Physiological and psychological effects of listening to nursery rhymes

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Dedication

To those who held me up over the years, my parents, and all my family members who took care of everything for me. I also dedicate this thesis to Prof. Arshia Khan, who has been an advisor, counselor, friend and encouragement to me every step of the way.

Abstract

Music has been known as a powerful tool that changes human moods and induces emotional responses. The purpose of this study is to monitor changes in healthy individuals' physiological and psychological responses to listening to nursery rhymes in three different scenarios: the songs were played by a professional musician, a robot called Pepper, and finally a boombox. These scenarios are plates in actively engaged or passive modes. To measure arousal response, individuals were exposed to the nursery rhymes, and an electrodermal activity (EDA) wristband was used to track changes in their physiological factors: heart rate variability and skin conductance. Electroencephalography (EEG) headset can measure Brain wave activity which is the psychological response to music. EEG signals of healthy individuals were captured before, during, and after listening to the nursery rhymes using a 14-channels EEG headset. Two self-report questionnaires were designed to investigate individuals' psychological responses after listening to the rhymes.

Ledalab and Kubios, Matlab toolboxes, were used to separate EDA data into its phasic and tonic components and extract non-linear, time and frequency-domain data from HRV data, respectively. Discrete wavelet transform (DWT) was applied on the EEG data to separate brain wave sub-bands. To understand how human brain activity changes, statistical features such as average, standard deviation and energy, and entropy of wavelet for alpha and beta waves are extracted. Furthermore, SPSS software was used for all statistical analyses in order to make the correlation coefficient between each pair of scenarios and between each pair of participants in each scenario was made.

After analyzing individuals' sensors data and their responses to the questionnaires, no statistically significant results were found that correlated all participants' physiological and psychological changes. However, inconsistent trends such as increases in heart rates, decreases in skin conductance, and reporting feelings such as lively, alert, happy, cheerful, calm and relaxed were observed for some participants. Also the results indicated a direct relationship between human responses to the human and a robot player, while there was not any relation between boombox and robot or human players.

Keywords: Music therapy, Brain waves, Physiological signals, Psychological signals, EDA, EEG, Alpha waves, Beta waves

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Chapter 1

Introduction

Dementia is an umbrella term for several progressive disease that affect memory, language, thinking and problem-solving ability of individuals, and interferes with their activities of daily living (ADL's) [1].

1.1 Types of dementia

Figure 1.1 shows the different types of dementia. Among all types of dementia, Alzheimer's is the most common. Early symptoms of Alzheimer's are problems with remembering individual names, recalling short-term memory, and mood fluctuation/lability [2]. Vascular dementia happens as a result of stroke (CVA/TIA) and the majority of people suffer from this type of dementia. They usually experience some level of depression, which ranges from adjustment related depression to major depression in many cases [2]. Another type of dementia is frontotemporal dementia, which affects the frontal and temporal lobes of the brain and causes language, and behavioral disorders [1]. Semantic dementia, which is one type of frontotemporal dementia, is identified by loss of semantic memory which causes verbal and non-verbal understanding of the surrounding [3].

1.2 Stages of dementia

Each type of dementia has 3 stages, mild (early stage), moderate (middle stage), severe (late stage). Individuals who are in the early stages of dementia are the most

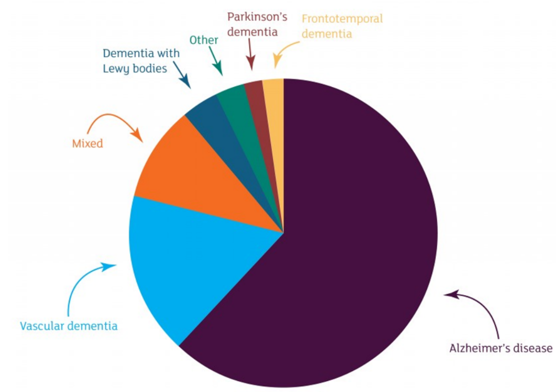


Figure 1.1: Different types of dementia
[4]

independent and are able to perform tasks of daily living activities independently with little help. At this stage the affected individual has problems with language like remembering words, communication, and focusing. This stage usually lasts for 2 to 4 years [5]. Individuals in the middle stages of dementia, have difficulties with expressing themselves and their thoughts, working independently, recalling memory, and self and environment awareness. In addition, they experience other symptoms of dementia such as depression (especially in vascular dementia), agitation, wandering, sleep and appetite disorder. This stage usually lasts for 2 to 10 years [5]. At the late stages of dementia, individuals have all of the middle stage symptoms, along with additional symptoms such as disorientation of place, time, person, and/or situation [5]. This stage lasts for 1 to 3 years and based on the Alzheimer's Association, %40 of the total time with dementia is spent in this stage.

1.3 Incidence of dementia

World Health Organization (WHO) report shows that there are 50 million people around the world suffering from dementia and each year about 10 million new cases are added to this number. The total number of people living with dementia (PWD) is projected to reach 82 million in 2030 and 152 in 2050. Statistics published by the Alzheimer's Association in 2019 show that around 5.8 million Americans are suffering from Alzheimer's disease. It has been forecasted that the number of American patients with Alzheimer's will rise to 14 million by 2050.

1.4 Impact of dementia

Economic impact: Records show that the cost of caring and preventing symptoms of Alzheimer's disease is huge. In 2019 this cost was 290 billion dollars for the nation, and WHO estimated that this cost will raise to 1.1 trillion dollars by 2050. Dementia has many social and economic impacts that affect individuals, caregivers, families, and the society as a whole [6]. WHO statistics show the total cost of global gross domestic product (GDP) of dementia fluctuates between %0.2 to %1.4 for low and high income countries, respectively.

Individual Impact: Based on the WHO statistics, dementia affects individuals' memory, thinking, learning capacity, lifestyle, and abilities such as comprehension and calculation. Some individuals affected with dementia lose their ability to speak, walk or perform everyday activities independently over a period of time as the disease progresses. Social communication problems with family members or caregivers is another issue that PWD may experience [7, 8]. Dementia can cause behavioral and psychological symptoms, such as agitation, anxiety, irritability, depression, apathy (lack of interest, involvement, energy, and motivation), delusions, hallucinations, and sleep disorder [9, 10].

1.5 Dementia death

Dementia has been known as one of the leading causes of death among the elderly [11]. In 2017, about 262,000 deaths were recorded in the USA due to the different types of dementia. Between different kinds of dementia, Alzheimer's disease had the highest rate of death [12]. Based on Alzheimer's association report, 145 percent increase in deaths from 2000 to 2017 was reported because of Alzheimer's disease [2]. In America, Alzheimer's has been ranked as the sixth common reason of deaths. By recognizing the early symptoms of dementia and taking preventive treatment, individuals often survive for 8 or more years post-diagnosis [8].

1.6 Treatment Methods

There are various kinds of therapy methods for managing dementia symptoms; pharmacological (cholinesterase inhibitors) and non-pharmacological.

1.6.1 Pharmacological treatments

Unfortunately, there are no effective medications that can reverse dementia. The existing medications barely slow the progression, and there is little evidence of improvement with some symptoms such as anger, agitation, wandering and apathy [10]. Although there is some evidence that drug therapy can delay and somewhat control behavioral disorders in people, it cannot cure dementia [7]. Pharmacological methods like drug therapy can calm dementia symptoms and potentially decrease behaviors, but are only for short-term, almost for 6-18 months [13]. Unfortunately, drug therapy also has negative side effects on individuals' health such as causing cardiac episodes, accelerating cognitive decline, drowsiness, and a high risk of falls [10]. Because of the high rate of adverse effects of pharmacological therapy finding other therapy methods that can maintain and improve the quality of life and delay dementia symptoms is necessary.

1.6.2 Non-pharmacological therapies

Some popular non-pharmacological therapies are:

- Pet therapy [14]
- Robot therapy [15]
- Reminiscence therapy [16]
- Aromatherapy [17]
- Person-centered care [18]
- Occupational therapy [19]
- Massage and touch therapy [20]
- Doll therapy [21]

- Light therapy [22]
- Art therapy [23]

Among the non-pharmacological therapy methods, music therapy (MT), which is a type of art therapy, has been known as safe, cost effective and non-invasive. MT has not been limited to dementia and has been employed in many other health areas such as autism [24], children and elderlies with psychopathology [25], cancer [26], and migraine [27].

Art therapy integrates dance/movement, music, visual art (painting), and playing basic musical instruments. Art therapy usually is provided by art therapists, artists, or caregivers to groups of individuals in a clinical environment. Sometimes activities like playing games, solving word-puzzles, gardening and engaging in mental or physical activities in combination with art therapy have shown to improve or postpone dementia symptoms. Also, individuals who engage in social activities demonstrate improvement in communication skills [23]. Studies have shown that involving with creative arts makes individuals feel better and do not feel they are alone. Additionally, it decreases the need for extra medications and frequent doctor visits [28].

Music Therapy is applying music or musical elements in an attempt to improve an individual's well-being [13, 28]. Music therapy has been found to show high benefits by engaging individuals' attention and making them enjoy, improving their self-esteem and communication, which leads to improvement in their behavior [28]. Some researchers pointed out that applying non-pharmacological treatments like music therapy, in addition to pharmacological therapy, can mitigate symptoms of anxiety and depression in people with mild dementia [29]. Unlike drug therapy, music therapy (MT) usually does not have any side effects. For this reason, many physicians and caregivers promote and encourage MT as a beneficial and alternative method for treatment [30].

Activities like cycling, enjoying music, dancing, and playing baseball are slow to go with time. Thus, individuals who used to do these activities could have problems remembering people, but they will not forget these activities that they have learnt when they were young [31]. Therefore, MT can be considered as a powerful therapy method, especially for age-related neurological diseases such as dementia and stroke. Music activates procedural memory that is involved with processing musical information

[10, 32].

Types of music therapy: MT can be represented as individual [33] or group [34, 35] therapy at home or in nursing home facilities in two different forms, active or passive [36]. Active music therapy encourages the PWD to sing along, play basic musical instruments individually or within the group, and move their body to the rhythm or dance with the song. While in passive music therapy, Individuals passively listen to the live, taped or background music without any interaction or reaction [37]. Active music therapy improves people's listening ability and helps them be aware of themselves, the environment and people around them. Group music therapy boosts communication and interaction skills between individuals, and improves their relation with their caregivers, and family members [28]. Singing can decrease behavioral disorders, improve mood and cognitive functioning. Singing also raises the heart rate and hormone levels [34, 38]. Playing a musical instrument can prevent or postpone the onset of dementia symptoms [34, 39].

Benefits of MT: MT has shown to improve cognition, communication, emotional and social needs of people [40]. MT has several physiological and psychosomatic impacts; the physiological impact of music helps in balancing vital signals such as blood pressure, heart rate, and respiratory rate [41]and the psychological effects of music help in the reduction of mood fluctuations and behavioral disorders like: depression, stress, agitation and aggressive behavior. MT also helps in boosting communication skills, well-being, intimacy, quality of life, memory, self and environment awareness, ability to distinguish between the surroundings and moments of the day, and managing pain [23, 41, 42, 43]. Among all of MT advantages, some of the most important ones are enhancement in verbal and non-verbal expressions, improvement of social activity and communication, raising of cognitive levels and self-awareness [44]. Individuals who have verbal communication problems can benefit from MT because it is a non-verbal communication solution that allows individuals to express themselves without inhibitions and helps enhance language skills [28].

Studies show that listening to music, specifically favorite and meaningful music, serves as a reminiscent and aids in recall of memory, and encourages more positive reactions such as smiling. Listening to music helps them relax and stay calm, and connect to their family members, caregivers, and other residents [45]. Although MT cannot cure dementia symptoms it can help reduce the symptoms [46]. Even with advanced dementia -when individuals have serious problems with judgement, planning, reasoning, speech and language- people's responses to MT are undeniable, and its impact can last for hours or even days after listening to music [31]. To retain the benefits of music therapy, PWD needs to receive regular music therapy, which is approximately 2 to 3 times a week [47].

Benefits of MT are not only limited to PWD but also it has some advantages for family members and caregivers. Several researches mentioned that going through music therapy can increase caregivers' satisfaction as well[48]. They examined music therapy on eight individuals with dementia and their caregivers and the recorded data at baseline (three baselines) and at least three records of data during music intervention. Professional music therapists taught caregivers to conduct the music therapy sessions by themselves at home. Comparison between the data revealed that both groups reported decrease in stress level, increase in relaxation, and happiness while PWD listened to their favorite music selected by the musician therapists and caregivers for eight to twenty sessions based on the caregivers decision.

1.7 Areas of dementia addressed by Music Therapy

Music therapy has been found to address various areas of dementia such as dementia symptoms or Azheimer's disease as following:

1) Depression: based on The Alzheimer's Association, depression is a common symptom for PWD especially in the early and middle stages. Some researchers mentioned that half of the individuals who have dementia experience depression which usually does not allow individuals to regulate their moods, and leads to frequent fluctuation in mood [49, 38]. Researchers concluded that MT has positive impact on decreasing depression in PWD [50, 51, 52].

2) Quality of life (QOL):WHO defines QOL as an individual's physical health, psychological state, personal beliefs, and social relationships. Some studies limited their focus to the impact of music on QOL [39, 53]. In a study which was performed on 29 dementia patients, active and passive music treatment was applied to see whether music can decrease negative symptoms of dementia and boost their quality of life by [53].

3) Well-being: Well-being is defined in terms of comfort, inclusion, identity, occupation and attachment [54]. Some researchers tested music therapy on well-being of patients with dementia [49, 55]. One study designed 6 month music therapy for dementia patients who lived at home receiving care from their family [33]. In their study each individual received 20 to 27 sessions of music intervention with length of 23 to 39 minutes based on the health situation of individuals. Although they did not notice any significant variation between pre and post-experiment data in general there were positive changes in individual's well-being and communication skills, they also expressed more positive emotions.

4)Apathy, engagement, and participation: that is, persistent loss of motivation to do things or showing a little interest in things [9, 41, 56]. Several researchers did study on patients who were in their early stage of dementia and did group activities like listening to nostalgic songs (such as nursery rhyme) and singing or playing musical instruments. Patients in the intervention group were divided into four groups, in each group there were nine patients involved with these activities for 50 minutes, three times a week for 12 weeks [57]. It was observed that doing these activities causes decrease in apathy level, while any changes in apathy level of 39 other patients in the control group was oberved.

5)Wandering: Dementia causes individuals to become disoriented and get lost which is caused by wandering [38]. Based on the Alzheimer's Association on average six out of ten PWD suffer from wandering. In a study that was run by [38], professional music therapists chose the music based on the patient preference. They included 132 patients (112 female and 20 male) with moderate to severe dementia in six group therapy sessions consisting of 4-6 individuals for two weeks. They designed different activities such as music and movement, singing, and tonal to see how activities related to music can change the patient's status. Comparing between the baseline, music intervention, and post treatment did not show any improvement in wandering behavior of patients.

6)Anxiety: some symptoms of anxiety are restlessness and difficulty in concentrating that impact the quality of life of PWD. Plenty of studies were done on anxiety by the researchers [43, 58, 51, 52]. Researchers showed that listening to preferred or favorite music can considerably decrease symptoms of anxiety. In a study by [59] comparison between 23 patients who received normal treatment and 29 patients who received music sessions for 6 weeks indicated that anxiety of patients in the music group declined significantly at six weeks.

7)Agitation: Agitation is defined as an inappropriate verbal, vocal, or motor activity which is usually developed in the middle stage of dementia [60]. Agitation shows itself with restlessness, frequent requests for attention and complaint. In ([9, 38, 43, 50, 61, 62] agitation was the main aim of music treatment. In [34] tested the efficiency of group music therapy on PWD. For this purpose, they divided 104 patients into two groups: control and experimental. While the control group received ordinary treatment, the experiment group took part in 12 group music therapy sessions. It was noticed that patients in the music therapy group showed better behavior at session 6 and 12 and one month after the treatment session due to the reduction in agitation level.

8)Memory and Cognition: Decline in cognitive function of patients with dementia causes problems with doing daily activities and thinking process [34, 57, 57, 63, 64]. More severe decline in memory usually happens in the late stage of dementia [43, 65]. In study by [52] they tried different types of activities to see how performing various activities impact cognitive function. They recruited 165 individuals with moderate dementia and grouped them into three groups: music with movement (n=58), music listening (n=54), and social activity (n=53) for 12 weeks. Data regarding cognition, depression, and anxiety level were gathered at baseline, six week and at the end of week 12. It was concluded that music with movement and listening to music may affect the memory and cognitive function. While there was considerable change in verbal fluency of individuals while they were involved in music-movement therapy, any differences were not observed during doing other activities. Regarding other symptoms such as anxiety and depression any significant differences between three groups was not noticed.

9)Mood and behavior: Although some of the studies limited their research to specific areas of dementia symptoms, some others considered the music impact of general behavioral changes in dementia [25, 48, 41, 43, 48]. In study by [58], they selected 99 patients with dementia and asked them to listen to 3 playlists of their favorite music while researchers captured their facial expression and behaviors. Interesting results were observed sadness increased in the most depressed patients, while those with the lowest level of depression, and high level of apathy, showed more enjoyment. Thus, they concluded it is important to look at patients' mental health history before deciding which kinds of music should be selected and played.

10)Physiological signals: some researchers looked at changes in physiological signals of individuals such as heart rate [53], combination of heart rate, skin conductance, skin temperature and bodily acceleration [55] or blood flow [66] to see how listening to music can affect these signals.

11)Alzheimer's disease: As it was mentioned before, Alzheimer's is one of the common type of dementia that attracted the attention of many researchers [67, 65, 64]. In a research by [43] was done on 22 patients with Alzheimer's disease the impact of listening to favorite music was considered. Researchers chose 20 favorite songs of each patient and played 20 seconds of each song which conveyed the most memorable moment and recognizable part of it. Looking at the fMRI data after music intervention showed that listening to favorite music can activate some parts of the brain which is related to memory of known music which also increases functional connectivity of the brain. Figure 1.2, illustrates the main focus areas of music study on dementia.

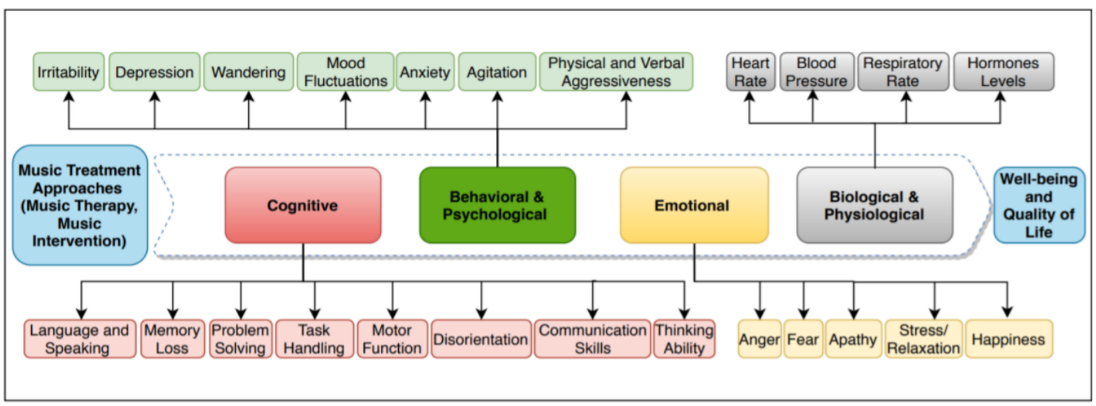


Figure 1.2: Dementia and Music Study Focus Areas

The Table 1.1 and Figure 1.3 illustrate the percentage of studies in each of the symptom areas of dementia and the type of music intervention design. Among all of these studies, individual music therapy on patients with dementia who live in nursing homes received more attention. Figure 2, shows that the most-studied areas based on the common symptoms of dementia, are behavioral and psychological symptoms, depression, QOL, and agitation, respectively.

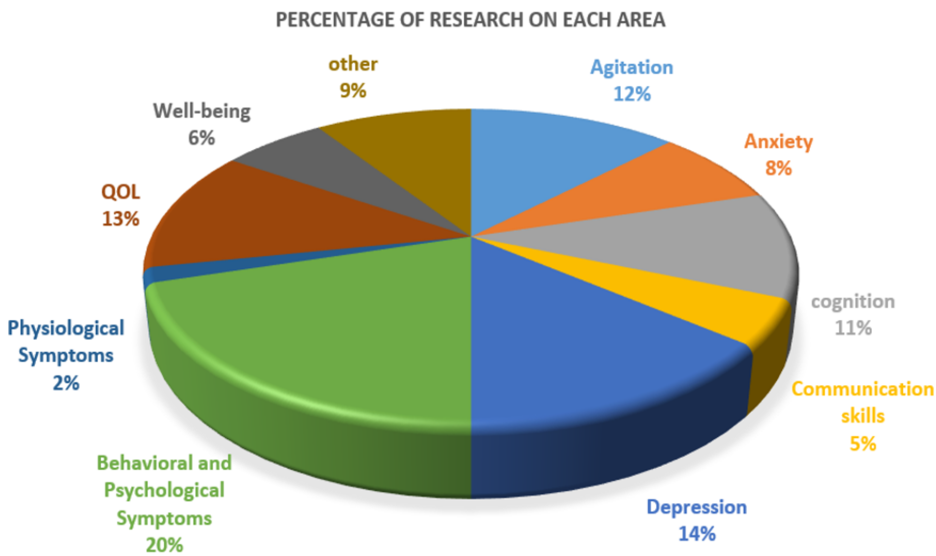


Figure 1.3: Percentage of Research on Each Area

Table 1.1: Areas of research interest and related percentages

Type of cognitive disorder	Intervention Type	Individual/Group Therapy	Intervention Place
Dementia: %75 Alzheimer: %10 Dementia and Alzheimer: %15	Active: %35 Passive :%60 Passive and Active: %0.05	Group: %30 Individual: %70	Living at Home: %13 Nursing Facility: %58

1.8 Measurement scales related to the dementia

To assess how MT can impact behavioral and psychological symptoms of PWD, various measurement scales were utilized by the researchers. Some of these can be implemented to better understand and measure the impact of music therapy.

1.8.1 Scales for measuring the severity of dementia symptoms

Researchers utilized various kinds of scales to assess the severity of dementia symptoms or the efficiency or efficacy of applying music as a therapy method for healing dementia symptoms as following:

Agitation: Cohen-Mansfield Agitation Inventory (CMAI) is an evaluation scale to measure the frequency of agitation level for PWD living in nursing homes. The questionnaire contains 29 agitated behaviors in which each behavior has a rating scale from one to seven, presenting severity of agitation [9, 34, 38, 50, 60, 61, 64].

Anxiety: Rating Anxiety in Dementia (RAID), this measurement scale for anxiety has 18 items grouped into four subgroups: worry, apprehension, vigilance, motor tension and autonomic hypersensitivity. Each subgrouped has a rating scale from one to three showing the severity level of anxiety [52, 59] and Geriatric Anxiety Inventory (GAI) a self-report questionnaire containing 20 questions with agree/disagree responses for assessing of anxiety [51].

Cognition: Mini mental state examination (MMSE) measures cognitive function with total score of 30, a score lower than 24 shows the severity of cognition disorder [34, 67, 57] and Montreal Cognitive Assessment (MoCA) has 30 questions that measure various levels of cognitive function including: orientation, short-term memory, executive function, language ability, and abstraction [64].

Wandering: Algase Wandering Scale (AWS) is a questionnaire consisting of 28 items based on five dimensions of wandering that assess the level of wandering behaviors [38].

Apathy: Apathy Evaluation Scale (AES) measured the engagement and motivation levels of PWD over age of 55. It contains 18 items that quantify apathy, each item has a score from 18 to 72 [57].

Depression: Cornell Scale (CS) is a self-report measuring tool with five subgroups for assessing symptoms of depression in PWD [67, 50, 38, 49], Geriatric Depression Scale (GDS) is also a self-report questionnaire consisting of 15 questions for evaluating level of depression [33, 39, 51, 52, 56, 68].

Quality of life (QOL): Cornell Brown scale for measuring QOL (CBQoL) is a measurement scale that looks at positive and negative feelings, and determine, the quality of life of individuals since having more positive emotions is an indicator for higher quality of life [67], Dementia QOL (DQoL) is a self-report questionnaire containing 29 items with five subgroups measuring negative and positive feeling [68], Bath Assessment of Subjective Quality of Life in Dementia scale (BASQID) is a self-report questionnaire measuring quality of life of PWD [69], and Behavioral Pathology in Alzheimer's Disease

(BEHAVE-AD) Rating Scale for evaluating by Behavioral and psychological symptoms of dementia like paranoid, and anxiety, delusional, hallucinations [32].

Social communication, emotional expression, and activity level: The Inventory to Assess Communication, Emotional Expression and Activity in Dementia (ICEA-D) which evaluates communication skill [39], Mutual Communal Behaviors Scale (MCBS) is a scale that shows communication behaviors between individuals and their caregiver [51].

Well-being: Dementia Care Mapping (DCM) is an observational tool for recording PWD behavior that helps caregivers understand the effectiveness of care [55].

Memory: Fuld's Object Memory Evaluation (FOME) that evaluates short-term memory functions for identifying dementia [52], Foster and Valentine's autobiographic memory questionnaire which measures remote, mid-remote, and recent areas of memory and ANOVA memory test for evaluating performance of memory [65].

Verbal fluency: Modified Fluid Verbal Fluency Test (MVFT) is a Chinese test in which individuals are asked to make new words belonging to a specific category [52].

Dementia symptoms: Neuropsychiatric Inventory (NPI) measures 12 neuropsychiatric symptoms in PWD; such as delusions, hallucinations, agitation, depression, anxiety, elation, apathy, disinhibition, irritability, motor disturbance, nighttime behavior, and appetite [33, 39, 50, 51, 55, 67]. The Table 1.2, shows other scales for measuring dementia symptoms that were rarely used by researchers.

Table 1.2: Other measurement scales for measuring dementia symptoms

Type of cognitive disorder	Intervention Type
Frontal Systems Behavior Scale ([9]	Functional Independence Measure ([9]
Visual analog Scale [48]	Global Deterioration Scale [39]
Positive Aspects of Caregiving Questionnaire [51]	Nerve Index and Faces Scale behavioral [53]
Bristol Activities of Daily Living Scale [56]	Mixed multivariate analysis of variance [52]
Music Listening Experience Scale [69]	Revised Memory and Behavior Problems Checklist [48]
Repeatable Battery for Assessment of Neuropsychological Status [63]	Digit Span Test [52]

Additionally, other measurements were utilized for monitoring changes in the brain and body signal during therapy sessions such as magnetic resonance imaging (MRI)

[43, 70].

1.9 Gaps in the research

There are some drawbacks with recent studies as following:

Sample size: One of the shortcomings of some of the explored studies is that the sample size of the experiment was small consisting of one to nine individuals [48, 67, 71]. In [71] studied MT on nine individuals with dementia and observed their positive and negative behaviors such as communication level, pleasure feeling, balance in their emotion, agitation, and aggressive behavior. In another study by [33], they also analysed behavior of nine patients and observed positive changes in their well-being, communication level and expressing more positive emotion. [56] did music study on four Alzhemeir's patients, any changes in measurement scale was not detected while observed data showed boosting in communication and mood of the individuals. While some researchers included a large population in their research and mentioned that they did not observe any changes or no significant changes in individuals symptoms. [72] played taped music for 75 patients in the public area of the nursing home during afternoon from 3pm to 7pm for 4 weeks. During the time that the study was conducted individuals were allowed to wander by going to their room and coming back to the public area. Listening to other types of music, other than the time for listening to Baroque music was allowed. Nurses recorded patients' physical and verbal aggressive, agitation, wandering and inappropriate sexual behaviors twice in the day, from 3 PM-11 PM and 11 PM- 8 PM. The results of this study showed calming impact of listening to Baroque for the participants.

Quantitative scales: Most of the studies employed quantitative measurement mechanisms that used clinical scales on patients or caregiver interviews, caregiver observation, or questionnaires that were filled by caregivers after the MT intervention to measure patients' behavioral changes. A few of the studies used wearable sensors to measure physiological signals [55, 66, 32]. The drawback of focusing on statistical analysis of the observed or neurological data is that the data gathered in these studies dealt with mostly subjective data rather than taking into consideration the physiological and psychological data that was gathered using wearable sensors, which can capture more accurate changes in physiological and psychological symptoms [73].

Short-term effect: Some studies found that music had a short-term impact [28, 61] and it is not clear if music therapy can be beneficial in the long-term. For example, [9] put individuals under music therapy for three weeks but any changes in agitation behavior did not observe. In another study considered the efficiency of MT for 12 weeks, but they did not see any changes in cognition level [57]. The longest period for MT was 6 months [33, 34, 59, 63].

Control group: To make comparisons between those who experienced music therapy and other individuals who just received regular treatment or were involved in other activities, it is necessary to divide individuals into two groups: comparison or study group. This allows comparisons between the two groups. Although some researchers included both groups in their studies [9, 41, 50, 59, 60, 65, 61, 67, 72], some studies did not include a control group in their experiment [33, 38, 64, 66, 71, 74, 75, 76]. Thus, because of the lack of control group it is hard to make a conclusion that music changed individuals' well-being.

Impact on agitation, wandering, and cognition: The impact of music therapy on agitation, wandering, and cognition between moderate and severe dementia is not completely clear. While some studies talked about a reduction in agitation [34, 41, 77, 38, 60, 39, 61, 9] reported no change in agitation. In [38] did not observe any improvement in wandering and [57] did not see any enhancement in cognition.

Gender: Although researchers included different genders (females and males) in their study, none of the studies identified the impact of music therapy based on gender.

Selecting an appropriate music and professional therapist: Some researchers tried to use the patient's favorite song [59, 48, 75, 68, 50, 60, 64, 76, 69] or trained caregivers to perform as a music therapist. And some researchers played songs that they thought may have a calming effect, but in fact had a negative impact [72]. This variation and inconsistency in the delivery of the music therapy make it hard to generalize the results.

Lack of clear measurement scale: Although most of the studies clarified which measurement scale they used for monitoring patient status, there are some researchers that did not apply any particular measurement scale. They tracked changes in individuals moods and behavior by observation [77, 71, 58], looking at body or facial expression

[32, 58] or self-reports [66, 48].

Combination of music and other activities: Although some studies proved that listening to music has a positive impact on PWD, the number of researchers who combined various therapy methods is rare. For example [39], applied both music and game therapy to reduce agitation, aggression, apathy, and anxiety level and enhance communication skills and improve emotional expressions. [21] compared being engaged in social activity, listening to music, and music with dance. They concluded that combination of music and dance can improve cognitive function, memory, and depressive symptoms. But, it seems there is no consensus between researchers because in a study by [61] it was mentioned that making individuals do general daily activities or going under music therapy can only reduce agitation in the short-term. They corportad 77 PWD in their study, and compared changes in behavior of individuals while listening to the music, singing with the song and dancing/ or doing daily recreational activities such as: handwork, solving a puzzle, cooking, and other activities designed by the occupational therapists. Outcomes indicated that making individuals involved with social activities may help with declining dementia symptoms.

1.10 Discussion and Conclusion:

Although most of the previous studies reported some improvement in patients' physiological or psychosomatic behaviors [41, 59, 68, 62, 39, 71, 52, 49, 78, 79], some others did not reach any clear conclusion about effectiveness of MT [29, 61, 60, 56].

Few studies found no evidence or any significant enhancement in patients' behavior and mood. For example [41] reported no differences between experiment and music group. [69] did not observe any changes in clinical scales. Some researchers noted that music does not have any effect on wandering [38]. [57] did not find any differences in individual's cognition level and [69] did not observe any considerable changes in clinical scale. Also, [56] did not observe any fluctuations in measurement scales but researcher's observation showed variations in patient mood and social interaction. Even in one of the studies, more behavioral disturbance was observed between individuals who took part in the experiment than people in the control group [72]. Additionally, some researchers did not find any change in wandering, agitation, and cognition [38, 9, 57]. From these reviews it can be deduced that music has a mixed effect on the patient's mood and behaviors. Thus, it is hard to reach a generalized conclusion regarding MT. It seems that music has a mixed outcome that does not guarantee music to be a long-term therapy solution.

Additionally, there are no clear differences between playing live or taped music. Some studies observed that listening to live music and being engaged with the singer and/or singing the song and/or playing musical instrument to boost general well-being, mood, QOL and individuals' relationships with others [68, 66, 53, 71, 38, 49, 74]. However, in some papers some improvement in patients health status were observed even during listening to taped music ([9, 59, 77, 72, 50, 58]. This implies that there is little difference between passive and active music therapy. Thus, it means that emotion connected to music can change the individual's mood.

In general, although there was not one standard protocol or methodological approach applied for designing music therapy sessions, it was observed that in most cases music therapy can be used as one of the low cost treatment approaches without any side effects. Thus, the demand for designing a comprehensive non-pharmacological music therapy approach, which helps caregivers and family members improve patient well-being, is necessary.

Chapter 2

Background

2.1 Music and Brain

Evidence shows that listening to music can alter human psychological and physiological signals. Listening to music can reduce a person's stress and improve moods [80, 81, 82], pain [83], blood pressure level and heart rate [84], and boosts the sleep cycle [85]. It can improve the memory function of patients with memory disorders [86], and aid patients with recovery from seizures, brain injuries, or strokes [87, 88, 89]. Music can have a relaxing or disturbing effect on humans; thus, researchers explore changes in physiological and psychological signals to understand how music stimulates and consequently changes human emotion. One of the areas explored by many researchers is emotion recognition in people while listening to music.

There is ample evidence that music can boost brain activity and jog deeply embedded memories. Music plays many important emotional and social roles in a person's life by arousing emotions and changing an individual's mood [66, 89, 90]. It can reduce anxiety, tension, stress, and blood pressure and alleviate depression and pain [91, 92, 80, 86, 83]. The impacts of music for researchers include memory recollection, brain relaxation, and increases in attention and learning process [66, 91, 92, 80], memory performance. Researchers found music to be an effective therapy treatment for improving the mental balance of patients who suffer from disorders such as depression and dementia [87, 81, 88, 93].

Researchers study brain activity to understand how music can change human body signals. Brain waves consist of five sub-bands based on their frequency range from 0 to 35 Hz as shown in Figure 2.1.

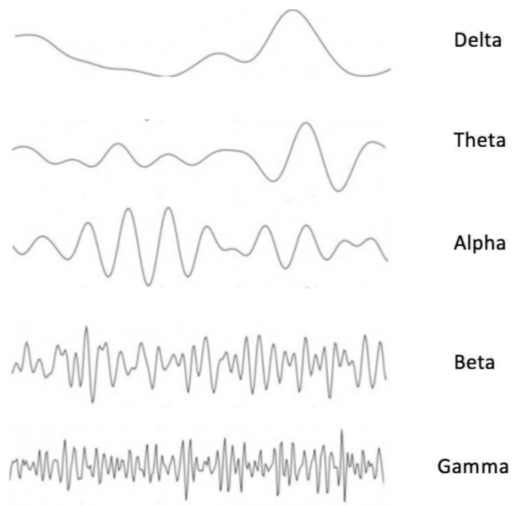


Figure 2.1: Brain waves

The table 2.1 shows that each of these waves can be dominant wave for a period of time, which gives information about a person's brain state based on their underlying neuronal brain activity [82].

Table 2.1: Brain sub-bands and status

Wave name	Frequency	Brain Status
Gamma	less than 35 Hz	Concentration
Beta:	12-35 Hz	Anxiety dominant, engaged, external stimulus
Alpha	8-12 Hz	Resting state with eyes closed, very relaxed, passive attention
Theta	4-8 Hz	Deeply relaxed, light sleep, inward focused
Delta	.5-4 Hz	Deep sleep, certain brain disease

2.1.1 Brain waves

Brain wave patterns alter with the level of a person's arousal - if a person is relaxed, then the EEG has many slow waves (delta or theta); if a person is excited, then the

EEG has many fast waves like beta [82]. Each pattern varies from person to person and it's unique for everybody.

Electroencephalography (EEG) headsets or caps is one of the devices, which is used for reading and capturing brain waves from the scalp [85, 84]. These devices have several electrodes that are labeled according to adjacent brain areas: F (frontal), C (central), T (temporal), P (posterior), and O (occipital). The letters are accompanied by odd numbers on the left side of the head and with even numbers on the right side [85]. Each of these electrodes are placed close to a special part of the brain center, for example:

- F3 and F7 are located near centers for approach behavior, which help with mood regulation, processing of positive emotion, and conscious awareness [82, 84].
- F4 and F8 are near the center for avoidance behavior, which helps with empathy conscience, processing of negative emotions such as anger, rage, anxiety, fear [82, 84].
- O1 and O2 are above primary visual areas, which help with visual processing, dreaming, visual perception [82, 84].
- T7 and T8 are placed in an area close to auditory and visual perception, which helps with visual perception of what an object is, processing and perception of auditory input, linguistic perception and comprehension [84]
- FC5 and FC6 are close to sensory motor function, which helps with awareness of body, body position, body movement [84]
- AF3 close to visual working memory, which helps with verbal retrieval [84]
- AF4 close to the area for face and object processing [82]
- P3 and P4 close to the areas for cognitive processing [84]

2.2 Literature review

Previously, researchers have examined the impact of different music genres on the human brain by studying EEG signals. It has been reported that listening to music may have a sedative effect on the human brain, which means an increase in alpha wave activity and a decrease in beta wave activity [94].

In one study, the effects of classical music and white noise was considered using EEG signals [81]. It was concluded that participants felt relaxed during listening to classical music, while they were anxious listening to white noise. In another study, twenty-eight healthy individuals were chosen to listen to recorded Al-Quran and classical music. Comparisons between their left and right brain activity showed that listening to Al-Quran increased brain activity up to %12.7. Also, listening to Al-Quran increased alpha wave activity more than listening to classical music. For participants of this study listening to Al-Quran was more calming and relaxing rather than classical music [95]. Some researchers utilized a positron emission tomography (PET) scan, which is a nuclear medicine function imaging technique, to measure the consumption of blood sugar at cellular level [96]. They observed that music without any vocal track, for example meditation songs, increases brain activity in the right hemisphere. An increment in beta waves during an attentive state of mind such as thinking and concentrating and a decrease in alpha while the brain is in a relaxation mood such as sleeping or doing meditation was noticed. Some researchers considered the frequency and amplitude spectrum density of brain signals while individuals were exposed to a melody at low volume and rock at high volume [97]. Three brain waves, alpha, beta, and theta, were selected for more investigation. Final results indicated that listening to the melody was related to high amplitudes of alpha and low amplitudes of beta, which means that the participants were in a relaxed situation. In contrast, rock music was related to low amplitudes of alpha and high amplitudes of beta, which means that the participants were in disturbed and stressful situations. Researchers explored the impact of listening to calming music, which is a kind of relaxation music, on ten participants. Statistical analysis of maximum amplitude and standard deviation, and the power spectrum of alpha and beta waves using FFT indicated that listening to calming music maximizes the amplitude of beta waves [98]. On the other hand, there were no significant changes in standard deviation, and it remained stable during and after calming music experiment. In total, it was concluded that listening to Alpha music can keep the brain in a relaxed state. In another study, twenty-nine participants were exposed to some stressful visual simulation containing disturbing pictures provided by the International Affective Picture

System (IAPS) [99]. Then, they listened to happy and sad music and white noise in order to understand whether listening to the respective sound could relieve their feelings after watching the disturbing pictures. Both physiological and psychological signals including EEG, skin conductance, heart rate variability, facial blood flow, respiration rate were collected and evaluated. Being exposed to bothering pictures declined heart rate, facial blood flow, velocity and temporal slow alpha and increased skin conductance level, response frequency, and fast beta power. Additionally, listening to happy and sad music brought the participant signals to their based data, while listening to white noise did not show any changes in the data. It was interesting that listening to happy and sad music had the same effect on the body signals. While it was thought happy music should enhance the recovery process after watching bothering images. Several studies considered the impact of listening to live violin music on the learning process and brain activities. It was concluded that live violin music can help the learning process by stimulating the alpha waves in both the left and right side of the brain [87]. Additionally, it can balance theta, alpha, and beta brain waves in both brain hemispheres [**?**].

In study by [89] the impact of various types of sound on human brain activity was examined. When participants listened to different genres of sound including meditation, rock, Mozart, jazz and Al-Quran, changes in alpha and beta waves were captured. Listening to either Rock, Al-Quran, and Mozart or relaxed and Jazz puts the brain in an attentive state, which in turn causes an increase in beta wave. In [100] individuals' alpha wave activities were studied while listening to Nasyid, a popular and traditional Malagian music containing advice and motivational words, and rock. The main aim of the study was to identify which of these music genres can help individuals feel more relaxed. The outcomes revealed that by listening to Nasyid music, more alpha wave activity was observed in the brain in comparison to listening to rock music. Also, listening to Nasyid music increased the percentage of participants who felt happy, while listening to rock decreased the number of people who felt happy. It is interesting that for some participants, an increase in alpha level was observed in the left side of the brain; for others, it was observed in the right side of the brain. In [101], researchers played Mozart music's "Für Elise" Beethoven' sonatas for three groups of participants' 10 young healthy adults, 10 healthy elderly, and 10 patients with mild cognitive impairments. The experiment consisted of two musical stimuli, and each section consisted of two stages.

In the first stage, before listening to any kind of music in a rest situation, EEG data was captured for 10 minutes. In the second stage, music was played for participants and their EEG data gathered. The Fast Fourier Transformation (FFT) method was applied on the data, and three main frequency features including peak power, main dominant, and median were extracted for further consideration. Although there were no changes in EEG data for patients who had cognitive impairments, there was an increase in alpha wave and median frequency indexes of background alpha activity for both young healthy adults and healthy elderly after listening to Mozart, while for Beethoven, no changes were detected. It was concluded that listening to Mozart may increase attention level and cognitive functions.

Music can be played by humans or a machine like a robot or boombox. In the past robots had industrial applications, but nowadays they are used in healthcare and entertainment centers. In the healthcare section, robots are used to for entertaining, assisting, and making communication with elderly people and patients with mental problems. In one study researchers used Pepper- a semi-humanoid robot manufactured by SoftBank Robotics- to see how children collaborate with it. It seemed that children like adults engaged easily with the robot regardless in which age they are [101]. In another study, Pepper was used as a motivator to increase the mobility of elderly. Results revealed that elderly who had Pepper beside themselves during the walking felt less tension and stress, and tried to increase their walking speed to reach the same speed as Pepper [102]. Music can also be experienced actively or passively. Actively means that participants are allowed to sing with the song, play a musical instrument, or dance. In contrast, in passive mode of music listening participants just listen to the song without doing any activity.

The emotions that individuals experience in reaction to the same music differ from person to person [103]. An effective tool for studying music emotion recognition and understanding stress levels is exploring physiological signals. This data can be recorded from photoplethysmography, respiration, skin temperature, electrocardiography and electroencephalogram (EEG), electrodermal activity (EDA) [89, 90, 98]. EDA data includes two components: skin conductance level (SCL) and skin conductance response (SCR) [89, 90]. SCL and SCR are the tonic and phasic changes in electrical conductivity of skin, respectively. SCL is an indicator of the general changes in arousal during the entire experiment, and SCR indicates quick changes in EDA after sudden arousal. Another tool to measure music emotion recognition is using heart rate variability (HRV) that shows the tiny changes in beat to beat interval between consecutive heartbeats (RR intervals)[100].

Researchers have examined the impact of silence and noise on individuals by monitoring skin conductance along with data on heart and respiration rate [90]. Among all of the selected parameters, skin conductance has been known as a good indicator of arousal level. Study results on 30 individuals showed significant changes in the mean value of skin conductance for all participants while experiencing silence. Also, it was observed that intensifying silence, which has an intensifying effect, has an incrementally increased physiological signals. While relieving silence, which has a relaxing effect, had an incrementally decrease in physiological signals [90]. In another study, the emotional response of individuals to visual, auditory, and a combination of audio and visual input were explored using EDA [66]. EDA data of 12 participants was monitored before and after watching, listening, or both watching and listening to the stimuluses. Researchers observed that the visual-auditory scenario had a higher average value of electrodermal amplitude and the highest correlation between EDA and tension, while the audio stimulation had the lowest values. Additionally, no correlation between mode of stimuli was recorded. Another study investigated the effect of emotional music on healthy individuals and patients with impairments in their ventromedial prefrontal cortex (VMPFC) or right somatosensory cortex (RSS) [91]. Skin conductance data and self-reporting was used to understand how listening to emotional music can alter participant's feelings. Music simulations containing happy, sad, and fearful emotions were chosen from movie tracks because they convey high emotional responses. The VMPFC patient showed responses based on both skin conductance and self-reporting. The RSS patients' skin conductance showed no responses, but their self-reported feelings indicated that music conveys emotion [91]. In one study, researchers observed differences between heart rate variability (HRV) features while individuals were watching video stimuli containing sad and happy scenes [98]. Researchers also used HRV data to classify positive and negative emotional responses of healthy individuals and patients with traumatic brain injury while passively listening to music [**?**]. A study investigated how live music therapy affects HRV, stress and anxiety of women with high-risk pregnancies [101]. After the therapy session, participants used a questionnaire to indicate their stress and anxiety levels. Although the questionnaires did not show considerable changes in stress and anxiety, changes in HRV features were detected. Another study considered the impact of music therapy on HRV in patients with vascular dementia. The outcomes showed that music therapy decreased sympathetic and increased parasympathetic nervous activity, which in turn caused a decrease in anxiety and an increase in relaxation and comfortness [102].

2.3 Gaps in previous studies

In most of the studies, the impact of music on physiological signals such as heart rate, blood pressure, and galvanic skin response has been investigated [99, 100]. However the number of research considering psychological changes using EEG is rare. In this exploratory study, we are exploring individuals' response before, during, and after listening to music, specifically nursery rhymes. The main objective of this study is to perform a comparative analysis of the brain's electrical activity in a human when listening to various genres of music.

Most of the studies have investigated the impacts of music on physiological signals. However, none of them has considered changes in both individuals' physiological and psychological while they are listening to nursery rhymes. We know that lower levels of heart rate, HRV, and tonic activity of the EDA, are associated with a calmer state and higher levels of heart rate, HRV, and, phasic activity of the EDA with higher stress [104]. Thus, the aim of this study is to explore the effects of listening to nursery rhymes on individuals' physiological signals gathered by using EDA wristbands and their psychological data using questionnaires and EEG. The following hypothesis was tested: Exposure to the nursery rhymes can make individuals calmer and more relaxed. We aim to investigate the following items:

- Compare individuals' brain activities
- Understand what happens to the electrical brain conductance before, during and after listening to music from different modes of players
- Observe how long the effect of music will last after the listening session

Chapter 3

Experiment

3.1 IRB Protocol

3.1.1 Study Endpoints/Events/Outcomes

The primary outcome of this study is to perform a comparative analysis of the psychological (EDA and HRV) and physiological (EEG) changes in a individuals when listening to three different modes of music communication: musician, robot, or boombox.

We will also explore the differences between passive versus actively engaged listening (as, for example, through dancing or singing along) to see how delivery systems impact this. The music experience will be measured in three different ways using wearable sensors. One - by monitoring the physiological activity using the Empatica E4 EDA sensor; two - by monitoring and tracking brain electrical conductivity using EMotiv EPOC EEG sensor, and three - by two surveys- one that asks for music preferences and the other is a combine POMS [105] and PANAS [106] survey.

3.2 Study Design

3.2.1 Participants

All of the participants of our experiments were recruited from healthy faculties, staffs and students of the University of Minnesota Duluth, between 18 and 45 years of age. In total, 42 participants enrolled in this study, 18 for the live human player, 18 for the robot player, and 6 for the boombox player. All procedures were approved by the appropriate IRB, and written consent was obtained from each participant.

3.2.2 Stimuli

The stimuli for this study was selected by a group of musicians at the department of music of UMD. They chose seven nursery rhymes: “Baba Black Sheep,” “Itsy Bitsy Spider,” “Mulberry Bush,” “Old MacDonald Had a Farm,” “Ring Around the Rosie,” “Twinkle Twinkle Little Star,” and “You Are My Sunshine.” The music chosen for this purpose was nursery rhymes which were played into two different modes of actively engaged verses of passive listening formats. These songs were played for individuals in three scenarios: by a musician, robot, or boombox. The musician was recruited from the Music Department at the University of Minnesota Duluth; she played the piano while singing the rhymes. The robot chosen for this study was Pepper, a semi-humanoid robot manufactured by SoftBank Robotics that has the ability to sing the rhymes and move its body parts [107]. The boombox was a transistorized portable music player.

3.2.3 Experimental Procedure

Before starting the experiment, each participant was instructed by researchers on how to follow the experiment steps. As shown in Figure 3.1, this study has three phases: data gathering, signal pre-processing, and signal analysis. Figure 3.2 shows the amount of time of data gathering in each step of experiment, in the first phase, EEG data was captured in three steps, before (baseline) for one minute, during, and after (post) experiment.

Participants were asked to sit on a chair in a comfortable and relaxed situation while their baseline EEG data was gathered for one minute. Then, according to the selected modes, one of the mechanisms (musician, robot or boombox) played seven nursery rhymes for 10 minutes while participants' brain data was recorded. Based on the chosen modes, this session was either passive or engaged. If the mode was passive, then the participant was seated on a chair without any movement, and the music was played based on the modes chosen (either by the live musician, the robot or the boom box). If the mode was active, then participants were allowed to sing along or move their

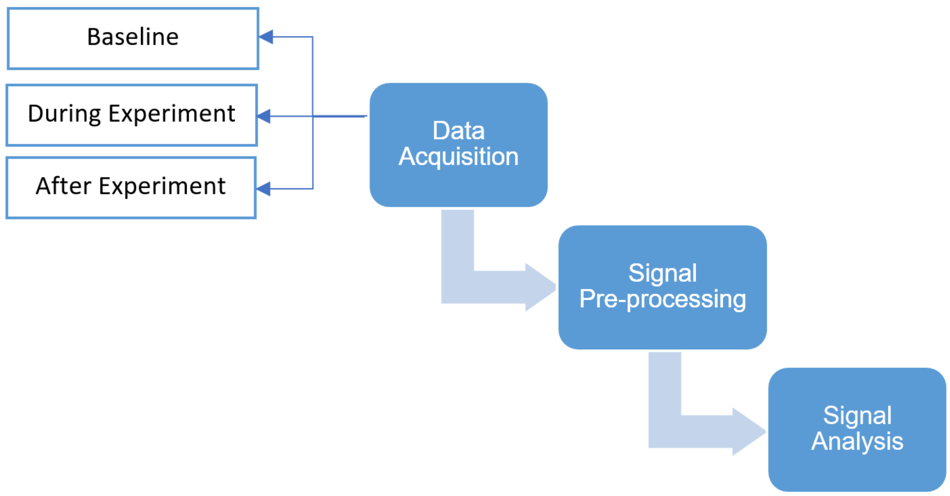


Figure 3.1: Experiment Steps

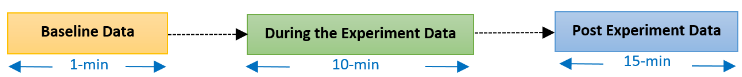


Figure 3.2: Experiment Steps

body parts.

After the end of the experiment, EEG data of each participant was gathered every two minutes for about 15 minutes.

The experiment was arranged in three sessions: baseline, experiment (music listening), and post-experiment. The participants sat on comfortable chairs, read the consent forms, and then an instructor described the experiment procedure. Participants were randomly assigned to one of the three conditions: musician, robot or boombox. Fifteen participants listened to the musician (6F, 9M), thirteen to the robot (6F, 7M), and six to the boombox (2F, 4M). Participants wore EDA wristbands that measured EDA and heart rate variability (HRV). Their baseline EDA and HRV values were taken prior (baseline data), during, and after the experiment (post-experiment). These data are indicators for the level of arousal, stress, and anxiety. Individuals' base-line, experimental, and post-experimental data were repeatedly captured for one, ten, and fourteen minutes, respectively.

3.2.4 Questionnaire

There are two questionnaires: to be filled by the participants after the experiment and consists of a rating scale of low to high with reference to the music playing mechanism. One questionnaire is the modified POMS and PANAS questionnaires combined together and the other survey is the music preference survey.

3.2.5 Ethical issues addressed

The research protocol addressed the following ethical issues:

- **Consent Process**: If the participant passes the inclusion and exclusion criteria, the participant will be informed of the data collection process and will have the opportunity to participate in the study by signing the consent form. Individuals will be informed of all aspects of the study and experimentation procedure before participation. Also, they will be made aware of any risks associated with data collection and the identifiable data storage procedure.

- **Data Banking:** The data that we collect for this activity would be anonymous and would not be linked to the individuals. The data collected would be labeled as the participant number corresponding to the sensor data.

- **Storage and Access**: The data gathered would be stored for 1-2 years only, on a password protected University owned or University approved laptop. The data will also be backed up on University owned location, in accordance with UMN data storage standards. The only people having access to the data would be the principal investigator and student investigator of this study.

  The Data elements to be collected:

  - Participant ID
  - Electrodermal activity (EDA)
  - Heart rate variability (HRV)
  - Electroencephalography data (EEG)
  - Questionnaire completed by participants

- **Release/Sharings:** We do not anticipate any releasing of the data.

- **Sharing of Results with Participants:** The results of the study would not be shared with participants or others. However, the results would be sent for publishing.

3.3 Equipment and Data Acquisition

3.3.1 EEG Signal Acquisition

EEG data collected from the participants' scalp using Emotiv EPOC+ headset that are able to record EEG data at a sampling rate of 128Hz. This headset has 16 channels, 14 electrodes for collecting EEG, and two reference electrodes. EPOC+ electrode arrangement follows the international 10-20 standard, namely: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 positions (Figure 3.3). Captured EEG data transfers to the computer through wireless technology to EMOTIVPRO software. The software allows the user to collect the raw EEG data and save it as a "csv" or an European Data File (.edf) file (Figure 3.4).

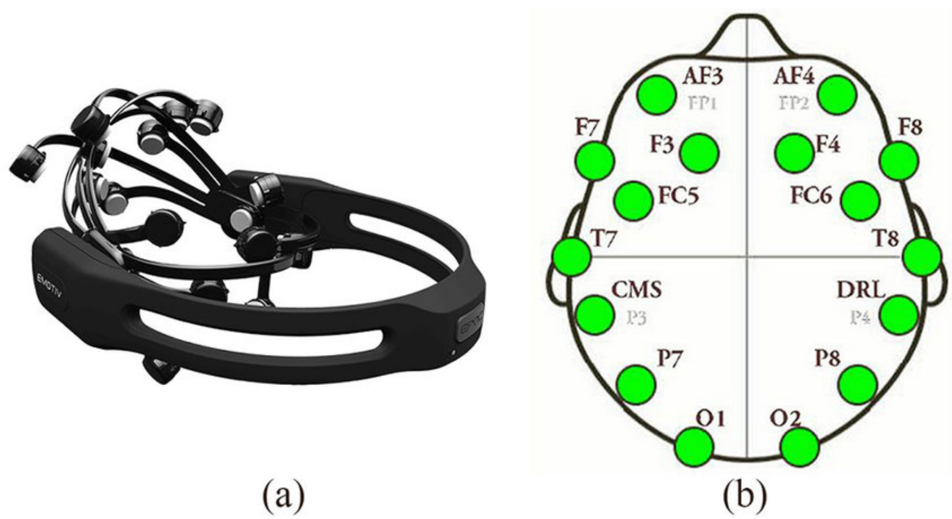


Figure 3.3: Emotiv EPOC+

Figure 3.4: EMOTIVPRO Environment

3.3.2 EDA Signal Acquisition

The processing of the physiological signals for EDA and HRV consist of four steps: noise reduction, signal segmentation, signal decomposition, and feature extraction. In this study, the collected baselines for each participant were compared to the data for other scenarios to determine whether there were major changes in physiological data. We used Ledalab 3.4.9 and Kubios 3.3 which are visual open source Matlab toolboxes. Ledalab separated EDA data into its phasic and tonic components (Figure 3.5). Since we were interested in analyzing skin conductance data, continuous decomposition analysis was applied on the EDA data [108].

Kubios provided us with time-domain data such as: Mean RR that is the time between two successive heart beats, RMSSD that reflects the root mean square of successive differences between normal heartbeats. It also gave the frequency-domain (mean HR), and non-linear data: stress index (SI) and Poincaré plots indexes: SD1 that In Poincaré plot, is the standard deviation perpendicular to the line-of-identity and SD2 that In Poincaré plot, is the standard deviation along the line-of-identity. Mean RR,

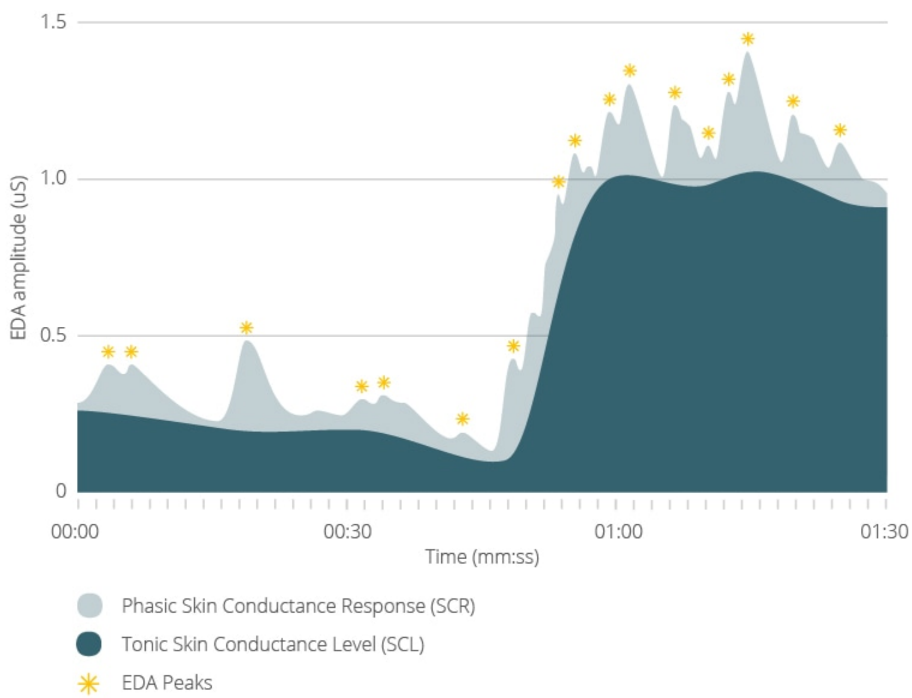


Figure 3.5: EDA Phasic and Tonic

RMSSD, SD1 mainly reflects parasympathetic nervous system (PNS) activity, whereas Mean HR, SI, SD2 mainly reflects sympathetic nervous system (SNS) activity (Figure 3.6). Furthermore, SPSS software was used for all statistical analyses.

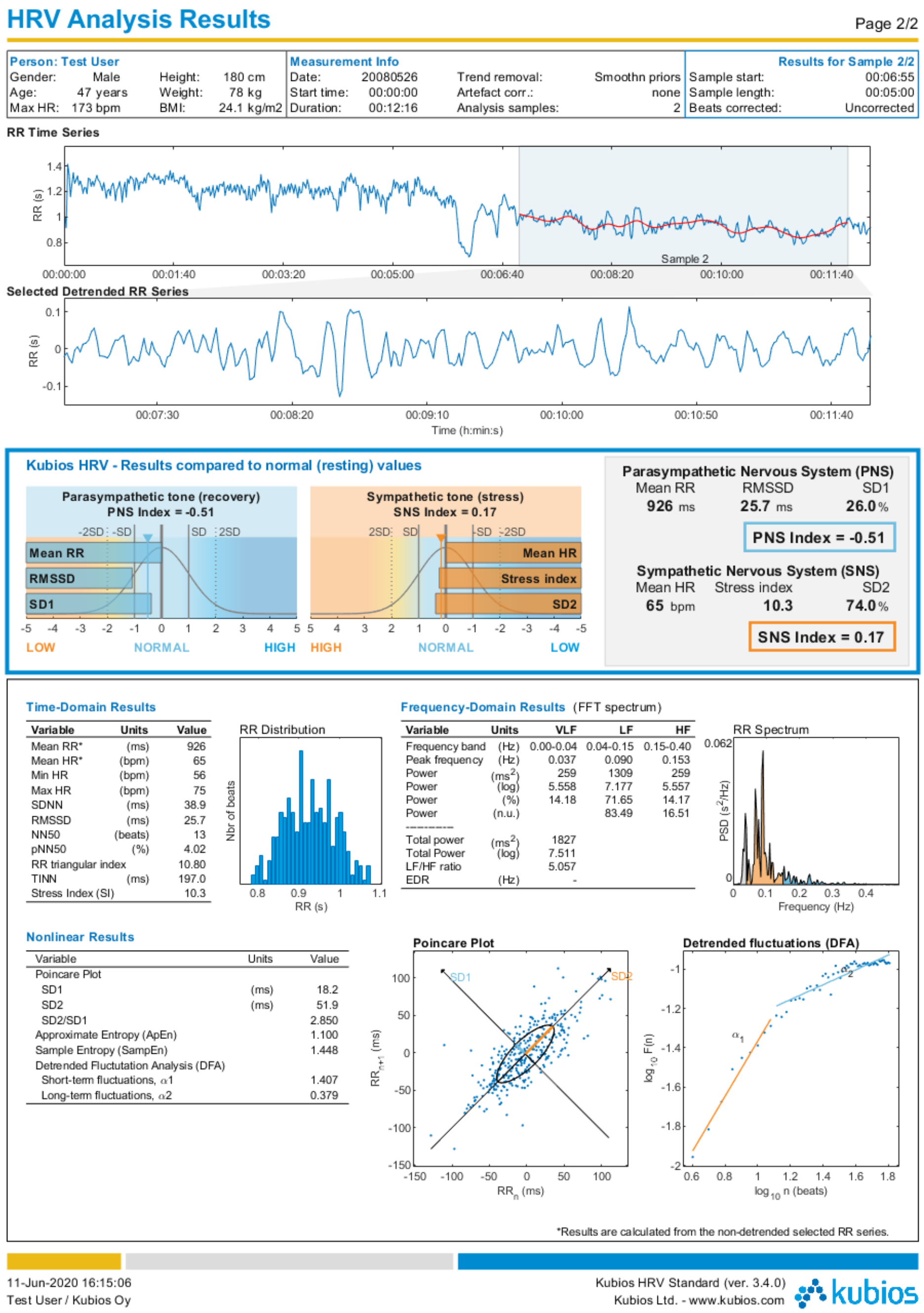


Figure 3.6: Kubios Result

Chapter 4

Data Analysis

4.1 EEG data analysis

As Figure 4.1 shows, the EEG data preprocessing step consists of several tasks: 1) filtering and artifact removal, and 2) channel separation.

4.1.1 Filtering and Artifact Removal

Raw EEG data always contain artifacts, which reduces the quality of the signal. These artifacts are grouped into physiological and non-physiological. Physiological artifacts occur due to individuals' eye blinks, eye movements, muscle activities, heartbeat, and head or body movements. Non-physiological artifacts include noises from the environment and malfunction of the EEG device. Performing data preprocessing is important due to the need to eliminate any potential data corruption that can occur due to presence of artifacts. Figure 4.2 shows 14 EEG channels that contain some of the physiological artifacts like eye blinks, muscle activities, and line noises. Artifact removal was performed in two sessions. First, unwanted noise like line noise and lower frequency noises was deleted by applying a bandpass filter that allows frequencies in the range from 0.5 to 60 Hz using Matlab software version 9.5

Second, the enhanced-wavelet-ICA (EAWICA), which is a fully automated artifact removal toolbox that uses wavelet transform, ICA, entropy and kurtosis concepts to identify and delete artifacts from all of EEG channels, was applied on the EEG data. This toolbox removes almost all of the artifacts related to eye blinks, muscle activities,

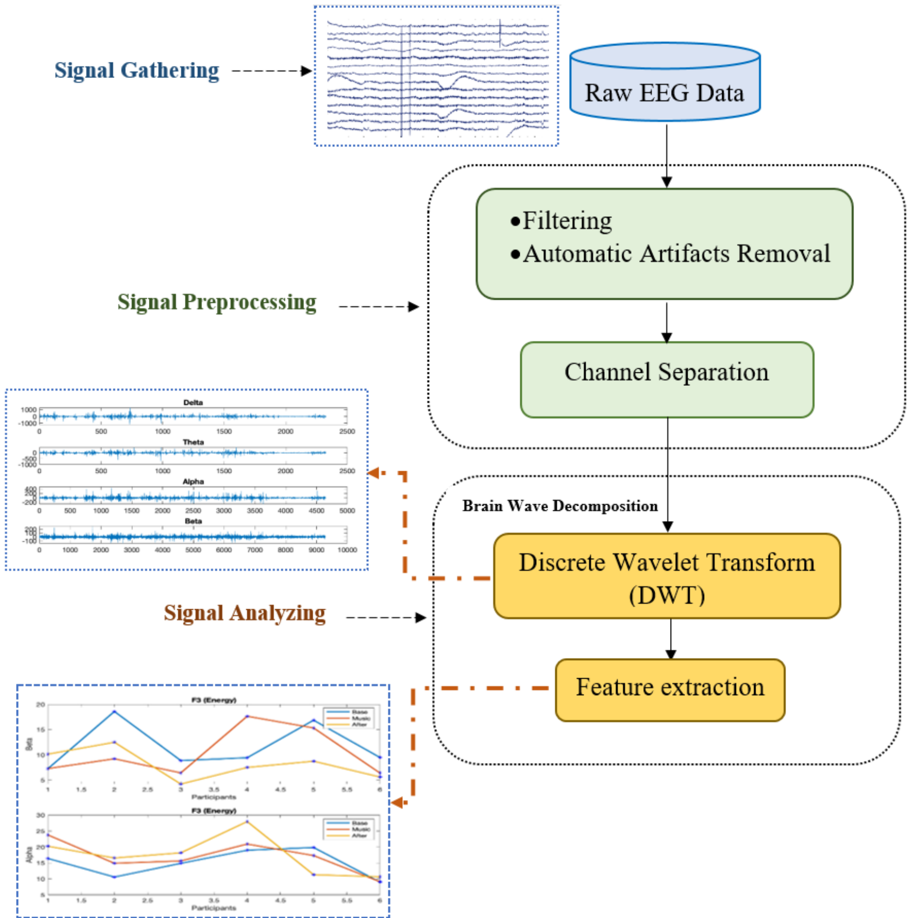


Figure 4.1: EEG Data Processing Steps

electrical shifts, and linear trends [109].

4.1.2 Chanel Separation

Based on previous studies four EEG channels including: F3-F7 and F4-F8, which are located in the frontal region of the left and right sides of the brain provide information about positive and negative emotions, respectively [82, 110]. Thus, we selected these channels for further investigation.

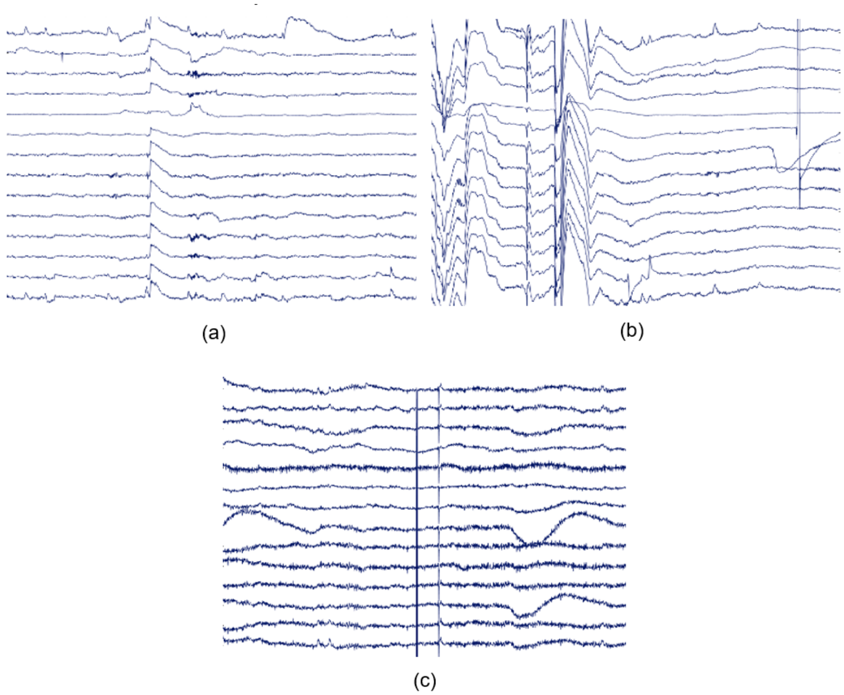


Figure 4.2: EEG Artifacts (a) Eye blink, (b) Muscle activity (c) Line noise

4.1.3 Signal Analysis

Discrete Wavelet Transform (DWT)

To analyze the relatively artifact-free EEG data, DWT has been widely applied in EEG data processing because EEG data is non-stationary with low frequencies; DWT performs better than other frequency domain techniques like FFT [111]. DWT allows us to deconstruct the mother signal into a set of scales called subbands. The general formula for wavelet transformation is:

$$X_{a,b} = \int_{-\infty}^{\infty} x(t) w_{a,b}(t) dt$$

In which x is the real signal, w is an arbitrary mother wavelet, a and b are scale and the translation, respectively. In DWT, the scale increases by the power of 2, and the translation is an integer greater than zeros. We chose Daubechies wavelet (db4) as our mother wavelet function to deconstruct the EEG signal into its sub-bands which are alpha, beta, theta, and gamma. Table 2, shows that each brain sub-band belongs to a related frequency. It was presumed that listening to nursery rhymes might relax individuals, and lower beta activity, and higher alpha activity could be observed. Therefore, only decomposition levels that show beta and alpha activities, (i.e., D3 and D4), were chosen for further investigation.

Table 4.1: Deconstructing EEG signal using DWT

Wave name	Frequency range (Hz)	Decomposition level
Theta	4-8	D5
Alpha:	8-16	D4
Beta	16-32	D3
Gamma	32-64	D2
Noises	64-128	D1

4.1.4 EEG Feature Extraction

In this step, features like energy, entropy, average, and standard deviation were calculated for each level of wavelet coefficient (frequency bands) and for each of the selected channels.

Entropy: The entropy of alpha and beta waves is computed as [111]:

$$ENT(j) = -\sum_{k=1}^{N} D_j^2(k) log D_j^2(k)$$

Where j is the level of wavelet decomposition and k is the number of wavelet coefficients.

Energy: The energy can be calculated by squaring the wavelet coefficients for each alpha and beta wave as follows [111]:

$$ENG(j) = \sum_{k=1}^{N} D_j^2(k)$$

Where Dj(k) is the calculated wavelet coefficient and k is the number of wavelet coefficients.

Average: The average value of alpha and beta waves is computed as:

$$Avg(j) = \sum_{k=1}^{N} \frac{D_j^2(k)}{N}$$

Standard Deviation: The standard deviation of alpha and beta waves is computed as:

$$Std(j) = \sqrt{\frac{\sum_{k=1}^{N}(D_j^2(k) - Avg(j))^2}{N-1}}$$

4.2 EDA and HRV data analysis

The processing of the physiological signals for EDA and HRV consist of four steps: noise reduction, signal segmentation, signal decomposition, and feature extraction [16]. In this study, the collected baselines for each participant were compared to the data for other scenarios to determine whether there were major changes in physiological data. We used Ledalab 3.4.9 and Kubios 3.3 which are visual open source Matlab toolboxes. Ledalab separated EDA data into its phasic and tonic components. Kubios provided us with time-domain data such as: Mean RR that is the time between two successive heart beats, RMSSD that reflects the root mean square of successive differences between normal heartbeats. It also gave the frequency-domain (mean HR), and non-linear data: stress index (SI) and Poincaré plots indexes: SD1 that In Poincaré plot, is the standard deviation perpendicular to the line-of-identity and SD2 that In Poincaré plot, is the standard deviation along the line-of-identity. Mean RR, RMSSD, SD1 mainly reflects parasympathetic nervous system (PNS) activity, whereas Mean HR, SI, SD2 mainly reflects sympathetic nervous system (SNS) activity. Furthermore, SPSS software was used for all statistical analyses.

4.2.1 EDA and HRV Feature Extraction

We extracted the mean as descriptive statistical features from both the tonic and the phasic components of EDA. From HRV, time-domain features such as Mean RR and HR, SDNN, and SI as a nonlinear feature were considered.

Chapter 5

Results

5.1 EEG data analysis results

5.1.1 Analysis of Selected Features

To monitor how participants' alpha and beta wave activities alter when listening to the nursery rhymes, extracted features from the EEG data for baseline, during, and post-experiment for each scenario were compared. Figures 5.1, 5.2, and 5.3 show the values of each feature for the boombox, musician, and robot scenarios.

Participants	Beta Wave (Mean Value)			Alpha wave (Mean Value)			Beta wave (Standard Deviation Value)			Alpha wave (Standard Deviation Value)		
	base	music	after	base	music	after	base	music	after	base	music	after
1	-0.59848	0.27721	1.749126	15.60022	8.821751	-14.7468	122.47	239.0383	113.9314	244.9989	530.039	247.7172
2	0.506399	-1.81392	0.775104	-0.32381	0.196117	0.447399	5.258985	12.59758	7.522719	7.326535	41.00331	11.01116
3	-0.16917	-0.42335	0.181787	2.954253	1.27995	-4.61981	30.07067	77.31767	45.79565	58.80749	134.763	116.7334
4	-0.345	0.145263	3.068624	1.219144	-0.93964	-6.08884	13.8521	48.16857	128.6667	27.86158	89.77161	345.0489
5	-0.0156	-0.75967	0.385446	2.750327	1.161188	-3.29769	30.15632	73.23636	32.77767	58.25945	115.1313	76.18508
6	0.058418	-0.01124	-0.09939	0.833189	0.061068	-0.38529	5.974119	13.3066	10.89766	9.422207	17.49226	18.4617
Participants	**Beta Wave (Entropy Value)**			**Alpha Wave (Entropy Value)**			**Beta Wave (Energy Value)**			**Alpha Wave (Energy Value)**		
	base	music	after	base	music	after	base	music	after	base	music	after
1	8.775859	9.766577	9.045112	22.4659	21.0496	18.32168	-2.6E+08	-1.5E+10	-3.1E+08	-5.7E+08	-4.9E+10	-8.1E+08
2	15.83988	9.922128	16.91859	14.90166	27.10321	17.41294	-112873	-1E+07	-276277	-186921	-1.5E+08	-391557
3	9.485762	8.559049	7.858703	19.66262	24.63069	15.97595	-4.2E+07	-1.5E+09	-3.5E+07	-8.5E+07	-4.8E+09	-1.6E+08
4	9.290064	15.59963	8.066985	18.89841	26.72681	29.32714	-1308900	-3.1E+08	-2E+08	-3225680	-5.7E+08	-8.3E+08
5	12.28916	13.54202	9.796886	21.54153	23.18445	15.29145	-4.2E+07	-1.5E+09	-2.2E+07	-8.5E+07	-4.6E+09	-9.2E+07
6	12.92676	16.27327	8.379215	16.00974	12.11797	10.49399	-192858	-1.1E+07	-777402	-468409	-1.2E+07	-1642965

Figure 5.1: Mean values of EEG features for the boombox scenario

Participants	Beta Wave (Mean Value)			Alpha wave (Mean Value)			Beta wave (Standard Deviation Value)			Alpha wave (Standard Deviation Value		
	base	music	after	base	music	after	base	music	after	base	music	after
1	-0.76035	0.149784	1.055427	0.441497	0.036214	25.24539	13.34183	71.26307	230.0719	13.74956	162.9351	555.8765
2	0.992685	-0.49263	0.696397	0.253579	-2.09221	0.22096	4.762834	15.67266	17.07982	7.265972	18.143	16.71251
3	1.182028	-0.48833	-0.24651	1.710394	-2.5988	0.735906	26.03554	27.03689	18.55246	42.14739	32.11648	21.18498
4	-0.00379	-0.38643	1.917161	0.448953	-0.16514	1.291305	11.69017	16.17545	13.04585	18.88034	27.06527	18.37381
5	-0.18631	0.325942	-0.21033	0.92876	-0.27756	-0.10339	8.384115	4.13204	2.943908	9.631605	3.950324	3.446807
6	0.102625	0.181654	-0.08727	0.031814	0.043317	-0.22252	1.168372	12.63588	12.49762	1.290833	19.13922	23.20276
7	-0.43304	0.126319	0.035254	0.640474	0.010832	0.997196	8.634517	16.27945	21.89902	10.5635	25.38412	30.95335
8	-0.34934	0.412554	1.40089	0.135933	-1.61478	-0.51109	7.272526	31.16	21.45253	11.51015	43.5021	33.33272
9	-0.065	-0.0572	-0.38836	-3.44245	-0.27518	0.351894	18.71926	16.4936	17.14066	49.53679	21.01453	21.85269
10	0.173907	0.61648	0.654365	-0.71484	-0.66428	-0.10681	9.792915	15.8908	14.63118	24.88925	23.46433	15.72522
11	0.95535	1.096403	-2.38809	0.027074	0.397747	5.87907	8.347293	32.67678	42.26785	15.3624	65.43153	81.03364
12	0.013837	2.369732	-1.84419	-0.47987	1.447604	1.69285	6.354788	42.56447	24.97033	9.162669	88.29925	42.84861
13	-0.24363	-0.57437	-2.08731	-1.29424	-2.15678	2.699176	15.20431	44.76603	51.54715	33.13122	83.66098	119.0556
14	1.194301	-0.65332	-0.6075	-2.2006	0.819007	0.917844	15.25963	52.16277	24.79575	27.45935	124.4205	53.10127
15	-0.1317	0.090435	2.244741	-0.81231	1.656042	-2.16459	11.51649	75.88827	122.5145	45.37794	200.8845	228.6851

Participants	Beta Wave (Entropy Value)			Alpha Wave (Entropy Value)			Beta Wave (Energy Value)			Alpha Wave (Energy Value)		
	base	music	after	base	music	after	base	music	after	base	music	after
1	13.06959	12.79083	10.72929	6.936973	33.45037	31.54294	-3100333	-5E+08	-7.4E+08	-1708063	-1.5E+09	-2.4E+09
2	10.47049	22.86851	29.15187	11.83427	15.51939	14.00721	-37847.8	-1.5E+07	-1813341	-50594.5	-1.1E+07	-867813
3	6.049666	11.86473	21.52876	7.985177	8.427351	14.12325	-3891185	-5.9E+07	-2246836	-5578347	-4.1E+07	-1503010
4	11.1003	7.966286	14.08073	14.59763	11.15152	13.80858	-570254	-1.7E+07	-1014434	-785638	-2.8E+07	-1119580
5	11.68382	8.844574	12.64929	7.838057	4.038892	8.678488	-322195	-666577	-29073.3	-178669	-299812	-21546.5
6	14.62731	11.75385	12.28943	8.932807	13.48918	21.29068	-942.67	-7245467	-902768	-735.191	-9803103	-1943842
7	16.15913	11.53784	8.945736	12.20076	14.03264	8.991802	-251217	-1.7E+07	-3441448	-196604	-2.4E+07	-3900792
8	8.983379	6.994513	10.65159	11.31392	6.827701	12.87259	-162936	-1.2E+08	-3127848	-246817	-1.2E+08	-5070894
9	5.261924	18.20309	15.5683	18.65692	14.78377	12.71452	-1672158	-2.1E+07	-1857667	-7679001	-1.8E+07	-1654138
10	6.568754	13.92642	22.44174	21.39087	15.1785	13.00342	-347704	-1.9E+07	-1285945	-1731464	-2.4E+07	-779379
11	4.134191	7.947944	5.622168	6.96437	15.92589	10.40705	-234829	-7.8E+07	-1.5E+07	-544008	-1.8E+08	-3.4E+07
12	8.031084	6.047103	5.318895	8.435888	12.98139	7.841057	-115432	-1.8E+08	-4723462	-142363	-4.5E+08	-8025563
13	8.0133	7.185477	6.260866	19.19681	12.56017	16.76681	-982722	-2.6E+08	-2.7E+07	-2943151	-4.8E+08	-8.5E+07
14	5.087756	3.848344	6.619891	8.303764	10.95127	15.25421	-1223646	-3.3E+08	-4619813	-2087765	-1.1E+09	-1.5E+07
15	6.292462	5.293704	4.258682	49.23521	18.5568	7.455611	-696896	-8.2E+08	-1.8E+08	-7999702	-3.3E+09	-3.4E+08

Figure 5.2: Mean values of EEG features for the musician scenario

It was observed that during the time that boombox played the rhymes:

- For energy, entropy and standard deviation features, whenever the alpha waves were more dominant, the beta waves were weak and vice versa.
- For mean features, there was no considerable differences between alpha and beta waves activity.

For the musician and robot player scenarios the results showed that:

- For energy features, a clear pattern was seen between data of baseline and during the experiment or data of during and after experiment; for some participants more alpha activities and for others more beta activities occurred.
- For entropy and standard deviation, a same trend between alpha and beta waves was observed for both baseline and during experiment, and during and post experiment.

Participants	Beta Wave (Mean Value)			Alpha wave (Mean Value)			Beta wave (Standard Deviation Value)			Alpha wave (Standard Deviation Value)		
	base	music	after	base	music	after	base	music	after	base	music	after
1	1.035651	1.068445	-0.39813	-0.68378	-1.43317	0.352381	19.33241	18.4716	9.001501	23.53311	27.23306	24.35848
2	0.183554	-0.45658	-0.04997	1.610141	-0.49135	0.135073	14.74397	10.21747	5.547835	22.62887	13.31146	6.232163
3	-1.76041	-1.12908	-1.12272	-0.49524	-0.76003	-0.41998	18.41076	13.6913	7.016907	26.77055	23.41541	8.813008
4	-3.6103	1.538863	-0.37334	6.578683	3.497921	1.39841	300.4358	174.348	23.40837	610.5997	371.8524	47.32707
5	-35.7043	-6.46663	-5.48802	-39.317	-5.26711	-10.2402	787.7216	738.6159	278.1357	1040.061	944.3255	359.5794
6	0.606679	1.070964	0.157798	-0.08373	-2.21194	-0.39538	11.72076	10.98732	4.814515	24.89455	14.49681	6.386717
7	0.132753	0.053175	0.075184	0.678212	0.020108	-0.10655	16.78252	13.8428	13.47498	22.88809	25.31965	23.04287
8	0.107642	-0.01698	0.172072	0.069144	0.300651	-0.23323	15.61108	10.2753	7.729067	32.202	23.75687	10.64798
9	1.850444	-1.33904	0.021795	0.283182	-0.75995	0.248757	12.12274	25.44784	5.698833	23.67269	43.69669	7.384462
10	-1.59997	-0.57083	0.382911	0.180566	-0.17857	-1.32282	16.2449	25.5804	23.06389	24.63841	62.8562	57.92039
11	0.708299	-0.31499	0.292595	0.945871	-2.04802	-0.22366	31.52197	53.88769	11.22335	26.65457	118.4453	14.9932
Participants	Beta Wave (Entropy Value)			Alpha Wave (Entropy Value)			Beta Wave (Energy Value)			Alpha Wave (Energy Value)		
	base	music	after	base	music	after	base	music	after	base	music	after
1	16.25584	19.85234	11.14948	11.23277	16.0788	23.32155	-3008265	-2.7E+07	-582725	-2581739	-4.2E+07	-6789599
2	11.91712	17.13208	14.03084	14.47123	14.5734	8.982065	-1458733	-5923878	-116787	-2328422	-5696246	-77903.6
3	17.18348	8.194725	11.73237	18.0847	11.45775	8.113336	-2779496	-1.4E+07	-226527	-3224085	-2.6E+07	-214867
4	7.167633	6.14001	8.776939	14.71968	13.98784	17.3785	-1.3E+09	-4E+09	-4300218	-3E+09	-1.1E+10	-1.1E+07
5	38.39358	46.19564	43.25079	33.62066	38.1469	36.35466	-1.1E+10	-8.6E+10	-7.6E+08	-9.9E+09	-7.3E+10	-6.7E+08
6	10.4201	12.22424	13.61136	17.19437	10.69421	12.19296	-928916	-7354244	-70651.7	-3878099	-7480815	-72531.9
7	17.42162	8.135995	8.743766	14.28682	12.5181	10.96249	-1806160	-1.3E+07	-1161152	-2094718	-3E+07	-2346255
8	11.0054	6.78944	11.58466	18.3855	18.21558	11.13172	-2137861	-7148762	-359759	-7744749	-3.4E+07	-537503
9	7.968725	4.476769	13.40979	14.37253	6.56817	11.21764	-1035336	-7.5E+07	-136516	-2603936	-1.2E+08	-140614
10	15.4745	5.261325	5.602302	16.53741	16.03451	19.01118	-1820129	-6.8E+07	-2119195	-2573815	-2.5E+08	-8987796
11	32.07782	1.945592	9.180045	10.60251	4.692468	8.081063	-7751773	-3.6E+08	-476799	-2657297	-9.9E+08	-493852

Figure 5.3: Mean values of EEG features for the robot scenario

- For mean features, no considerable differences between alpha and beta activities were detected.

Additionally, to compare participants' brain responses to listening to nursery rhymes in each scenario, a Pearson correlation coefficient between each pair of participants was calculated and compared. The results are summarized in Figure 5.4

- Based on Figure 5.4, for the musician player scenario, there is a negative strong correlation between EEG data of participant 1 with 11 and 13 ($r=0.9$, $p<.001$), participant 2 with 3 ($r=0.8$, $p<.001$), participant 5 with 10 ($r=0.7$, $p<.001$), participant 7 with 9 ($r=0.9$, $p<.001$), participant 11 with 15 ($r=0.9$, $p<.001$), participant 12 with 15 ($r=0.91$, $p<.001$), participant 13 with 14 ($r=0.9$, $p<.001$), and participant 14 with 15 ($r=0.9$, $p<.001$). Also There is positive strong correlation between EEG data of participant 7 with 8 ($r=0.7$, $p>.05$).

Correlation coefficient between participants for musician player
MP: Indicated that participants listened to the rhymes played by a musician

	MP1	MP 2	MP3	MP 4	MP 5	MP6	MP7	MP 8	MP9	MP10	MP1 1	MP1 2	MP1 3	MP1 4	MP15
MP1	1.0	0.0	0.2	0.5	-0.1	-0.1	0.0	-0.4	0.4	0.1	**0.9**	0.4	**0.9**	0.5	-0.7
MP2	0.0	1.0	**0.8**	0.4	0.5	0.5	0.0	0.6	0.0	0.4	-0.1	-0.6	0.3	0.0	-0.2
MP3	0.2	0.8	1.0	0.3	0.6	0.4	0.1	0.2	-0.2	0.0	0.2	-0.2	0.5	0.0	-0.6
MP4	0.5	0.4	0.3	1.0	-0.1	-0.4	0.4	0.3	0.0	0.3	0.0	-0.6	0.2	0.1	0.0
MP5	-0.1	0.5	0.6	-0.1	1.0	0.6	0.5	0.4	0.6	**0.7**	-0.2	0.1	0.2	-0.6	-0.4
MP6	-0.1	0.5	0.4	-0.4	0.6	1.0	-0.1	-0.1	0.2	-0.1	0.1	0.0	0.2	0.6	-0.2
MP7	0.0	0.0	0.1	0.4	0.5	-0.1	1.0	**0.7**	**0.9**	0.6	-0.9	-0.2	-0.2	-0.8	0.0
MP8	-0.4	0.6	0.2	0.3	0.4	-0.1	0.7	1.0	-0.2	0.7	-0.7	-0.6	-0.3	-0.7	0.4
MP9	0.4	0.0	-0.2	0.0	0.6	0.2	0.9	-0.2	1.0	0.6	0.5	0.4	0.6	0.7	-0.2
MP10	0.1	0.4	0.0	0.3	0.7	-0.1	0.6	0.7	0.6	1.0	-0.1	-0.1	0.2	-0.1	0.1
MP11	0.9	-0.1	0.2	0.0	-0.2	0.1	-0.9	-0.7	0.5	-0.1	1.0	1.0	1.0	0.6	**0.9**
MP12	0.4	-0.6	-0.2	-0.6	0.1	0.0	-0.2	-0.6	0.4	-0.1	1.0	1.0	1.0	0.2	**0.9**
MP13	0.9	0.3	0.5	0.2	0.2	0.2	-0.2	-0.3	0.6	0.2	1.0	1.0	1.0	**0.9**	-0.9
MP14	0.5	0.0	0.0	0.1	-0.6	0.6	-0.8	-0.7	0.7	-0.1	0.6	0.2	1.0	1.0	**0.9**
MP15	-0.7	-0.2	-0.6	0.0	-0.4	-0.2	0.0	0.4	-0.2	0.1	1.0	1.0	-0.9	1.0	1.0

Correlation coefficient between participants for robot player
RP: Indicated that participants listened to the rhymes played by a robot

	RB1	RB 2	RB3	RB 4	RB 5	RB6	RB 7	RB8	RB9	RB1 0	RB11
RP1	1.0	-0.2	-0.5	-0.6	-0.1	**0.8**	-0.3	-0.6	0.3	-0.7	0.5
RP2	-0.2	1.0	0.3	0.5	-0.8	0.1	**0.9**	-0.2	0.4	0.2	**0.7**
RP3	-0.5	0.3	1.0	**0.8**	0.2	-0.5	0.2	-0.3	-0.4	0.3	-0.2
RP4	-0.6	0.5	0.8	1.0	-0.1	-0.4	0.6	0.0	-0.5	0.6	-0.2
RP5	-0.1	-0.8	0.2	-0.1	1.0	-0.3	-0.8	0.0	-0.7	0.2	-0.7
RP6	0.8	0.1	-0.5	-0.4	-0.3	1.0	0.1	-0.4	0.2	-0.2	**0.8**
RP7	-0.3	0.9	0.2	0.6	-0.8	0.1	1.0	0.2	0.2	0.4	0.6
RP8	-0.6	-0.2	-0.3	0.0	0.0	-0.4	0.2	1.0	-0.1	0.5	-0.3
RP9	0.3	0.4	-0.4	-0.5	-0.7	0.2	0.2	-0.1	1.0	-0.5	0.6
RP1 0	-0.7	0.2	0.3	0.6	0.2	-0.2	0.4	0.5	-0.5	1.0	-0.1
RP1 1	0.5	0.7	-0.2	-0.2	-0.7	0.8	0.6	-0.3	0.6	-0.1	1.0

Correlation coefficient between participants for boombox player
MP: Indicated that participants listened to the rhymes played by a boombox

	BP1	BP2	BP3	BP4	BP5	BP6
BP1	1.00	-0.19	**0.81**	0.68	0.64	**0.88**
Bp2	-0.19	1.00	-0.34	-0.10	0.18	-0.23
BP3	0.81	-0.34	1.00	0.85	**0.83**	0.64
BP4	0.68	-0.10	0.85	1.00	**0.85**	0.51
BP5	0.64	0.18	0.83	0.85	1.00	0.53
BP6	0.88	-0.23	0.64	0.51	0.53	1.00

Figure 5.4: Correlation coefficients between participants for each scenario, ((a) musician scenario, (b) robot scenario (c)) boombox scenario

- Based on Figure 5.4, for the robot player scenario, there is a considerable relationship between EEG data of participants 1 with 6 (r=0.8, p<.001), and participant 2 with 7 and 11 (r=0.9, p<.001; r=0.7, p<.05), participant 3 with 4 (r=0.8, p<.001), and participant 6 with 11 (r=0.8, p<.05).

- Based on Figure 5.4, for the boombox player scenario, a negative strong correlation is detected for participant 1 with 6 (r=0.88, p<.001), participant 3 with 5 (r=0.83, p<.001), and participant 4 with 5 (r=0.85, p<.001). Also there is a positive strong correlation between EEG data of participant 1 with 3 (r=.81, p>.05).

In conclusion, it is not possible to generalize the changes in brain activity for all participants in each unique scenario. No same brain wave activity for all of the participants in a scenario was detected. While for some participants, music made them calm or relaxed, it had a negative effect on other participants.

5.1.2 Comparison between Different Scenarios

Comparison between different scenarios (a musician, robot, or boombox player) was made by calculating Pearson correlation coefficient and one-tailed t-test techniques between different scenarios and participants in each scenario. The results are summarized in Figure 5.5 and Figure 5.6.

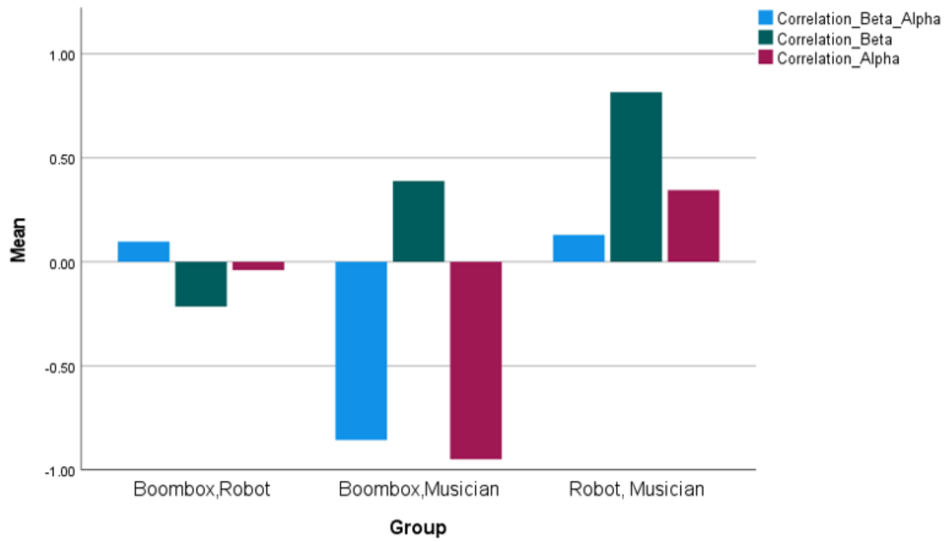
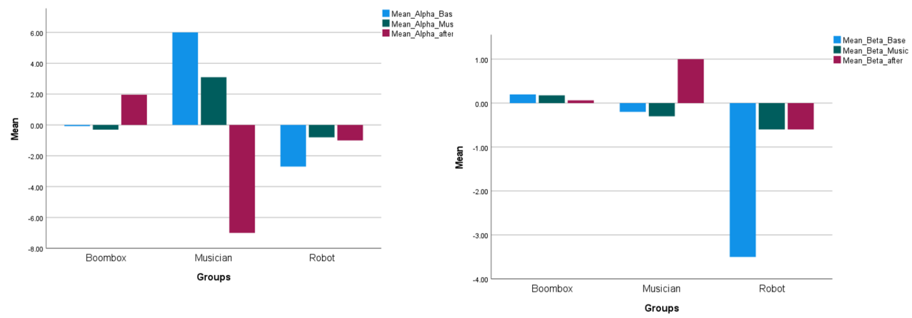


Figure 5.5: Average of Pearson correlation coefficient of brain activity for each pair of scenarios

Figure 5.5, shows the plot of Pearson correlation coefficients between each pair of scenarios. There is no correlation between listening to rhymes using a boombox or a robot player during and post-experiment. In addition, there is no correlation between listening to rhymes when played by a boombox or a musician before and after experiment. The correlation coefficient between musician and robot player shows a significant correlation between these scenarios. Therefore, listening to live nursery rhymes, played by a robot or a musician, may not have the same impact on the brain as being exposed to boombox player.

Figure 5.6, presents a comparison between average value of alpha and beta waves for all participants in each scenario. This figure shows that:

- For average value of alpha waves, the data indicates that for the musician player scenario, the baseline data was higher than the boombox and the robot. Also for musician scenario, significant drop in average value of alpha wave was seen during and after the exposure to the music. The average value of alpha waves showed a small fluctuation for participants in the boombox player scenario during the experiment, while it increased after the experiment. There was a reverse trend for



a) Average of alpha waves b) Average of beta waves

Figure 5.6: Comparison between average alpha and beta activity for all participants during various scenarios

the average value of alpha waves for the robot player scenario; it increased during the experiment and a decreased after the experiment.

- For the average value of beta waves, the data did not show any significant differences between the different scenarios at baseline. A declining trend during and after the exposure to the nursery rhymes for boombox was seen. The average of beta waves also dropped for participants in the musician player scenario after the experiment, while it increased after the experiment. For the robot player scenario, increase in the average value of beta waves was noticed during the experiment with no changes seen after experiment. Also, no statistically significant differences were found between scenarios at baseline.

T-test results (one-tailed, alpha value = 0.05)

		Boombox-Robot	Boombox-Musician	Robot-Musician
Beta waves	Baseline	t(15) = 0.72, p = .23	t(19) = -1.58, p = .06	t(24) = -1.31, p = .09
	Experiment	t(15) = 0.31, p = .37	t(19) = -1.28, p = .11	t(24) = -1.32, p = .09
	After Experiment	**t(15) = 1.85, p = .04**	t(19) = 1.56, p = .06	t(24) = -1.18, p = .12
Alpha waves	Baseline	t(15) = 1.35, p = .10	**t(19) = 1.80, p = .04**	t(24) = -0.84, p = .20
	Experiment	t(15) = 1.49, p = .07	t(19) = 1.58, p = .06	t(24) = -0.89, p = .18
	After Experiment	**t(15) = -1.71, p = .05**	**t(19) = -2.46, p = .01**	t(24) = -1.53, p = .06
Average of Beta and Alpha waves	Baseline	t(15) = 1.17, p = .13	**t(19) = 1.68, p = .05**	t(24) = -1.08, p = .15
	Experiment	t(15) = 1.34, p = .10	t(19) = 1.24, p = .11	t(24) = -1.21, p = .12
	After Experiment	t(15) = -1.25, p = .11	**t(19) = -2.30, p = .02**	t(24) = -1.65, p = .06

Figure 5.7: T-test results (one-tailed, alpha value = 0.05)

The results of hypothesis testing using one-tailed t-test technique indicate the value of p<.05 for both alpha and beta waves for data of after experiment between boombox and robot players, which means that there is a significant difference between these modes. Additionally, the value of $p<.05$ for both alpha and average value of alpha and beta waves was observed for baseline and after experiment data between boombox and musician players, which means that there is a difference between these modes. The hypothesis testing shows no significant differences between musician and the robot player Figure 5.7.

Based on Figure 5.8, the average value of beta and alpha waves for all participants in the different scenarios showed a negative correlation between alpha and beta activities. Whenever alpha increased beta decreased and vice versa. Additionally after the experiment, participants in both robot and musician player scenarios were more relaxed than participants in the boombox.

Scenario	Results
Boombox player	Baseline alpha < baseline beta During experiment alpha < During experiment beta After experiment alpha > After experiment beta Post-experiment observation: Increase in alpha and decrease in beta
Musician player	Baseline alpha > Baseline beta During experiment alpha > During experiment beta After experiment alpha < After experiment beta Post-experiment observation: Decrease in alpha and increase in Beta
Robot player	Baseline alpha > Baseline beta During experiment alpha > During experiment beta After experiment alpha > After experiment beta Post-experiment observation: Increase in alpha and decrease in beta

Figure 5.8: Comparison between average value of alpha and beta of participants in each scenario (<: lower than, >: higher than)

5.2 EDA data analysis results

Figure 5.9 shows the mean values for EDA and HRV features for all participants at each of the three stages in the three scenarios. The Mean RR and RMSSD components were expressed as power and were measured as ms, SD1 and SD2 were measured as %, Mean HR was measured as bpm.

		Mean±Std (Robot Scenario)	Mean±Std (Boombox Scenario)	Mean±Std (Musician Scenario)
EDA	Phasic_Baseline	.04±.05	**.14±.19**	.09±.10
	Phasic_Experiment	.01±.01	.03±.02	**.14±.14**
	Phasic_After	.04±.05	.04±.03	**.10±.11**
	Tonic_Baseline	**.36±.51**	.90±.80	**6.08±14.36**
	Tonic_Experiment	**.76±.82**	1.41±1.08	**5.87±9.20**
	Tonic_After	**.84±.99**	1.97±2.29	**2.67±3.71**
PNS	Mean RR_Baseline	**907.8±163.7**	849.1±139.6	772.5±110.3
	Mean RR_Experiment	**905.8±160.1**	850.0±167.8	766.5±79.73
	Mean RR_After	**882.8±126.4**	843.6±178.8	743.1±100.7
	RMSSD_Baseline	63.22±30.94	80.75±31.75	**140.9±293.4**
	RMSSD_Experiment	**64.08±32.29**	44.15±9.15	52.80±22.26
	RMSSD_After	**48.81±23.52**	30.03±10.76	51.75±18.99
	SD1_Baseline	**49.78±9.82**	48.56±8.29	45.40±8.10
	SD1_Experiment	**49.49±9.05**	46.20±7.02	41.80±7.47
	SD1_After	**46.70±8.87**	42.48±10.90	42.14±7.52
	PNS Index_Baseline	.71±1.33	**.89±1.47**	-.16±.98
	PNS Index_Experiment	**.71±1.28**	-.11±.75	-.30±.89
	PNS Index_After	**.16±1.05**	-.35±.84	-.44±.83
SNS	Mean HR_Baseline	**67.87±11.42**	72.00±10.7	78.92±10.21
	Mean HR_Experiment	**68.00±10.46**	72.67±13.1	79.25±8.39
	Mean HR_After	**69.27±9.33**	73.50±14.3	80.08±11.42
	SI_Baseline	12.17±3.85	**8.63±1.67**	12.20±4.02
	SI_Experiment	11.20±3.65	**11.41±1.45**	11.10±3.79
	SI_After	12.42±4.20	12.55±2.36	**10.45±2.81**
	SD2_Baseline	**50.22±9.82**	51.43±8.29	54.60±8.10
	SD2_Experiment	**50.51±9.05**	53.80±7.02	58.19±7.47
	SD2_After	**53.30±8.87**	57.51±10.90	57.85±7.52
	SNS Index_Baseline	.36±1.18	**.10±.85**	1.14±1.08
	SNS Index_Experiment	**.22±1.06**	.60±.71	1.01±.98
	SNS Index_After	**.52±1.14**	.88±1.02	1.11±1.01

Figure 5.9: Average and standard deviation values of EDA and HRV features for all participants of each scenario for different levels of obtained data

5.2.1 Statistical analysis of EDA features

In the musician scenario, the mean value of both tonic and phasic was high, meaning that participants experienced higher levels of stress. In the robot scenario, during the baseline, the tonic level had the lowest mean values and participants were calmer than in the other two scenarios. We expected the tonic portion of the EDA to continue to decline during and after listening to the nursery rhymes, however a slight decline was noticed. In the boombox scenario similar to the robot scenario, during the baseline, participants had the lowest mean value of the tonic component while it started to increase during and after the experiment; this means that participants had more stress during and after the experiment. Also in this scenario, the highest mean value of the tonic portion was observed during the baseline in comparison to the other two scenarios.

5.2.2 Statistical analysis of HRV features

In the musician scenario, for the mean values of PNS activity during the baseline, the mean value of RMSSD was higher than the other two scenarios. While the mean values of Mean RR and SD1 were lower than those in the boombox scenario, the mean values of the RMSSD were higher than the boombox scenario. In this scenario, for the mean values of SNS activity after the experiment, the mean value of SI was lower than the other two scenarios. Also the mean values of SD2 after the experiment was higher than the boombox scenario.In the boombox scenario, for the SNS activity, except the mean value of RMSSD during the baseline all values were lower than the musician. Also for the PNS activity, the mean values of the SI during baseline and experiment were much lower than the other two scenarios.In the robot scenario, during and after the experiment, the mean values of the PNS activity was high while the mean values of the SNS activity were low. These outcomes did not show which scenario could relieve the participants.

5.2.3 Pearson correlation

To measure the strength and direction of linear relationship between pairs of obtained data (baseline, during and after the experiment), a Pearson correlation coefficient was applied on all of the scenarios for different levels of obtained data. Pearson correlation coefficient values change from -1.0 to 1.0, in which -1.0 presents a perfect negative correlation and 1.0 is an indicator of perfect positive correlation. Figure 5.10 2 presents a complete list of correlation between EDA and HRV features.

5.2.4 Pearson Correlation between EDA features

By looking at EDA features, it was observed that for the musician scenario, there were considerable correlations between mean value of the both tonic and phasic components for baseline and during ($r=0.83$, $r=0.95$) and after the experiment ($r=0.76$, $r=0.83$), and during and after the experiment ($r=0.94$, $r=0.97$), respectively. It was noticed that for the robot scenario, there were moderate correlations between mean values of both phasic

		PNS features of HRV						SNS features of HRV						HED features			
	Scenarios	Mean RR Music	Mean RR After	RMSSD Music	RMSSD After	SD1 Music	SD1 After	Mean HR Music	Mean HR After	SI Music	SI After	SD2 Music	SD2 After	Phasic Music	Phasic After	Tonic Music	Tonic After
Mean RR Base	Robot Boombox Musiciani	.97** .98** .81**	.87** .98** .71**														
Mean RR Music	Robot Boombox Musician		.88** .99** .90**														
RMSSD Base	Robot Boombox Musiciani			.70* .11 .37	.57* -.13 .19												
RMSSD Music	Robot Boombox Musician				.61* .65 .83**												
SD1 Base	Robot Boombox Musiciani					.79** .82* .50	.71** .82* .14										
SD1 Music	Robot Boombox Musician						.63* .87* .86**										
Mean HR Base	Robot Boombox Musician							.96** .97** .87**	.90* .98** .73**								
Mean HR Music	Robot Boombox Musician								.93** .99** .84**								
SI Base	Robot Boombox Musician									.50 .02 .81**	.26 -.04 .66*						
SI Music	Robot Boombox Musician										.68** .50 .77**						
SD2 Base	Robot Boombox Musician											.79* .82* .50	.71** .82* .14				
SD2 Music	Robot Boombox Musician												.63* .87* .86**				
Phasic Base	Robot Boombox Musician													.45 .25 .83**	.53* .51 .76**		
Phasic Music	Robot Boombox Musician														.45 .93** .94**		
Tonic Base	Robot Boombox Musician															.66** .52 .95**	.42 .51 .83**
Tonic Music	Robot Boombox Musician																.79** .93** .96**

Figure 5.10: Pearson correlation between the mean values of HRV and EDA features

and tonic for baseline and during the experiment (r=0.53, r=0.66), respectively. Also for the tonic portion a notable correlation for during and after the experiment (r=0.79) was observed. It was seen that for the boombox scenario, there were significant correlations between mean values of both phasic and tonic components for during and after the experiment (r=0.94, r=0.96), respectively.

5.2.5 Pearson Correlation between HRV features

For the musician scenario, strong correlations between the mean values of Mean RR, Mean HR, and SI for baseline and during (r=0.81, r=0.87, r=0.81) and after the experiment (r=0.87, r=0.73, r=0.66) and during and after the experiment (r=0.90, r=0.84, r=0.77), for RMSSD, SD1, and SD2 for during and after the experiment (r=0.83, r=0.77, r=0.86), respectively were seen. For the other features, minor or moderate correlations between each feature for each different state of data gathering was observed. For the robot scenario, significant correlations between the mean values of Mean RR, RMSSD, SD1, Mean HR, and SD2 for baseline and during (r= 0.97, r=0.70, r=0.79, r=0.96, r=0.79) and after the experiment (r=0.87, r=0.57, r=0.71, r=0.90, r=0.71) and during and after the experiment (r=0.88, r=-0.61, r=0.63, r=0.93, r=0.63), respectively were noticed. Additionally, a moderate correlation between mean value of SI for during and after the experiment (r=0.77) was seen. Similar to the musician scenario, minor or moderate correlations between each feature for each different state of data gathering was seen. For the boombox scenario, similar to the robot scenario, significant correlations between the mean values of Mean RR, SD1 and Mean HR for baseline and during (r=0.98, r=0.82, r= 0.97) and after the experiment (r=0.98, r=0.82, 0.98) and during and after the experiment (r=0.99, r=0.87, r=0.99), respectively were noted. Additionally, minor negative correlations between the mean value of RMSSD for baseline and after the experiment (r=-0.13) were seen. Like the other two scenarios, for other features, slight or moderate correlations between each feature for different states of data gathering was noticed.

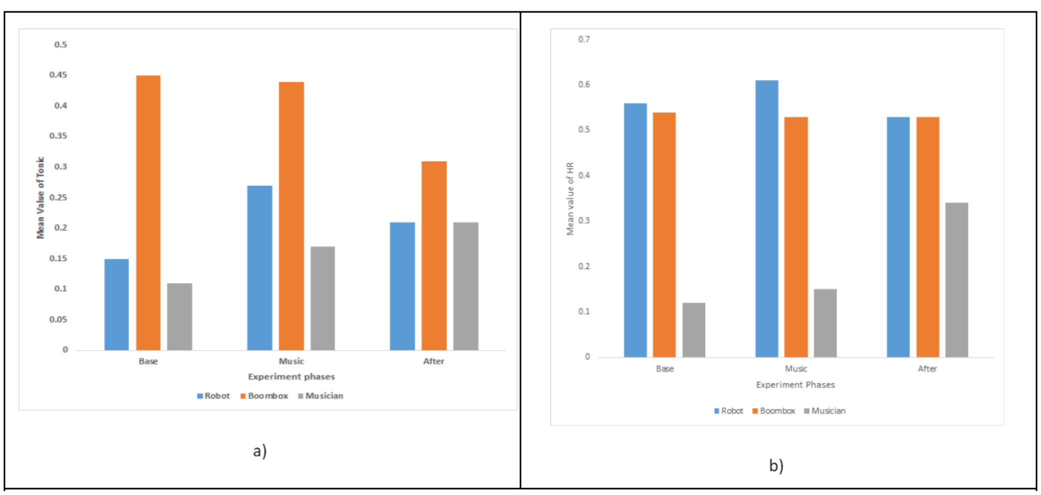


Figure 5.11: Mean value of Tonic and HR for all scenarios

Figure 5.11 demonstrated the mean values of the tonic component and the HR of all of the experiment scenarios. The findings indicate that listening to the nursery rhymes live considerably changed the EDA tonic level, while the recorded songs (robot and boombox) had no significant impact on the EDA data. By looking at HRV data, it was noted that no matter which scenario was chosen, nursery rhymes slightly changed the mean value of the HRV, while the correlation was strong between the data of each pair of baseline, during, and after the experiment.

5.2.6 Comparison between data of EDA, HRV, and EEG

The results indicated that while for some participants nursery rhymes was relaxing for others it was disturbing. Also, The results suggest that both human to human and human to robot contact are more complicated than human to boombox contact. For this study, our aim was to understand whether there is any relation between the EEG, the EDA, and the HRV data.

We know that a combination of HRV, EDA, and EEG features such as higher levels of PNS and alpha waves, lower levels of SNS and beta waves, tonic data is an indicator that a person is relaxed or calm. For this purpose, we normalized the mean of these features for each level of obtained data (baseline, during and after the experiment) for each scenario, and the results are summarized in Figure 5.12.

Based on Figure 5.11 and box plots in Figure 5.12, participants in the musician scenario had lower average values for SNS and tonic data, but their average values of the PNS activity and alpha waves were not higher than those of the participants in the other two scenarios. Also, their mean values of beta waves were not lower than those of the participants in the other two scenarios. Thus, these results suggest that none of these three scenarios clearly made the participants relaxed.

5.2.7 Results of self-report questionnaires

The response of 31 participants was analyzed, because some of the 42 participants declined to complete the questionnaires. Figure 5.13 shows the participants' two most and three least favorite music genres of the 15 choices provided. The values show that classical music is the most popular genre among all of the participants, while religious music was the least preferred genre

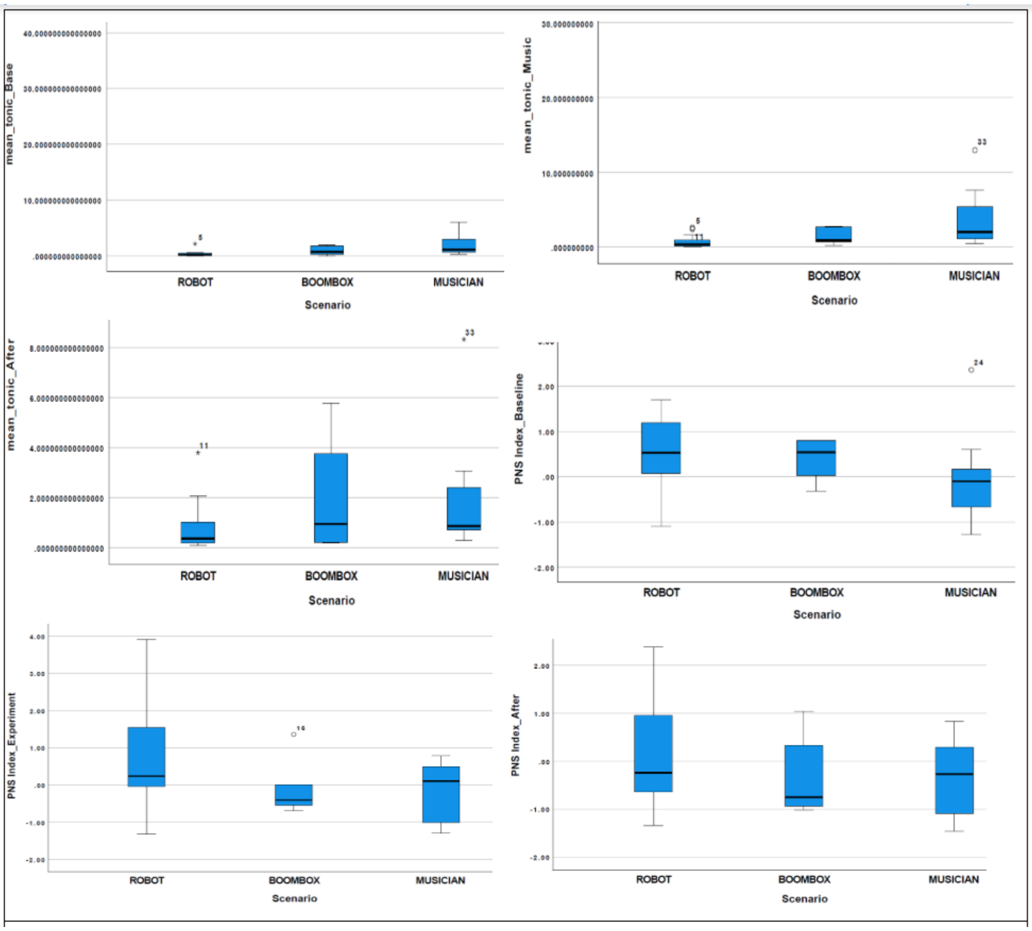


Figure 5.12: Normalized mean value of Tonic level of EDA and PNS activity of HRV for all scenarios

The participants' most common feelings were lively, alert, happy, cheerful, and calm and relaxed after the experiment. However, Figure 5.14 shows that listening to nursery rhyme made some participants in all of the three scenarios nervous, slowed, sluggish or exhausted. Also, it was interesting some participants in the musician scenario reported feeling listless, and some participants in the robot scenario felt annoyed after the experiment.

We applied one-way ANOVA to test whether a statistically significant difference exists between participants' emotional experience in the different scenarios. The outcomes

	Most favorite		Least favorite		
Scenario	**Classical**	**Rock**	**Religious**	**Gospel**	**Heavy Metal**
Robot	5.00	5.33	3.22	3.33	3.33
Boombox	5.67	5.67	2.00	2.83	3.67
Musician	5.19	6.06	3.44	3.88	3.75

Figure 5.13: Mean values of the most and least preferred music genres

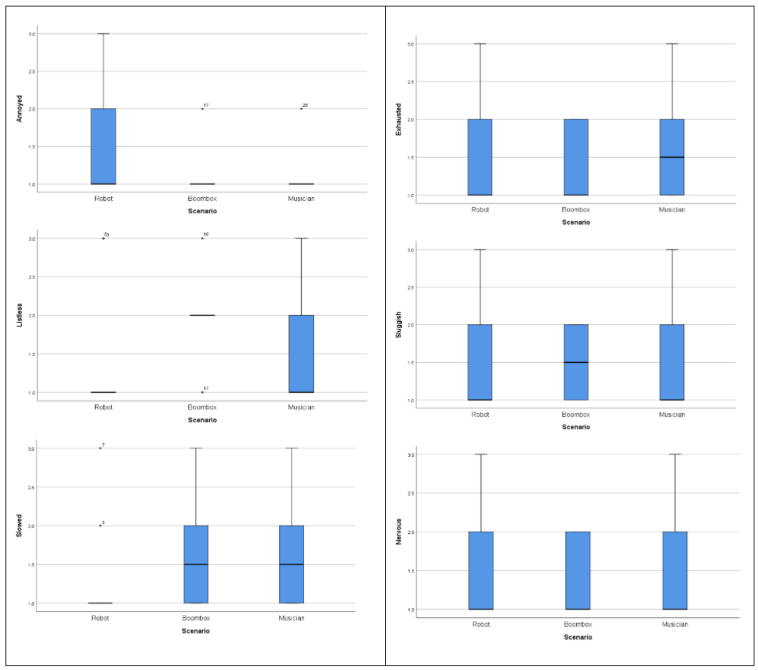


Figure 5.14: Box plot of experienced emotion after experiment

of ANOVA and Tukey post hoc tests showed that cheerful emotions in the musician scenario were higher than in the robot scenario. They resulted in a value of p=0.003, which is below 0.05, which means that the only statistically significant difference F(2,28)= 7.14 was for cheerful emotions. There was no statistically significant difference between the musician and boombox (p=0.071) or boombox and robot scenarios (p=0.716).

The ANOVA and Tukey post hoc tests on emotion and gender, and scenarios and music preference did not show any significant results. However, emotions and age groups showed significant differences for cheerful between age 26-30 and over, angry between age 18-20 and 26-30 and 21-25 and 26-30, exhausted between age 21-25 and over 35, and demoralized and sad between age 21-25 and 26-30, and 26-30 and over 35. The results are summarized in Figure 5.15.

Emotion	ANOVA Results	Ages
Cheerful	F(2,28)=3.41, (p=0.023)	{26-30} and {over 35}
Angry	F(2,28)=6.1,(p=0.001)	{18-20} and {26-30}, {21-25} and {26-30}
Exhausted	F(2,28)=3.30, (p=0.026)	{21-25} and {over 35}
Demoralized and sad	F(2,28)=2.89, (p=0.042)	{21-25} and {26-30}, {26-30} and {over 35}

Figure 5.15: One-way ANOVA on emotion and gender

Chapter 6

Conclusion and Discussion

6.1 Strengths and Limitations

This pilot study shows that while for some participants, nursery rhymes was relaxing for others, it was disturbing. Also, for most of the participants the impact of nursery rhymes on brain waves did not last after the experiment. The results suggest that individuals' brain response to a musician or a robot player is similar. However, the musician's presence might not allow participants to express their emotion. Also the robot might distract the participants so instead of focusing on the songs the robot might catch participants' attention.

One of the limitations was the accuracy of the data collected. It is important to ensure that the EEG device is collecting legible data with few artifacts. In the current study, a significant amount of data (data of 10 participants) was lost because of too many artifacts and malfunction of the headset or software. Another limitation was that participants may have been biased because they knew they were being observed as part of the study; thus, we may not have noticed the expected trend in the data. Using an EEG device for gathering the brain data during passive or engaged listening may not be good. When participants are engaged, they move their body parts and even small movements can easily be considered as an artifact and have a negative impact on the quality of recorded EEG. Therefore, during the EEG data acquisition it is very important to ask subjects to be in a relaxed and non-movement state. Further, it is necessary to make sure that individuals are attentive otherwise; it may have a negative impact on EEG signals. Another main limitation is to consider Individuals' preference, past memories, and culture. Having a chance to pick the music genre may have a different impact on the brain state. If the music genre is not the favorite one, it may not change brain wave activities. This means that listening to the preferred music can balance brain waves or even relax the mind in comparison to disliked music. Associated memory with the selected music can put the brain in a relaxed (increase in alpha waves and decrease in beta waves) or disturb (increase in beta waves and decrease in alpha waves) state.

The outcomes indicated that none of these three scenarios clearly increased the individuals' comfort and relaxation levels. Although Pearson correlation coefficients showed positive correlations for the EDA data, some negative correlations for mostly the boombox were noticed for the HRV data. This may have happened because the number of participants in this scenario was much lower than that in the other two scenarios. Individuals' sensor data and their responses to the questionnaires indicated that many, but not all of the results aligned with our hypothesis that "Exposure to the nursery rhymes can make individuals calmer and more relaxed.

The results of both sensors and the questionnaires may be misleading because the number of participants in each scenario was not equal. To determine statistically significant results, further testing needs to be performed with a larger population. It also is important to make sure participants in all of the scenarios have similar characteristics such as age and gender. It may be useful to utilize the boombox for the control group, as it may yield relevant and useful correlations between the musician and the robot. In general, the outcomes of the signals and questionnaires expressed that while listening to nursery rhymes can mitigate some individuals in each scenario, it made others anxious, exhausted or listless.

6.2 Future work

Music therapy finds its meaning when the selected music is the individual's favorite music. For future study, it is suggested to play music based on individual music preferences. Additionally, it is crucial to put participants' brains in a relaxed situation before any data collection. This study also suggests that to draw a general conclusion it is necessary to consider the impact of music on the brain long-term and on a larger scale.

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Appendix A

A.1 Music Preference Questionnaire

Music Preference Questionnaire-2

What is your gender?

- ☐ Female
- ☐ male

What is your age?

- ☐ 18-20
- ☐ 31-35
- ☐ 21-25
- ☐ 35 and older
- ☐ 26-30

How many hours do you spend listening to music per day?

- ☐ Less than one hour
- ☐ 1-2 hour
- ☐ 3-4 hours
- ☐ More than 4 hours

Where do you most listen to music?

- ☐ At home
- ☐ While exercising
- ☐ In the car
- ☐ At a party
- ☐ At work
- ☐ With friends
- ☐ Other (Please specify)

Choose the top three genres of music that you listen to most often

- ☐ Classical/Instrumental
- ☐ Metal
- ☐ Country
- ☐ Alternative/Folk
- ☐ Christian
- ☐ Jazz
- ☐ Pop
- ☐ Blues
- ☐ Classic Rock
- ☐ Broadway
- ☐ Heavy metal
- ☐ Funk
- ☐ Rap/ Hip Hop
- ☐ Other (Please specify)

Music Preference Questionnaire-2

In what ways do you listen to music?

- ☐ Spotify
- ☐ Sound Cloud
- ☐ I-Tunes/Music Purchasing Apps
- ☐ IPod/MP3 Player
- ☐ MTV
- ☐ Youtube
- ☐ Radio
- ☐ I Heart Radio
- ☐ Pandora
- ☐ Other music websites
- ☐ Music channels on TV
- ☐ Other
- ☐ I don't listen to music
- ☐ CDs
- ☐ Cassettes

Which of the following devices do you own for listening to music?

- ☐ Ipod
- ☐ MP3 Player
- ☐ IPhone
- ☐ IPad
- ☐ Television
- ☐ CD Player
- ☐ Walkman
- ☐ Tablet(not apple)
- ☐ Smartphone(not apple)
- ☐ Laptop
- ☐ Radio
- ☐ Cassette Player
- ☐ Other
- ☐ I don't listen to music

How open are you to listening to new music?

- ☐ Not at all
- ☐ I'm not bothered either way.
- ☐ I am very open to new music.

Music Preference Questionnaire-2

What's your favorite thing about music?

- ☐ It gets me through rough times
- ☐ It makes happy times even happier!
- ☐ It's fun to dance too
- ☐ I love to sing to it!
- ☐ I love to learn to play it on an instrument!
- ☐ It's so fun to jam out to in the car
- ☐ It makes parties way better
- ☐ It's a fun hobby
- ☐ Learning all the lyrics is so fun
- ☐ I don't know, I just love it!
- ☐ I'm not a big fan of music
- ☐ Music inspires me to do bigger and better things
- ☐ Music allows me to express myself
- ☐ It calms me down
- ☐ It wakes me up
- ☐ Other

Music Preference Questionnaire-2

Please indicate your basic preference for each of the following genres using the scale provided.

--------1---------------2-------------3----------------4----------------5-----------------6-----------------7-------

1	2	3	4	5	6	7
Dislike Strongly	Dislike Moderately	Dislike a Little	Neither like nor dislike	Like a little	Like Moderately	Like Strongly

- ☐ Alternative
- ☐ Bluegrass
- ☐ Blues
- ☐ Classical
- ☐ Country
- ☐ Dance/Electronica
- ☐ Folk
- ☐ Funk
- ☐ Gospel
- ☐ Heavy Metal
- ☐ World
- ☐ Jazz
- ☐ New Age
- ☐ Oldies
- ☐ Opera
- ☐ Pop
- ☐ Punk
- ☐ Rap/hip-hop
- ☐ Reggae
- ☐ Religious
- ☐ Rock
- ☐ Soul/R&B
- ☐ Soundtracks/theme song

A.2 POMS- Profile of Mood States Questionnaire

POMS- Profile of Mood States Questionnaire

On a scale of 1 to 5 rate how you are feeling now

1: Slightly or not at al, 2: A little, 3: Moderately, 4: Quite a bit, 5: Extremely
VIG = Vigour, **ANG** = Anger, **FAT** = Fatigue, **DEP** = Depression, **CON** = Confusion

Emotion	1	2	3	4	5
Lively	VIG				
Energetic	VIG				
Cheerful	VIG				
Alert	VIG				
Active	VIG				
Nervous	TEN				
Angry	ANG				
Annoyed	ANG				
Spiteful	DEP				
Furious	ANG				
Listless	FAT				
Exhausted	FAT				
Sluggish	FAT				
Worn out	FAT				
Fatigued	FAT				
Slowed	FAT				
Happy	VIG				
Demoralized and sad	DEP				
Calm and relaxed	VIG				
Anxious	TEN				

A.3 Data analysis code

```
/*---------------------EEG Signal Seperation---------------------*/

my_data_B= xlsread('URL');
my_data_M= xlsread('URL');
my_data_A= xlsread('URL');

[rows, columns] = size(my_data_B);

for k = 1:rows
  myfilename = sprintf('B%d.xlsx', k);
  xlswrite(myfilename,my_data_B(k,:));
end

for k = 1:rows
  myfilename = sprintf('M%d.xlsx', k);
  xlswrite(myfilename,my_data_M(k,:));
end

for k = 1:rows
  myfilename = sprintf('A%d.xlsx', k);
  xlswrite(myfilename,my_data_M(k,:));
end

/*-------------EEG after experiment data combination------------*/

 num_files = 5 ;
max = 0;

% finding maximum number of column-After Music Data
for k = 1:num_files
    filename = sprintf('filename%d.xlsx', k);
    %disp(filename);
    num = xlsread(filename);
    [rows, columns]=size(num);
    %disp(columns);
    if columns> max
        max = columns;
    end
end
```

```

% Fixing the size of each excel file
for k = 1:num_files
    mydata = xlsread(sprintf('filename%d.xlsx', k));
    [rows, columns]=size(mydata);
    if columns ~= max
        zero_column = zeros(14,max-columns);
        new_data = [mydata, zero_column];
        %disp(new_data);
        xlswrite(sprintf('filename%d.xlsx', k),new_data);
    end
end

%Calculating sum of each rows of all excel files
 for k = 1:num_files
    filename = sprintf('filename%d.xlsx', k) ;
    num = xlsread(filename) ;
    if k == 1
       temp = num ;
    else
       temp = temp + num ;
    end
 end
 xlswrite('URL',temp/num_files);

/*--------------------EEG data analysis using Wavelet----------------*/

wname = 'coif4';    % wname is wavelet name
i = 6;
my_data= xlsread('URL');

%Returns the wavelet decomposition of the 'my_data' at level '4' using wname
[C,L] = wavedec(my_data,4,wname);

%Extract the detail coefficients from the decomposition.
[cd1,cd2,cd3,cd4] = detcoef(C,L,[1 2 3 4]);

%Find maximum column size of detail coefficients
max = numel(cd1);
```

```
if numel(cd2) > max
    max = numel(cd2)
elseif numel(cd3) > max
    max = numel(cd3)
elseif numel(cd4) > max
    max = numel(cd4)
end

% Fixing the size of each detail coefficients
if numel(cd1) ~= max
    zero_column = zeros(1,max-numel(cd1));
    cd1 = [cd1, zero_column];
end

if numel(cd2) ~= max
    zero_column = zeros(1,max-numel(cd2));
    cd2 = [cd2, zero_column];
end

if numel(cd3) ~= max
    zero_column = zeros(1,max-numel(cd3));
    cd3 = [cd3, zero_column];
end

if numel(cd4) ~= max
    zero_column = zeros(1,max-numel(cd4));
    cd4 = [cd4, zero_column];
end

%Reconstruct the approximation signals and coefficient signals at all level
A1 =  wrcoef('a',C,L,wname,1);
A2 =  wrcoef('a',C,L,wname,2);
A3 =  wrcoef('a',C,L,wname,3);
A4 =  wrcoef('a',C,L,wname,4);
D1 =  wrcoef('d',C,L,wname,1);
D2 =  wrcoef('d',C,L,wname,2);
D3 =  wrcoef('d',C,L,wname,3);
D4 =  wrcoef('d',C,L,wname,4);
```

```
sheet = i;
xlRange = 'A1';
xlswrite('URL',A1,sheet,xlRange);
xlRange = 'A2';
xlswrite('URL',A2,sheet,xlRange);
xlRange = 'A3';
xlswrite('URL',A3,sheet,xlRange);
xlRange = 'A4';
xlswrite('URL',A4,sheet,xlRange);

xlRange = 'A5';
xlswrite('URL',D1,sheet,xlRange);
xlRange = 'A6';
xlswrite('URL',D2,sheet,xlRange);
xlRange = 'A7';
xlswrite('URL',D3,sheet,xlRange);
xlRange = 'A8';
xlswrite('URL',D4,sheet,xlRange);

xlRange = 'A9';
xlswrite('URL',cd1,sheet,xlRange);
xlRange = 'A10';
xlswrite('URL',cd2,sheet,xlRange);
xlRange = 'A11';
xlswrite('URL',cd3,sheet,xlRange);
xlRange = 'A12';
xlswrite('URL',cd4,sheet,xlRange);
%}

/***********************************************************************/
/*---------------------EDA time stamp---------------------*/
%timestamp=1537379731;
sample = 4;
filename = '/Users/mahsa/Documents/ThesisData/Music_e4/004/part2/EDA.csv';
newfile = '/Users/mahsa/Documents/ThesisData/Music_e4/004/part2/EDA_t.csv';

%read the CSV file
```

```
d = csvread(filename);
disp(size(d));
m = d;

timestamp = m(1);
z = zeros(length(d),1);
count = 0;

%for i = 3 : length(d)
for i = 4 : length(d)
    count = count + 1;
    z(i,1) = timestamp;
    if count == 4
        timestamp = timestamp + 1;
        count = 0;
    end
end
f = [m z];

dlmwrite(newfile,f,'precision',12)


/*---------------EDA data seperation and analysis----------------*/
%Base
load('EDA_b.mat')
phasic_b = analysis.phasicData;
tonic_b =  analysis.tonicData;

%Music
load('EDA_1.mat')
phasic_m = analysis.phasicData;
tonic_m =  analysis.tonicData;

%After
load('EDA_2.mat')
phasic_a = analysis.phasicData;
tonic_a =  analysis.tonicData;
```

```
% Feature Extraction
%Mean
mean_phasic_b = mean(phasic_b);
mean_tonic_b = mean(tonic_b);
mean_phasic_m = mean(phasic_m);
mean_tonic_m = mean(tonic_m);
mean_phasic_a = mean(phasic_a);
mean_tonic_a = mean(tonic_a);

%Max
max_phasic_b = max(phasic_b);
max_tonic_b = max(tonic_b);
max_phasic_m = max(phasic_m);
max_tonic_m = max(tonic_m);
max_phasic_a = max(phasic_a);
max_tonic_a = max(tonic_a);

%std
std_phasic_b = std(phasic_b);
std_tonic_b = std(tonic_b);
std_phasic_m = std(phasic_m);
std_tonic_m = std(tonic_m);
std_phasic_a = std(phasic_a);
std_tonic_a = std(tonic_a);

results = [mean_tonic_b,mean_tonic_m,mean_tonic_a,...
           mean_phasic_b,mean_phasic_m,mean_phasic_a,...
           max_tonic_b,max_tonic_m,max_tonic_a,...
           max_phasic_b,max_phasic_m,max_phasic_a,...
           std_tonic_b,std_tonic_m,std_tonic_a,...
           std_phasic_b,std_phasic_m,std_phasic_a];

dlmwrite('Robot.csv',results,'-append');
```