:  Name, 23; Genre, 5

Fixed effects:
                 Estimate Std. Error t value
(Intercept)      -62.81909   30.18832  -2.081
Mistakes           5.30835    0.51282  10.351
Favourite          3.63362    5.79482   0.627
DeltaWaveAverage   8.58396   13.65052   0.629
ThetaWaveAverage -17.39743   23.36930  -0.744
AlphaWaveAverage  11.92428   25.25707   0.472
BetaWaveAverage   30.00085   33.19983   0.904
GammaWaveAverage -38.69699   22.68618  -1.706
Scale1            -0.95857    2.14474  -0.447
Scale2             0.09766    2.04031   0.048
Scale3             0.11208    1.99093   0.056
Scale4            -0.11471    2.33411  -0.049
Gyro_X            -6.89684    4.22655  -1.632
Gyro_Y            -6.59282    4.10288  -1.607
Gyro_Z            -0.96337    2.81874  -0.342

$Genre
  (Intercept)
1           0
2           0
3           0
4           0
5           0
```

Figure 4.5: Results from Short-Term Memory Linear Mixed Model

higher frequency in Gamma waves will drastically increase your performance in memory.

In terms of the emotion scales, the model indicates that the being happy and being tense helps increase the performance, while being relaxed and excited tended to have a negative effect on the performance. Unlike the previous test, the genre of music had 0 affect on the time of completion, which is also highlighted in Figure 4.6, as the genres did not seem to have an identifiable effect on emotions either.

4.1.3 'Dual Task Test' – Multitasking Ability

The last of the experiments was testing the multitasking ability of participants, where they would have to select the highest valued number while getting the stick-man to jump over the hurdles. The KNN and LR had the worst data fit out of the three tests with a mean squared error of 0.97 and 0.92 respectively, though is still a good fit for emotion classification. Looking at Figure 4.7, the model predicted a large spread in emotions across

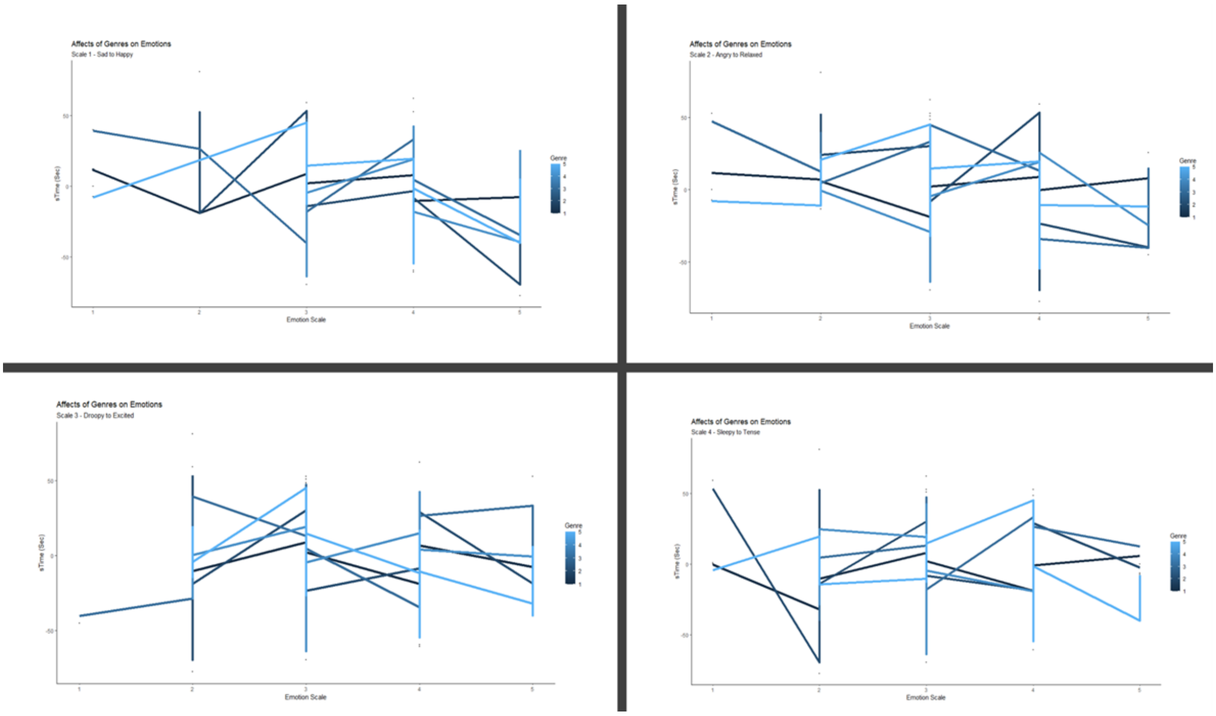

Figure 4.6: Effect of Genre on Emotions and Time

the tests with most being closer to neutral. This could indicate that perhaps participants found this test to be at a good level of difficulty and therefore, were upset when making mistakes or happy when they performed better.

The results from the LMM indicate a better fit then the KNN and LR with a mean absolute error of 5.35 and root mean squared error of 0.882 showcasing a very strong fit to the data. Analysing the brainwave activity showcases that Theta wave and Beta wave are decreasing the performance of participants on average and that higher averages in Delta, Alpha and Gamma waves would reduce the time taken to complete the tasks.

Looking at Figure 4.8, it can also be seen that participants that were in a positive mindset where they were happy, relaxed, droopy and a little tense performed were predicted to perform the best. This is backed up by Figure 4.9, where Hip Hop and R&B (genres 3 and 4) resulted in the lowest times being scored with R&B reducing an average of 0.55 seconds on average. This is contrasted with rock, as it seemed to increase the average time taken by 0.233 seconds.

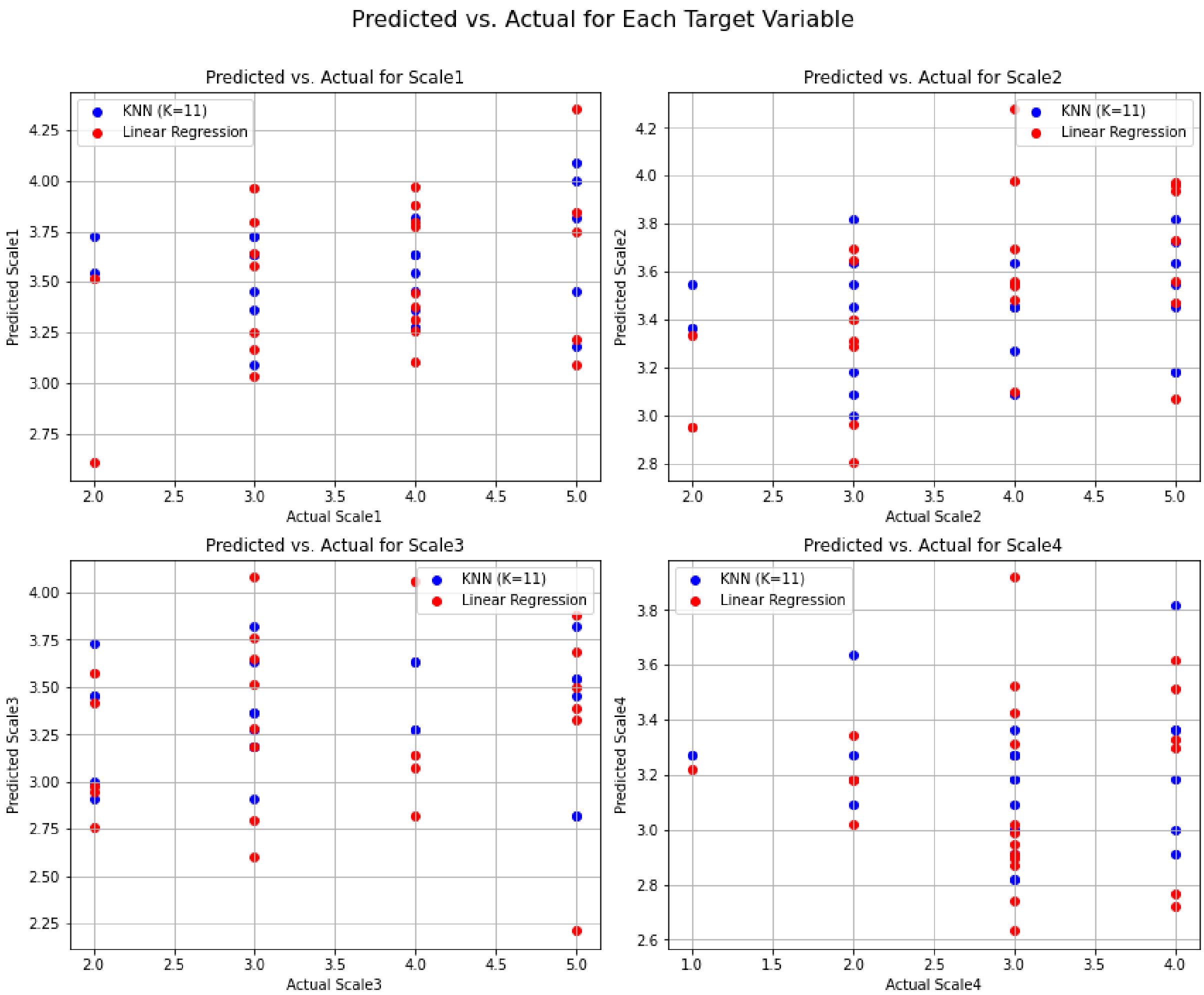

Figure 4.7: Emotion Prediction from 'Dual Task' Test

```
Linear mixed model fit by REML ['lmerMod']
Formula: sTime ~ Mistakes + Favourite + DeltaWaveAverage + ThetaWaveAverage +
    AlphaWaveAverage + BetaWaveAverage + GammaWaveAverage + Scale1 +
    Scale2 + Scale3 + Scale4 + Gyro_X + Gyro_Y + Gyro_Z + (1 |      Name) + (1 | Genre)
   Data: filtered_data

REML criterion at convergence: 783.7

Scaled residuals:
     Min       1Q   Median       3Q      Max
-2.11088 -0.48206 -0.04354  0.43688  2.55653

Random effects:
 Groups   Name        Variance Std.Dev.
 Name     (Intercept) 359.5761 18.9625
 Genre    (Intercept)   0.8586  0.9266
 Residual              72.5581  8.5181
Number of obs: 110, groups:  Name, 22; Genre, 5

Fixed effects:
                 Estimate Std. Error t value
(Intercept)      -30.7571    16.1063  -1.910
Mistakes           5.4253     0.4325  12.545
Favourite          5.9713     2.9839   2.001
DeltaWaveAverage  -6.5615     9.1522  -0.717
ThetaWaveAverage  23.7177    12.1510   1.952
AlphaWaveAverage -17.5853    15.4113  -1.141
BetaWaveAverage    4.2545    20.7358   0.205
GammaWaveAverage  -1.5771    13.1724  -0.120
Scale1            -1.9919     1.3500  -1.476
Scale2            -0.1992     1.2020  -0.166
Scale3             0.6846     1.2755   0.537
Scale4            -1.4237     1.4700  -0.968
Gyro_X             2.6906     2.4980   1.077
Gyro_Y            -1.0962     2.1638  -0.507
Gyro_Z             3.0004     1.7055   1.759
```

```
$Genre
  (Intercept)
1  0.45251204
2  0.07569497
3 -0.21213642
4 -0.54970712
5  0.23363653
```

Figure 4.8: Results from Dual Task Memory Linear Mixed Model

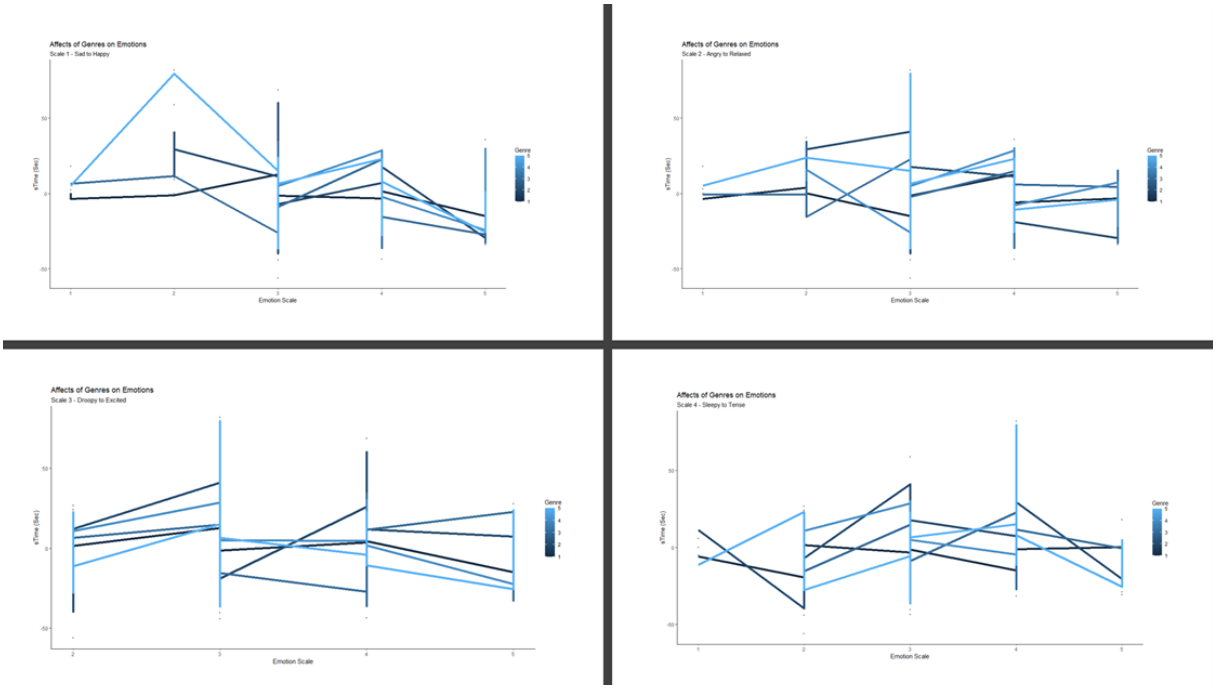

Figure 4.9: Effect of Genre on Emotions and Time

4.2 Experiment 2 – Long-Term Cognitive Performance Analysis in Response to Video Game Intervention

4.2.1 Bahrain Grand Prix - No Music

Starting with the Bahrain Grand Prix, Figure 4.10 showcases the progression of learning through an 8 day period. Starting with participant 1 - Rajiv, it can be seen that the times had spiked in both improvement and decline in improvement from each day. On the second day of testing it can be seen that there was a large improvement on time which when compared to the third day had increased by approximately 20seconds showing a still overall improvement. Then during the remaining days there would be a large increase in performance while then starting to stabilise towards the end of the 8 days with a large 10 second improvement on the last day. Looking at the feature importance it is interesting to note that they Gyro-Y or vertical movement had the largest affect on the driving and that all emotion scales except for Droopy-Excited played little role in the performance.

This is contrary to the second participant - Ravi, where it can be seen that the first few days showed constant improvement where in the middle section overall time of completion had increased while it goes back to improving by the end of the experiment. Then when comparing the feature importance it also clear that the emotions felt by participant 2 had a large impact on time as Sleepy-Tense had the largest influence. Looking at the

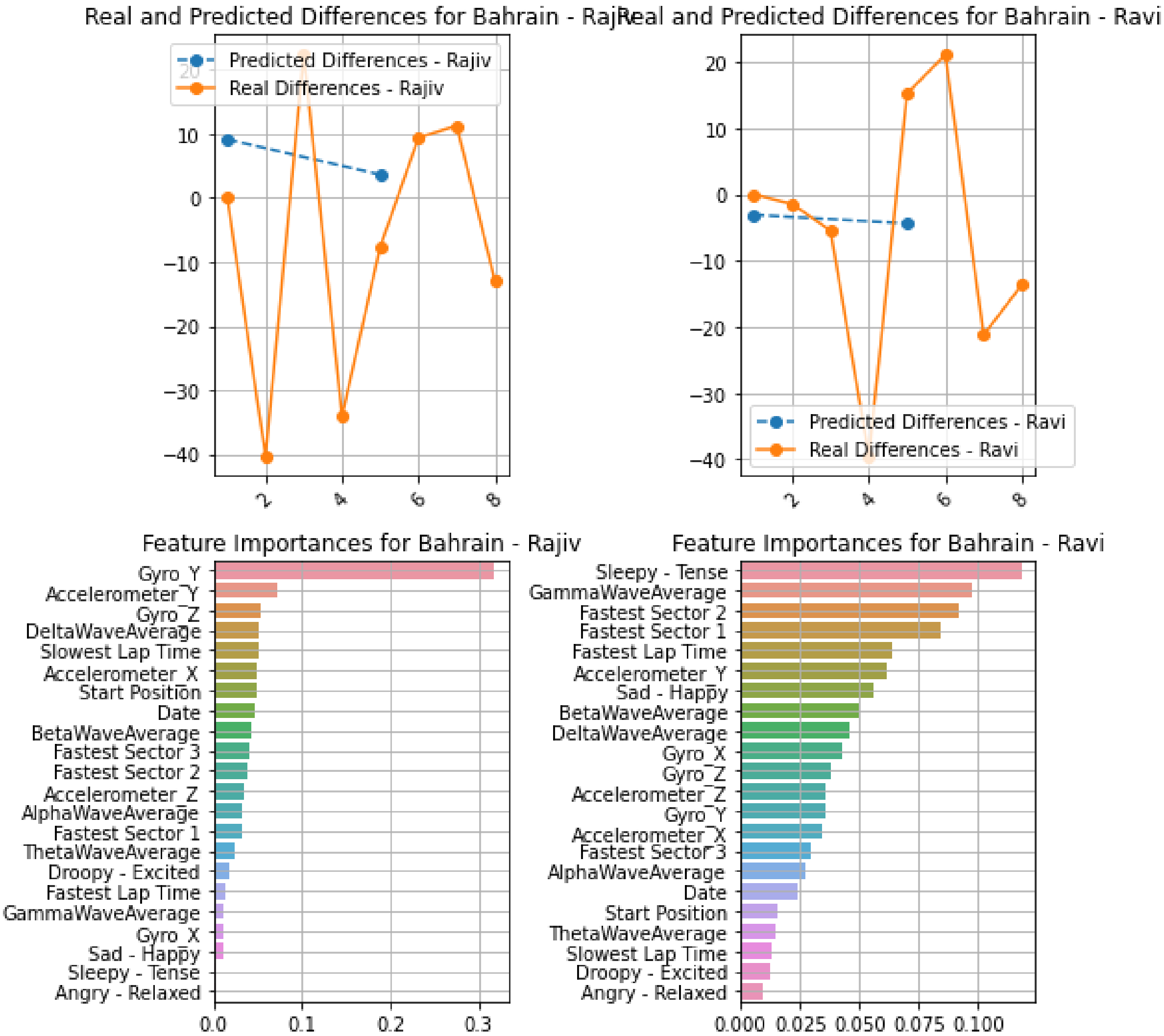

Figure 4.10: Bahrain Time Series and Feature Importance Plots

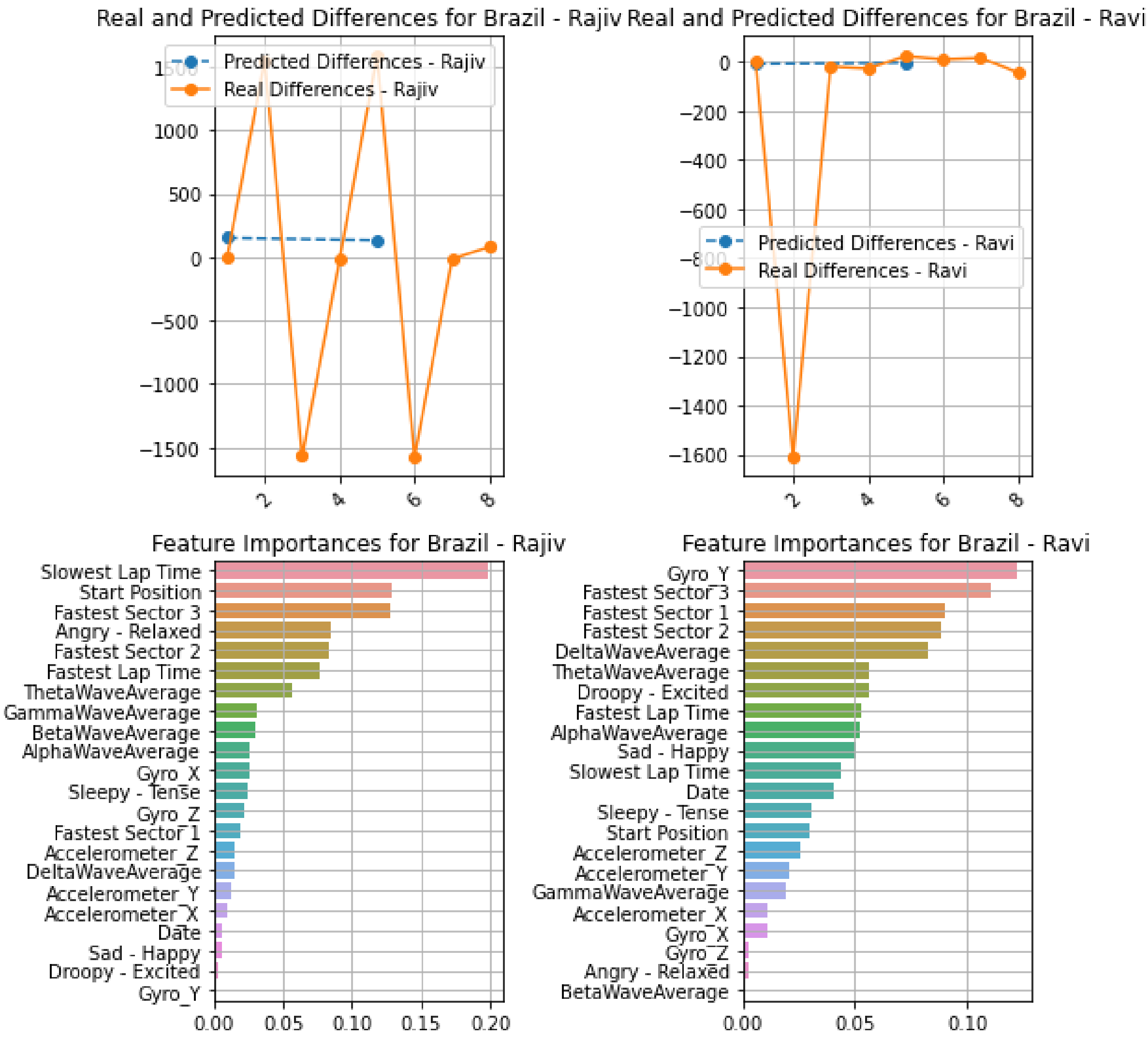

Figure 4.11: Brazil Time Series and Feature Importance Plots

other predictors in particular Fastest Sector 1 and 2 plus fastest lap time it is clear that a conclusion can be made that participant 2 felt super tense as he tried to beat his own fastest lap at each session. This could also explain some of the decrease in performance during the middle of the experiment as slowest lap times are significant and could explain mistakes during the race.

4.2.2 Brazil Grand Prix - Lyrical Music

Similar to the results in the Bahrain Grand Prix, participant 1 had no consistent improvement throughout the 8 days of testing. Looking at the feature importance plot in Figure 4.11 it can be seen that the slowest lap time and the Angry-Relaxed emotion scale appeared to have some the largest impact on the time. This could be an indication that

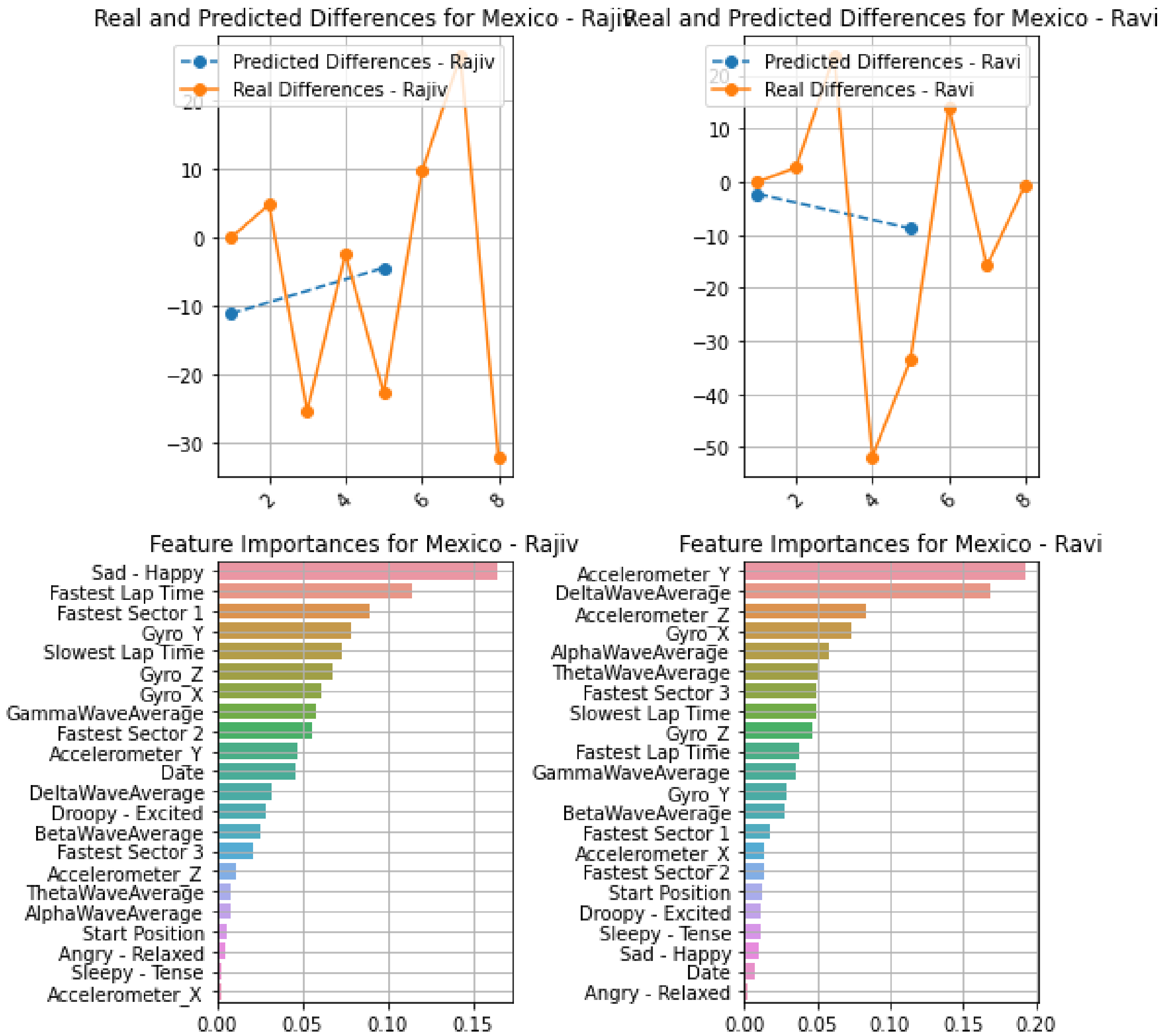

Figure 4.12: Mexico Time Series and Feature Importance Plots

the participant 1 struggled and made many mistakes which caused either DNFs as the results varied by 1500 seconds each day.

On the other hand, looking at the time series plot and feature importance plot for participant 2, there was not a consistent change in his results after the second day. Rather there can be small consistent improvements as the races went on. This is backed by the feature plot as Gyro-Y the 3 fastest sectors and Droppy-Excited and Sad-Happy all contributed significantly to the model. This indicates that participant 2 enjoyed the music and the race a lot more as Gyro could be seen as head bopping to the music indicating a large increase in performance compared to Bahrain.

4.2.3 Mexico Grand Prix - Instrumental Music

Figure 4.12 almost shows a complete opposite of what had occurred for the Brazil Grand Prix trials. Participant 1 had very large increases in performance for most of the sessions except for days 6 and 7 which where it then drastically dropped on the last day. This is backed by the feature importance graph where participant 1s reported to be extremely happy which also resulted in a quicker fastest lap time.

This then contrasts with participant 2, where through the middle period of the experiment he had large improvements but then struggled to improve past day 6 and ended up stagnating his results with only small improvements. The feature importance confirms this as the emotion scales appear to have a limited effect on the model and with his brainwave activity being a heavy influence on the model. This could indicate a level of focus as it is possible that he did not care for the music being played or that he was able to drown it out and focus on the race.

4.3 Discussion

Looking at experiment 1 and 2 it is clear that the results of each experiment show a direct linkage between different genres of music, emotions and cognitive performance. Experiment 1 proved that when it came to the brain processing speeds rock music seem to have the greatest positive impact with movie scores also giving a positive results and the others hampering the completion time. The memory test showed that on average participants were not affected by music but being in a negative state resulted in a higher completion time. It also showed that when it came to multi-tasking that Hip Hop and Rhythm and Blues had the most positive impact on scores and emotions while the others have had an on average negative impact on performance.

Then looking at the experiment 2, it was clear that the music selection had a different effect on both participants. For instance participant 1 became widely inconsistent in the races where lyrical music was being played as it indicated that the participant became more distracted and caused more errors during those races. Then when it came to racing with no music, the participant 1 showed gradual improvement through the experiment but not as much as when listening to instrumental music which showcased a positive mindset and in turn, faster performance in those races. This compared to participant 2 where almost the opposite happened, where gradual improvement was happening with no music, but in the lyrical race the participant showed constant improvement in race pace throughout the experiment as the features indicated a willingness to try harder and set faster sector times. Then when compared to the instrumental race, the participant could not seem to be consistent and had to focus more as a result.

Therefore, looking at the results of both experiments, it can be argued that music can have both a positive and negative affect on emotions and cognitive ability. When it comes to completing tasks that do not require constant thought or memory, the ability to get into the rhythm appears to have a very beneficial affect on performance but when it is too distracting or requires constant focus then no music appears to be the best choice due to consistency in results.

Chapter 5

Limitations, Future Works and Conclusion

Due to the nature of the study a few apparent limitations occur. The main being sample size for both experiments were quite low, with experiment 1 not reaching the number of participants required to satisfy central limit theorem, indicating that it can not predict the population [43]. The same could also be said about the second experiment as well, as having only 8 days worth of testing time meant that the random forest regression algorithm could not accurately predict results. Coming back to experiment 1, due to the little time needed to complete the quizzes, the EEG collection was quite low and in turn, could not be put through the same cleaning process as other literature.

Therefore, in understanding these limitations, future works to build on this study would be to change the methods of testing to increase the time of testing individual cognitive tasks as well as the sample size and age range to definitively come up with accurate emotion prediction algorithms and exploring the linkage between music, emotions and cognitive ability.

To conclude this research, from this paper it is clear that different genres of music can heavily influence the emotions and cognitive ability of people and that dependent on the task being performed targeting the music listened to will overall increase performance in cognitive based tasks.

Chapter 6

Appendix

6.1 Ethics Approval

Science & Engineering Subcommittee
Macquarie University, North Ryde
NSW 2109, Australia

10/09/2021

Dear Professor Mukhopadhyay,

Reference No: 520211045132027
Project ID: 10451
Title: EEG-Mechatronic System Interface

Thank you for submitting the above application for ethical review. The Science & Engineering Subcommittee has considered your application.

I am pleased to advise that ethical approval has been granted for this project to be conducted by Cameron Brooks Aume, and other personnel: Professor Subhas Mukhopadhyay and Mr Kevin Pham.

This research meets the requirements set out in the National Statement on Ethical Conduct in Human Research 2007, (updated July 2018).

Standard Conditions of Approval:

1. Continuing compliance with the requirements of the National Statement, available from the following website: https://nhmrc.gov.au/about-us/publications/national-statement-ethical-conduct-human-research-2007-updated-2018.
2. This approval is valid for five (5) years, subject to the submission of annual reports. Please submit your reports on the anniversary of the approval for this protocol. You will be sent an automatic reminder email one week from the due date to remind you of your reporting responsibilities.
3. All adverse events, including unforeseen events, which might affect the continued ethical acceptability of the project, must be reported to the subcommittee within 72 hours.
4. All proposed changes to the project and associated documents must be submitted to the subcommittee for review and approval before implementation. Changes can be made via the Human Research Ethics Management System.

The HREC Terms of Reference and Standard Operating Procedures are available from the Research Services website: https://www.mq.edu.au/research/ethics-integrity-and-policies/ethics/human-ethics.

It is the responsibility of the Chief Investigator to retain a copy of all documentation related to this project and to forward a copy of this approval letter to all personnel listed on the project.

Should you have any queries regarding your project, please contact the Faculty Ethics Officer.

The Science & Engineering Subcommittee wishes you every success in your research.

Yours sincerely,

6.2 Experiment 1 - Song List

Genre	**Song**	**Artist**
Rock	Don't Stop Me Now	Queen
Rock	Eye of the Tiger	Survior
Rock	Holding Out for a Hero	Bonnie Tyler
Rock	What I've Done	Linkin Park
Rock	Never Gonna Give You Up	Rick Astley
Rhythm and Blues	Low	Flo Rida, T-Pain
Rhythm and Blues	24K Magic	Bruno Mars
Rhythm and Blues	Starboy	The Weekend, Daft Punk
Rhythm and Blues	Mask Off	Future
Rhythm and Blues	DJ Got us Fallin; in Love	Usher, Pitbull
Hip Hop	Without Me	Eminem
Hip Hop	HUMBLE	Kendrick Lamar
Hip Hop	The Next Episode	Dr Dre, Snoop Dog
Hip Hop	In Da Club	50 Cent
Hip Hop	It Was A Good Day	Ice Cube
Film Score	Imperial March	John Williams, London Symphony Orchestra
Film Score	Hedwig's Theme	John Williams
Film Score	Arrival to Earth	Steve Jablonsky and Nick Glennie-Smith
Film Score	The Avengers	Alan Silvestri
Film Score	He's a Pirate	Geofferey Zenelli, Hans Zimmer, Klaus Badel

6.3 Experiment 2 - Song List

Table 6.1: Instrumental Music List

Song Title	**Artist**	**Lyrical/Instr**
Adrenaline	Jack Wall	Instrumental
Aerodynamic	Daft Punk	Instrumental
Archangel	Thomas Bergersen,Two Steps from Hell	Instrumental
Autobots Reunite	Steve Jablonsky	Instrumental
The Avengers	Alan Silvestri	Instrumental
Battle of the Heroes	John Williams,London Symphony Orchestra	Instrumental
Cantina Band	John Williams,London Symphony Orchestra	Instrumental
Coconut Mall (From Mario Kart Wii)	Arcade Player	Instrumental
Duel of the Fates	John Williams,London Symphony Orchestra	Instrumental
Feel the Beat	Darude	Instrumental
Flight Of The Silverbird	Two Steps from Hell,Thomas Bergersen	Instrumental
Formula 1 Theme	Brian Tyler	Instrumental
Grass Skirt Chase	Spongebob Squarepants	Instrumental
Heart of Courage	Thomas Bergersen,Two Steps from Hell	Instrumental
Iron Man 3	Brian Tyler	Instrumental
Kyoto (feat. Sirah)	Skrillex,Sirah	Instrumental
Lost but Won	Hans Zimmer	Instrumental
Mission: Impossible Theme	Michael Giacchino	Instrumental
Mushroom Gorge	The Greatest Bits	Instrumental
None Shall Live	Two Steps from Hell,Thomas Bergersen	Instrumental
Pacific Rim (feat. Tom Morello)	Ramin Djawadi,Tom Morello	Instrumental
Playmaker	Mitsune Nobuyoshi	Instrumental
Revolution 909	Daft Punk	Instrumental
Rock Anthem For Saving The World	Martin O'Donnell,Michael Salvatori	Instrumental
Sandstorm	Darude	Instrumental
Scary Monsters and Nice Sprites	Skrillex	Instrumental
Scorponok	Steve Jablonsky	Instrumental
Spider-Man 2 pizza theme	Little Jacob	Instrumental
STH1 Green Hill Zone Mega Drive version	Masato Nakamura	Instrumental
Strength of a Thousand Men	Thomas Bergersen,Two Steps from Hell	Instrumental
Unyielding	Martin O'Donnell,Michael Salvatori	Instrumental
passionate duelists(Re-arranged)	Mitsune Nobuyoshi	Instrumental

Table 6.2: Lyrical Music

Song Title	Artist
1 Thing	Amerie
All The Stars (with SZA)	Kendrick Lamar,SZA
Another Way to Die	Jack White,Alicia Keys
BACK ON THE ROCKS	MEGA NRG MAN
Chambea	Bad Bunny
Cinema - Skrillex Remix	Benny Benassi,Gary Go,S
Crazy Little Love	Nuage
Don't Let me Down - Extended Remastered	Madison
DON'T STOP THE MUSIC	Lou Grant
Don't Wanna Fall in Love	Jane Child
DON'T YOU (FORGET ABOUT MY LOVE)	Sophie
ELDORADO	dave rodgers
Ferrari	James Hype,Miggy Dela
THE FORMULA	will.i.am,Lil Wayne
Gimme More	Britney Spears
Glamorous	Fergie,Ludacris
Golden Age	Max Coveri
HEARTBEAT	Nathalie
Hey Ya!	Outkast
HUMBLE.	Kendrick Lamar
Kids	Robbie Williams,Kylie M
Lady - Hear Me Tonight	Modjo
Lean On (feat. MO, DJ Snake)	Major Lazer
Like A Thunder	Max Coveri
Master Of Puppets	Metallica
messy in heaven	venbee,goddard.
Metalingus	Alter Bridge
Miracle (with Ellie Goulding)	Calvin Harris,Ellie Gould
Mission Impossible - Extended Version	Nick Mansell
Moves Like Jagger - Studio Recording From The Voice Performance	Maroon 5,Christina Agui
Music Sounds Better With You	Stardust,Benjamin Diam
NO ONE SLEEP IN TOKYO	EDO BOYS
Only Girl (In The World)	Rihanna
Pump It	Black Eyed Peas
Rainfall (Praise You)	Tom Santa

Chapter 7

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