Spring 5-1-2023

# Use of EEG-Based Machine Learning to Predict Music-Related Brain Activity

Charles Skutt
*University of Lynchburg*, skuttc389@lynchburg.edu

Use of EEG-Based Machine Learning to Predict Music-Related Brain Activity

Charles Skutt

**Senior Honors Project**

**Submitted in partial fulfillment of the graduation requirements**
**of the Westover Honors College**

**Westover Honors College**

May, 2023

David O. Freier, PhD

Price Blair, PhD

Cynthia Ramsey, DMA

## Abstract

Music has many awe-inspiring characteristics. Some may refer to it as a "universal language" with the ability to transcend the barriers of speech, while others may describe its ability to evoke intense emotional experiences for the listener. Regardless of the description, it is a commonly held view that music can have many profound effects. Studies of music's effects have found these beliefs to be more than pure conjecture, finding that music interacts with and changes our brains in physical and emotional ways.

Music can even have clinical applications, such as music therapy. This type of therapy has been shown to be beneficial in many areas, ranging from stroke rehabilitation to mental health treatment. The mechanisms behind music's therapeutic benefit has to do with neuroplastic effects; Being able to harness this benefit in a therapeutic setting could make treatments for mental disorders and brain injuries even more effective.

This thesis aimed to discover whether musical thoughts could be interpreted using machine learning, potentially opening the door to the use of thought-based musical training for therapeutic benefit. For this study, EEG data was collected while people were thinking of 5 melodies, then machine learning models were trained on labeled datasets. The models were then tasked with categorizing unlabeled sets of EEG data - in other words, predicting which melody a subject was thinking of while the data was being recorded. The accuracy of the predictions ranged from 45% to 80%, which means that the programs were 2-4 times more accurate than random guessing. This shows that these programs could potentially be used to examine the effects of musical thinking on neuroplasticity.

While this topic is still exploratory and requires more research, these results could lead to a promising future of development of music-based brain-computer interfaces.

# Introduction:

Why Study This Topic? The Benefits of Music Therapy and the Mechanisms Behind it

---

This section aims to provide a clear rationale for conducting this study. The therapeutic benefits of music have been widely recognized, and the mechanisms of neuroplasticity that may explain why music is therapeutic are highlighted. An overview of the relevant brain areas involved in music processing is provided, and the mechanisms through which music can impact these areas to facilitate neuroplasticity is explained. Numerous studies are cited to support these claims. Moreover, the importance of investigating EEG-based machine learning for predicting music-related brain activity is discussed, as this subject has the potential to contribute to the development of effective music-based therapies. By providing a clear and evidence-based rationale, this project aims to contribute to the growing body of literature on the therapeutic effects of music.

## 1 Music Therapy

Listening to and creating music can engage the brain in a variety of ways, which opens up the possibilities for its use in the treatment of mental illnesses or neurological issues. Music therapy has been shown to be an effective tool in treating a variety of mental health conditions, as well as in the recovery process for those who have suffered from strokes. This section will cover examples of music therapy at work.

### 1.1 Music Therapy and Mental Disorders

Some specific examples of the benefits of music therapy are found in the management and treatment of individuals living with schizophrenia. A small, exploratory study (n=16) found that involvement with improvisational-based music therapy was correlated with improved memory skills for people with schizophrenia (Ceccato et al., 2010), while a larger study (n=272) found that after just one month of listening-based music therapy, people living with schizophrenia significantly improved their levels of anergia, depression, and activation. Patients also significantly improved their scores for positive and negative symptoms using the Positive and Negative Symptom Scale for Schizophrenia (PANSS) (De Sousa, 2010). Playing relaxation-based music before sleeping is another form of music therapy found to have a correlation with improved sleep efficiency and latency, with patients showing improved scores on their levels of depression, anxiety, and total psychopathology scores using the PANSS (Bloch et al., 2010).

A meta-analysis of 17 different music therapy studies for schizophrenia concluded that these findings are consistent, stating: “music therapy improved psychotic symptom management, depression and anxiety management, social and cognitive functioning, behavior, and quality of life of the participants". This meta-analysis also determined that the most influential factor on the success of the therapy was the dosage, or the amount of time spent participating in music therapy. Due to the influence of dosage, programs which involved both active and passive participation (playing and listening) resulted in the greatest outcomes (Chung, 2016). While all the examples were done in combination with classical treatments of schizophrenia, these results show that music therapy is a valuable tool for treating the disorder.

The positive benefits of music therapy for mental health disorders are not exclusive to the treatment of schizophrenia. A systematic review of music therapy used for treatment of people with psychosis, depression, and other serious mental disorders showed that combining music therapy with standard treatment leads to significant and powerful improvements in overall well-being, typical symptoms, negative symptoms, depression, anxiety, and daily functioning (Gold et al., 2009). There was a clear correlation between the amount of music therapy received and improvement measured, which is a similar conclusion as the previously mentioned review done by Chung. In other words, the benefits became “more substantial” with longer courses or more frequent sessions.

### 1.2 Music Therapy and Neurorehabilitation

Music therapy has been widely recognized for its significant impact in assisting with neurorehabilitation. Research has demonstrated a high potential for success in helping individuals who have suffered from a stroke and have subsequently lost important abilities such as fine motor skills, speech, and language comprehension. This approach has proven to be a valuable tool in patient’s rehabilitation, offering people with stroke-related impairments a new and effective way to regain their abilities. Furthermore, music-based treatments are often engaging and enjoyable for patients, which can serve as a motivation for continued participation and a positive outlook towards the rehabilitation process.

One example of musical neurorehabilitation in action can be seen in the recovery of fine motor hand skills using a form of music-supported therapy (MST). This method, first investigated by Schneider et al. in 2007, encouraged patients to play simple melodies with their impacted hand using a piano or electronic pads. Not only were patients of the MST method able to regain their motor abilities faster, but they did so with improved smoothness, timing, and precision when compared with patients who did not use MST.

Nonfluent aphasia is another complication that can arise from a stroke and affects a person's ability to communicate using speech. This does not arise from any physical ailments preventing a person from speaking, but rather from damage to the area of their brain responsible for producing speech. Nonfluent aphasia is seen in people with damage to the area responsible for generating speech, meaning that they can understand others but cannot speak intelligibly. Interestingly, patients with nonfluent aphasia are often able to sing lyrics better than simply speaking the same words. This observation led to a music-based therapy called Melodic Intonation Therapy (MIT), involving the melodic intonation of words while also tapping the left hand at the same rhythm as syllables are produced. While both a control therapy method and MIT produced significant improvements in the outcome of patients, those who used MIT during their recovery had extensively greater improvements (Keith, Aronson 1975, Albert et al., 1973, Sparks, Holland, 1976).

This overview of music therapy for the treatment of mental disorders and for neurorehabilitation shows the potential benefits of using music in conjunction with traditional treatments. All the mentioned examples used direct methods of interaction with music, ranging from simply listening to and engaging with music, to using music creation such as singing or playing piano to aid in recovery. However, this thesis aims to establish the possibility for an entirely different method of engaging with music - through a brain-computer interface. This new method of interacting with music could have new, different, or similar effects on the brain. However, to monitor these effects, neuroplasticity (the mechanism which helps promote the positive benefits of music therapy) must be understood. Due to the technical nature and terminology of these mechanisms, it is first necessary to delve into the anatomy of the brain and how it processes reward-based and musical stimuli. This will lay the foundation for a better understanding of the mechanisms of neuroplasticity and will enable better exploration of its potential as a therapeutic tool.

## 2 Brain Organization - From Neurons to Lobes

Understanding the structures of the brain involved with musical processing, reward stimulus, and learning is pertinent knowledge needed to comprehend the ways that music therapy affects the brain. In this section, relevant brain anatomy involving the description of neurons, networks, and structures will be explained.

Up until relatively recently, the internal structure and function of the human brain has largely been a mystery. However, with the expansion of neuroscience – specifically, the development of more precise imaging tools – our collective knowledge of the inner workings of the brain has exploded in the last 100 years.

It is now common knowledge that the brain consists of a complex layering of billions of brain cells (neurons) which communicate using electrochemical signals. There is a complex web of connections between neurons which allows for the calculations and activity needed to create our sense of perception. Neurons communicate using chemical signals known as neurotransmitters - for the focus of this thesis, the neurotransmitters dopamine and serotonin are particularly relevant, due to their roles in memory, emotional responses, and feelings of motivation.

Put simply, neurons connect to each other using dendrites and axons. The dendrite of a neuron receives neurotransmitters from the axon of another neuron, leading to a change in the receiving neuron's charge. Once a threshold charge is reached, the neuron sends an action potential signal down its axon to the axon terminals. At the axon terminals, the neuron releases more neurotransmitters to communicate to the dendrite of another connected neuron. These connections between axon terminals and dendrites are called synapses, and the activity here forms the basic building block of all brain activity.

Groups of millions to billions of neurons connect to form webs and networks of activity. Various groupings have different responsibilities, ranging from controlling body temperature to forming complex thoughts and planning for the future. The matter that we know of as “the brain”, is made up of these billions of neurons and supporting cells.

The largest area of the brain is called the cerebrum, and it forms the outside layers of the brain. The cerebrum is divided into two lateral hemispheres, the left and the right. It is a general belief that these hemispheres house our higher functions like thinking and planning, and that each hemisphere is responsible for the sensory and motor processes on the contralateral side of the body as well. The two hemispheres are also known to not be perfectly symmetrical, with some functions being delegated mostly to one side or the other, such as speech (left side) or abstract thinking (right side).

The outside layers of these hemispheres are divided into four main regions, known as *lobes*. These lobes are responsible for different functions of the brain, and are as follows:

- *The Frontal Lobes*: Responsible for planning, executive decision making, emotional regulation, and complex thinking. Also responsible for planning movements and sending movement information to the body.
- *The Temporal Lobes*: Responsible for memory, audio processing, object and language recognition, and speech.
- *The Parietal Lobes*: Responsible for visually guided movements, spatial navigation, receiving and interpreting sensory information from the body, and ensuring that movements are smooth and coordinated.
- *The Occipital Lobes*: Responsible for dissecting and interpreting visual information, including form, color, and movement.

For the purposes of this project, the temporal and frontal lobes will be involved. This is because music and controlled thinking are the two main processes that will be involved with a music-based brain-computer interface. The temporal lobes deal with auditory processing, such as identifying what sounds are being heard or the frequency at which they are being created (Chauvel et al., 1998), while the frontal lobes hold the job of monitoring this activity (Halwani et al., 2011). The frontal lobes are also responsible for planning and/or generating self-referential information (Herold et al., 2016), which may be an important part of being able to “play” a melody in one’s head without external stimulus.

The temporal lobe also has an important role in memory and learning due to its proximity to a deeper brain structure, the hippocampus. The hippocampus has been widely associated with memory and learning (Morris 2003), and these functions are widely utilized in therapeutic settings - for example, therapy designed to learn new behaviors or re-learn old ones. The activity here in the hippocampus is crucial for encoding new memories, thought processes, and behaviors. Other regions that are relevant for memory (and thus some forms of therapy) include the ventral tegmental area (VTA) and the nucleus accumbens (Bao et al., 2001, Montague et al., 1996). These two areas contain high concentrations of dopamine neurons and have been shown to mediate reinforcement signaling in the hippocampus, which is a crucial step in the brain's learning process and memory development. Other studies have shown that additional relevant areas of the brain involved in music therapy may include the neural networks involved in learning and reward (Chanda & Levtin, 2013) and the orbitofrontal cortex - a necessary component for encoding the time/rhythm-based aspects of memory and emotional processing (Duarte et al., 2010).

Working in tandem, these regions of the brain are key elements to the core component of the effectiveness behind music therapy - neuroplasticity.

## 3 Neuroplasticity

The process behind how music can create such an impact on the brain has to do with neuroplasticity, or the way that the brain is able to create connections and rewire itself. This plasticity can be expressed by the brain in many different ways (Rugnetta, 2023), but can generally be be sorted into two main categories: Neuronal regeneration/collateral sprouting (including concepts like synaptic plasticity and neuronal growth), and functional reorganization (Puderbaugh and Emmady, 2022). Synaptic plasticity and neuronal growth are key components of neuroplasticity, and result in long-lasting changes in the strength of neural connections and neural networks (Mateos-Aparicio and Rodriguez-Moreno, 2019), while functional reorganization has larger impacts that can cause entire regions of the brain to learn new functions or change their activity based on changes in other areas of the brain or body (Finger, 2009). There are many different factors that influence neuroplasticity, ranging from medications and neurotransmitters (Carrillo-Mora et al., 2019), to external factors like certain types of movement therapy (Johansen-Berg et al., 2002).

One famous example of neuroplasticity at work was shown in the brains of taxicab drivers. Due to their need to memorize over 25,000 streets and navigate their way through them, London taxi drivers were observed to have significantly larger posterior hippocampi. The longer the person had been a taxi driver, the larger their posterior hippocampus was (Maguire et al., 2000). This area of the hippocampus is believed to be responsible for spatial memory, and the results of this study provided strong evidence to support this theory. Additionally, Maguire et al. concluded that the evidence pointed towards a capacity for plastic change in the brains of adults, contrary to prior beliefs in the scientific community that the brain was only plastic during development.

There are specific mechanisms which are responsible for this plastic effect, ranging from within a single synapse to entire networks of neurons. Given that the benefits of neuroplasticity may be useful for therapists hoping to treat their patients (Kloos et al., 2020), comprehension of what is happening from a cellular to a network perspective will provide professionals with a deeper understanding of these processes and why they are beneficial for patients. In this section, details about the cellular mechanisms of neuroplasticity, as well as the ways that music works with and induces these mechanisms, will be discussed.

### 3.1 Neuroplasticity - Neurons and Networks

The brain's ability for plastic changes can be observed in areas as small as the synaptic activity between neurons. Certain synapses can become stronger or weaker with time, depending on how often they are active. A phenomenon known as long-term potentiation (LTP) was first observed by Bliss and Lomo (1973), when they noticed that a short burst of high-frequency stimulation, lasting no longer than a couple of seconds, produced enhanced synaptic activity which lasted as long as several weeks.

Further research by Nicoll et al. (1988) demonstrated that the LTP response of a neuron was controlled by a specific type of receptor, called N-methyl-Daspartate (NMDA). This receptor is normally bound to a magnesium molecule, which blocks it from binding to anything else. However, during strong stimulation, the magnesium is removed from the NMDA receptor, allowing for the receptor to facilitate the influx of calcium into the postsynaptic neuron. Calcium entering the cell in this manner triggers the LTP response for the synapse, causing it to have strengthened activity for extended periods of time afterwards. It is important to note that the NMDA receptor is only on the receiving side of the synapse and is only open when there is intense stimulation. This means that the LTP effects are specific to certain synapses and not the entire neuron (Purves et al., 1997).

There has not been enough research into synaptic plasticity to demonstrate a link between these mechanisms and human behavior, but the baseline concepts describe the mechanisms by which the brain is able to “remember” the connections that are the most active. This is a key function for a brain that is able to learn and encode information in memory and provides the cellular picture of how neuroplasticity works.

The next level up from the synapses of a single neuron is a neuronal network. Neuroplasticity is observed in networks of neurons in the form of increased levels of excitability or inhibition, as well as strength of connections between different networks of neurons. The effects of LTP are demonstrated on this scale, as increased stimulation will cause increased synaptic activity in the network (Purves et al., 1997). However, there is a flip side to the effects of stimulation on synaptic activity, known as long term depression (LTD). LTD, in contrast to LTP, is characterized by long periods of low stimulation and triggers mechanisms that lead to decreased synaptic activity. (Mulkey & Malenka, 1992). This is also modulated by the NMDA receptor, with the difference between LTP and LTD being the amount of calcium that enters the cell. For LTP, large amounts of sodium enter the cell, while for LTD, there is a small amount of calcium influx. With these two functions, the strength of connections as well as the overall excitability and inhibition of a network of neurons can be modulated and adapted.

### 3.2 Neuroplasticity - Neurotransmitters

Communication between neurons via neurotransmitters also has an impact on the plasticity of the nervous system. One of the most important neurotransmitters when it comes to neuroplasticity is dopamine. On a neuronal level, this chemical helps facilitate synaptic plasticity by generating LTP effects, causing the synapses between neurons to become stronger and more active (Neuropraxis, 2020). From a network-level perspective, dopamine is a crucial element of the reward and reinforcement systems of the brain, which are responsible for modulating the brain regions associated with learning and memory. In other words, the release of dopamine in this system provides a good, rewarding sensation, and the brain learns to repeat whatever just happened to feel that good sensation again (Mcleod, 2023).

The specific name for this reward system is the mesolimbic dopamine pathway, which connects the regions of the brain responsible for releasing dopamine (ventral tegmental area) motivation (nucleus accumbens), emotions (amygdala) and memory (hippocampus). Dopamine release in the hippocampus stimulates the synaptic plasticity of hippocampal neurons, causing the strengthening of connections which helps the brain remember the conditions related to that dopamine release (Mcleod, 2023).

Another neurotransmitter that has a large impact on neuroplasticity is serotonin. Serotonin has a strikingly large number of responsibilities in the human nervous system, ranging from sleep, mood, hunger, and cognition, but it can also have meaningful effects on synaptic-based and network-based plasticity (Kraus et al., 2017). Put simply, cellular effects of serotonin have been shown to have impacts on the shaping of neural networks, especially during developmental periods of growth.  From a more detailed perspective, serotonin accomplishes this by modulating the transmission of glutamate between neurons - glutamate is the main "excitatory" neurotransmitter in the brain, and glutamatergic transmission has been linked to LTP and NMDA-dependent synaptic plasticity. Therefore, increased levels of serotonin can cause LTP effects by increasing glutaminergic transmission. Serotonin can also alter the expression of certain genes and proteins that are involved with the process of neuroplasticity, such as increasing the amount of cell adhesion molecules and brain-derived neurotrophic factor (BDNF). BDNF is an important protein for neuroplasticity, as it promotes the growth and survival of new neurons and synapses, as well as the strengthening and remodeling of existing connections - higher levels of BDNF is shown to result in more neuroplasticity (Frye, 2020). Increasing levels of serotonin via reuptake inhibition (using SSRIs) has been suggested to activate this plasticity, and other studies looking at increasing serotonin through other methods such as pharmaceuticals, navigation experience, or musical training have been shown to have similar effects.

### 3.3 Neuroplasticity - Larger Impacts

Different levels of activity and neurotransmitters can either strengthen or weaken the connections between neurons, but there can also be widespread impacts on higher-level areas and functions of the brain. For example, the organization of areas of the brain that respond to certain stimuli, such as sensory areas, can be changed with different environments and circumstances. A well-documented instance of this is seen in people who have lost a limb or had one amputated. In these patients, the somatosensory cortex (responsible for receiving sensory signals from body parts) will adjust its representation of the body to account for the loss of the limb. In a person who has lost their hand, the area of the somatosensory cortex responsible for the hand may be remapped to take over other responsibilities, because it is no longer needed for the missing hand's sensory signals (Merzenish et al., 1984). This expression of neuroplasticity does not involve the growth of new neurons, but rather the strengthening, weakening, or realignment of already-existing connections to meet the needs of the changed circumstances.

These larger impacts of neuroplasticity, known as cortical remapping, are essential components of therapy targeted towards adults - This is because  the brain becomes almost fully "wired" after the mid-20s, and new neuronal growth decreases after this point (Gogtay et al., 2004). A lack of new neuronal growth does not mean that the brain cannot continue to change, learn, and be "plastic", but rather that the tools to create positive changes in the brain must instead focus on altering pre-existing neural connections.

### 3.4 Neuroplasticity and Music - Overview

The human brain can adapt to its environment using neuroplasticity in a number of ways, but one of the most impressive drivers of this adaptation is music. The mechanisms involved range from the production of neurotransmitters to cortical remapping of the brain areas needed to engage with music. Additionally, the benefits of music in the brain is not necessarily limited to the functions that a musician requires. Music-induced neuroplasticity can be utilized as a tool to strengthen connections and learn new behaviors in areas completely unrelated to music by association. In a sense, engaging with music acts as a "reward" to the brain, encouraging it to remember what was happening during and around the engagement with music, as well as the complexity of music promoting connections between many far-reaching areas of the brain. This can be combined with therapeutic exercises to promote faster learning of the intended outcome.

### 3.5 Neuroplasticity and Music - Neurotransmitters

So, what is it about music that encourages such noticeable neuroplastic changes? Several research projects suggest that the answer lies in emotions and motivation. After all, positive emotions and feelings of motivation are associated with learning and memory, which promote plasticity in the relevant areas of the brain (Sun et al., 2018). Engaging with music has been shown to produce these effects (Schäfer et al., 2013, Ever, Suhr 2000, Salimpoor et al., 2011), and dopamine and serotonin are key players on this stage. The roles of dopamine and serotonin in generating neuroplasticity have been demonstrated already, and thus the relationship between music and these neurotransmitters provides a strong hypothesis as to why music can be a driving factor for neuroplasticity.

One study looking at the relationship of music and serotonin found that when subjects listened to music they described as “pleasant”, there were significantly higher levels of serotonin transmitted between neurons. When the music was described as “unpleasant”, serotonin transmission was significantly lower. These results correlated with the subject’s subjective attitude towards the music, leading the authors to suggest that the listener’s attitude towards music has an influence on the neurotransmission induced by the music (Ever, Suhr, 2000). Given the aforementioned relationships of serotonin and neuroplasticity, this could provide an explanation for how music drives neuroplasticity and provides positive benefits when used in conjunction with traditional treatment. Listening to “good” music (as judged by the patient) could increase serotonin levels in the patient, which in turn facilitates plastic changes and provides a reward to the patient.

Dopamine is another neurotransmitter that has been shown to be related to music. One neuroimaging study showed that listening to music can stimulate dopaminergic regions such as the striatal system, which is a system involved in reward and emotions (Salimpoor et al., 2011). In this study, the researchers found that the most dopamine release occurred when people reported a peak of emotional arousal. However, there was also dopamine release in other distinct pathways unrelated to the experience of peak pleasure, showing that music can facilitate dopamine release in many areas of the brain. Another study tested the relationships of music and dopamine by giving different groups of participants a supplement prior to listening to music. The supplement changed depending on the study group, with one group receiving L-DOPA which increased the amount of dopamine in their brain, another group receiving risperidone, which decreased the effect of dopamine, and a control group that received a placebo that had no effect on dopamine levels (Ferreri et al., 2019). The L-DOPA group reported having higher musical pleasure and motivation than the control group, while the risperidone group reported having reduced musical pleasure and motivation compared to the control group. While discussing this study, Ferreri said that it did not conclude that simply taking a music supplement will increase musical pleasure - rather, “listening to the music you love will make your brain release more dopamine” (Dolan, 2019).

In conclusion, listening to and engaging with music has been shown to increase the activity and release of dopamine and serotonin. Given that these two neurotransmitters have been shown to facilitate neuroplasticity, these observed increases could provide a piece of the puzzle as to why music is such a driving force of plastic changes in the brain.

### 3.6 Neuroplasticity and Music - Cortical Reorganization

The release of neurotransmitters is not the only reason that music is able to provide extensive neuroplastic changes. In fact, the reason for these widespread changes is partially related to the widespread nature of music itself. Listening to and making music involves many different structures of the brain, such as the auditory cortex (to understand what is being heard), the motor cortex (to move the body in the right way to dance or play an instrument), areas for multisensory integration, and emotional association structures (Chatterjee et al., 2021). Because of the broad number of functions needed, the brain must make massive amounts of connections between areas that may have otherwise not been connected.

Specific examples of differences between the brains of skilled musicians and non-musicians show the vast increases in connection that playing music promotes. Among these include the areas of the brain responsible for the physical motions of playing an instrument or singing (Amunts et al., 1997, Gaser & Schlaug, 2003), or the connections between the two halves of the brain needed for coordinating actions between multiple parts of the body (Hyde et al., 2009). There are also changes in areas of the brain responsible for more abstract concepts - such as the cerebellum, responsible for tempo and timing (Gaser & Schlaug, 2003, Hutchinson et al., 2003), or increased numbers of connections between the frontal and temporal regions, which are responsible for monitoring the perception of sounds and what they mean (Halwani et al., 2011). All of these sizable changes were observed in people who began musical training at a young age, but this doesn’t mean that people who pick up music at a later age don’t also experience neuroplastic changes. In people who started learning music later, similar changes were observed, but instead of the increased neuronal growth seen in long-time musicians, their brains adapted by rewiring previously existing connections and recruiting nearby neurons to help with the new tasks.

### 3.7 Neuroplasticity - Application

To use the effects of neuroplasticity in a beneficial manner, activities that induce or generate neuroplasticity can be combined with therapeutic settings focused on brain recovery, behavior therapy, or learning new skills. The use of neuroplasticity-inducing methods has been explored in conjunction with behavioral treatments before, such as a study done by Abumaria et al. in 2011. In this study, it was found that elevated magnesium levels in the brain enhanced the synaptic plasticity of the hippocampus in rats. The rats treated with higher levels of magnesium (and thus with higher levels of neuroplasticity) displayed increased retention of fear extinction. In other words, they “unlearned” fear behaviors faster than other rats, and this effect lasted longer than it did in other rats.

Clinics that focus on patient rehabilitation following traumatic brain injuries (TBIs) use methods that induce neuroplasticity to help patients recover faster, with strong results. For example, one study that used exercise to increase levels of BDNF before treatment reported significant improvement in persistent concussion symptom scores (McGeown et al., 2018). Meanwhile, another clinic which focuses on promoting neuroplasticity through physical and cognitive exercises had patients self-report a 60% improvement of self-reported post-concussion symptoms (Fong & Loewen, 2023).

The neuroplastic effects of music have been utilized for recovery as well. In one example, patients with behavioral and cognitive deficits following injury to the orbitofrontal cortex were treated with music-supported therapy. This therapy was shown to not only induce significant neuroplastic changes, but also improve cognitive performance, overall well-being, and social behavior (Vik et al., 2019). This study focused on giving patients piano lessons to boost their musical engagement and found that both the effect of neurotransmitters and cortical remapping could explain the observed neuroplastic effects. For neurotransmitters, the brain areas which showed recovery all received dopaminergic connections of some kind, providing support to the hypothesis that dopamine can facilitate neuroplasticity. The brain scans of patients involved also revealed significant evidence that musical practice has a causal relationship with the reorganization of neural networks, demonstrating the effects of cortical remapping. The study concluded that despite limitations in study size, engaging directly in music may induce neuroplasticity through these avenues, explaining the increased social interaction, well-being, and cognitive performance.

One of the driving factors for the rehabilitative properties of music is the process of cortical remapping, and this has been demonstrated in several studies. For example, stroke victims who have been treated with music-based intervention show increased connections between their auditory-motor regions, leading to improvements in motor function (Ripolles et al., 2016). There is also evidence that musical training leads to cognitive improvements due to a reorganization of neural networks in patients with a traumatic brain injury (Vik et al., 2018), and that elderly musicians have stronger memory and visuospatial connections than non-musicians (Grassi et al., 2016).

These studies show that utilizing the effects of neuroplasticity to help patients recover from brain injuries and mental deficits can be a fruitful effort.

## 4 - So, Why Study This Topic? Conclusions From Part 1

The investigation of using EEG-based machine learning to predict music-related brain activity is a compelling research topic for several reasons. Primarily, music has been shown to have therapeutic effects, both in the areas of neurorehabilitation and treatment of mental deficits. Numerous studies have demonstrated how playing or listening to music can influence the brain and induce neuroplasticity, giving rise to these positive effects. However, it is unknown if the process of training a person to “think” music instead of playing it could also provide these benefits. To determine whether this method could be effective, it is necessary to monitor an individual’s progress by observing their musical thoughts. The objective of this project is to determine whether this is a feasible task via a “proof of concept” for interpreting musical thoughts.

If a proof of concept is established, it could serve as the foundation for a technology that can provide markers of someone’s progress and ability at “thinking” music. These markers can be used to observe whether there are neuroplastic effects as a result, and that can be compared to the neuroplastic effects of playing music. This could give insight into ways to enhance the efficacy of music therapy interventions or provide new methods to create specific interventions based on a person's specific needs. In conclusion, this study's significance lies in its potential to enhance our understanding of how music influences the brain, particularly in the context of neuroplasticity and music therapy.

# **Methods**

How to Study This Topic? Brain Imaging and Machine Learning

This section provides a comprehensive overview of the EEG method for brain observation in the context of the current project. First, various brain activity observation methods are examined, and EEG is identified as the optimal choice. The use of machine learning for EEG data analysis is then discussed, along with the types of data that EEG provides and their relevance to the study. Lastly, the rationale behind the selection of the Muse 2 EEG headset is explained. Factors such as affordability, research quality data, and ease of data retrieval are highlighted as reasons for its suitability.

## **Brain Visualization Techniques**

Some of the most important developments in the field of neuroscience have been technologies that allow for accurate imaging of the brain and its functions. These tools allow scientists and doctors to observe the structures inside the brain, and more importantly, the activity inside. This can be beneficial in many ways. One benefit is the ability to map the functions of specific areas of the brain. Another benefit is the ability to monitor brain activity in real time and use that information for external purposes.

Different methods of imaging and monitoring brain activity have different advantages and disadvantages, mostly relating to spatial and temporal resolution. Some of the most common brain visualization techniques are as follows:

*Functional Magnetic Resonance Imaging (FMRI)* – FMRI is a non-invasive method to observe changes in neural activity. This technique is based on the properties of magnetic resonance of elements. Specifically, the magnetic resonance of oxygen is utilized due to the high presence of oxygen in blood.

A basic overview of how FMRI works is simple. From a technological viewpoint, the FMRI machine takes frequent “snapshots” of the amount of oxygen levels throughout the brain. When a brain region is more active, there is a higher rate of blood flow – and as a result, oxygen around that area. Because the FMRI can calculate the location and density of oxygen levels in the brain, the technique is able to determine when a brain activity is more or less active due to a stimulus.

For a very basic example, imagine a person who is left in the dark. Let's call this person Mary. While in the dark, Mary's primary visual cortex in her occipital lobe will be less active due to the lack of stimulus. Thus, when a light is turned on and the primary visual cortex becomes more active, there will be a rush of blood to her primary visual cortex. The oxygen in this blood is then observed by the FMRI machine. The measured increase in oxygen levels in this area allows for the conclusion that this area becomes more active when presented with a visual stimulus.

While the spatial resolution of FMRI is very precise, the time-based resolution is low. This is due to the fact that blood is not immediately delivered to an active brain region and is not immediately removed from a brain region that becomes less active. This time delay of blood flow creates a delay in the measurement of the FMRI. This lack of time-based precision makes it so that this technique is not as useful for purposes which require more instant feedback.

Since FMRI only utilizes a harmless magnetic field in its measurement procedure, this process is very safe for human subjects and presents minimal health risks. The largest risks from this procedure would be a result of a person having metal implanted in their body in any way, such as a pacemaker or a screw holding a joint together.

*Positron Emission Tomography (PET)* - Positron Emission Tomography is another method of measuring brain activity by observing changes in blood flow. However, instead of using a magnetic field to observe the amount of oxygen in various regions of the brain, this technique uses radioactive isotopes of elements.

To measure the blood flow, PET is based on the idea that brain areas absorb glucose when they are active. To measure this absorption of glucose, the patient is given a form of glucose that holds a radioactive isomer inside of it. Then, the PET device can monitor the concentrations of gamma rays emitted from the radioactive isomer in order to determine where the glucose is being absorbed, and in what amounts. This allows for the mapping of which areas are most active based on the amount of glucose being absorbed.

While this method can create an image of the metabolic activity in the brain, the spatial resolution is lesser than FMRI. The time-based resolution of PET is also sub-optimal. Similar to FMRI, this is due to the mechanism of action with which glucose is absorbed - it is not instant, so the observation of brain activity comes with an inherent delay as the glucose needs to be absorbed to be measured.

While the radioactive isotopes are not believed to be harmful to patients, they pose a greater inherent risk than that of the magnetic field used with FMRI. However, PET would be much safer for people who have metal implanted in their body due to the lack of a magnetic field.

*Magneto-Encephalography (MeG)* - MeG is a method of brain visualization that does not rely on scanning for specific elements or biological components within the brain. Instead, MeG measures magnetic fields generated by the brain.

How does this work? Put simply, neurons “fire” in an electrochemical manner - there is a flow of electrically charged ions into and out of the cell to produce a signal that gets transmitted to the next cell via neurotransmitters. This electrical activity generates a very small electromagnetic field. While the magnitude of the electromagnetic field generated by a single neuron is negligible, the net field of a large group of neurons can be detected using extremely precise equipment. This equipment is known as a SQUID - a Superconducting Quantum Interference Device.

To measure the extremely small magnetic fields generated by brain activity (the fields are about 1 billion times weaker than the earth’s magnetic field!), the SQUID must be hosted in ideal conditions. This includes a magnetically shielded room and a large liquid helium bath within the MeG machine to keep the superconductors within the low range of impedance needed to measure such small fields. This makes an MeG machine a very expensive, resource-consuming piece of equipment.

These technological and economic barriers are not without benefit, however. A MeG machine produces extremely high spatial and temporal resolution. Compared to an FMRI or PET machine, an MeG machine provides better spatial resolution because it is able to measure direct neural activity instead of the indirect neural activity (based on blood flow around neurons) measured by an FMRI. MeG is also able to collect measurements thousands of times per second, giving it unrivaled temporal resolution when compared to other brain visualization methods.

*Electroencephalography (EEG)* - Similar to MeG, EEG is a measurement of electrical activity inside the brain. However, instead of measuring the magnetic fields produced by groups of neurons, electroencephalography measures the direct electrical activity.

As mentioned previously, neurons fire in an electrochemical fashion. This firing releases an electromagnetic signal, which can be measured through different techniques. An EEG is similar to the previously mentioned MeG in that it measures these electromagnetic signals. However, while a MeG measures the magnetic elements of the electromagnetic signal, an EEG measures the electrical elements of the signal.

An EEG device consists of electrodes that are placed directly on the scalp. These electrodes pick up the electrical signals that are generated by the brain which can make their way through the skull and out into the scalp. These electrical signals are then amplified so that they can be read and interpreted more clearly. Because of the speed of electrical transmission, the temporal resolution of EEG is very high.

One benefit of EEG is the simplicity of the hardware. The electrodes in an EEG headset do not require magnetic shielding, are relatively inexpensive to manufacture, and do not take up very much space. Due to these aspects, EEG recording is one of the most widely used methods of brain imaging.

The main drawback of using EEG measurement is the lack of spatial resolution. Because the electrodes are only placed on the scalp, they pick up the summation of electrical signals coming through the skull and out through the skin. This makes it impossible to locate exactly where the electrical signals are coming from. This can be mitigated by adding a higher concentration of electrodes, but this element of signal convolution makes precise spatial measurements difficult.

For this thesis, the objective is to be able to recognize what melody a person is thinking in their head. In relation to the method of data collection to be used, this means that there must be high temporal precision due to the time-based nature of a musical melody. Spatial resolution could also be important, but not as much as the need for temporal resolution. Due to the limited resources and scope of this project, the data collection must also be relatively cheap and accessible to use. These factors make it clear that an EEG device is the most appropriate option for data collection for this project, due to its temporal precision, ease of use, and affordability.

## EEG Device Selection

After consideration, an EEG device was determined to be the best method for data collection in this project. In this section, an outline is provided of the various EEG devices that were evaluated, as well as a justification for the final selection of the Muse 2 EEG headset.

### EEG Device Options

There were two main criteria that an EEG device had to meet to be used for this project. Firstly, the headset had to be able to collect research-quality data that would not create inconsistent results based on poor device quality. This is obviously very important, as poor data will invalidate the results of the project. Secondly, the device had to be able to generate raw data signals without needing to work through proprietary software specific to the manufacturer. This would allow for secure collection of data as well as make it easier to process the data for the desired purpose.

Given these criteria, there were two clear candidates - the Emotiv Epoc and the Muse 2. These two headsets stand out from the rest of the field due to their research-quality data and commercial availability. The comparisons between the two headsets are shown below:

**Emotiv Epoc+:**

**Pros:**

- 14-channel EEG collection
- Can detect important EEG markers known as event-related potentials (p300 waves) with reliable, research-quality accuracy (Fouad et al., 2021). The authors concluded that this device could be used to set up a robust and reliable system for detecting p300 waves.
- Emotiv’s software for detecting thoughts and mental commands shows a level of accuracy high enough for use in personal or research projects (Taylor and Schmidt, 2012)

- There is open-source software for collecting raw data from the headset, called OpenVIBE (Fouad et al., 2021).

**Cons:**

- Software for detecting thoughts and mental commands is proprietary, so the precise nature of signal manipulation is unknown to the user (Taylor and Schmidy, 2012).
- This headset is expensive ($800+ for one unit) and has limited availability.
- Can be difficult to set up due to its need for saline gel sensors, would require participants to have shorter hair to prevent signal interference.

**Muse 2:**

**Pros:**

- Is suitable for meditation and thought-based research applications (Saganowski et al., 2020)
- Can detect event-related potentials (p300 waves) (Krigosolon et al., 2017)
    - "Our work highlights that with a single computer and a portable EEG system such as the MUSE one can conduct ERP research with ease thus greatly extending the possible use of the ERP methodology to a variety of novel contexts."
- Open-source software is easy to use and provides many forms of data analysis and preprocessing (Muse Mind Monitor).
- Uses dry sensors, making it very easy to set up with participants. Headband format means that participants can have any hairstyle or headwear and not interfere with data collection.
- Not as expensive as Emotiv Epoc. Less than $300/unit.

**Cons:**

- Only 7-channel EEG collection
- Headband format means that sensors are only on the forehead and temples instead of located all around the head.

The comparison between the Emotiv Epoc and the Muse 2 makes it clear that both headsets are suitable for research purposes. However, the Muse 2 was selected over the Emotiv Epoc for several reasons, first of which being the software for getting raw data - the Muse Mind Monitor software is more accessible and efficient than the OpenVIBE software for the Emotiv Epoc. Another reason was the ease in setup and use. While the Epoc has more sensors which cover a greater area of the head, the complexity of the setup could make it difficult for a sole researcher to perform data collection, and people with longer hair could present complications for the collection process. Meanwhile, the Muse 2's headband design makes it much easier to put on and take off of participants and doesn't introduce hair interference or require saline solution. Another factor in this decision was affordability. The Muse 2 is less expensive than the Epoc despite having similar research-quality results, making it possible to purchase two Muse 2 devices for the price of a single Epoc device. This would mitigate the risk of damage or malfunction in the product during the project. The final factor for this decision came from consultation with researchers who have worked with both headsets in the past for similar purposes. Dr. Rafaella Folgieri of the University of Milan provided personal experience with the Emotiv Epoc and the Muse 2, stating that the Epoc has a tendency to malfunction and break despite its larger price tag. Overall, this background research into the two headset options leads to the conclusion that the Muse 2 is the better choice for this project.

Using the Schewel Research Fund provided by the University of Lynchburg, two Muse 2 headsets were purchased from the parent company, ChooseMuse. The purchase of two separate headsets would ensure that if there was an equipment malfunction in one of the headsets, the project would be able to continue without a major delay.

## Machine Learning for EEG Data

While the Muse 2 is the clear choice for HOW to collect EEG data, the data still needs to be analyzed and interpreted. In order to associate EEG data with certain mental states and actions, relevant features must be identified. Examples of relevant features might be the frequency spectrum and dominant rhythms of the signal (determined via a Fast Fourier Transform), or the statistical properties of the signal such as mean, variance, and skewness (used to capture complexity and variability of activity) (Natarajan, 2020). However, raw data can be noisy and full of artifacts. This makes it difficult for even human experts to interpret.

Machine learning techniques can be applied to various EEG-related tasks, allowing for the diagnosis of neurological disorders, monitoring of cognitive states, detection of emotions, and control of brain-computer interfaces. While there is no definitive answer to whether machine learning is faster or more reliable than human experts in all areas, it does have its advantages and disadvantages. For starters, machine learning can process and learn from large amounts of data much faster than humans and can do so without needing prior knowledge or having prior assumptions about the underlying mechanisms and patterns. This can allow for a much more efficient system, which is crucial in a speech based brain-computer interface (for example) where high accuracy and speed is necessary. However, as with humans, machine learning programs can also be affected by noise and outliers. This enforces the importance of data preprocessing for reliable results (fortunately, there are machine learning programs that specialize in preprocessing as well). Reliable programs can also require large amounts of data and processing resources to train, test, and deploy, which can be a hurdle for applications which have limited access. (Sanei and Chambers, 2021, Aggarwal and Chugh, 2022)

For this project, efficiency, and the ability to process and draw conclusions from large sets of EEG data is required. Machine learning techniques will serve as a valuable tool for this objective. To understand how they will be used, it is important to first know how machine learning techniques work.

## Overview of Machine Learning

Machine learning can be used in a variety of ways, depending on the nature of the data and the desired outcome of an application. There are two main styles of machine learning, unsupervised and supervised learning, each of which can be used for different types of tasks and objectives. The main difference relates to the amount of human guidance during the training process.

**Unsupervised learning:** In unsupervised learning, a model is given unlabeled data without any external feedback with the objective of detecting patterns inside the data. This can be used to *detect abnormal data points, group similar data together,* or *reduce the number of features within a dataset*. This type of machine learning will be used in this project to prepare EEG data for this project by removing outliers and averaging out missing data.

**Supervised learning:** In a supervised learning example, input data is labeled to train the model to make predictions on future input data. This model will learn from the examples that it's given, attempt to make predictions, and then modify itself depending on the outcome of the predictions to minimize error. Supervised learning can be used for *regression*, *forecasting*, and *classification* tasks.

*Regression***:** This form of machine learning aims to determine the relationship between previously existing values and predict a value to describe this relationship. An example of regression learning in action is seen in predicting the price of a house - based on the location, square footage, number of bedrooms or bathrooms, etc., a regression model would make a prediction as to what the value of the house is.

*Forecasting***:** A forecasting machine learning model focuses on predicting future values or events based on previous data. An obvious example of forecasting is seen in a model that predicts weather patterns and probabilities of weather events like rainstorms, tornadoes, or hurricanes.

*Classification*: This form involves assigning a label to an input based on a collection of criteria. The program will interpret several variables in an input and then assign a classification to the input (for this project, there will be 5 different variables for classification). The assigned classifications can either be binary (where a program chooses between two classification labels) or multiclass (more than two possible classifications). An example of this in action would be a program that determines whether an email is spam based on the content, source email address, or title.

## Applied Use of Machine Learning - XGBoost Classification

To determine which style of supervised machine learning should be used for this project, I considered the main objective: To use machine learning to predict which melody a person is thinking in their head. In other words, a machine learning program will be used to "look" at a set of EEG data and determine which melody a person was thinking of while the data was recorded. Given that the program will be predicting which melody the participant was thinking of out of several potential options, this would fall under the classification style of machine learning - the program is being asked to determine which classification (melody) a certain set of EEG data belongs to. Therefore, this project will be using a supervised classification model.

There are many different types of machine learning algorithms that can be used for classification tasks. One of the most accurate and efficient classification algorithms is called XGBoost Classification. This algorithm works by using extreme gradient boosting (this is where the "XGBoost" in the name comes from) of decision trees and has gained popularity in recent years after winning many competitions for predicting and describing datasets (NVidia, 2023). In relation to EEG data classification, XGBoost algorithms have been shown to be among the most accurate classification algorithms available (Parui et al., 2019, Khan et al., 2022). For these reasons, this project used an XGBoost algorithm for classification of the EEG data sets collected from participants. To understand how it works, it's vital to grasp the concepts at play: decision trees and gradient boosting.

A *decision tree* is a model that predicts a label using a flow chart of tests about the data. Each test, called a "node" produces multiple branches for each of the possible answers. For example, a setup for a home-price decision tree might look like:

Is the # of Bedrooms > 1?

If yes, home price = $100,000 If no, home price = $200,000

The "node" of this tree would be the question "Is the # of Bedrooms > 1?", while the "branches" are the resulting answers to the question. While this is a basic example, this shows the basis of how a decision tree functions. In reality, decision trees are much more complex and can have tens of thousands of connected nodes and branches.

Gradient boosting for decision trees is built on the idea that you can "boost" simple trees by combining them with other simple trees (For reference, a single model of an XGBoost classification algorithm will initially create hundreds - if not thousands - of separate decision trees before combining them). A simple tree is not very good at the job of classification, but when combined with many other simple trees, they become much better and more accurate. This is called a strong tree.

Gradient boosting is a style of "boosting" that uses mathematical formulas to find the best way to combine the simple trees together and make the strongest tree possible. This is done by looking at how accurate each tree is and then focusing on increasing the level of accuracy as much as possible by changing simple trees slightly and adding new ones. The formulas determine the most efficient step at any given point to increase the accuracy of the model, and the model takes that step. Following the most efficient step each time is called following the gradient of the error and allows for the best combination of simple trees to create the best possible strong tree (NVidia.com, 2023).

## Applied Use of Machine Learning - Microsoft Azure

Microsoft Azure is a cloud computing platform that can be used for a variety of services, ranging from storage, networking, computing, and analytics. Among the services that Azure offers is a graphical machine learning studio, enabling users without extensive programming experience to create unique machine learning pipelines for a variety of tasks, ranging from image classification to dataset forecasting. Microsoft Azure also offers a program called “Azure for Students”, which provides access to all Azure products for the use of education, teaching, non-commercial research, or testing of software applications. For this project, Microsoft Azure was used to analyze and classify the collected EEG data using the XGBoost Classification algorithm.

The relevant terminology for Microsoft Azure Machine Learning Studio is as follows:

*Experiment:* This is a structure for storing multiple “jobs” that can then be compared to each other or share data and results.

*Job:* A single machine learning job creates models that are trained on a specific data asset with the objective of computing a specific target. A single job can create dozens or hundreds of models to complete the objective.

*Model:* A model is a file that contains the learned patterns from a set of data and can be used to predict a desired target datapoint based on those observed patterns.

*Data Assets:* These are the sets of data that Azure uses to train and test machine learning models.

*Metrics:* Measurements that are used to evaluate the performance of a model during training and testing.

*Accuracy*: One of the metrics used to evaluate classification models. This metric presents how often the model correctly predicts the class of an observation.

*AUC:* Stands for “Area Under Curve” and is used as a metric for classification methods.

## EEG Data and Rhythms - Brainwaves

An EEG device takes a straightforward measurement - the charge of a sensor placed on the scalp. This charge is influenced by the activity of neurons inside the brain. As neurons fire with electrical signals, these electrical signals combine and seep out through the scalp and are picked up by the sensors. Fluctuations in the charge of this sensor can provide information about the inner workings of the brain including mental states and specific thought processes.

To determine these inner workings of the brain, the changes in raw charge of the sensors must be analyzed. One of the most widely applied methods for this is called a Fast Fourier Transform. This method of data analysis uses a formula to represent a change in data over time as a combination of the different frequencies that make up the changing data signal. By applying a Fast Fourier Transform to an EEG signal, the raw signal can be represented as different “brainwaves”.

Different frequencies of brainwave activity have been associated with different cognitive, sensory, and mental processes and experiences. The ranges of brainwaves and their associated processes/experiences are as follows (Hermann, 1997, Abhang et al., 2016):

- **Delta (0.5-4 Hz)**: Mostly present during deep sleep or while under anesthesia.
- **Theta (4-8 Hz)**: Associated with light sleep, mediation, and creativity.
- **Alpha (8-13 Hz)**: Predominantly present during waking moments of relaxation and calmness.
- **Beta (13-30 Hz)**: Associated with alertness, concentration, and problem-solving.
- **Gamma (>30 Hz)**: High level information processing and cognitive functioning.

In this project, the data collected by the Muse 2 EEG headset was preprocessed via Fast Fourier Transform to provide both raw values and brainwave values for each sensor on the headset. This information was then organized as outlined in the “Data Organization Methods” section below, and used to train the Microsoft Azure machine learning models as outlined in the “Data Analysis Methods”.

# Experimental Design:

Setup, Methods, Results, Conclusion, and Discussion

---

## Overview

The experimental procedures for this project were straightforward. First, 5 melodies were selected. Then, EEG data was collected from subjects while they played each of the 5 melodies in their head, and half of the EEG data was used to train a machine learning model. The trained machine learning model was then tested using the other half of the EEG data, by asking it to predict the melody value for each recording. The accuracy of the model in predicting the correct value was recorded and served as the key metric to determine the success of the model. Because this project was aiming to predict which of 5 melodies a person was thinking about for a single instance of EEG data, the model has a 1 out of 5 (20%) chance of getting it right if it makes random guesses. Therefore, if a model shows overall accuracy significantly greater than 20%, then this model is successfully predicting the melody value better than random based on the patterns it found in the EEG datasets during training.

## Setup

A room was reserved for this experiment and the data collection occurred in this room for all participants. The room had several chairs and tables, all white walls and ceiling with whiteboards on 2 walls, and was isolated from outside activity by a wooden door. There were no auditory distractions and the room was quiet. The tables were set up so that the participants were sitting directly across from the researcher, with only the researcher's laptop in between.

The experiment required 5 different melodies for participants to listen to and play back in their head. These melodies were chosen based on a couple criteria - genre, popularity, and length. Each of the 5 melodies are from different genres (classical, rock, pop, rap, and R&B), less than 5 seconds long, and popular enough to be on the Billboard top 100 during their peak. The 5 melodies used for this project were:

1) Für Elise - Beethoven (Classical)
2) Smoke on the Water - Deep Purple (Rock)

3) Levitating - Dua Lipa (Pop)
4) Bad and Boujee - Migos (Rap)
5) The Hills - The Weeknd (R&B)

For participants to listen to the melodies, simplified versions were created using Ableton Live 11, a digital audio workstation for creating music. Midi tracks were programmed to play each melody, and an operator synthesizer emulating a wurlitzer piano was used to generate the sound. Then, the clips of the 5 isolated melodies were rendered and saved as .mp3 files. These 5 files were used in the experiment as the reference melody for participants to listen to before playing the melody in their own head.

To set up the Microsoft Azure machine learning studio, a student Microsoft Azure account was created and a Machine Learning Workspace with the title “Senior Thesis” was created. Inside this workspace, a standard compute cluster with 4 vCPUs and 14GB of ram was reserved and titled “SeniorThesisCluster”. This would allow for the machine learning programs to execute the training and testing of models.

## Data Collection Methods

Data was collected using the program Muse Mind Monitor. This program required a Bluetooth connection between the Muse headset and a mobile device, as well as a Wi-fi connection for the mobile device to upload recorded files to secure cloud storage. The data was recorded by going into “recording mode” on the Muse Mind Monitor program. Recorded data was saved as plain text CSV (comma separated values) files and uploaded to the secure cloud storage online.

To begin, the participant was greeted and given an informed consent form going over the details of the experiment. This form can be found in the additional materials section of this thesis. After agreeing to the informed consent form, participants were seated directly across from the researcher at a table in the data recording room. Participants were given a QR code which linked to a google form to fill out background information. The google form collected anonymous responses to keep the identity of the participants confidential, and included these questions:

- Please provide the number given to you by the researcher:

    - Note: These numbers were given to participants in ascending order (1, 2, 3, etc.) and served as their “Subject #” for later use in the project. For example, the first participant received the number 1, and was later referred to as Subject 01. The second was given number 2, and was later referred to as Subject 02.
- What is your age?
- What is your  major (if applicable)?
- What is your cultural background?
- What is your ethnic background?
- Do you have any background playing musical instruments? If yes, what instrument(s), and for how many years total?
- Please rank your preference for the following musical genres, with "1" being your favorite and "5" being your least favorite.
    - Classical
    - Rock
    - Pop
    - Rap
    - R&B

The participants were given a verbal description of the data collection procedures as outlined in the informed consent form, and then were given a brief demonstration of how to adjust and put on the Muse 2 headset. Once the participant felt comfortable proceeding, they were given the headset to put on and the researcher ensured that  a good connection had been formed. Data collection proceeded as outlined by the following procedures:

1) Sitting still, the participant listened to a melody being played out loud on the researcher's laptop 3 times.
2) The participant was then instructed to “play” the melody in their head 5 times, with a single blink between each instance. This blink was to provide a marker in the EEG data for later use. During this step, EEG data was recorded via the Muse Mind Monitor software.
3) This process was repeated for each of the 5 melodies.
4) Steps 1-3 were repeated a total of 3 times.

By the end of the data collection, the participant had listened to each melody 9 times and "played back" each melody 15 times. With no exceptions, the melodies were played in the following order during each round:

1) Für Elise - Beethoven (Classical)
2) Smoke on the Water - Deep Purple (Rock)
3) Levitating - Dua Lipa (Pop)
4) Bad and Boujee - Migos (Rap)
5) The Hills - The Weeknd (R&B)

This data collection produced 15 total CSV data files per participant (3 files for each of the 5 melodies). After the data was recorded, it was uploaded to a dropbox folder linked to the Muse Mind Monitor app. Once the session concluded, the data files were exported from the dropbox folder and transferred into a secure Google Drive folder. Then, they were permanently deleted from the dropbox location to ensure data safety and security.

In total, the data collection sessions as outlined above were completed in approximately 30 minutes.

## Data Organization Methods

To analyze the data, it was first organized into separate data files for each instance of the melody being played in the participants' heads. This was necessary because each recorded data file contained data of the participant thinking the melody 5 different times. To separate the 5 different instances, the biomarker provided by the participant blinking was used - this is because blinking creates a unique signal on EEG data that can be clearly identified. Thus, by having the participants blink in between each time they "thought" the melody, this provided clearly defined markers of where to separate the data. Using these markers, the data files containing 5 repetitions of a single melody were spliced into 5 separate files. These files were named according to the following criteria, and the naming procedure was kept consistent for all of the data collected from all of the participants.

[Subject #] _ [Melody #] _ [Playback #]

For example, the data corresponding to Subject 2 “playing” the third melody for the seventh time would be labeled:

Sub02_M3_P7

Additionally, a column titled “Melody #” was added to each file and all rows were populated with the corresponding melody number (Fur Elise = 1, Smoke On the Water = 2, Levitating = 3, Bad and Boujee = 4, The Hills = 5). This would serve as the target column for the machine learning models to predict in the analysis step of the experiment.

Following the organization of all the data files for a subject, the files were separated into two separate groups - Odd-numbered data (P1, P3, P5, … P15), and even-numbered datasets (P2, P4, P6, … P14). This allowed the machine learning programs to be trained on one half of the data and tested on the other half, without any overlap between the two sets. Once all the data was organized in this manner for the subject, it was ready to be used to train machine learning programs for analysis.

## Data Analysis Methods

Organized data were uploaded to Microsoft Azure in the form of data assets for use in training and testing machine learning models. These data assets were titled according to the following formula:

“[Subject #]_M-ALL_[POdds or PEvens]”

While the subject number and differentiation between odd-numbered and even-numbered data varied depending on what data was uploaded, all the data assets contained recordings from all 5 melodies, hence the “M-ALL” in the [Melody #] section of the file title format.

Once data assets had been uploaded, an Azure experiment folder was created for each subject, titled as “[Subject #]_PTrained”. Inside of each Azure experiment, two jobs were created - one job where the models were trained on the POdds data asset (job title: “[Subject #]_OddTrained_EvenTested”), and another where the models were trained on the PEvens data asset (job title: “[Subject #]_EvenTrained_OddTested”). The procedure for creating these jobs was as follows:

- “Create New Automated ML Job” option was selected.
- The desired training data asset was selected from the list of data assets.
- Under “Experiment”, the relevant existing experiment was selected (Figure 1).
- For “Target Column”, the column “Melody # (Integer)” was selected (Figure 1).
- For “Select compute type”, the “compute cluster” option was selected, with the previously created SeniorThesisCluster being the selected Azure ML compute cluster (Figure 1).
- Under the “Select Task and Settings” page, the “Classification” task was selected, and deep learning was enabled. Under additional configuration settings, the “Use all supported models” option was deselected and only the XGBoostClassifier model was selected as an allowed model. Under “Exit Criterion”, training job time was changed from 24 hours to 2 hours (Figure 2).
- On the “Validate and Test” page, the “train-validation split” validation type was selected, and 15% of the data was reserved for validation. The test data asset provided was the opposite data asset for that subject - if the model was trained on a POdd data asset, the PEven data asset was used for testing and vice versa (Figure 3).
- The “Finish” button was selected, and the job was created.

By selecting the “Melody #” column as the target column, this instructed the job what value it was being asked to predict. As this column contained integers ranging from 1 to 5, the model was trained to predict what the value for this column would be in a certain row, based on the patterns of the data in the training set. Because the integer value of this column correlated with the melody that the subject was playing in their head, this makes it so that the model is essentially predicting what melody was being “played” while the data for a certain row was being recorded.

Once the job was created, it was allowed to run to completion and the 5 best models, as determined by the AUC metric, were selected to be tested. In a situation where a job created more than 5 models with “perfect” AUC scores (1.0), then 5 models were chosen at random from the selection of perfectly trained models. Each of the chosen models were then tested for accuracy, using the other half of the data for that subject.

Because two jobs were created for each subject, and the 5 best models of each job were tested for accuracy, there were 10 total models that were tested per subject. The 10 accuracy metrics from these tests were recorded and used to create an average accuracy score for the subject.

New jobs and models were created for each subject's data, and there were not any instances where a model trained on one subject's data was tested with another subject's data. This led to unique models and accuracy results for each subject.

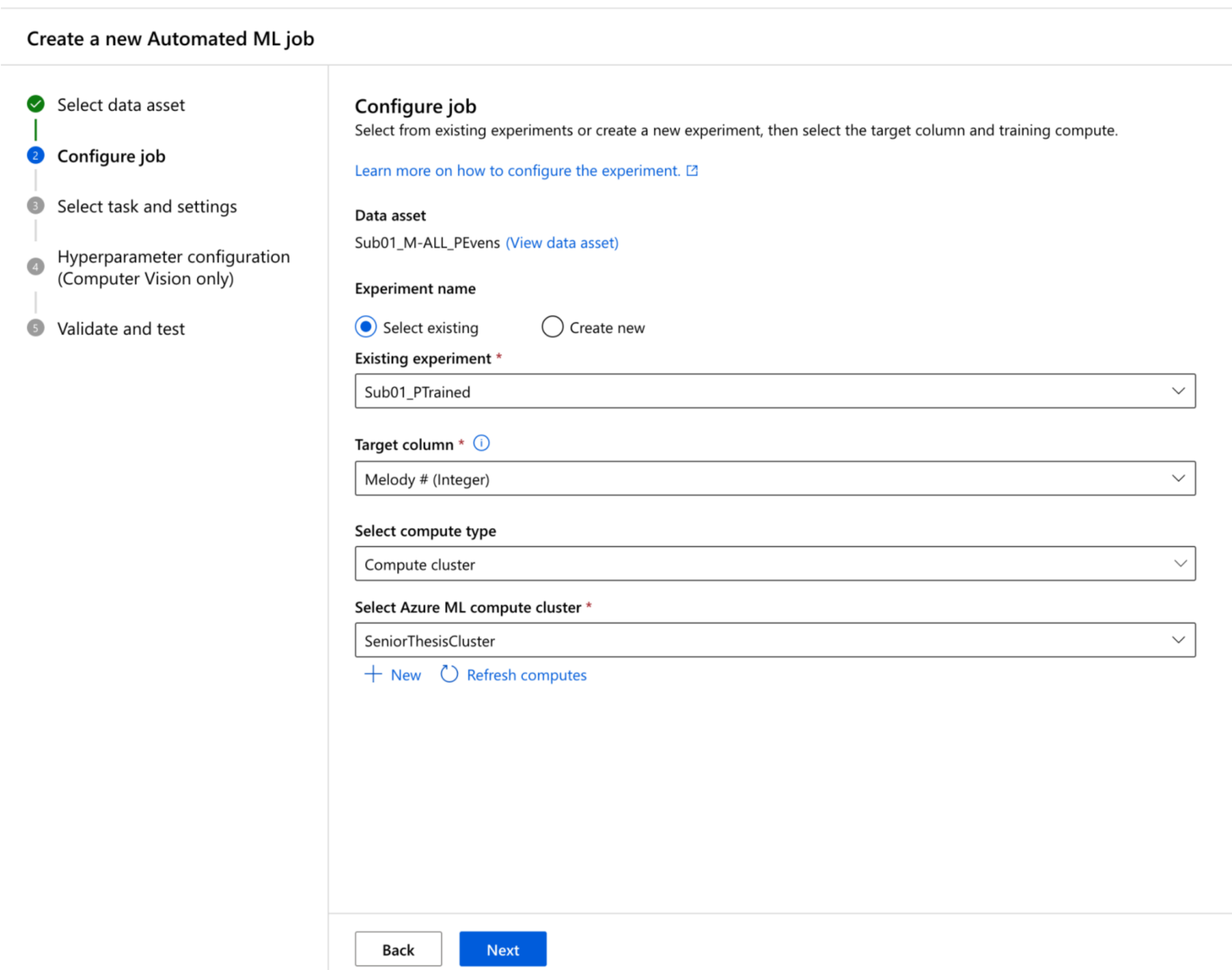


*Figure 1.* Showing an example of the job configuration settings for the automated machine learning jobs used to analyze the EEG data for this project using Microsoft Azure.

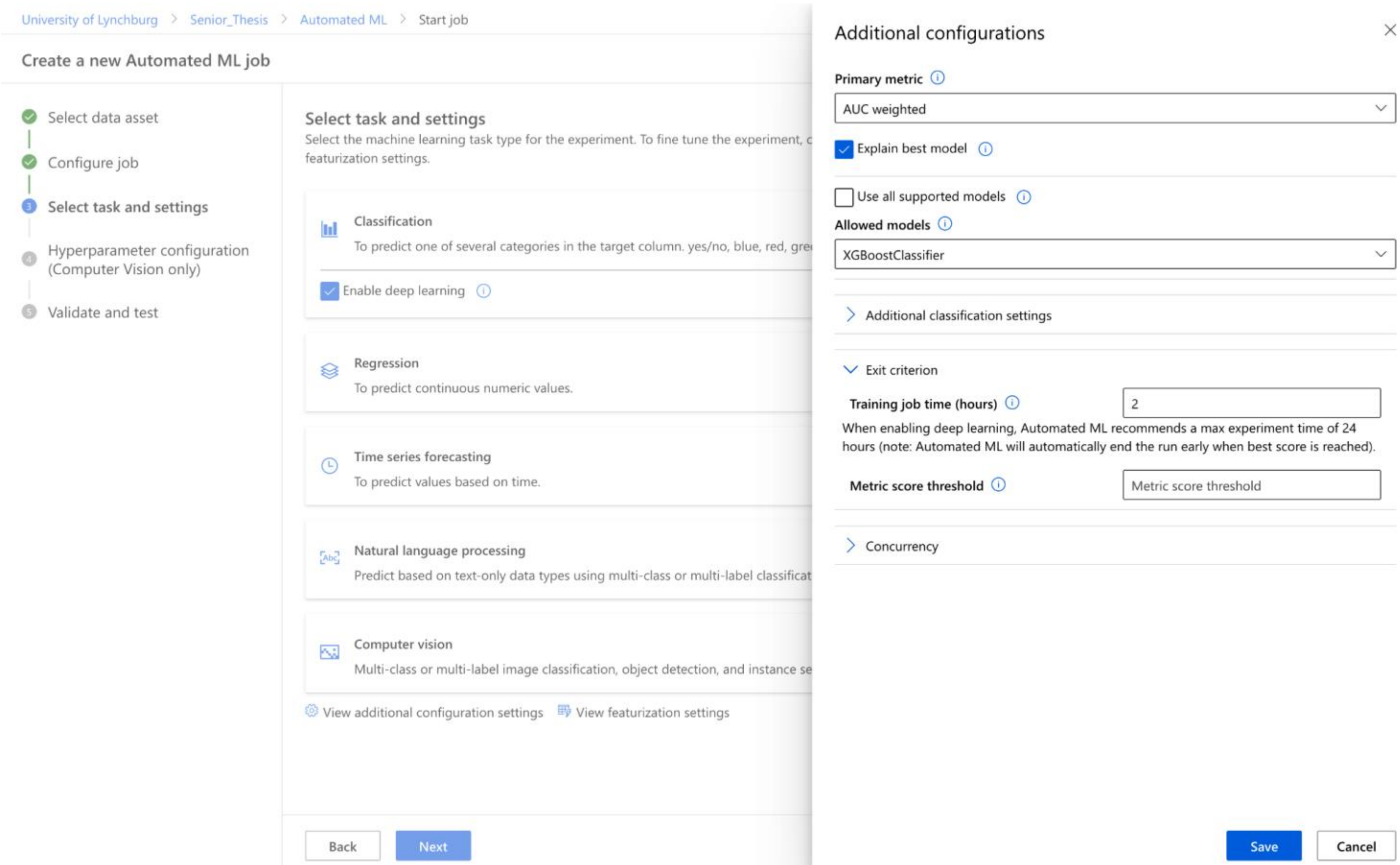


*Figure 2.* Showing an example of the Task and Settings preferences for the automated machine learning jobs to analyze the EEG data for this project using Microsoft Azure.

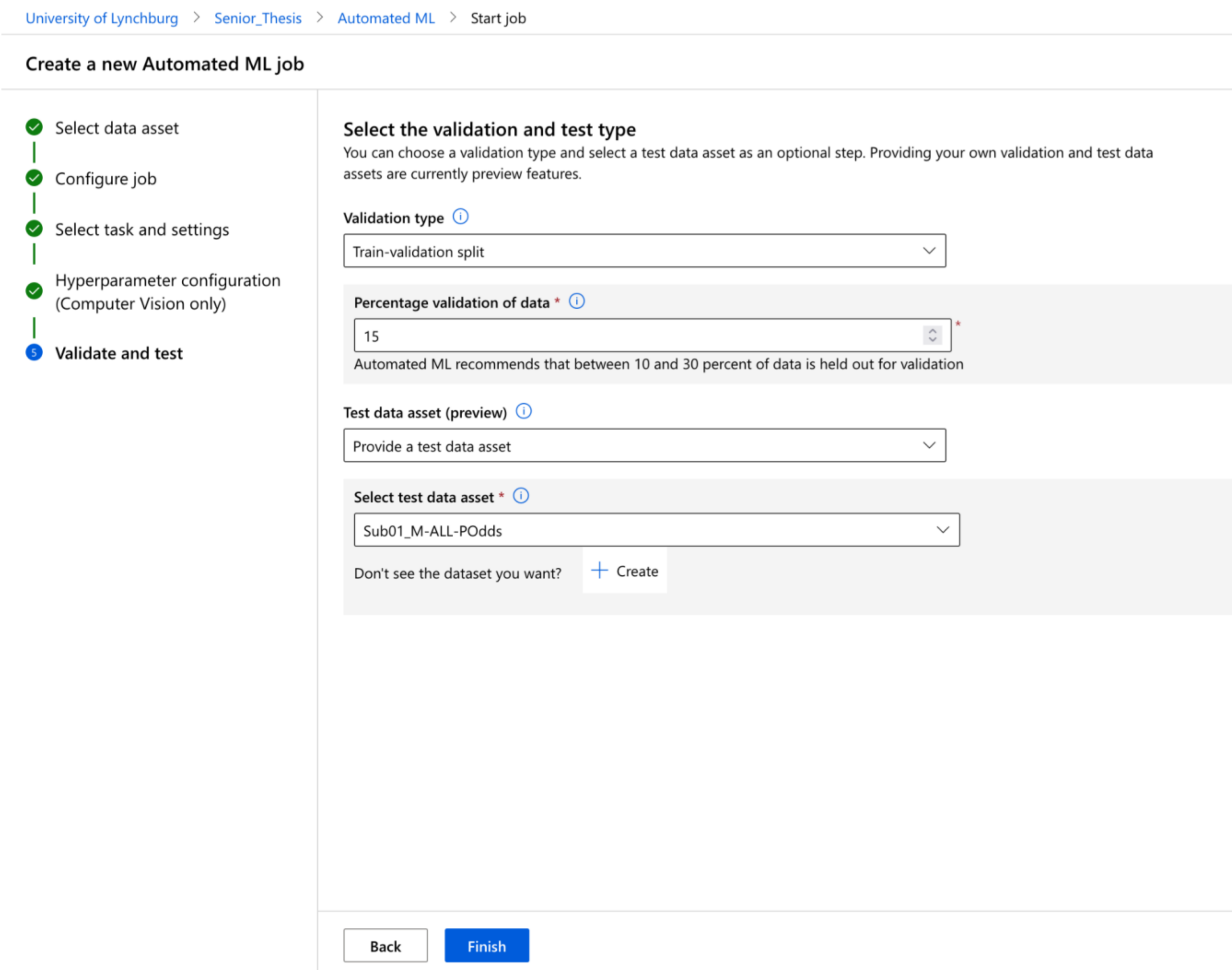


*Figure 3.* Showing an example of the validation and test type settings for the automated machine learning jobs to analyze the EEG data for this project using Microsoft Azure.

## Results

The average accuracy of the models generated for each subject ranged from ~40% accuracy to ~80% accuracy, depending on the subject. The average accuracies and standard deviations for all subjects is shown in Figure 4. The age, specific accuracies of each model, average model accuracy, and standard deviation of the average accuracy for all subjects is shown in Table 1. The relationship between the years of musical experience per subject and the average accuracy of the machine learning models is shown in Figure 5.

| Subject # | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Age | 22 | 21 | 21 | 22 | 22 | 22 | 18 | 21 | 20 | 20 | 22 | 22 |
| Combined Years of musical experience | 8 | 0 | 19 | 11 | 12 | 15 | 16 | 0 | 8 | 7 | 10 | 4 |
| Accuracy 1 | 52 | 47.6 | 78.7 | 45.9 | 72.9 | 41 | 45.4 | 74 | 47.6 | 55.2 | 44.7 | 73.1 |
| Accuracy 2 | 58 | 43.3 | 80.9 | 46.7 | 80.6 | 38.7 | 39.7 | 73.8 | 47.2 | 61.3 | 46.8 | 76.5 |
| Accuracy 3 | 54.4 | 45.3 | 74.1 | 47.8 | 54.7 | 38.6 | 45.8 | 68.9 | 42.8 | 57.2 | 46.8 | 70.7 |
| Accuracy 4 | 56.8 | 38.7 | 81 | 45.5 | 61.9 | 40.1 | 48.2 | 75 | 46.1 | 57.4 | 43.2 | 70.9 |
| Accuracy 5 | 57.2 | 41.9 | 80.7 | 45.7 | 83.2 | 37.8 | 45.2 | 71.9 | 45.7 | 57.5 | 40.4 | 76.8 |
| Accuracy 6 | 47 | 52.2 | 81.7 | 40.9 | 80.6 | 44.8 | 46.6 | 71.6 | 44.7 | 62.2 | 38.2 | 70.4 |
| Accuracy 7 | 54.7 | 49.1 | 83 | 38.9 | 66.9 | 41.7 | 46.6 | 73.9 | 44 | 66.4 | 43.8 | 74.9 |
| Accuracy 8 | 47.7 | 45.8 | 80.6 | 39.7 | 80.7 | 42.5 | 48.5 | 72.5 | 47 | 64.5 | 44.1 | 67.5 |
| Accuracy 9 | 48.5 | 55.2 | 80 | 40.4 | 81.6 | 44.6 | 46.5 | 71.7 | 46.4 | 61.8 | 45.2 | 69.7 |
| Accuracy 10 | 47.8 | 52 | 83.2 | 37.4 | 75.9 | 46.3 | 46.5 | 67.8 | 46.4 | 61.8 | 44.8 | 69.7 |
| Average Accuracy | 52.41 | 47.11 | 80.39 | 42.89 | 73.9 | 41.61 | 45.9 | 72.11 | 45.79 | 60.53 | 43.8 | 72.02 |
| STDEV | 4.13 | 4.87 | 2.44 | 3.59 | 9.21 | 2.77 | 2.3 | 2.18 | 1.45 | 3.4 | 2.55 | 2.99 |

*Table 1.* Showing the subject number and their corresponding age, combined years of musical experience, the accuracy of their 10 best models generated by the Microsoft Azure program, the average accuracy of the models, and the standard deviation of the model accuracies.

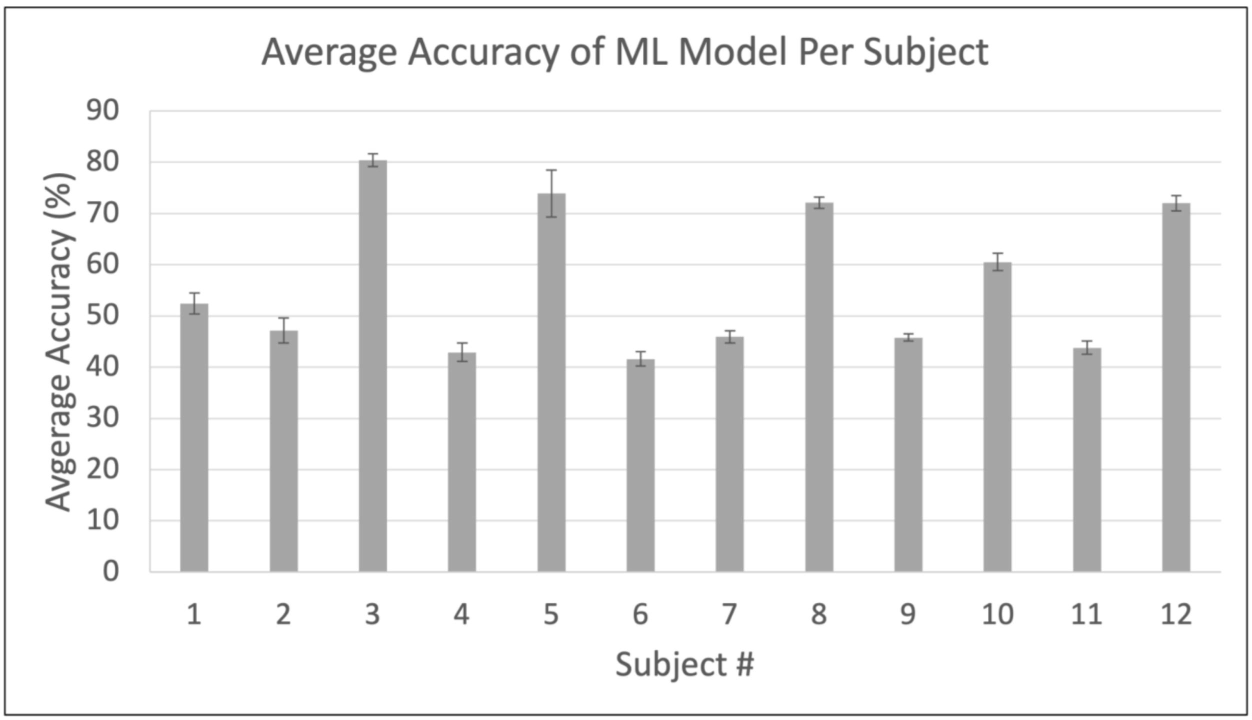


*Figure 4.* A bar graph showing the average accuracy for each subject. Standard deviation for each subject is shown using error bars.

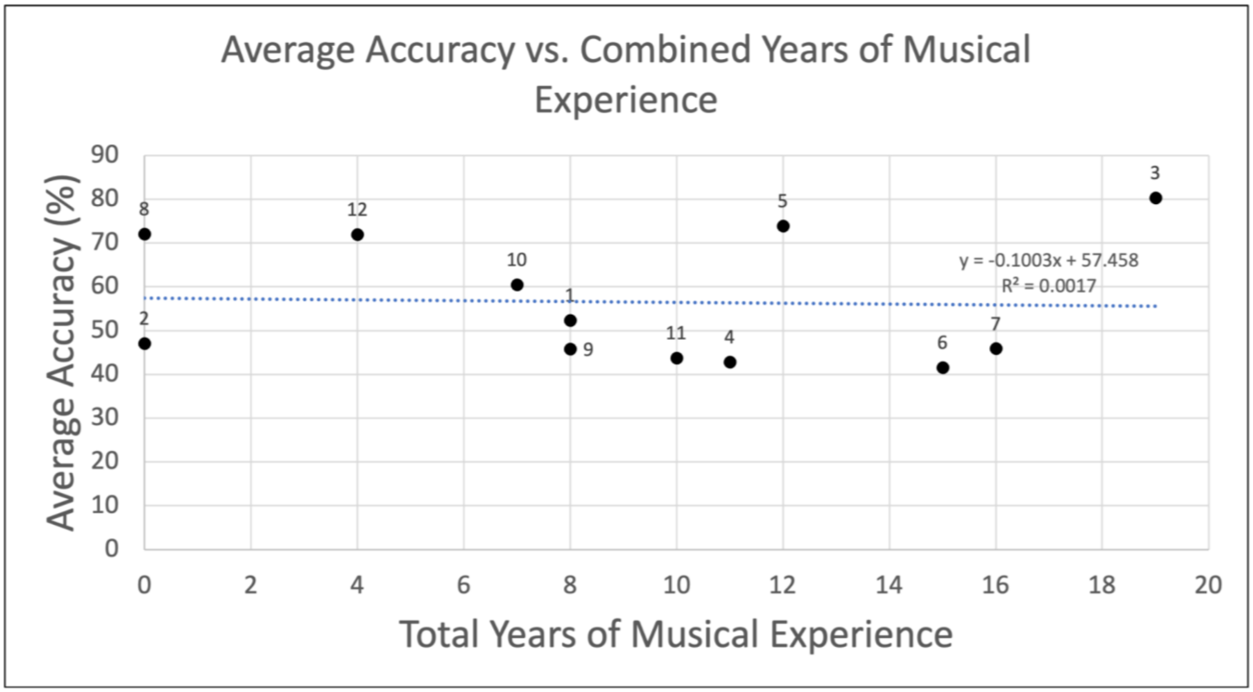


*Figure 5.* Showing the relationship between a subject's combined years of musical experience and the average accuracy of the machine learning models generated by Microsoft Azure.

## Statistical Analysis Methods

For statistical analysis, the SPSS Statistics software created by IBM was used to determine the significance of the results. To do this, the average accuracy for each subject was input and the software was configured to test the significance of the values against the value 20. The reason that 20 was chosen as the test value is because a program that was guessing the melody number randomly would achieve an average accuracy of ~20%, due to there being a 1 in 5 chance of choosing the correct melody. Therefore, determining whether the average values were significantly greater than 20 would demonstrate that the results were significantly better than random guessing. The program was configured to return values including the sample mean accuracy, p-value, 95% confidence interval range, and Cohen's d value.

The mean accuracy value was calculated by averaging all of the average accuracy values for each subject. This created one mean average accuracy value for all 12 subjects, which was 56.5%. The p-value was created to determine the significance of the results - the value is equal to the percent chance that the results were a product of random events with no significance. A desired p-value would be less than 0.05, as this would indicate that there is a <5% chance that the results were influenced by random events. The 95% confidence interval range provides a range of mean values that would still be significantly different with a p-value of <0.05. If the mean accuracy falls within the range, it is a statistically significant finding. Finally, Cohen's D value indicates that the difference between the test number (20) and the mean average accuracy was greater than 2 standard deviations, providing further evidence that the results are statistically significant.

## Discussion

These results show promising data for the potential development of a system using machine learning to interpret musical thoughts for use in therapeutic settings. Given that a 20% accuracy would be as good as random guessing, the models are significantly better than random, with average accuracy ranging from 40 to 80%. A one-sample t-test was conducted to confirm whether the sample mean was significantly different from the test value of 20%, and it was determined that the sample mean accuracy (mean accuracy=56.64%, STDEV = 14.38) was significantly higher than 20%, ($p<0.001$, 95% confidence interval: 27.4 to 45.67, Cohen's d = 2.54). This means that the machine learning models can "predict" what melody a participant was thinking of based on their EEG data with a significant degree of accuracy, as high as 80% in some cases.

In this study, there is no statistical correlation between the years of musical experience a participant had and the accuracy of the machine learning program, as evidenced by the trendline in Figure 5 ($R^2 = 0.0017$). This means that the difference between accuracies of the models generated for the participants is not correlated with their years of musical experience but rather with some other factor that was undetermined in this project. Because these factors are unknown and can contribute to a large difference in the accuracy of the machine learning model, future research into this area might focus on determining these correlating factors via a more intensive background survey and/or a broader study group.

The results of this study are generally consistent with other research in the field. In 2023, Dr. Ian Daly of the University of Essex used EEG and fMRI in conjunction with machine learning to decipher what song a person was listening to with 72% accuracy (n=18) (Daly, 2023). While Dr. Daly achieved a higher mean accuracy, this is likely due to his use of more advanced imaging technology and more diverse data collection - Dr. Daly's study used 36 different full songs over multiple sessions, while this study only focused on 5 short melodies in one session per person. Another study examined whether people were able to produce musical notes with a high degree of accuracy by controlling their brainwaves, and found that people could produce a desired note between 57% and 67% of the time (Deuel et al., 2017). A third study identified the EEG signals associated with a person listening to specific notes on a scale, and were able to identify note values with an accuracy of 70% (Tsekoura & Foka, 2020). Overall, these studies all have very similar findings to the one presented in this paper, with accuracies ranging from ~60-70% while this thesis had a slightly lower mean average accuracy with 56.5%. This shows that the obtained results are not outliers in the field of music detection using EEG technology.

Overall, the results show that machine learning systems *can* predict a person's music-related brain activity in an isolated environment using a small amount of training data. With this project serving as a proof-of-concept, future developments in this field could be utilized to monitor a person's ability to think and control musical thoughts. Having this capability could allow for research examining whether training people to think musically has any positive benefits on neuroplasticity or therapeutic outcomes.

## Limitations

Limitations to this study are largely related to the study size and capacity. One of the largest limitations was the small number of participants - with just 14 total participants, there is a high probability of random events to influence the results. Further limitations had to do with the lack of diverse background information. This caused the factor which caused some participants to have a higher average accuracy to remain unknown.

Malfunctions of the EEG recording instrument provided further challenges for this study. Out of the 14 total participants, the EEG data for 2 participants was unusable due to the malfunction of the Muse 2 headset - in these instances, the sensors had not been connected properly despite positive feedback from the headset, leading to meaningless data which was not able to be analyzed by the ML program.

## Conclusion

The study presented in this paper serves as a compelling proof-of-concept for utilizing machine learning models in predicting brain activity related to music. However, it is important to note that more extensive data and comprehensive research are necessary before implementing such models in therapeutic settings. Further studies are warranted to validate and refine the potential applications of machine learning in this context.

## References


Abhang, P. A., Gawali, B. W., & Mehrotra, S. C. (2016). Technological Basics of EEG Recording and Operation of Apparatus. Introduction to EEG- and Speech-Based Emotion Recognition, 19–50. https://doi.org/10.1016/b978-0-12-804490-2.00002-6

Abumaria, N., Yin, B., Zhang, L., Li, X.-Y. ., Chen, T., Descalzi, G., Zhao, L., Ahn, M., Luo, L., Ran, C., Zhuo, M., & Liu, G. (2011). Effects of Elevation of Brain Magnesium on Fear Conditioning, Fear Extinction, and Synaptic Plasticity in the Infralimbic Prefrontal Cortex and Lateral Amygdala. Journal of Neuroscience, 31(42), 14871–14881. https://doi.org/10.1523/jneurosci.3782-11.2011

Aggarwal, S., & Chugh, N. (2022). Review of Machine Learning Techniques for EEG Based Brain Computer Interface. Archives of Computational Methods in Engineering, 29. https://doi.org/10.1007/s11831-021-09684-6

Ahmad, S. (2020, January 10). The Link Between BDNF and Neuroplasticity | Psychology Today United Kingdom. Www.psychologytoday.com. https://www.psychologytoday.com/gb/blog/balanced/202001/the-link-between-bdnf-and-neuroplasticity

Albert, M. L., Sparks, R. W., & Helm, N. A. (1973). Melodic Intonation Therapy for Aphasia. Archives of Neurology, 29(2), 130–131. https://doi.org/10.1001/archneur.1973.00490260074018

Amunts, K., Schlaug, G., Jäncke, L., Steinmetz, H., Schleicher, A., Dabringhaus, A., & Zilles, K. (1997). Motor cortex and hand motor skills: Structural compliance in the human brain. Human Brain Mapping, 5(3), 206–215. https://doi.org/10.1002/(sici)1097-0193(1997)5:3%3C206::aid-hbm5%3E3.0.co;2-7

Bao, S., Chan, V. T., & Merzenich, M. M. (2001). Cortical remodelling induced by activity of ventral tegmental dopamine neurons. Nature, 412(6842), 79–83. https://doi.org/10.1038/35083586

Bloch, B., Reshef, A., Vadas, L., Haliba, Y., Ziv, N., Kremer, I., & Haimov, I. (2010). The Effects of Music Relaxation on Sleep Quality and Emotional Measures in People Living with Schizophrenia. Journal of Music Therapy, 47(1), 27–52. https://doi.org/10.1093/jmt/47.1.27

Blood, A. J., & Zatorre, R. J. (2001). Intensely pleasurable responses to music correlate with activity in brain regions implicated in reward and emotion. Proceedings of the National Academy of Sciences, 98(20), 11818–11823. https://doi.org/10.1073/pnas.191355898

Carrillo-Mora, P., Juan Manuel Alcantar-Shramm, Almaguer-Benavides, K. M., Macías-Gallardo, J., Alim Caelli Fuentes-Bello, & María Rodríguez-Barragán. (2017). Pharmacological Stimulation of Neuronal Plasticity in Acquired Brain Injury. Clinical Neuropharmacology, 40(3), 131–139. https://doi.org/10.1097/wnf.0000000000000217

Ceccato, E., Caneva, P., & Lamonaca, D. (2006). Music Therapy and Cognitive Rehabilitation in Schizophrenic Patients: A Controlled Study. Nordic Journal of Music Therapy, 15(2), 110–120. https://doi.org/10.1080/08098130609478158

Chanda, M. L., & Levitin, D. J. (2013). The neurochemistry of music. Trends in Cognitive Sciences, 17(4), 179–193. https://doi.org/10.1016/j.tics.2013.02.007

Chatterjee, D., Hegde, S., & Thaut, M. (2021). Neural plasticity: The substratum of music-based interventions in neurorehabilitation. NeuroRehabilitation, 48(2), 155–166. https://doi.org/10.3233/nre-208011

Daly, I. (2023). Neural decoding of music from the EEG. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-022-27361-x

De Sousa, A., & De Sousa, J. (2010). Music Therapy in Chronic Schizophrenia. Journal of Pakistan Psychiatric Society, 7(1), 13. http://www.jpps.com.pk/article/musictherapyinchronicschizophrenia_2394.html

Deuel, T. A., Pampin, J., Sundstrom, J., & Darvas, F. (2017). The Encephalophone: A Novel Musical Biofeedback Device using Conscious Control of Electroencephalogram (EEG). *Frontiers in Human Neuroscience*, *11*. https://doi.org/10.3389/fnhum.2017.00213

Dolan, E. W. (2019, February 2). Listening to the music you love will make your brain release more dopamine, study finds. PsyPost. https://www.psypost.org/2019/02/listening-to-the-music-you-love-will-make-your-brain-release-more-dopamine-study-finds-53059#:~:text=A%20new%20study%20has%20found%20that%20dopamine%20%E2%80%94

Duarte, A., Henson, R., Knight, R., Emery, T., & Graham, K. (2010). The orbitofrontal cortex is necessary for temporal context memory. Www.semanticscholar.org. https://www.semanticscholar.org/paper/The-orbitofrontal-cortex-is-necessary-for-temporal-Duarte-Henson/8b674dd9eaeaeec1e1444e31dd231d3a115319d7

Evers, S., & Suhr, B. (2000). Changes of the neurotransmitter serotonin but not of hormones during short time music perception. European Archives of Psychiatry and Clinical Neuroscience, 250(3), 144–147. https://doi.org/10.1007/s004060070031

Ferreri, L., Mas-Herrero, E., Zatorre, R. J., Ripollés, P., Gomez-Andres, A., Alicart, H., Olivé, G., Marco-Pallarés, J., Antonijoan, R. M., Valle, M., Riba, J., & Rodriguez-Fornells, A. (2019).

Dopamine modulates the reward experiences elicited by music. Proceedings of the National Academy of Sciences, 116(9), 3793–3798. https://doi.org/10.1073/pnas.1811878116

Finger, S., Boller, F., & Tyler, K. L. (2009). History of Neurology. Elsevier.

Fong, A. (2023, March 8). Neuroplasticity Treatment: How It Can Help You Recover From a Brain Injury. Www.cognitivefxusa.com. https://www.cognitivefxusa.com/blog/neuroplasticity-treatment-for-concussions

Gaab, N., Keenan, J. P., & Schlaug, G. (2003). The Effects of Gender on the Neural Substrates of Pitch Memory. Journal of Cognitive Neuroscience, 15(6), 810–820. https://doi.org/10.1162/089892903322370735

Gaser, C., & Schlaug, G. (2003). Brain Structures Differ between Musicians and Non-Musicians. The Journal of Neuroscience, 23(27), 9240–9245. https://doi.org/10.1523/jneurosci.23-27-09240.2003

Gogtay, N., Giedd, J. N., Lusk, L., Hayashi, K. M., Greenstein, D., Vaituzis, A. C., Nugent, T. F., Herman, D. H., Clasen, L. S., Toga, A. W., Rapoport, J. L., & Thompson, P. M. (2004). Dynamic mapping of human cortical development during childhood through early adulthood. Proceedings of the National Academy of Sciences, 101(21), 8174–8179. https://doi.org/10.1073/pnas.0402680101

Gold, C., Solli, H. P., Krüger, V., & Lie, S. A. (2009). Dose–response relationship in music therapy for people with serious mental disorders: Systematic review and meta-analysis. Clinical Psychology Review, 29(3), 193–207. https://doi.org/10.1016/j.cpr.2009.01.001

Grassi, M., Meneghetti, C., Toffalini, E., & Borella, E. (2017). Auditory and cognitive performance in elderly musicians and nonmusicians. PLOS ONE, 12(11), e0187881. https://doi.org/10.1371/journal.pone.0187881

Halwani, G. F., Loui, P., Rüber, T., & Schlaug, G. (2011). Effects of Practice and Experience on the Arcuate Fasciculus: Comparing Singers, Instrumentalists, and Non-Musicians. Frontiers in Psychology, 2. https://doi.org/10.3389/fpsyg.2011.00156

Hermann, N. (1997, December 22). What is the function of the various brainwaves? Scientific American. https://www.scientificamerican.com/article/what-is-the-function-of-t-1997-12-22/

Herold, D., Spengler, S., Bastian Sajonz, Usnich, T., & Bermpohl, F. (2016). Common and distinct networks for self-referential and social stimulus processing in the human brain. Brain Structure & Function, 221(7), 3475–3485. https://doi.org/10.1007/s00429-015-1113-9

Hyde, K. L., Lerch, J., Norton, A., Forgeard, M., Winner, E., Evans, A. C., & Schlaug, G. (2009). Musical Training Shapes Structural Brain Development. Journal of Neuroscience, 29(10), 3019–3025. https://doi.org/10.1523/jneurosci.5118-08.2009

Johansen-Berg, H., Dawes, H., Guy, C., Smith, S. M., Wade, D. T., & Matthews, P. M. (2002). Correlation between motor improvements and altered fMRI activity after rehabilitative therapy. Brain, 125(12), 2731–2742. https://doi.org/10.1093/brain/awf282

Keith, R. L., & Aronson, A. E. (1975). Singing as therapy for apraxia of speech and aphasia: Report of a case. Brain and Language, 2(4), 483–488. https://doi.org/10.1016/s0093-934x(75)80085-x

Khan, Md. S., Salsabil, N., Alam, Md. G. R., Dewan, M. A. A., & Uddin, Md. Z. (2022). CNN-XGBoost fusion-based affective state recognition using EEG spectrogram image analysis. Scientific Reports, 12(1). https://doi.org/10.1038/s41598-022-18257-x

Kloos, A., Gomes-Osman, J., & Boyd, L. (2020). Harnessing Neuroplasticity for Functional Recovery. Journal of Neurologic Physical Therapy, 44(2), 119–120. https://doi.org/10.1097/npt.0000000000000307

Kraus, C., Castrén, E., Kasper, S., & Lanzenberger, R. (2017). Serotonin and neuroplasticity – Links between molecular, functional and structural pathophysiology in depression. Neuroscience & Biobehavioral Reviews, 77, 317–326. https://doi.org/10.1016/j.neubiorev.2017.03.007

Liegeois-Chauvel, C. (1998). Contribution of different cortical areas in the temporal lobes to music processing. Brain, 121(10), 1853–1867. https://doi.org/10.1093/brain/121.10.1853

Maguire, E. A., Gadian, D. G., Johnsrude, I. S., Good, C. D., Ashburner, J., Frackowiak, R. S. J., & Frith, C. D. (2000). Navigation-related structural change in the hippocampi of taxi drivers. Proceedings of the National Academy of Sciences, 97(8), 4398–4403. https://doi.org/10.1073/pnas.070039597

Maier, M., Ballester, B. R., & Verschure, P. F. M. J. (2019). Principles of Neurorehabilitation After Stroke Based on Motor Learning and Brain Plasticity Mechanisms. Frontiers in Systems Neuroscience, 13. https://doi.org/10.3389/fnsys.2019.00074

Mateos-Aparicio, P., & Rodríguez-Moreno, A. (2019). The Impact of Studying Brain Plasticity. Frontiers in Cellular Neuroscience, 13(66). https://doi.org/10.3389/fncel.2019.00066

McGeown, J. P., Zerpa, C., Lees, S., Niccoli, S., & Sanzo, P. (2018). Implementing a structured exercise program for persistent concussion symptoms: a pilot study on the effects on salivary brain-derived neurotrophic factor, cognition, static balance, and symptom scores. Brain Injury, 32(12), 1556–1565. https://doi.org/10.1080/02699052.2018.1498128

Mcleod, S. (2021, July 8). Brain Reward System - Simply Psychology. Www.simplypsychology.org. https://www.simplypsychology.org/brain-reward-system.html

Menon, V., & Levitin, D. J. (2005). The rewards of music listening: Response and physiological connectivity of the mesolimbic system. NeuroImage, 28(1), 175–184. https://doi.org/10.1016/j.neuroimage.2005.05.053

Merzenich, M. M., Nelson, R. J., Stryker, M. P., Cynader, M. S., Schoppmann, A., & Zook, J. M. (1984). Somatosensory cortical map changes following digit amputation in adult monkeys. The Journal of Comparative Neurology, 224(4), 591–605. https://doi.org/10.1002/cne.902240408

Montague, P., Dayan, P., & Sejnowski, T. (1996). A framework for mesencephalic dopamine systems based on predictive Hebbian learning. The Journal of Neuroscience, 16(5), 1936–1947. https://doi.org/10.1523/jneurosci.16-05-01936.1996

Morris, R. G. M. (2003). Long-term potentiation and memory. Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 358(1432), 643–647. https://doi.org/10.1098/rstb.2002.1230

Natarajan, K. (2020, June 18). Feature extraction in EEG signals. Medium. https://medium.com/@kalaivaaninatarajan/feature-extraction-in-eeg-signals-f8e5dfb94cdf

NeuroPraxis. (2020). How Does Dopamine Help Neuroplasticity? NeuroPraxis. https://neuropraxis.com/resource/how-does-dopamine-help-neuroplasticity/

Nvidia. (n.d.). What is XGBoost? NVIDIA Data Science Glossary. https://www.nvidia.com/en-us/glossary/data-science/xgboost/

Pfeiffer, C. F., & Sabe, L. R. (2015). Music therapy and cognitive rehabilitation: Screening of music cognition in adult patients with right hemisphere stroke. Psychomusicology: Music, Mind, and Brain, 25(4), 392–403. https://doi.org/10.1037/pmu0000123

Puderbaugh, M., & Emmady, P. D. (2020). Neuroplasticity. PubMed; StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK557811/

Ripollés, P., Rojo, N., Grau-Sánchez, J., Amengual, J. L., Càmara, E., Marco-Pallarés, J., Juncadella, M., Vaquero, L., Rubio, F., Duarte, E., Garrido, C., Altenmüller, E., Münte, T. F., & Rodríguez-Fornells, A. (2015). Music supported therapy promotes motor plasticity in individuals with chronic stroke. Brain Imaging and Behavior, 10(4), 1289–1307. https://doi.org/10.1007/s11682-015-9498-x

Rugnetta, M. (2018). Neuroplasticity | Different Types, Facts, & Research. In Encyclopædia Britannica. https://www.britannica.com/science/neuroplasticity

Saeid Sanei, Chambers, J. A., & Wiley, J. (2021). EEG signal processing and machine learning. Wiley.

Salimpoor, V. N., Benovoy, M., Larcher, K., Dagher, A., & Zatorre, R. J. (2011). Anatomically distinct dopamine release during anticipation and experience of peak emotion to music. Nature Neuroscience, 14(2), 257–262. https://doi.org/10.1038/nn.2726

Schäfer, T., Sedlmeier, P., Städtler, C., & Huron, D. (2013). The psychological functions of music listening. Frontiers in Psychology, 4(511). https://doi.org/10.3389/fpsyg.2013.00511

Schneider, S., Schönle, P. W., Altenmüller, E., & Münte, T. F. (2007). Using musical instruments to improve motor skill recovery following a stroke. Journal of Neurology, 254(10), 1339–1346. https://doi.org/10.1007/s00415-006-0523-2

Sparks, R. W., & Holland, A. L. (1976). Method: Melodic Intonation Therapy for Aphasia. Journal of Speech and Hearing Disorders, 41(3), 287–297. https://doi.org/10.1044/jshd.4103.287

Sricheta Parui, Kumar, A., Samanta, D., & Chakravorty, N. (2019). Emotion Recognition from EEG Signal using XGBoost Algorithm. IEEE India Conference. https://doi.org/10.1109/indicon47234.2019.9028978

Sun, Q., Gu, S., & Yang, J. (2018). Context and Time Matter: Effects of Emotion and Motivation on Episodic Memory Overtime. Neural Plasticity, 2018, 1–13. https://doi.org/10.1155/2018/7051925

Tsekoura, K., & Foka, A. (2020). Classification of EEG signals produced by musical notes as stimuli. *Expert Systems with Applications*, *159*, 113507. https://doi.org/10.1016/j.eswa.2020.113507

Vik, B. M. D., Skeie, G. O., & Specht, K. (2019). Neuroplastic Effects in Patients With Traumatic Brain Injury After Music-Supported Therapy. Frontiers in Human Neuroscience, 13. https://doi.org/10.3389/fnhum.2019.00177

Vik, B. M. D., Skeie, G. O., Vikane, E., & Specht, K. (2018). Effects of music production on cortical plasticity within cognitive rehabilitation of patients with mild traumatic brain injury. Brain Injury, 32(5), 634–643. https://doi.org/10.1080/02699052.2018.1431842

What is Magnetoencephalography (MEG)? | I-LABS. (n.d.). Institute for Learning and Brain Sciences. https://ilabs.uw.edu/what-magnetoencephalography-meg/