Mood Detection and Memory Performance Evaluation with Body Sensors

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DEDICATION

This document is dedicated to the graduate students of the McGill University.

ACKNOWLEDGEMENTS

The list of people I would like to thank for their invaluable help and support is very long. Everyone who helped in the making of this project deserves credit. Without their precious help and support, I would not be able to accomplish such a great task. First of all, I would like to thank my parents for their time and dedication. My parents helped me prepare the experiment tests which would assess how effective is my application at detecting the mood and mental performance of individuals. They also gave me advice on how to improve my Android application so every user of that application could understand it and have no trouble using it in their daily lives. Giving their time and effort, they taught me that nothing is impossible without serious efforts, hard work, and strict discipline. Following their advice at all times, I was successful and my work made them proud. I would like to thank my sister for her knowledge and contribution to this project. The time she gave to this project was invaluable, and her help was crucial. Her knowledge in the field of medicine proved to be invaluable and her advice is the reason my project is complete, clear, and concise. Furthermore, I would like to thank my supervisor Professor Zilic for his knowledge, his help, his support, and his guidance. The course he taught me, VLSI Testing, which is about Android programming, is what inspired and motivated me to work on that project. This course which he taught me gave me the knowledge and tools I needed to create my first "mood detection and memory evaluation" application and to start writing my thesis on it. I am thankful for his help and his guidance which is the reason my project could be completed. At last, I would like to thank a friend and a student, Andrey Tolstikhin, for his idea on building an application capable of detecting the mood and memory performance of every individual. This idea is brilliant and is the reason I am now writing my thesis on that topic. Finally, I would like to thank all family, friends, and colleagues who participated in my experiment. Without their help, a critical part of my thesis would have been missing and my thesis work would have been incomplete. At last, I would like to thank the internet community, in particular the Stack Overflow community for providing me with invaluable knowledge and tools required to create my application and write my thesis. The academic world has become a better place with their help and knowledge and they play a fundamental role in the writing of my thesis.

ABSTRACT

This thesis provides the design of a system employing an Android application connected to body sensors, which is capable of assessing the mood and memory performance of humans. The mood detection is based on the heart rate, its variability, as well as on the captured brain waves. The memory performance is evaluated based on specific brain waves observed as well. The application requires the connection of sensors to an Android device to obtain data. Sensors for the heart and brain were used along with the Android device to obtain data. The Sensors are connected to the Android device via Bluetooth Low Energy. Data was gathered and processed from these sensors using clever algorithms. Data was filtered using the right filters, a Hanning window was applied to it, and finally the fast Fourier transform was computed to provide data for a range of frequencies.

The application was tested to assess how effective it was at finding the mood and memory performance levels of humans. To do so, we selected an adult population consisting of male and female individuals. The tests consisted of visual and auditory stimuli which drived the users to a particular mood such as sad, relaxed, angry, engaged, aroused, happy, and stressed. Furthermore, a short memory test was given to assess the memory performance level of each user.

The mood experiment has been successful at raising the mood levels of the majority of participants when being shown stimuli composed of images and sounds. Negative or neutral mood levels could be explained by participants having other thoughts or emotions during the experiment, and by the attenuation and dampening of the body

sensors' signals. The ability of participants to reach a particular mood (relaxed, engaged, sad) more quickly in response to a conducive stimulus is related to a person's physical characteristics; for example, younger participants reach a particular mood more quickly than older participants. The memory experiment has been successful at raising the memory levels of the majority of participants when being asked to perform a modified Sternberg memory task. Results show a positive memory activity for the majority of participants, even in the presence of signal attenuation in the body sensors.

ABRÉGÉ

Cette thèse fournit la conception d'une application Android capable de mesurer l'humeur et la performance de la mémoire de toute personne humaine. Cette application est destinée à un usage médical et à la recherche. L'application est conçue pour être facile à utiliser, rapide et fiable pour les utilisateurs de tous sexes et âges. L'application a de nombreuses fonctions utiles, comme la détection de l'humeur, l'évaluation de la performance de la mémoire, une section historique de l'humeur qui nous donne les valeurs en pourcentage de l'humeur (triste, heureux, calme) et de la performance de la mémoire, une section conseils de l'humeur qui donne à l'utilisateur des informations utiles relatives à élever les niveaux de bonne humeur et à diminuer les niveaux de mauvaise humeur, une section journal où l'utilisateur peut écrire au sujet de son humeur et assurer le suivi de cette information, une section pour comparer l'humeur et la performance de la mémoire de l'utilisateur courant aux niveaux d'humeur et de performances de la mémoire appartenant à d'autres utilisateurs, une section pour tracer le graphe de l'humeur et de la performance de la mémoire pour l'utilisateur courant, une section pour définir les objectifs de l'humeur et la performance de la mémoire pour une certaine période de temps, une section pour vérifier toutes les informations personnelles de l'utilisateur, et enfin une section pour écouter de la musique qui réjouit le coeur.

L'application nécessite le raccordement de capteurs à un appareil Android en vue d'obtenir des données. Des capteurs pour le coeur et pour le cerveau seront utilisés avec l'appareil Android (smartphone ou tablette) afin d'obtenir des données. Les

capteurs sont connectés à l'appareil Android via Bluetooth Smart et/ou Bluetooth Low Energy. Les données seront recueillies et traitées à partir de ces capteurs à l'aide d'algorithmes astucieux. Les données seront filtrées, une fenêtre de Hanning sera appliquée aux données, et enfin la transformation rapide de Fourier sera calculée de sorte que nous puissions avoir les données pour une gamme de fréquences.

L'application permettra également de faire usage de la boite d'envoi de données vers le Cloud ou sur le Web. L'API (application programming interface) utilisé dans ce cas est le Dropbox Core API. Il fournit un moyen flexible de lire et d'écrire sur Dropbox. Il inclut la prise en charge des fonctionnalités avancées telles que la recherche, la révision et la restauration de fichiers.

Enfin, l'application sera testée pour évaluer comment elle est efficace à trouver l'humeur et la performance de la mémoire de toute personne humaine. Pour ce faire, nous sélectionnons une population adulte composée d'individus mâles et femelles. Les tests se composeront de stimuli visuels et auditifs qui conduiront les utilisateurs à une ambiance particulière comme triste, détendue, en colère, engagée, suscitée, heureuse et soulignée. En outre, un court test de mémoire sera donné pour évaluer le niveau de performance de la mémoire de chaque utilisateur. Les résultats obtenus pour chaque personne pendant l'expérience sont importants puisqu'ils indiqueront si une personne nécessite un type quelconque de traitement et/ou des médicaments pour troubles de stress, troubles anxieux, dépression, la perte de mémoire ou la maladie d'Alzheimer, et plus.

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CHAPTER 1
Introduction

Mood detectors can identify trends pointing to a person's mood. Mood detectors can be found in modern computers, laptops, smartphones, tablets, sensors such as skin sensors, electroencephalography sensors, and voice recognition sensors. Thanks to existing technology, they can be carried everywhere and accessed anytime. Furthermore, these devices feature lower costs, high speed, low power consumption, and many other benefits for the subject, clinician or researcher.

Mood detectors can be integrated in our daily lives, such as when driving a car. The driver might feel stressed and tired when driving long distances. A car with sensors can understand the driver's emotion and feelings and prevent an accident, which could save many lives. Sensors could nest in the steering wheel and door handles to pick up electric signals from the skin. A camera mounted on the windshield could analyze facial expressions. When the driver is stressed, the car sensors could soften the light and music, or broaden the headlight beams to compensate for the loss of vision.

The importance of mood detection has been increasingly recognized because it could prevent mood disorders from affecting us and harming us in our daily lives. Mood disorders include depression and bipolar disorders. Anyone can be affected from mood disorders: Children, teenagers, adults, and the elderly. Stressful events in our lives can result in transitory depression, or any of several mood disorders.

Symptoms include being sad, anxious, hopeless, helpless, and having low self-esteem. These symptoms can be overcome with the knowledge of one's current mood by using the above-mentioned devices and taking the right actions, such as a psychiatric consultation and/or the commencement of medication.

Memory loss can be detected in many ways: Using brain sensors, taking memory tests, noticing difficulty in completing a familiar task, noticing confusion with time and place, and noticing changes in mood and personality. Early memory-loss detection helps ensure that maximum benefit can be derived from the available treatments, provides more time to plan for the future, and helps the patient and his/her loved ones. Much memory loss can be cured through early detection by using the methods described above and by scheduling an appointment with a physician. Practitioners of neurology, psychiatry, psychology, and geriatrics should be consulted for this purpose.

1.1 System Features

Mood detection is a growing and rapidly developing field. Many existing devices can approximate one's current mood. Devices such as wrist sensors can provide information on stress levels when worn. They can communicate this information via the internet. For example, a sensor worn on a child's wrist might detect that the child is stressed. The stress signal is communicated via the internet and the parent can see on his/her smartphone that the child is stressed, thereby enabling the parent to take action to reduce that stress level.

In recent years, many applications for smartphones and tablets capable of telling a person his/her mood have been released. Samsung has developed a smartphone that can tell your mood based on how you are using the phone. For example, it monitors the speed at which the user is typing some text, and how much the device shakes. The "mood detection and memory evaluation" Android application combines many of the features from the above mentioned applications:

- The system requires Bluetooth Low Energy in order to work.
- Mood is measured using brain and heart sensors, so it is very accurate.
- Mood data and user data is sent to the Web on a Dropbox Web Server, which is safe and secure.
- Mood data can be compared between users.
- Mood data for each user can be graphed, so it is easy for the user to compare his/her mood on a daily basis.

1.2 Thesis Organization

The thesis document is organized as follows: Chapter 2 discusses existing related work done by others on that topic. Chapter 3 talks about essential background information the reader needs to know about such as how the human brain works, information on resting heart rate and heart rate variability, information on sensors used, information on the valence/arousal model used to classify different moods such as happy, sad, angry, and relaxed. Chapter 4 talks about the software design of the Android application. A diagram shows how every component of the application interacts with other components. All features that this application has to offer are discussed in detail. Furthermore, mood and memory performance algorithms used to evaluate the mental health of individuals, the Bluetooth Low Energy protocol used to communicate data between the Android device and the external sensors, and the application libraries used to create such an application are discussed in length in this chapter. Chapter 5 discusses the procedure done to extract the mood and memory performance level of male and female individuals, all adults. Furthermore, it discusses how heart rate and EEG (electroencephalogram) data was processed and analyzed to obtain meaningful results. At last, it shows the results of the experiment in the form of graphs and a discussion of the results is formed based on these findings. Finally, Chapter 6 concludes on the thesis work and speculates on the future of this growing field.

CHAPTER 2
Related Work

Mood detection and memory evaluation are not entirely new concepts, but have been more developed in this thesis than prior works. There are many devices (software and hardware) available to the user that can detect mood and/or evaluate the user's memory. They are going to be discussed in this section of my thesis.

2.1 Mood Detection

2.1.1 Mood Detection From Facial Expressions

- Project Oxford from Microsoft features an online application capable of recognizing different emotions given facial expressions in any image. Emotions such as anger, contempt, disgust, fear, happiness, neutral, sadness, and surprised can be recognized from a given image. Please note that the supported image format are: JPEG, PNG, GIF, and BMP. [34]
- Noldus, a company that develops and delivers innovative software and hardware solutions for the measurement and analysis of behavior, made a new application called NRGY which measures the user's physical, mental, and emotional energy level, all within 90 seconds. This application is available for download at their website. [35]

2.1.2 Mood Detection From Voice Input

- Researchers from the University of Michigan developed an application that monitors a person's voice during phone calls to detect mood changes in people who have bipolar disorder. This application is called PRIORI.[36]
- EmoVoice, an application that has been developed by students from the Augsburg University, can recognize emotions from speech. The process works as follows: First, we extract the raw audio content which is the speech of the user. Then, we extract the features of this raw speech using smart algorithms. Finally, we classify the user's processed speech into emotions. The application can be downloaded directly from university's website.[37]

2.1.3 Mood Detection From Skin

- A new device developed by Affectiva, based in Waltham, Massachusetts, detects and records physiological signs of stress and excitement by measuring slight electrical changes in the skin. It is a wristband sensor, with a Q sensor that measures skin conductance, temperature, and motion to record a wearer's reaction to events. People can keep track of stress during everyday activities. The Q sensor stores or transmits a wearer's stress level throughout the day, giving doctors, caregivers and patients a way to monitor or keep track of the wearer's reactions.[38]
- Three graduate students the Deusto Institute of Technology, María Viqueira Villarejo, Begoña García Zapirain, and Amaia Méndez Zorrilla, developed a stress sensor based on galvanic skin response controlled by Zigbee. This sensor uses just two electrodes which are placed on the fingers. The stress sensor can

be used provided that the user is at a distance of less than 10 meters from the wireless receiver. [39]

2.1.4 Mood Detection From Heart

- The Zensorium Company developed a smartwatch that can monitor your mood every hour. In addition to monitoring the number of steps, calories, distance, and sleep tracking, it tells your mood by measuring your heart rate. With this device, you can know when you are distressed, excited, normal and calm. The smartwatch can also differentiate between "good stress" and "bad stress". [40]
- The Inner Balance Company has developed an application along with a sensor that can monitor your heart rate activity and your stress level. The sensor is a HeartMath Sensor for iOS which works only for iPhone, iPad, or iPod. The sensor's ear piece must be placed on your ear and the sensor must be connected to the iOS device. The ear sensor is used to capture your heart rate variability data, which is useful in determining your heart rhythm patterns. [41]

2.1.5 Mood Detection From Brain

- The Neurowear Company is developing a project called "mico" which consists of a headphone and an application for the iPhone. The headphone detects brainwaves through the sensors on the user's forehead. The application automatically analyzes the user's condition of the brain, and searches for music that best matches the user's current brain condition. [42]
- The InteraXon Company developed a headband called "Muse" which when placed on your forehead can read your brainwaves. It is meant to track your mood, picking up indications of focus, concentration, and stress. The "Muse"

application is available for both Android and iOS devices. This application monitors your current state such as active, neutral, or calm. It helps you relax and meditate. [43]

2.1.6 Mood Detection From Eye Blinks

- To increase excitement and stress detection accuracy, scientists consider measuring facial muscle activity through EMG (Electromyography), which detects the electrical discharges caused by contractions of muscle fibers such as the orbicularis oculi muscle located around the eye and responsible for blinking and winking, and contracting when smiling. An experiment was carried out by Riccardo Sioni and Luca Chittaro of the University of Udine where the facial muscle activity of two groups of users was measured when exposed to two different virtual environments. The first group was exposed to a low-stress and high-stress version of a virtual environment reproducing a multi floor school building. The second group navigated a low-stress and a high-stress version of a virtual environment reproducing a train station. The high-stress version of the school building simulated a fire emergency and the high-stress version of the train station simulated a terrorist attack. Results show that for both virtual environments, the mean EMG value for the facial muscle was higher when users experienced the high-stress version as compared to when they experienced the low-stress version. These results indicate that more stressful experiences elicited more intense negative emotions.[57]
- M. Haak, S.Bos, S.Panic, and L.J.M.Rothkrantz from the Delft University of Technology performed an experiment which measured the stress level of

participants who participated in a car driving simulation. Stressful emotions were triggered while the participants were driving through steep curves and attention seeking billboards. The eye blink frequency of participants is directly related to experienced stress, so a higher frequency of eye blinks is found in stressful situations. Eye blinks were detected using EEG. [58]

2.1.7 Mood Detection From Motion

- Rajesh Verma, a student of the department of Computer Application from the International Institute of Professional Studies, developed an approach for monitoring user's mood via smartphone usage. User's mood is analyzed by extracting the smartphone accelerometer data, which is then processed and classified into different moods. [44]
- Microsoft developed an application called MoodScope that detects the user's mood. This lightweight application is available for iOS and Android smartphones and makes use of the smartphone's internal sensors such as the accelerometer and gyroscope sensors to measure the user's motion and to decide on the user's current mood. This application also monitors phone calls, emails, text messages, browsing history, and geographic location. [45]

2.2 Memory Evaluation

2.2.1 Memory Evaluation From fMRI

fMRI (Functional Magnetic Resonance Imaging) is a functional neuroimaging procedure using MRI technology that measures brain activity by detecting changes associated with blood flow. [47]

A group of students from Tehran University worked on a project which consisted of localizing hippocampus activation during a memory task using fMRI (Functional Magnetic Resonance Imaging). The hippocampus is one of the brain structures responsible for episodic memory. Episodic memory is a type of long term memory which refers to the encoding, storage, and retrieval of recently experienced events. fMRI is a promising technique to examine brain cognitive functions such as memory. For example, for patients with TLE (Temporal Lobe Epilepsy) evaluation of memory function is important before performing the surgery. [46]

2.2.2 Memory Evaluation From rTMS

rTMS (repetitive transcranial magnetic simulation) is a non-invasive method used to stimulate small regions of the brain. rTMS can be used to evaluate damage from stroke, multiple sclerosis, and more. [47]

Massihullah Hamidi, Giulio Tononi, and Bradley R. Postle from the University of Wisconsin-Madison worked on a project which consisted of evaluating frontal and parietal contribution to spatial working memory with rTMS (repetitive transcranial magnetic simulation). A short term memory task was given to participants and rTMS was used to stimulate the activity of brain areas such as the dorsolateral prefrontal cortex, frontal eye fields, superior parietal lobule, and intraparietal sulcus. [48]

2.2.3 Memory Evaluation From MEG

MEG (Magnetoencephalography) is a functional neuroimaging technique for mapping brain activity by recording magnetic fields produced by electrical currents occurring naturally in the brain, using very sensitive magnetometers. [47]

Students from Université de Montréal used MEG to localize and lateralize verbal memory in patients with epilepsy. Areas in the brain such as the frontal lobe and the temporal lobe were analyzed. [49]

2.2.4 Memory Evaluation From EEG

EEG (Electroencephalography) is an electrophysical monitoring method used to record the electrical activity of the brain. [47]

Pega Zarjam, Julien Epps, and Fang Chen from the University of New South Wales, worked on a project which consisted of evaluating the working memory load using EEG signals. Mental workload is evaluated using statistical features such as mean, root mean, and correlation-based features derived from EEG signals. [50]

CHAPTER 3
Background Information

This chapter discusses important background information the reader needs to be aware of in order to understand the procedure of emotion recognition and memory performance assessment from heart and brain data.

3.1 Electroencephalography

Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain. EEG is used to diagnose epilepsy, sleep disorders, coma, encephalopathy, and brain death. [53]

3.1.1 Advantages

Some advantages of using EEG to study brain activity over other methods are:

- Significantly lower hardware costs.
- EEG sensors can be used in more places and have less equipment requirements than other brain sensors.
- EEG has a very high temporal resolution, on the order of milliseconds rather than seconds.
- EEG is relatively tolerant of subject movement and there even exists methods for minimizing, and even eliminating movement artifacts in EEG data.
- EEG is silent, which allows for better study of the responses to auditory stimuli.

- EEG does not involve exposure to high-intensity magnetic fields, as in some other techniques such as MRI.
- EEG can be extremely non-invasive, since electrodes are placed on the surface of the brain.

3.1.2 Disadvantages

Some disadvantages of using EEG to study brain activity compared to other methods are:

- Low spatial resolution of the scalp.
- EEG poorly measures neural activity that occurs below the upper layers of the brain.
- EEG cannot identify specific locations in the brain at which various drugs and neurotransmitters can be found.
- Poor signal-to-noise ratio, so sophisticated data analysis and relatively large numbers of subjects are needed to extract useful information from EEG.
- It often takes a long time to connect a subject to EEG, as it requires precise placement of dozen of electrodes around the head and the use of various gels, saline solutions, and/or pastes to keep them in place.

3.1.3 Electrode Placement Procedure

There are two approaches for capturing EEG signals which differ in the brain layer where the electrodes are placed to capture the signals. These approaches are:

- The invasive approach. Very small electrodes are implanted directly over the cortex during neurosurgery. The advantage of this approach is that it gives very high quality EEG signals. However, it requires surgical operation.

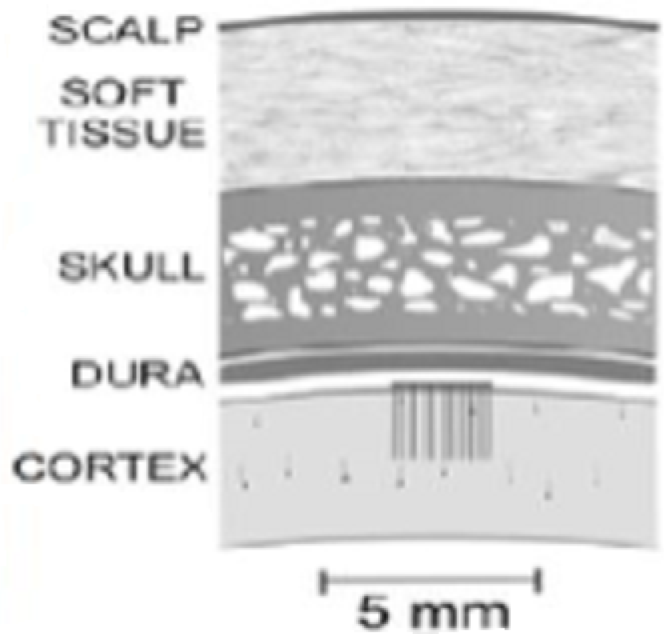

Figure 3–1: Invasive BCI

- The non-invasive approach. Electrodes are placed on the surface of the scalp. The problem with the non-invasive EEG recording is the poor quality of the signals because the skull dampens the signals, dispersing and blurring the electromagnetic waves created by the neurons. Another problem with this approach is the low spatial resolution. It is very difficult to determine the location in the brain from which the signals were sent or the actions of the individual neurons. I will be using the non-invasive approach to recognize emotions and to evaluate the memory performance of individuals.

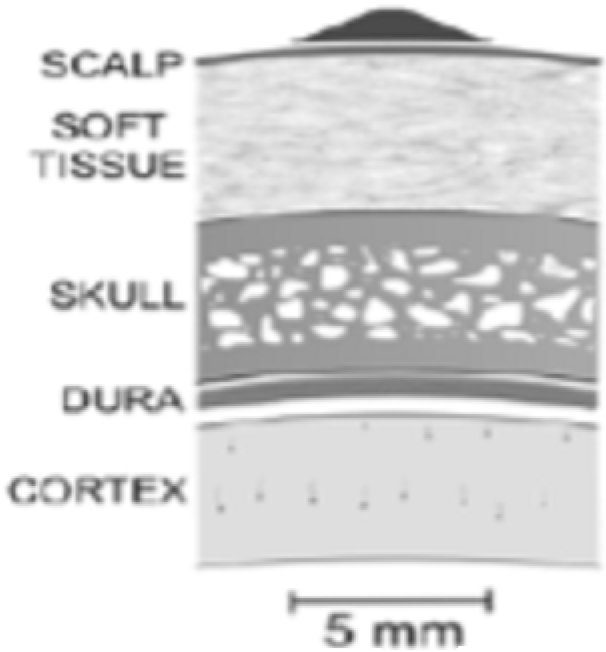

Figure 3–2: Noninvasive BCI

3.1.4 Medical Use

A routine clinical EEG recording involves recording from scalp electrodes and is used:

- To distinguish epileptic seizures from other type of spells (syncope, migraine, etc.).
- To differentiate "organic" encephalopathy or delirium from primary psychiatric syndromes such as catatonia.
- To serve as an adjunct test of brain death.
- To prognosticate, in certain instances, in patients with coma.

- To determine whether to wean anti-epileptic medications.

3.1.5 Research Use

EEG is extensively used in:

- Neuroscience
- Cognitive science
- Cognitive psychology
- Neurolinguistics
- Psychophysiological research

EEG is also used to:

- Detect the cognitive state of individuals such as working memory load. To be able to evaluate successfully the memory performance of individuals, we need many participants and the tests can take a lot of time as a lot of data is required to derive conclusions from findings. We also consider measuring the memory performance in real-time, so we must limit the number of EEG electrodes (less than 32 channels).
- Classify mental tasks such as rest, mathematical calculation, and geometric rotation. EEG "noise" values due to motion and artifacts such as eye movement have to be minimized to classify those mental tasks.
- Detect emotions in humans. A simple model can be used to detect emotions such as excitement, calm, and neutral. A more complex model can be used to detect emotions such as joy, anger, fear, and sorrow. Artifacts such as eye blinks must be removed in order to obtain meaningful data. We must consider using less channels or electrodes if we wish to detect emotions in real-time.

3.2 Human Brainwaves

Brainwaves are produced by synchronized electrical pulses from masses of neurons communicating with each other. They can be detected using sensors placed on the scalp. They are divided into bandwidths to describe their functions. Brainwaves change according to what we are doing and feeling. When slower brainwaves are dominant we can feel tired, slow, sluggish, or dreamy. The higher frequencies are dominant when we feel wired, or hyper-alert. [10]

3.2.1 Delta Waves (0.5 to 3 Hz)

Delta waves are the slowest but loudest brainwaves. They are generated in deepest meditation and dreamless sleep. Delta waves suspend external awareness and are the source of empathy. Healing and regeneration are stimulated in this state.

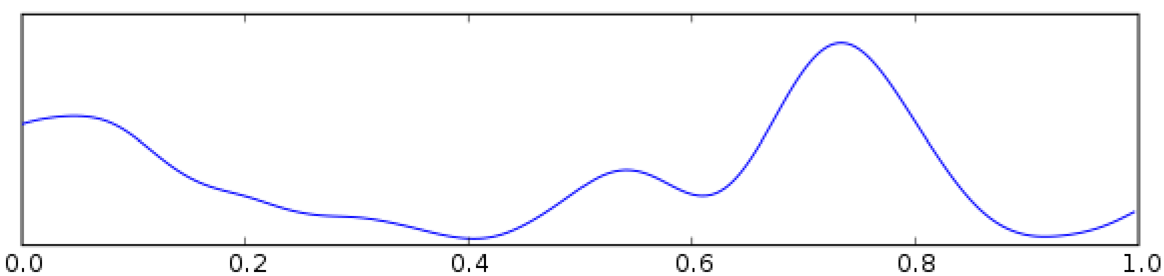

Figure 3–3: Delta Waves

3.2.2 Theta Waves (3 to 8 Hz)

Theta waves occur most often during sleep but are also dominant in deep meditation. They acts as our gateway to learning and memory. Theta waves are present when we dream, have vivid imagination, and hold information. It is where we hold our fears, troubled history, and nightmares.

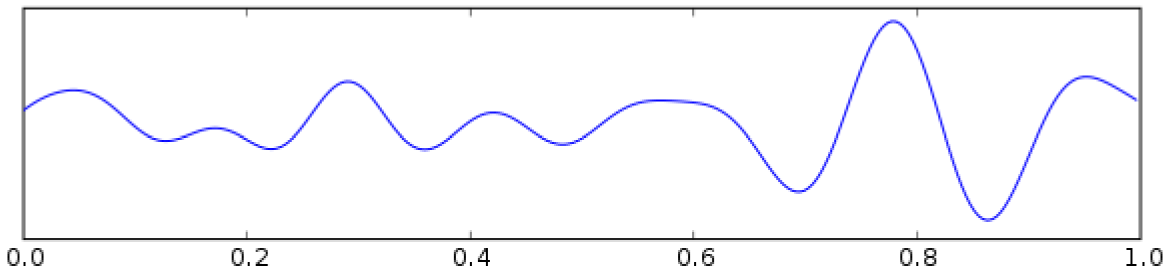

Figure 3–4: Theta Waves

3.2.3 Alpha Waves (8 to 12 Hz)

Alpha waves are dominant during quietly flowing thoughts, and in some meditative states. Alpha is the resting state of the brain. Alpha waves aid overall in mental coordination, calmness, alertness, mind/body integration, and learning.

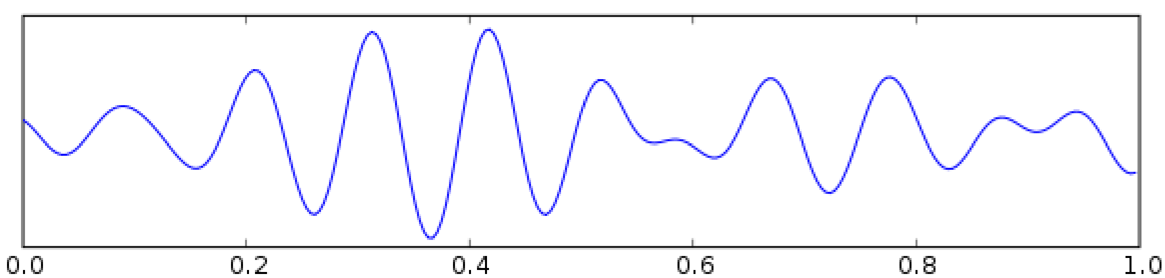

Figure 3–5: Alpha Waves

3.2.4 Beta Waves (12 to 38 Hz)

Beta waves dominate in our normal waking state of consciousness when attention is directed towards cognitive tasks and the outside world. Beta waves are present when we are alert, attentive, engaged in problem solving, judgment, decision making, and engaged in focused mental activity.

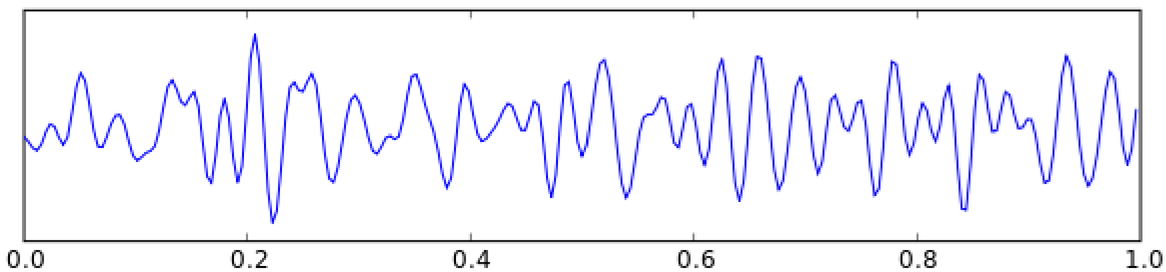

Figure 3–6: Beta Waves

3.2.5 Gamma Waves (38 to 42 Hz)

Gamma waves are the fastest brainwaves, and relate to simultaneous processing of information from different brain areas. Gamma brainwaves are active in states of universal love, altruism, and the 'higher virtues'. Gamma rhythms modulate perception and consciousness, disappearing under anaesthesia. The presence of gamma waves relates to expanded consciousness and spiritual emergence.

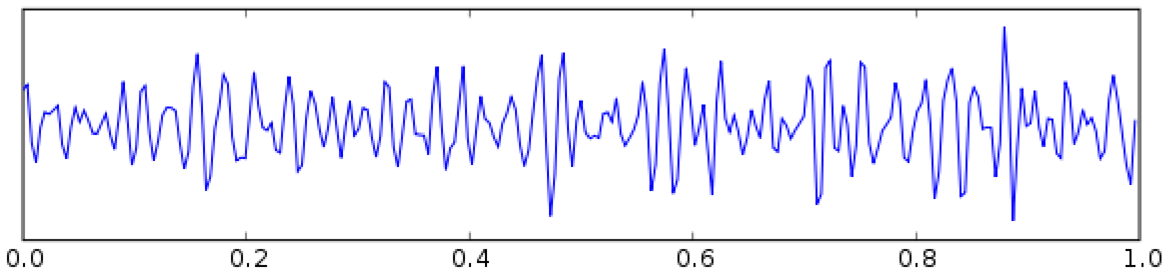

Figure 3–7: Gamma Waves

3.3 Human Brain Structure

The human brain can be identified by three major components:

- The Cerebrum
- The Cerebellum
- The Brainstem

The brainstem controls breathing, digestion, heart rate, and other autonomic processes, as well as connecting the brain with the spinal cord and the rest of the body. [7]

The cerebellum plays an important role in balance, motor control, and is also involved in cognitive functions such as attention, language, emotional functions, and in the processing of procedural memories.

The cerebrum makes up most of the brain weight and volume and is covered by a sheet of neural tissue known as the cerebral cortex. About 90 % of the brain's neurons are located in the cerebral cortex.

The cerebral cortex plays a key role in memory, attention, perceptual awareness, thought, language, and consciousness. It is divided into four main regions or lobes, which cover both brain hemispheres:

- The frontal lobe. It is involved in conscious thought and higher mental functions such as decision making, and plays an important part in processing short-term memories and retaining long-term memories which are not task-based.
- The parietal lobe. It is involved in integrating sensory information from the various senses, and in the manipulation of objects in determining spatial sense and navigation.
- The temporal lobe. It is involved with the senses of smell and sound, the processing of semantics in both speech and vision, including the processing of complex stimuli like faces and scenes, and plays a key role in the formation of long-term memory. The medial temporal lobe contains the hippocampus which is essential for memory function, particularly the transference from short-term and long-term memory and the control of spatial memory and behaviour. The amygdala which is also located in the medial temporal lobe performs a primary role in the processing and memory of emotional reactions and social and sexual behaviour, as well as regulating the sense of smell.
- The occipital lobe. It is involved mainly with the sense of sight.

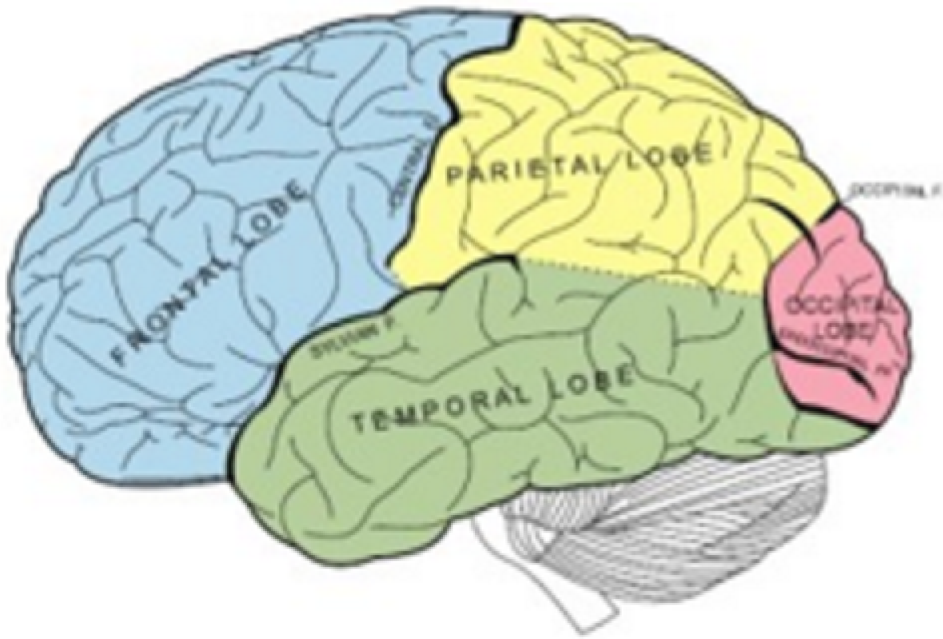

Figure 3–8: Lobes of the Cerebral Cortex

3.4 Resting Heart Rate

The resting heart rate is the heart pumping the lowest amount of blood. If a person is sitting or lying, and is calm, relaxed and in good health, his/her resting heart rate should range between 60 and 100 beats per minute. A heart rate lower than 60 could be explained by a medical condition, taking drugs such as beta blockers, or being physically active and very athletic. Active people often have lower resting heart rates because their heart muscle is in better condition and does not need to work as hard to maintain a steady beat. [26] Other factors that could affect the resting heart rate are:

- Air temperature. When the air temperature and air humidity soar, the heart pumps a little more blood, so pulse may increase, but usually not more than 5 to 10 beats per minute.
- **Emotions. When feeling stressed, anxious, really sad or really happy, emotions such as these can raise or decrease pulse. For example, fear and anger can raise pulse while happiness can decrease pulse.**
- Body size. It does not usually change pulse, but very obese individuals' resting pulse might be higher than normal.
- Medications. Medications that block a human's body adrenaline such as beta blockers tend to slow pulse while too much thyroid medication raises it.

3.5 Heart Rate Variability

Heart rate variability is the degree of fluctuation in the length of intervals between heart beats. A bigger regularity of heart beats lowers HRV and vice versa. Regularity of heart beats is derived from a quantity of numbers equal to the time elapsed between successive heart beats. These are named R-R intervals and are measured in milliseconds (ms).

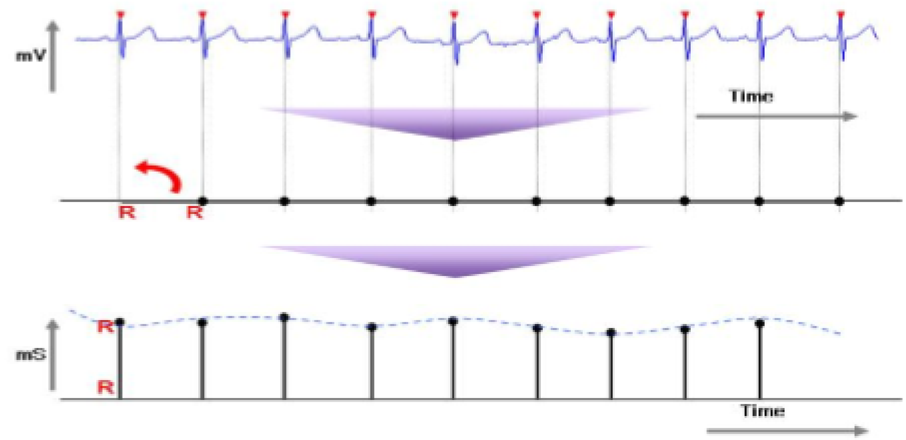

Figure 3–9: R-R intervals and their fluctuations

3.5.1 Time Domain Analysis

HRV can be assessed in two ways: As **Time Domain Analysis**; or, in the frequency domain, as **Power Spectral Density Analysis**. In this document, we will concentrate on **Time Domain Analysis** because it is more simple and straightforward.

Time domain measures are the simplest to calculate and include the mean normal-to-normal (NN) intervals during the entire recording and statistical measures of the variance between NN intervals. The most important time domain measures are the SDNN (HRV), and the RMS-SD.

- The SDNN is the standard deviation of the NN intervals, which is the square root of their variance. A variance is mathematically equivalent to the total power of spectral analysis, so it reflects all cyclic components of the variability in recorded series of NN intervals. It is inappropriate to compare SDNN values derived from the NN recordings of different lengths. A recording can last a short period of time, such as five minutes, or it can last a full 24-hour day. SDNN is measured in milliseconds.

- The RMS-SD is the square root of the mean squared differences of successive NN intervals. This measure estimate high-frequency variations in heart rate in short-term NN recordings that reflect an estimate of parasympathetic regulation of the heart. RMS-SD is measured in milliseconds.

Formulas to calculate these time domain measures are given below:

Let N be the total number of heart beats. Let MRR be the mean of RR (or NN) intervals. It is calculated as follows:

$MRR = \bar{I} = \frac{1}{N-1} \sum_{n=2}^{N} I(n)$

In this formula, I(n) is the value in milliseconds of the nth NN interval. The SDNN or HRV can be expressed as:

$SDNN = \sqrt{\frac{1}{N-1} \sum_{n=2}^{N} [I(n) - \bar{I}]^2}$

Finally, the RMS-SD can be expressed as:

$RMSSD = \sqrt{\frac{1}{N-2} \sum_{n=3}^{N} [I(n) - I(n-1)]^2}$

3.5.2 Usage of HRV

HRV is related to mood detection in that it is mainly used to:

- **Assess the level of physical fitness and stress coping ability.**
- **Confirm the effects of stress relaxation program (massage, exercise, meditation, light therapy, etc.)**

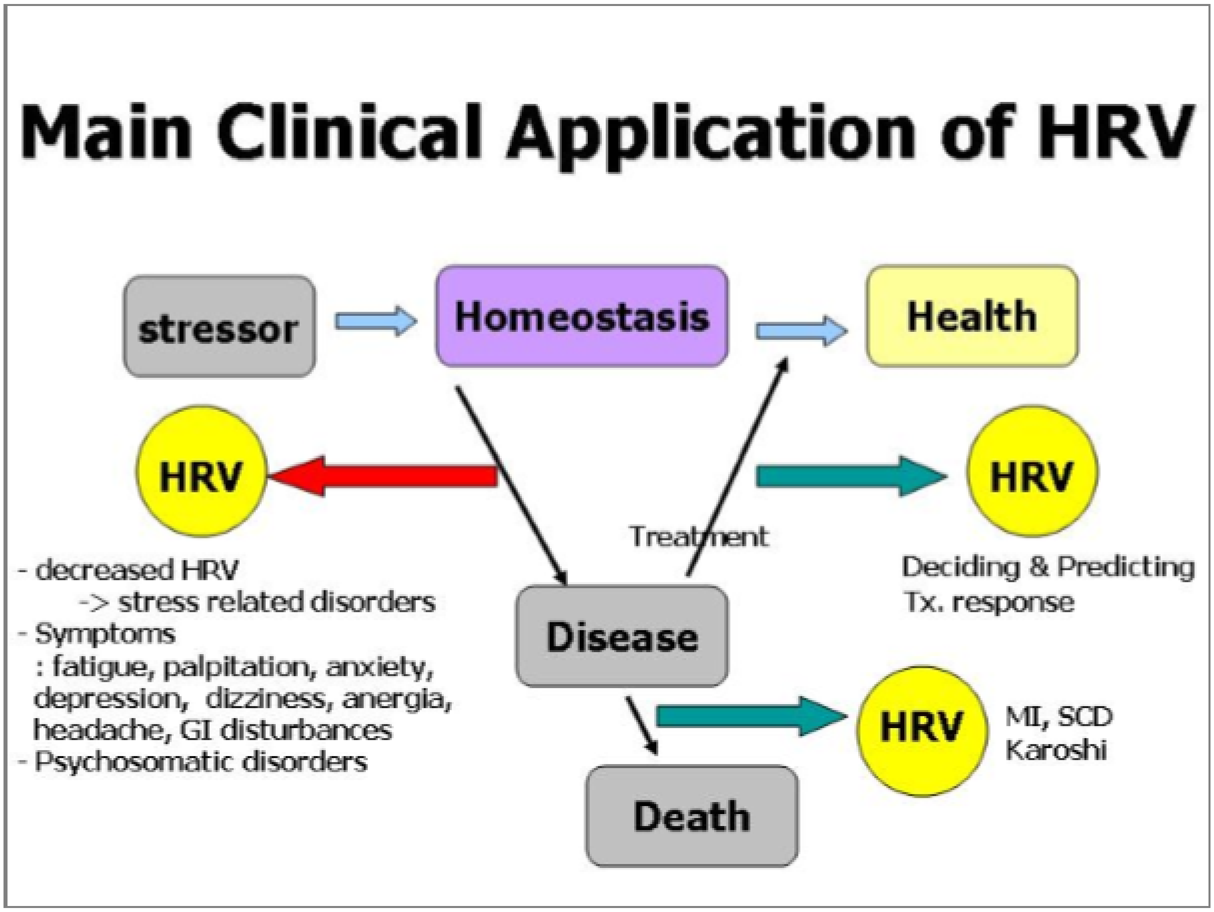

Figure 3–10: HRV Applications

3.5.3 HRV Reference

The following table shows the ideal SDNN or HRV values a person should have in order to be considered healthy given his/her age. Please note that this table will be used to help me classify the emotions of participants given their age.

<table>
<tr><th>Age</th><th>Mean SDNN</th><th>SDNN reference</th></tr>
<tr><td>10s</td><td>55</td><td rowspan="4">50↑: High normal, ANS's regulating function and stress coping ability is good
35~50: Low~Mid normal, ANS's regulating function and coping ability is normal
20~35: Low, there's risk of developing stress induced disease, weakened ANS function
20↓: Very Low, there's high risk of having chronic stress induced disease related to ANS dysfunction</td></tr>
<tr><td>20s</td><td>47</td></tr>
<tr><td>30s</td><td>41</td></tr>
<tr><td>40s</td><td>37</td></tr>
<tr><td>50s</td><td>32</td><td rowspan="2">40↑: High normal
20~30: Low~Mid normal
15~20: Low
15↓: Very low</td></tr>
<tr><td>60s</td><td>27</td></tr>
</table>

Figure 3–11: SDNN Reference

3.5.4 Lowered HRV

A lower HRV can be associated with the following health problems (here are a couple of those):

- Obesity
- Epilepsy
- Depression
- Anxiety Disorder
- Stress Induced Diseases
- Brain Injury

- Heart Disease
- Diabetes

3.6 Valence/Arousal Model

The 2D Valence/Arousal model is used to characterize emotions such as: Happy, sad, relaxed, and angry. Emotions are characterized based on their valence and arousal values. For example, happiness is characterized by a positive valence and high arousal, anger is characterized by negative valence and high arousal, relaxation is characterized by positive valence and low arousal, and sadness is characterized by negative valence and low arousal.

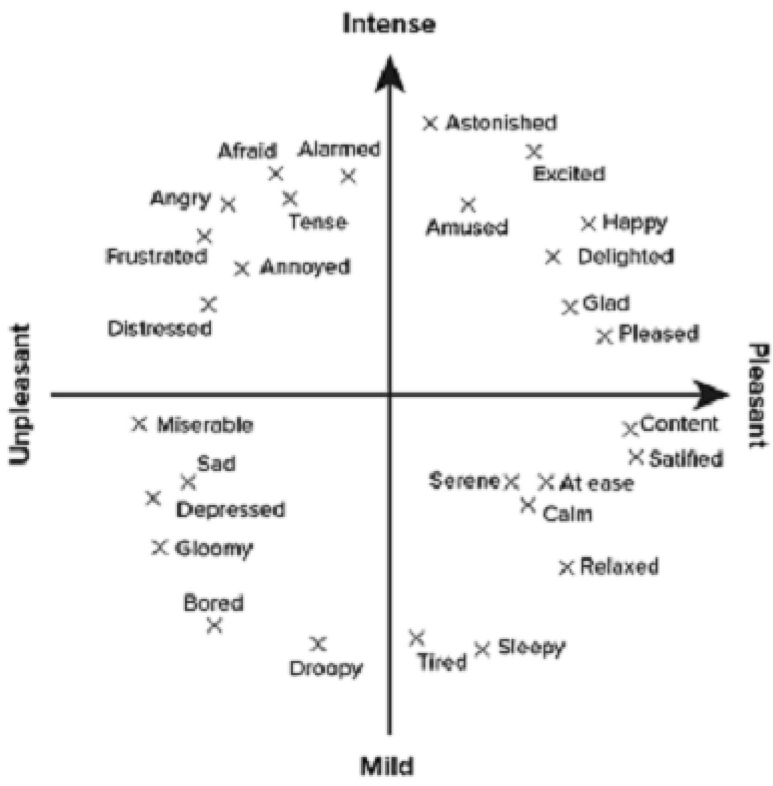

Figure 3–12: Valence/Arousal Model

High arousal (excitation) is characterized by a high alpha power and a low beta power (a high alpha activity and a low beta activity). The ratio of the beta to the alpha power characterizes the arousal level of a person ($Arousal = beta/alpha$). The arousal level of a person is measured using the frontal electrodes of the Emotiv Insight brain sensor. This relationship holds because beta brainwaves are associated with an alert or excited state, while alpha brain waves are associated with a relaxed state[6].

To determine the valence level, we compare the activation levels of the two cortical hemispheres. Left frontal inactivation is an indicator of a withdrawal response, which is often linked to a negative emotion. On the other hand, right frontal inactivation may be associated with an approach response, or positive emotion.

High alpha activity is an indication of low brain activity, and vice versa. Thus, an increase in alpha activity together with a decrease in beta activity may be associated with cortical inactivation. The frontal electrodes of the Emotiv Insight brain sensor, AF3 and AF4, are the most used positions for looking at this activity, as the frontal lobe plays a crucial role in emotion regulation and conscious experience.

We estimate the valence value in a person by computing and comparing the alpha power α and beta power β in channels AF3 and AF4, like so:

$valence = \frac{\alpha_{AF4}}{\beta_{AF4}} - \frac{\alpha_{AF3}}{\beta_{AF3}}$

3.7 Electrode Placement

The 10-20 electrode placement system will be used in order to describe and apply scalp electrodes in our experiment. In this model, the "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20%

of the total front-back or right-left distance of the skull. Furthermore, the letters F, T, C, P, and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. Even numbers refer to electrodes positions on the right hemisphere, and odd numbers refer to electrode positions on the left hemisphere. An electrode with a "z" means that it is located in the midline. "A" defines electrodes located in the earlobes, "Pg" defines electrodes in the nasopharyngeal site, and "Fp" defines electrodes in the frontal polar site.

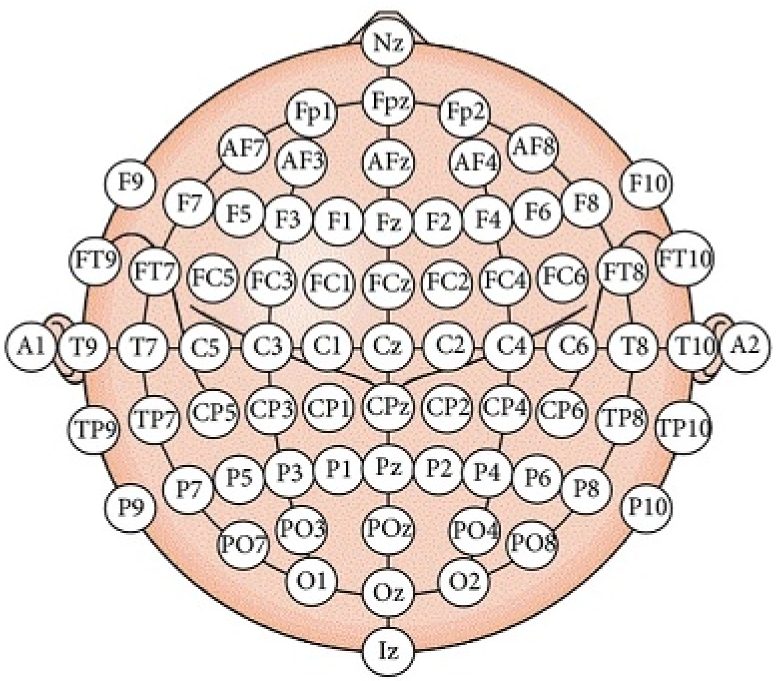

Figure 3–13: 10-20 Electrode Placement System

All the 5 electrodes of the Emotiv Insight brain sensor will be used in my experiment. AF3 and AF4 will be used for emotion detection while T7, T8, and Pz will be used for memory performance assessment.

3.8 BLE Sensors' Description

Bluetooth Low Energy sensors are used to obtain data from the external environment (temperature, humidity, and pressure) and from each participant (heart and brain data) during our experiment. Each are going to be discussed.

3.8.1 The TI BLE Sensor Tag

The Texas Instrument Bluetooth Low Energy Sensor Tag is a widely-popular battery powered, Bluetooth Low Energy device, with a number of different sensors that can be used for various applications and projects. The available sensors are:

- IR temperature sensor
- Ambient temperature sensor
- Humidity sensor
- Air pressure sensor
- 3-axis accelerometer
- 3-axis gyroscope
- 3-axis magnetometer

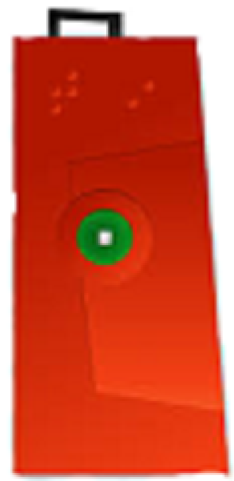

Figure 3–14: TI BLE Sensor Tag

3.8.2 The Polar H7 Heart Rate Monitor

The Polar H7 Heart Rate sensor measures in real-time the heart rate of any human. It features:

- A strap with plastic electrode areas used to detect the heart rate and a connector attached to the strap which sends the heart rate signal to the receiving device.
- The sensor works with Bluetooth Smart or Bluetooth Low Energy devices. It is compatible with some iPhones, iPads, and Samsung Galaxy phones with Android 4.3 or later.
- A long battery life, up to 350 hours.

Figure 3–15: Polar H7 Heart Rate Monitor

3.8.3 The Emotiv Insight Brain Sensor

The Emotiv Insight brain sensor is a sleek, 5 channel, wireless headset that records your brainwaves and translates them into meaningful data you can understand. It features:

- 5 EEG channels: AF3, AF4, T7, T8, and PZ, and 2 reference CMS/DRL noise cancelation channels. The sampling frequency for each channel is 128 Hz.
- It works with Bluetooth Smart or Bluetooth Energy.
- It has 4 hours minimum of battery runtime.
- 9-axis inertial sensors. Sensors include 3-axis gyroscope (roll, pitch, yaw), 3-axis accelerometer (vertical, lateral, longitudinal acceleration), and 3-axis magnetometer (absolute change in position and orientation).

Figure 3–16: Emotiv Insight Brain Sensor

3.9 Short-Term and Long-Term Memory

Memory is the process in which information is encoded, stored, and retrieved. Encoding refers to receiving, processing, and combining the received information. Storage of information refers to creating a permanent record of the encoded information in **short-term** or **long-term** memory. Retrieval of information is calling back the stored information in response to some cues for use in a process or activity. [54] The two main types of memory, **short- term** and **long-term** memory, are going to be discussed in this section.

3.9.1 Short-Term Memory

Short-term memory is also known as working memory. Short-term memory allows recall for a period of several seconds to a minute without rehearsal. Its capacity is very limited: Experiments were conducted and found that the capacity of short-term memory is $7 + -2$ items. However, short-term memory can be improved through a process called chunking. For example, in recalling a ten-digit telephone number, a person could chunk the digits into three groups: First, the area code (such as 123), then a three-digit chunk (456), and lastly a four-digit chunk (7890). [55]

Short-term memory may be affected by brain diseases such as Alzheimer's, Aphasia, Schizophrenia, and advanced age. For example, memory distortion in Alzheimer's disease is a very common disorder found in older adults. Research found that patients with Alzheimer's had reduced short-term memory recall. Episodic memory and semantic abilities deteriorate early in Alzheimer's disease. Likewise, advanced age is associated with decrements in episodic memory. [55] Please note that episodic memory refers to memory for specific events in time, as well as supporting their formation and retrieval.

The memory performance of adult participants will be evaluated in a short-term memory retention task (Sternberg task).

3.9.2 Long-Term Memory

Long-term memory can store much larger quantities of information for potentially unlimited duration as compared to short-term memory. Its capacity is immeasurable. While short-term memory encodes information acoustically, long-term memory encodes it semantically. Episodic memory is a part of long-term memory and it attempts to capture information such as "what", "when", and "where". For example, with episodic memory, individuals are able to recall specific events such as birthday parties and weddings. The hippocampus allows new memories to be stored into the long-term memory. [54]

Long-term memory can be affected by traumatic brain injury and by neurodegenerative diseases such as Alzheimer's disease, dementia, Huntington's disease, multiple sclerosis, Parkinson's disease, and schizophrenia. [56]

CHAPTER 4
Software Design

This chapter discusses the system and each of the system's components used to create the application, the application with all its components (classes and activities), the mood and memory performance algorithms, Bluetooth Low Energy, and the application libraries.

4.1 The System

The system is composed of the following components:

- External sensors, such as the Texas Instrument Sensor Tag, the Polar H7 heart rate sensor, and the Emotiv Insight brain sensor.
- The Cloud, where the Dropbox Core Api is used to store the users' data and access it anytime needed.

As shown in the system diagram on the next page, the application interacts with Dropbox or the Cloud to store and access data. Moreover, the application also interacts with the sensors using the Bluetooth Low Energy application layer to get data, which is then processed and classified using mood and memory performance algorithms. All these system components are discussed in this chapter.

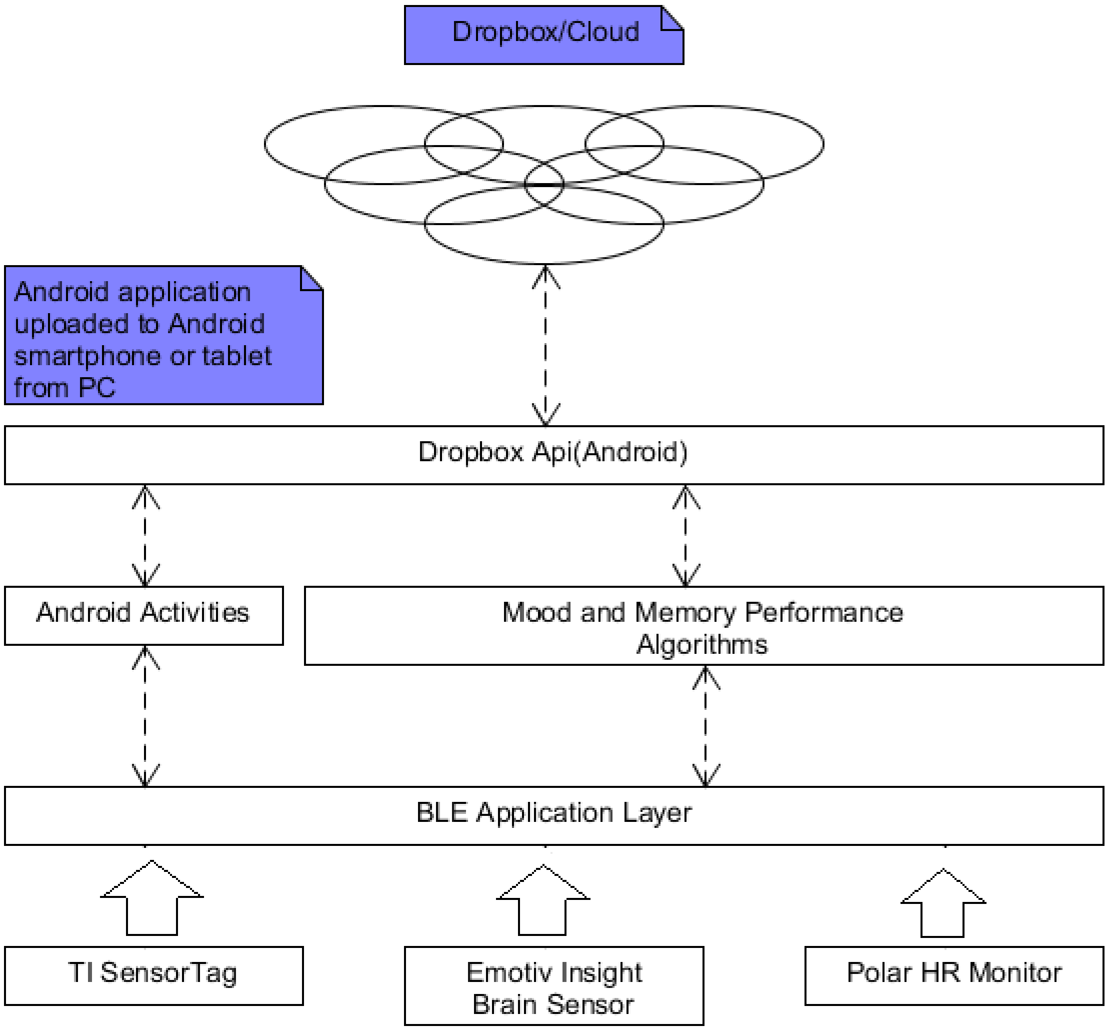

Figure 4–1: System Diagram

4.2 The Application

The application is not designed to perform one simple task. Rather, it is complex and consists of multiple components interacting with each other. This can be shown in the diagram below, which depicts all the application's activities, fragments, and services, and the interactions between them. The application can be broken into the following parts: The main menu, the user selection menu, the section to find the user's mood and memory performance, the section containing the history of all mood and memory performance values of the user, the mood diary, the section responsible for graphing the mood and memory performance levels of the user for a certain time period, the section responsible for comparing the mood and memory performance levels of the user with those of other users, the section showing all the user's personal information, the section to set the user's mood and memory performance goals for a certain time period, and finally, the section to listen to mood-lifting music.

4.2.1 Main Menu

The main menu can be broken into the following parts:

- The Dropbox authentication part. Each time the application is launched, the user is prompted to enter his/her Dropbox username and password so that all his/her information can be stored and accessed on his/her Dropbox account.
- The Create Account part, where the user is prompted to enter his/her a personal username and password, his/her age, his/her sex, his/her height, and his/her weight. Furthermore, the user has to take a picture of himself/herself. Once the user is done, he/she saves the information and is directed to the "Sign In" page.
- The "Sign In" part, where the user is required to enter his/her username and password in order to have access to all of the application's features.
- The "Important Information" part, where the user is informed of all the sensors required for the application to work, and what features of the application can be used without the sensors.

4.2.2 User Selections Menu

The "User Selections Menu" gives the user the option to select application features such as mood and memory performance assessment, mood diary, and mood lifting music. The user can "log out" of the application if he/she wishes to. The user's information will not be lost.

4.2.3 Find Your Mood and Memory Performance

This section of the application can be broken into the following parts:

- The "Device Scan" part, which scans for Bluetooth Low Energy heart rate sensors.
- A section explaining to the user how to connect the Bluetooth Low Energy sensors such as the Polar H7 heart rate monitor, and the Emotiv Insight brain sensor (required to find the user's mood and memory performance levels) to the Android device. Once the sensors are connected properly, the user can find his/her mood and memory performance levels on the "Mood" page.
- The "Mood" page, where the user can find his/her heart rate, heart rate variability, relaxation level, engagement level, stress level, anger level, happiness level, arousal level, sadness level, and memory performance level.

4.2.4 Mood and Memory Performance History

This section of the application shows to the user all the recorded mood and memory performance levels.

4.2.5 Mood and Memory Performance Tips

This section gives valuable information to the user on how to increase good mood levels such as happiness and relaxation levels, and how to decrease bad mood levels such as sadness and anger levels. Furthermore, it also gives information to the user on how to decrease his/her resting heart rate so he/she could stay fit and healthy and decrease his/her risks of cardiovascular disease. Tips on how to recover from memory loss are also given.

4.2.6 Mood Diary

This section can be broken into the following parts:

- The "Diary History" menu, which shows to the user all the diaries he/she saved and/or modified. The user can click on a diary to access, modify, or delete its contents.
- Once the user clicked on a diary in the "Diary History" section, he/she can access, modify, or delete its contents.
- The user can click on the diary icon located in the action bar menu (where all diaries are listed) to create a new diary. The user must enter a valid diary title and diary content before saving the diary.

4.2.7 Mood and Memory Performance Graphed

This section graphs all mood and memory performance levels for a given time period. Graphs can be obtained for the heart rate, relaxation level, engagement level, stress level, anger level, happiness level, arousal level, sadness level, and memory performance level. This section can be broken into the following parts:

- A graph menu section with selections, which when clicked on graphs a certain mood or memory performance level given a time period. For example, clicking on the "Relaxation Level" option will graph the relaxation level for each day of the selected time period.

- When a selection is clicked on in the graph menu, the user is prompted to select a starting and ending date. The graph is generated based on this information after clicking on the "Plot" button. The bar chart shows the values of the mood or memory performance level for each day of the time period selected.
- The user can click on the "Mood Levels Comparison" selection in the graph menu to compare all mood and memory performance levels within a certain time period (starting and ending date required). Please note that from left to right, the values are: heart rate, relaxation level, engagement level, stress level, anger level, happiness level, arousal level, sadness level, and memory performance level.

4.2.8 Compare Your Mood and Memory Performance With Other Users

This section can be broken into two parts:

- The user is shown in a grid view all users (with their usernames and pictures) who created an account and used the application features recently. The user can click on them to compare his/her mood and memory performance with their mood and memory performance. Please note that to respect the confidentiality of each participant, their pictures were removed.
- Once the user clicks on an existing user, he/she can find if his/her average, minimum, and maximum mood and memory performance levels are greater, equal, or less than the ones of the existing user.

4.2.9 Your Personal Information

This section of the application shows the user his/her personal information such as his/her age, sex, height, and weight. Furthermore, it shows the user his/her average, minimum, and maximum mood and memory performance levels. Please note that the mood and memory performance levels are in percent.

4.2.10 Set Your Mood and Memory Performance Goals

This section can be broken into the following parts:

- The goal menu, where all goals created and saved are shown. When the user clicks on a goal, he/she can modify or delete this goal.
- When the user clicks on an existing goal, he/she can modify or delete the goal.
- The user can create a new goal by clicking on the goal icon located in the action bar menu in the goal menu screen. Information such as the mood and memory performance levels in percent and the goal date period (starting and ending date) must be entered before saving the goal.

4.2.11 Listen to Mood Lifting Music

This section of the application is meant for the user to listen to mood lifting music tracks. There are 10 music tracks the user can listen to relax, meditate, feel happy, and aroused.

This section can be broken into 2 parts:

- The music menu, which consists of 10 music tracks the user can listen to.
- Clicking on a music track will bring the user to a screen where he could pause, play, forward, and rewind the music track.

4.3 Mood and Memory Performance Algorithms

This section discusses the procedure for measuring different emotions and memory performance in real time through the use of mood and memory performance algorithms. This section also shows a pseudocode implementation of the mood and memory performance algorithms.

The recognition of different emotions and memory performance is achieved as follows:

- First, we record the resting heart rate of the participants. Any significant rise in this heart rate (when the participant is seated and relaxed) is explained by strong emotions, such as excitement, happiness, anger, and arousal.
- Second, we record the heart rate variability of the participant. We calculate it by using the formulas described in the previous chapter. The heart rate variability is a useful feature in mood classification, since a bigger heart rate variability is an indicator of good health and a lower heart rate variability is an indicator of bad health, stress, and heart diseases.
- Third, we process the EEG data of the brain using the procedures described in the next subsection. The processed data consists of the EEG average band powers (alpha, beta, gamma, and theta). Using relations and formulas discussed in the next subsections, we obtain the arousal and valence information and we use this information along with the 2D valence/arousal model to recognize different emotions in real-time. Furthermore, memory performance evaluation follows almost the same procedure except that we look at the band powers,

especially the alpha band power to evaluate retention in a short-term memory task.

4.3.1 Android Pseudocode Implementation

The pseudocode implementation of the relaxation mood (how to find the relaxation level of an individual given some parameters such as heart rate) is shown as all other mood and memory performance algorithms follow a similar implementation.

Referring to Algorithm 1, RelaxHR% measures how relaxed a person is from heart rate. A value close to 0% indicates that a person is not relaxed, and a value close to 100% indicates that a person is very relaxed. RelaxSDNN% measures how relaxed a person is from heart rate variability (ageSDNN is the ideal SDNN a person should have given his/her age). RelaxEEG% measures how relaxed a person is from EEG. Together, these values are used to find the relaxation level.

Algorithm 1 Relaxation Mood Algorithm

Input: Heart rate, heart rate variability (SDNN), valence, and arousal.
Output: Relaxation level

```
RelaxHR% = ((1 - ((HR / HRRest) - 1)) * 100)
RelaxSDNN% = ((SDNN/ageSDNN)*100)
if (valence>0) then
  RelaxEEG% = ((1 - (arousal - 1)) * 100)
else
  RelaxEEG% = 0
end if
RL = RelaxHR%/4 + RelaxSDNN%/4 + RelaxEEG%/2
return RL
```

4.4 Bluetooth Low Energy

Bluetooth Low Energy (Bluetooth LE, BLE, marketed as Bluetooth Smart) is a wireless personal area network technology designed and marketed by the Bluetooth

Special Interest Group. BLE is used in applications such as healthcare, fitness, beacons, security, and home entertainment industries. BLE features reduced power consumption and cost while maintaining a similar communication range as compared to Classic Bluetooth. [51]

Bluetooth Low Energy supports the following operating systems:

- iOS 5 and later
- Windows Phone 8.1
- Windows 8
- Android 4.3 and later
- Blackberry 10
- Linux 3.4 and later through BlueZ 5.0
- Unison OS 5.2

4.4.1 Software Model

All Bluetooth Smart devices use the Generic Attribute Profile (GATT). The application programming interface offered by a Bluetooth Smart aware operating system will typically be based around GATT concepts. [51] GATT has the following terminology:

- Client: A device that initiates GATT commands and requests, and accepts responses, for example, a computer or smartphone.
- Server: A device that receives GATT commands and requests, and returns responses, for example, a temperature sensor.
- Characteristic: A data value transferred between client and server, for example, the current battery voltage.

- Service: A collection of related characteristics, which operate together to perform a particular function. For example, a Health Thermometer service includes characteristics for a temperature measurement value, and a time interval between measurements.
- Descriptor: A descriptor provides additional information about a characteristic. For example, a temperature value characteristic may have indication of units (Celsius), and the maximum and minimum values which the sensor can measure.
- Identifiers: Services, characteristics, and descriptors are collectively referred to as attributes, and are assigned a UUID (universally unique identifier). These identifiers are represented as 16-bit or 32-bit values in the protocol, rather than 128 bits (UUID value).

GATT operations include:

- Discover UUIDs for all primary services
- Find a service with a given UUID
- Find secondary services for a given primary service
- Discover all characteristics for a given service
- Find characteristics matching a given UUID
- Read all descriptors for a particular characteristic

4.4.2 Interaction of Android Device With BLE Device

The interaction of an Android Device with a BLE device can happen in two ways:

- Central versus peripheral. The device in the central role scans, looking for advertisement, and the device in the peripheral role makes the advertisement.
- GATT server versus GATT client. This determines how two devices talk to each other once they've established the connection.

To give an example, suppose that we have an Android phone and an activity tracker which is a BLE device. The phone supports the central role and the activity tracker supports the peripheral role. Once the phone and the activity tracker established a connection, they start transferring GATT metadata to one another. Depending on the kind of data transferred, one or the other might act as a server. The "Mood and Memory Performance" Android application (running on an Android device) is the GATT client. This application gets data from the GATT server, for example a BLE heart rate monitor. [52]

4.5 The Application Libraries

The application libraries are files coded in Java/Android which have been made by Android developers to facilitate the use of many features such as graphing data or sending and receiving data from the Cloud. They have to be included in an Android application/project following the simple methods described in the web documentation. Libraries used in our application include the Dropbox library, the Emotiv Insight Brain sensor library, and the graphing library. They are discussed in this section. These libraries were essential in the making of our application and therefore deserve to be mentioned in this document.

4.5.1 Dropbox Library

The Dropbox Core API is the Dropbox API that we use in our application. The Core Api provides a flexible way to read and write to Dropbox. It includes support for advanced functionality like search, revisions, and restoring files. The Core API SDK is available for download for Python, Java, Android, Ruby, PHP, iOS, and OS X. The Core API is based on HTTP and OAuth and provides low-level calls to access and manipulate a user's Dropbox account. The first step in using the Dropbox Core API in an Android application is to register a new application on the App Console. Creating an application on the "App Console" requires the user to select an API such as the Dropbox API or the Dropbox Business API. For this application, we chose the Dropbox API. Then, the user selects the type of access such as App folder or Full Dropbox. App folder gives access to a single folder created specifically for the user's application and Full Dropbox gives access to all files and folders in a user's Dropbox. Full Dropbox access was selected for this application. An application key and an application secret were given once all these steps have been completed.

4.5.2 Emotiv Insight Brain Sensor Library

The Emotiv Insight Brain Sensor SDK is available for download on Github. It supports Windows 32-bit and Windows 64-bit, Mac, Linux, Android, and iOS. It includes the libraries and code examples for all these platforms. Code examples for Android include: Processing EEG data composed of the EEG average band powers of the alpha (8-12 Hz), beta (12-25 Hz), gamma (25-45 Hz), theta (4-8 Hz) bands, detecting a facial expression, detecting a mental command, and detecting motion using the 3-axis accelerometer, gyroscope, and magnetometer of the Emotiv Insight brain sensor.

4.5.3 Graphing Library

The graphing library chosen for this application is the "MPAndroidChart" library. It is available for download on Github. This graphing application features 8 different chart types, scaling on both axes (with touch gesture, axes separately on pinch-zoom), dragging/panning (with touch gesture), combined charts (line charts, bar charts, scatter charts, pie charts, bubble charts, radar chart, and candle-data charts), legends, and animations (on both the x and y axes). Documentation on how to use this library for Android projects is available online at the Wiki or Javadoc documents.

CHAPTER 5
Experimental Study

The experiment is performed to assess how effective is the system at finding the mood and memory performance levels of each participant. It presents all of the results obtained from performing the experiment and a discussion based on these results.

5.1 Subjects

Sixteen subjects (ages 22-80, 12 males and 4 females) performed the experiment, which consisted in evaluating their mood and memory performance levels while their heart and brain data was recorded. Informed consent was obtained from each subject prior to the study.

5.2 Stimulus

Both pictures and music were used to be the stimulus to elicit emotion. To represent good moods such as relaxation, happiness, engagement and arousal, we selected pictures representing beautiful nature scenery, people jumping out of joy, beautiful birds, plants, and animals. To represent bad moods such as sadness, anger, and stress, we selected pictures representing angry and wild animals, people crying, and children all alone sleeping in the streets. Three to four music pieces were chosen to represent each mood. Each lasted 30-60 seconds. For example, we selected annoying alarm clock sounds to represent stress, bomb siren sounds to represent anger, "Don't Worry be Happy" by Bobby McFerrin to represent relaxation, "Chariots of

Fire" theme song to represent arousal, the theme song from the movie "Pirates of the Caribbean" to represent engagement, "Happy" by Pharrell Williams to represent happiness, and "Very Sad Violin" classical music to represent sadness.

This procedure achieved stimulation by increasing and decreasing the neural activity of the brain. The cerebral cortex became synchronized at any given moment. The limbic system's cingulate gyrus, which connected actions with emotional responses, became synchronized. This synchronization happened mostly in brain parts responsible of processing sights, sounds, and emotions.

5.3 Testing Procedure

Each participant was asked to read carefully and sign a participant consent form before participating in our experiment. The participant consent form outlined the purpose of the experiment, the experimental procedure, potential benefits, and compensation. Participation was voluntary and if a participant chose to participate his/her personal information would be stored on Dropbox and encrypted using the Boxcryptor software. The participant's personal data will be shared only with our supervisor.

The experiment took 45 minutes of the participants' time. Data was recorded using a tablet (Samsung Galaxy Tab 4). The participant was instructed to sit and not to move his/her head for the entire duration of the experiment. The polar H7 heart rate sensor was placed on the participant's bare chest and the Emotiv Insight Brain Sensor was placed on the participant's head. The tablet communicated with the sensors using Bluetooth Low Energy. The data was stored on a Dropbox account. For added security, the data in the Dropbox account was encrypted using Boxcryptor.

Boxcryptor features a fast and easy Dropbox encryption, a state-of-the art AES-256 encryption standard, and top security for all private and business needs. The application was launched and the participant was prompted to create an account. Creating an account requires him/her to enter a username, a password, his/her height, his/her weight, and his/her sex. The participant was prompted to take a picture of himself/herself. Creating the account took approximately 5 minutes. The air temperature, the air humidity, and the air pressure were recorded using the Texas Instrument Bluetooth Low Energy Sensor Tag. The participant was asked if he/she was relaxed or not and if not, he/she was given a short period of time (2 minutes) to relax. When relaxed, the participant's resting heart rate was recorded. Then, for each stimulus composed of pictures and sounds (each representing a particular mood such as relaxed, engaged, stressed, happy, angry, aroused, sad) which was displayed on a laptop screen, the data was recorded on a tablet before evoking the stimulus, the stimulus was evoked, and the data was recorded on a tablet after evoking the stimulus. At the end of each stimulus, there was a relaxation period of 1 minute. The first part of the experiment took 35 minutes. In the second part of the experiment, the subject was first given a 1-minute resting period. The memory test was given immediately afterward, and the test subjects' memory performance level was recorded. For the memory test, the participant was shown three sets of 4-6 letters displayed on a laptop screen. After being shown each set of letters, the participant was given a brief moment (2-5 seconds) to memorize the set of letters. The participant was then shown a letter which may or may not be part of the set of letters previously shown to him/her. The participant was asked to state whether or not this letter belongs to the set of letters previously shown to him/her. There were three sets of letters and three probes in my memory experiment. EEG data was recorded twice per set of letters: Before showing the set of letters to the participant and just after showing the set of letters to the participant while he/she was busy memorizing them. The second part of the experiment took 10 minutes, for a total experiment time of 45 minutes.

The procedures followed in this research were sufficient in achieving the intended effects since they were based on previous mood and memory evaluation experiments. These experiments required that participants remained seated with minimal head movement in order to minimize brain signal noise resulting from muscle movement. Participants were required to tell if they were relaxed or not so that their resting heart rate could be compared to other instances such as when they were not relaxed. For example, if the participant was experiencing fear, his/her heart rate must be greater than the extracted heart rate at rest, which was measured at the beginning of the experiment when the participant was relaxed, or at rest. For the memory test, previous experiments have shown that a Sternberg memory task revealed that the alpha brain wave activity increased when the participant was retaining information in memory and decreased otherwise.

5.4 Data Processing

The procedure for data processing to obtain mood and memory performance levels works as follows: First the DC offset and slow drift in the raw signal is removed. The best way to do this is with a high-pass filter with a cut-off frequency greater than 0.16Hz. The data segment is then multiplied by a tapered window function which smoothly forces the two ends of the data segment to match exactly. Step changes and start-finish differences will put fake responses into FFT data since the algorithms assumes an infinitely repeating copy of the segment of data. The FFT algorithm is then executed. The FFT algorithm returns a complex set of values at each frequency increment. The magnitude of these complex numbers is squared by multiplying each complex number by its complex conjugate. Power is proportional to the square of the magnitude, so now we have the power per frequency interval. The powers are added up for each element of the frequency range of interest, so now we have the average EEG band powers.

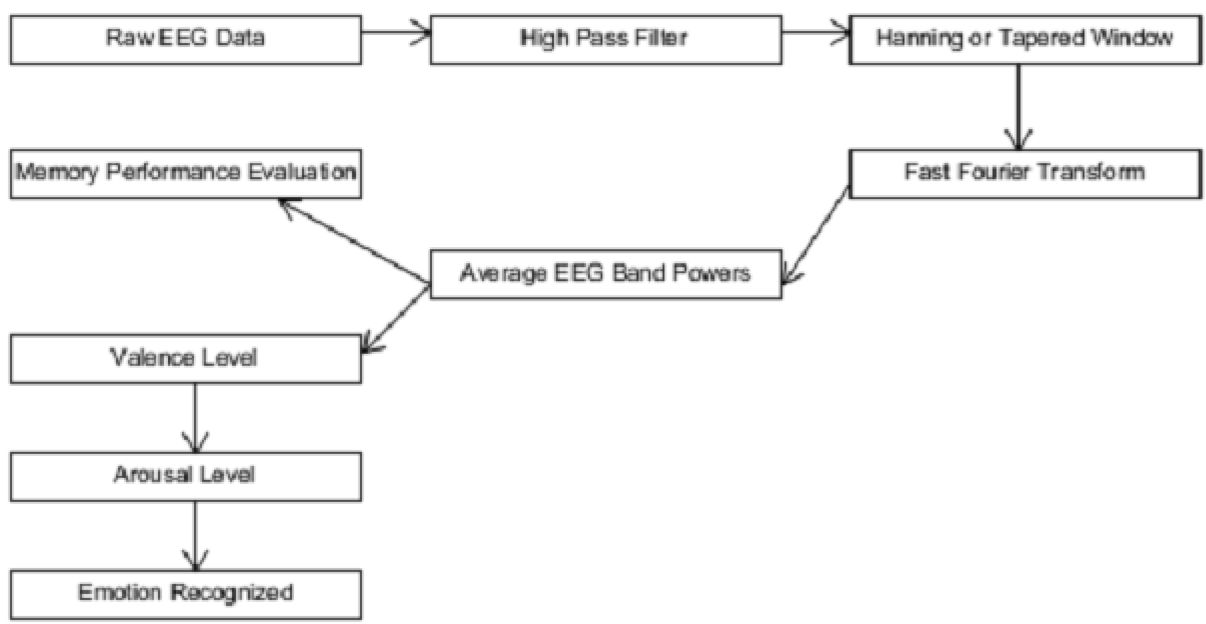

Figure 5–1: Data Processing Overview

5.5 Results

Results were gathered from the participants' brain and heart data under the following environmental conditions: The temperature ranged from 60.28 deg/F to 67.57 deg/F, the humidity ranged from 32.25 %rH to 48.18 %rH, and the pressure ranged from 999.70 nPA to 1032.32 nPA. All participants confirmed that they were relaxed at the beginning of the experiment. All participants remained seated and did not move their heads for the entire duration of the experiment. Results contain mood data graphs such as the mood level recorded before evoking the stimulus and the mood level recorded after evoking the stimulus for each participant, the age, height (in meters), and weight (in kilograms) of each participant versus the difference in the mood level recorded after evoking the stimulus and the mood level recorded before evoking the stimulus. The memory performance level for each trial (total of 3 trials) before memorizing the set of letters and after memorizing the set of letters was plotted for each participant. Mood and memory performance levels are in percent. A mood level of 0% suggests that the participant is not feeling at all in that particular mood and a mood level of 100% suggests that the participant is feeling very strongly in that particular mood. A memory performance level close to 100% may be associated with strong memory activity, whereas a very low memory performance level, approaching 0%, may be associated with no memory activity.

5.5.1 Relaxation Level Graphs

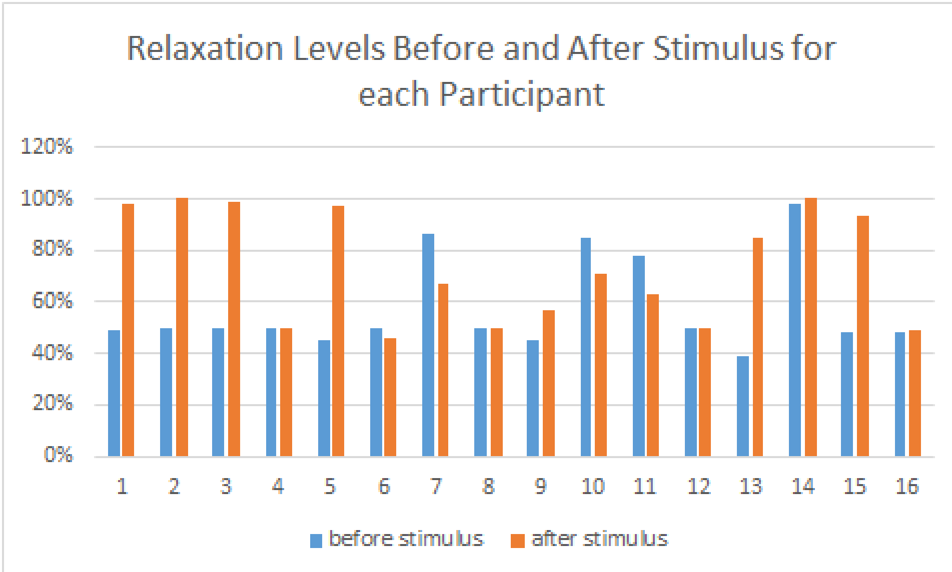

Figure 5–2: Relaxation Level Before and After Evoking Stimuli for Each Participant

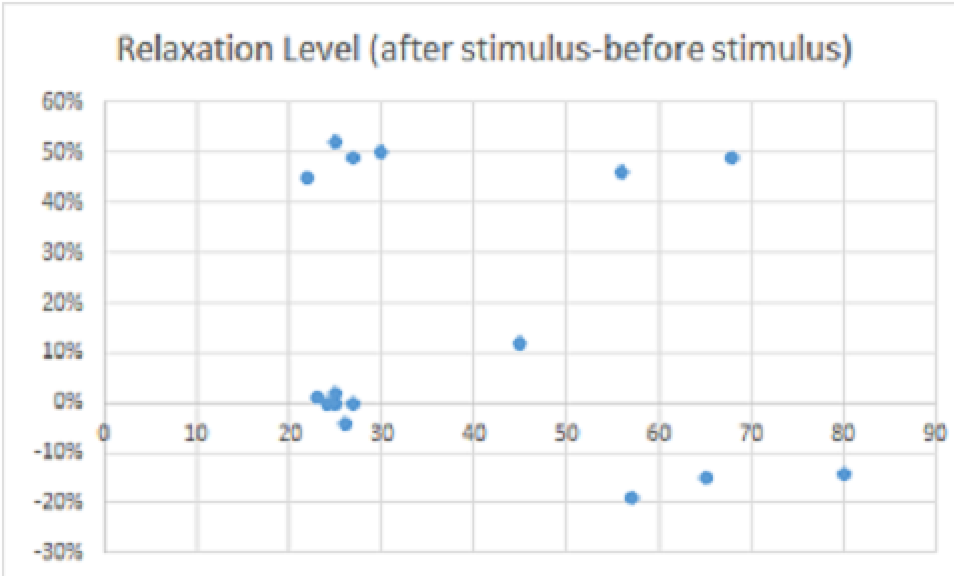

Figure 5–3: Relaxation Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Age

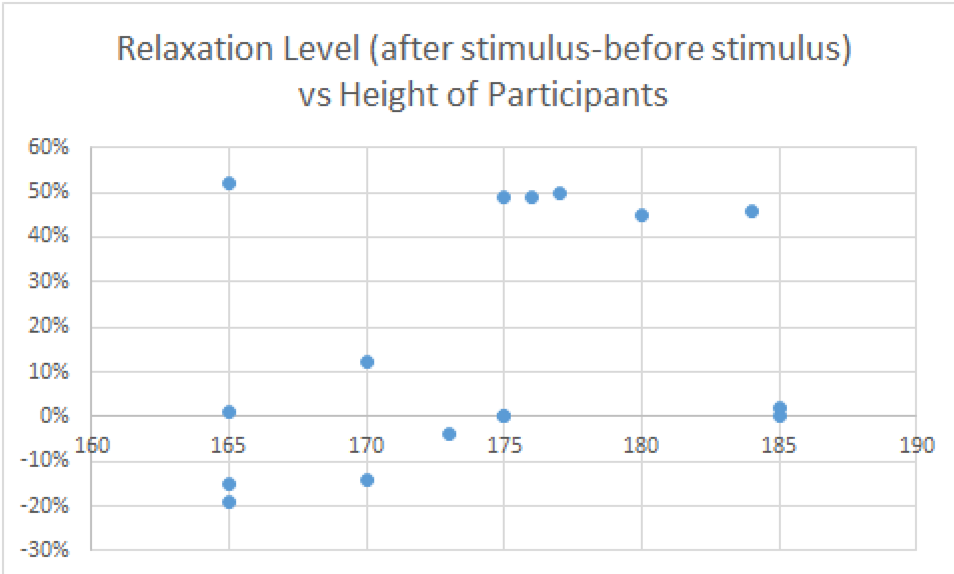

Figure 5–4: Relaxation Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Height

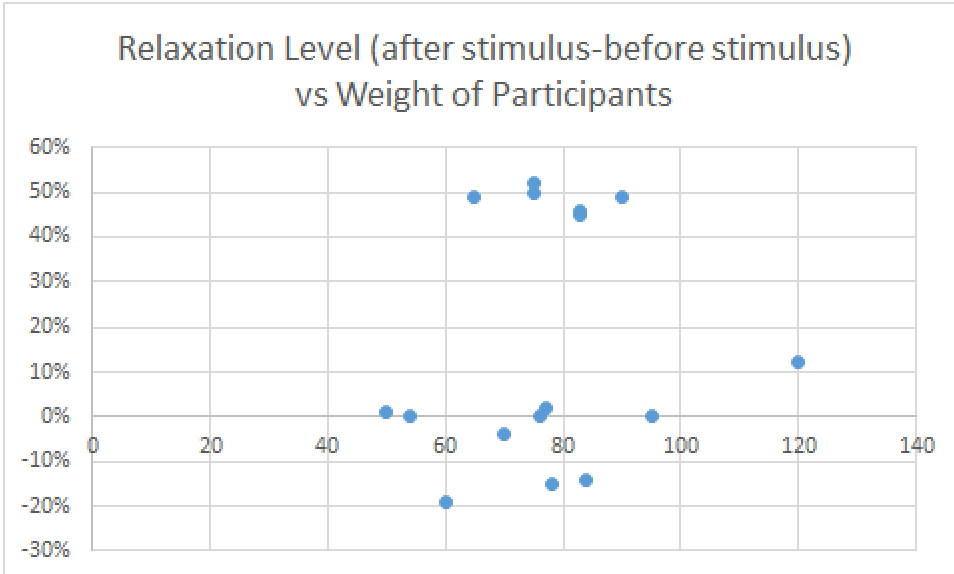

Figure 5–5: Relaxation Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Weight

5.5.2 Engagement Level Graphs

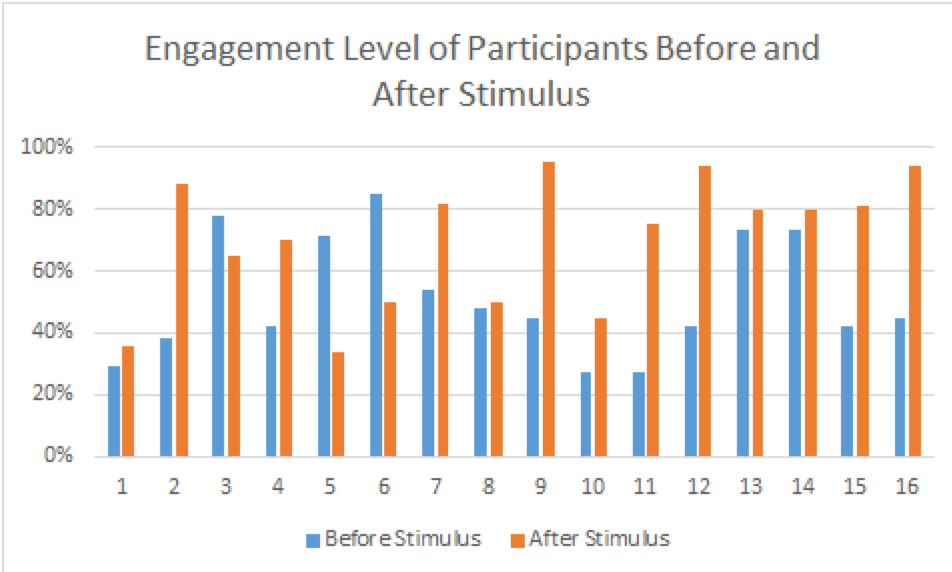

Figure 5–6: Engagement Level Before and After Evoking Stimuli for Each Participant

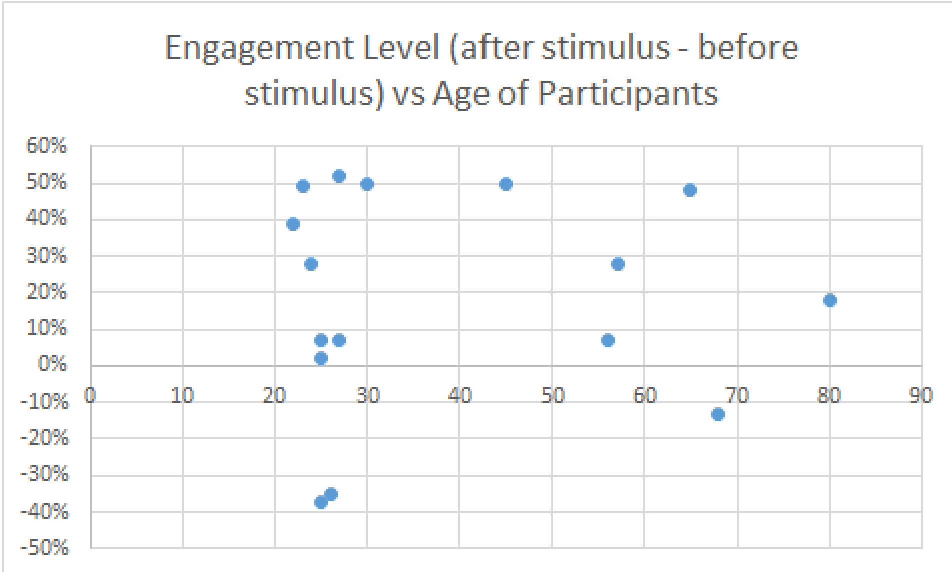

Figure 5–7: Engagement Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Age

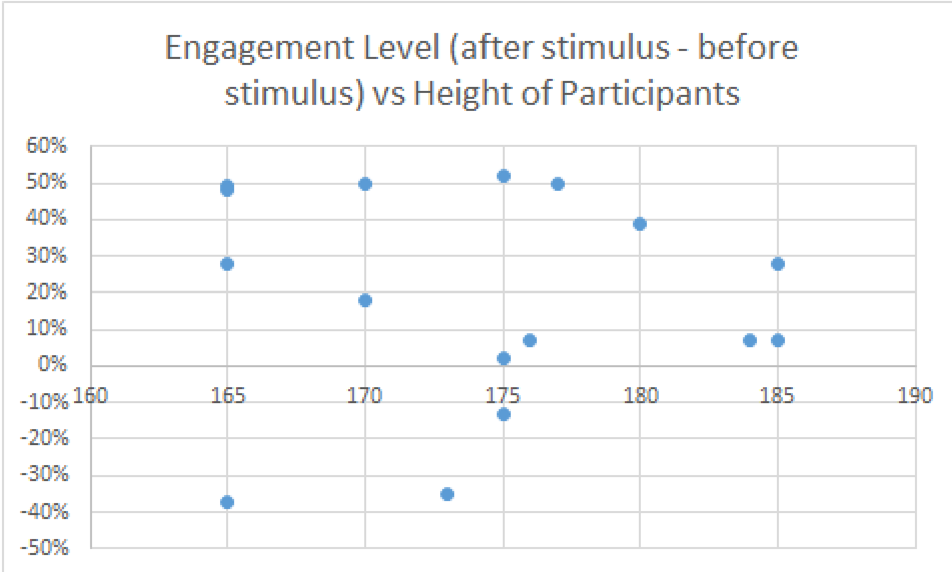

Figure 5–8: Engagement Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Height

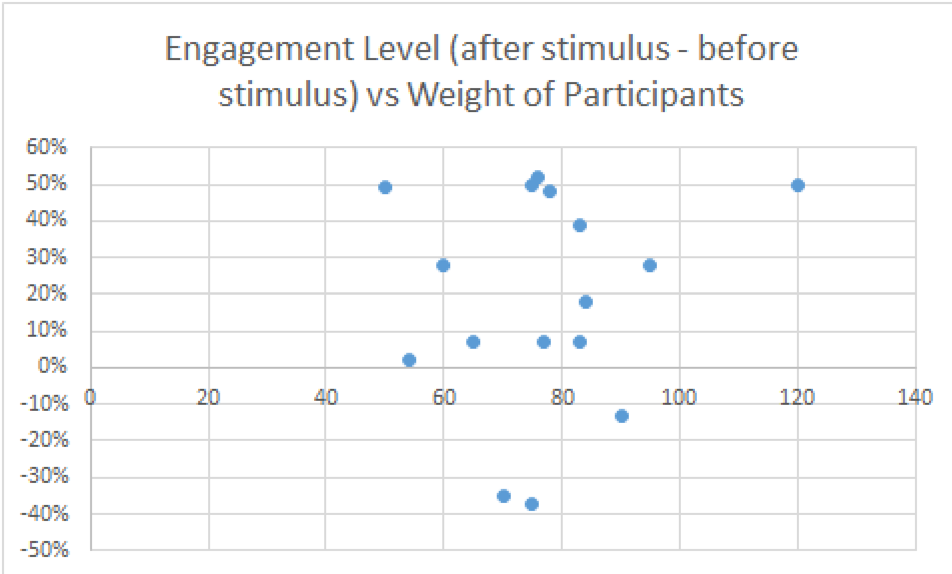

Figure 5–9: Engagement Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Weight

5.5.3 Stress Level Graphs

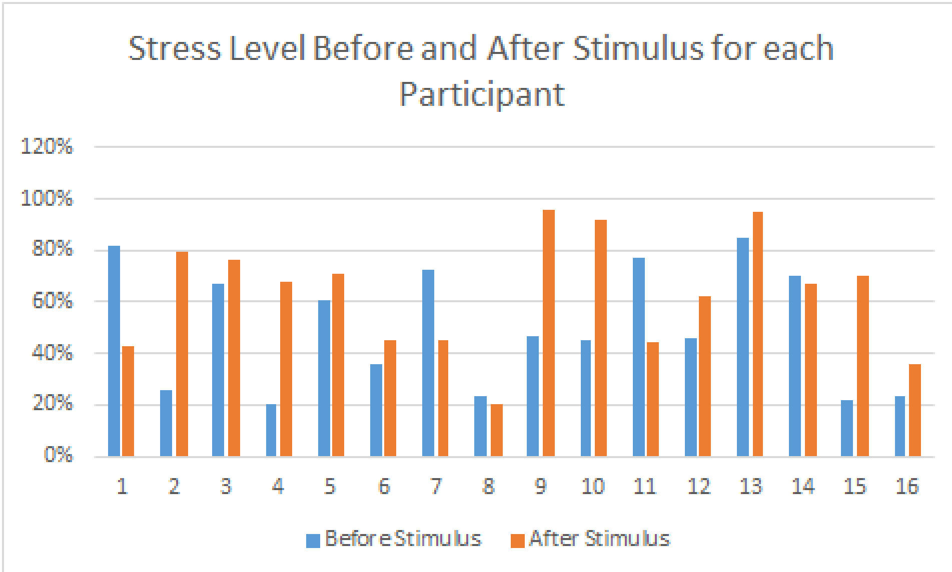

Figure 5–10: Stress Level Before and After Evoking Stimuli for Each Participant

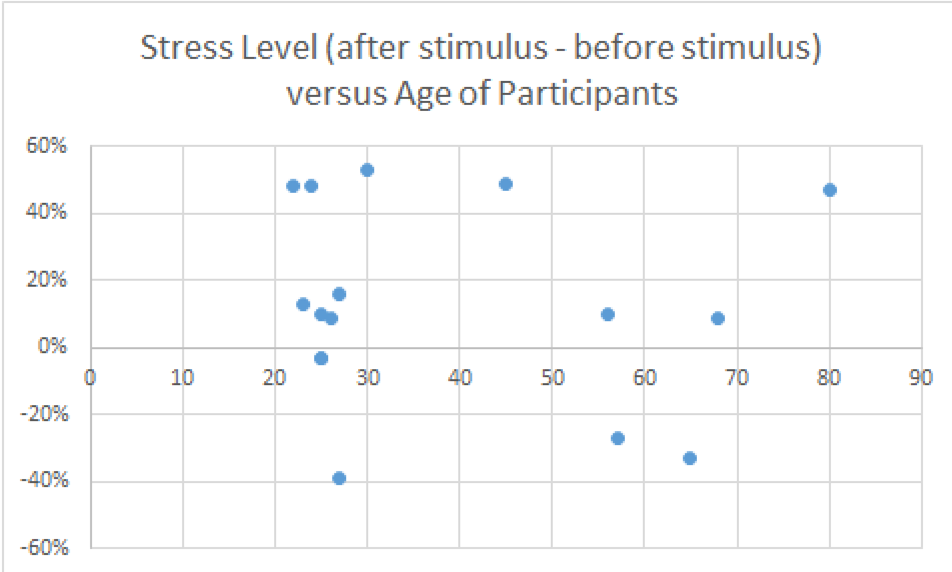

Figure 5–11: Stress Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Age

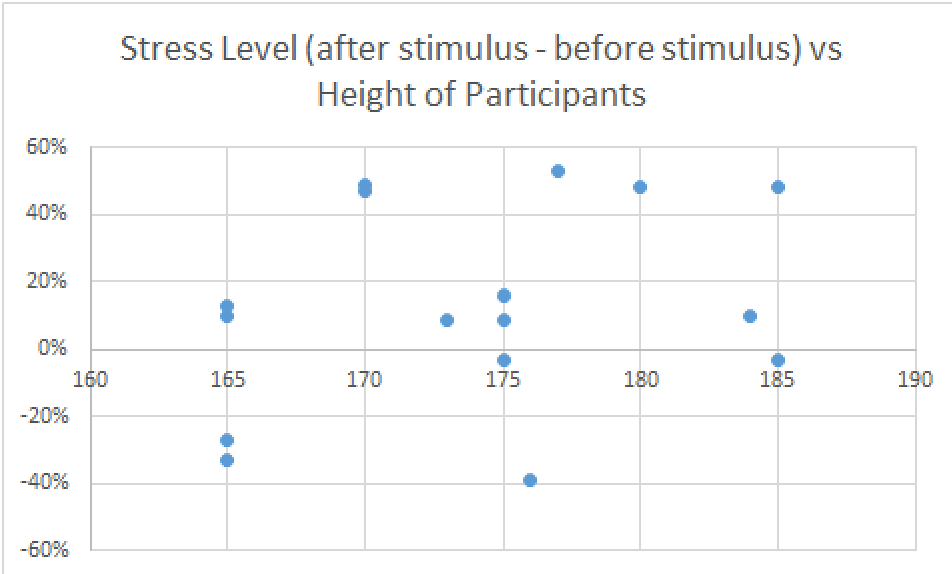

Figure 5–12: Stress Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Height

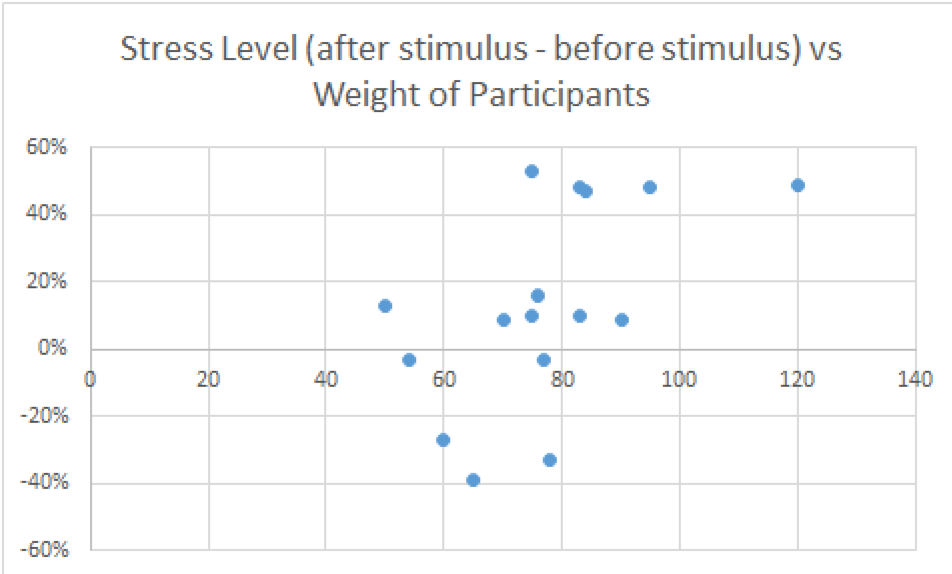

Figure 5–13: Stress Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Weight

5.5.4 Anger Level Graphs

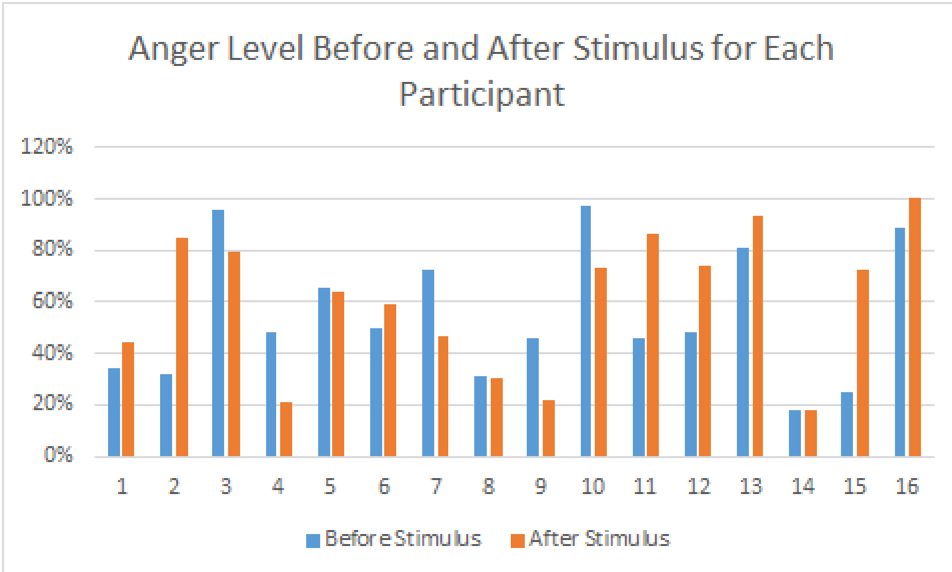

Figure 5–14: Anger Level Before and After Evoking Stimuli for Each Participant

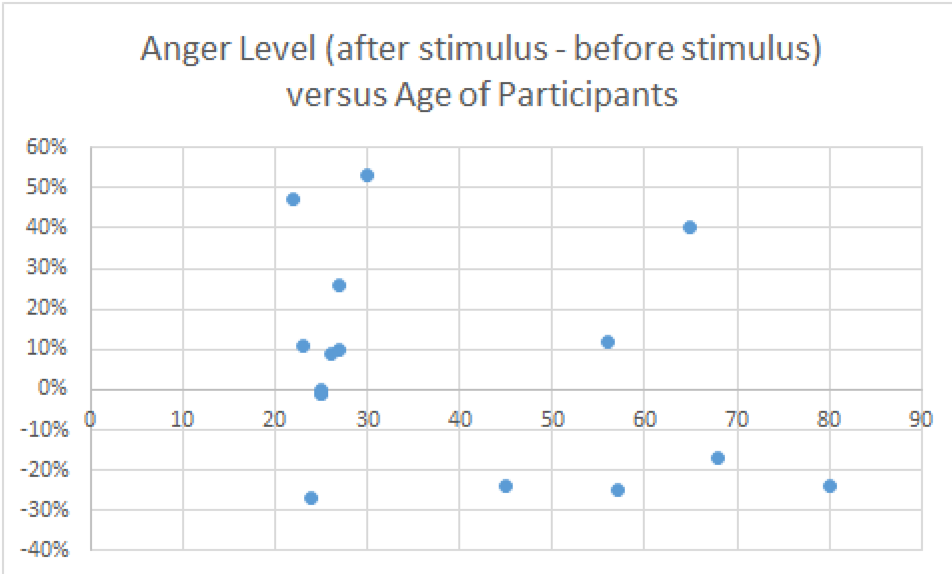

Figure 5–15: Anger Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Age

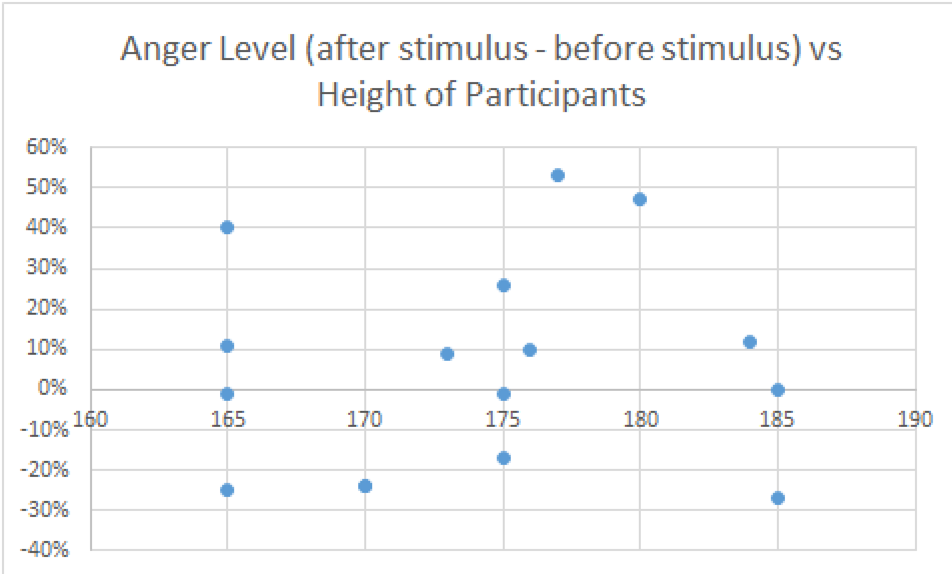

Figure 5–16: Anger Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Height

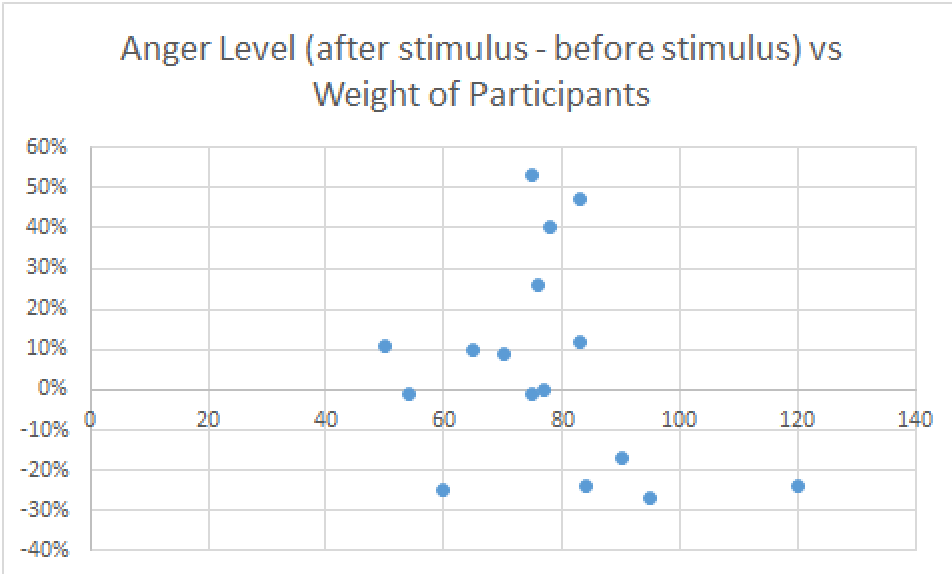

Figure 5–17: Anger Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Weight

5.5.5 Happiness Level Graphs

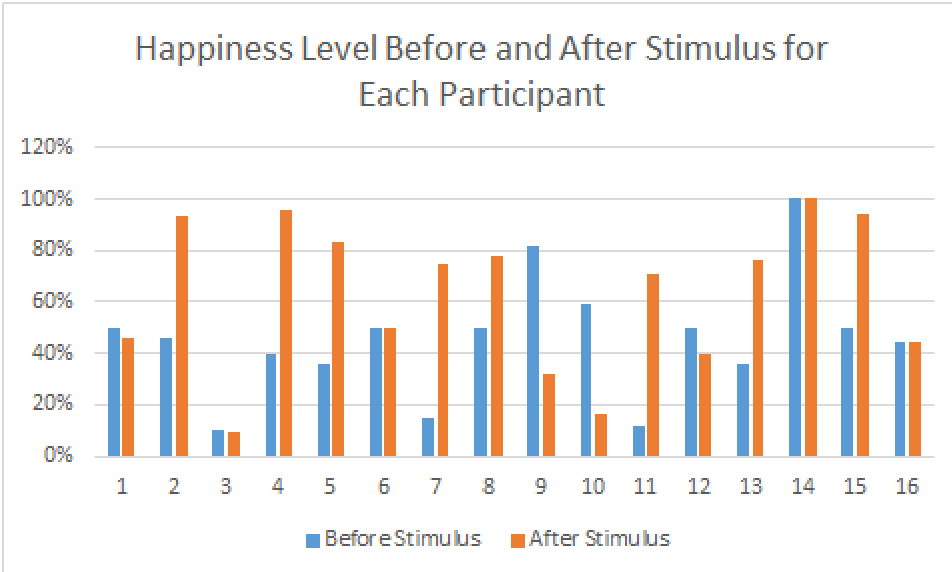

Figure 5–18: Happiness Level Before and After Evoking Stimuli for Each Participant

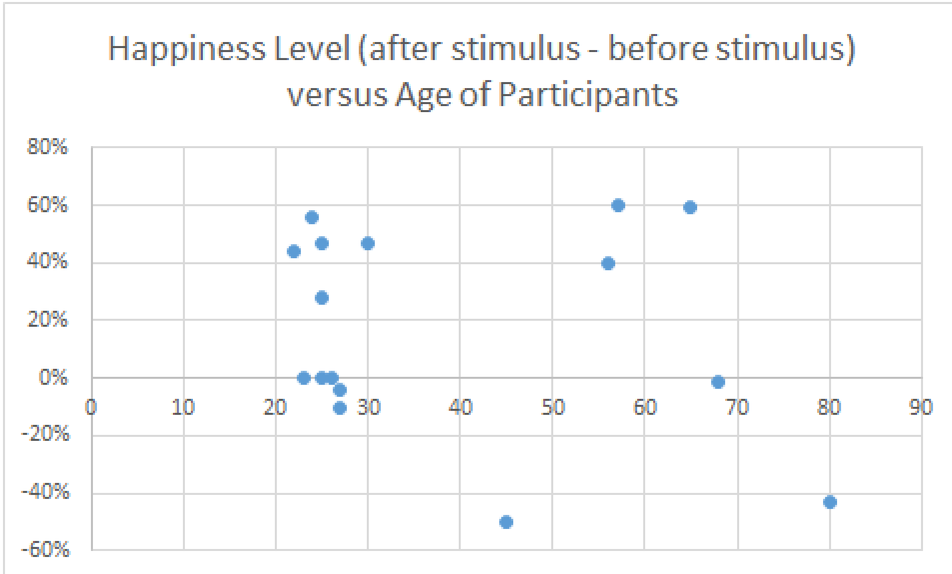

Figure 5–19: Happiness Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Age

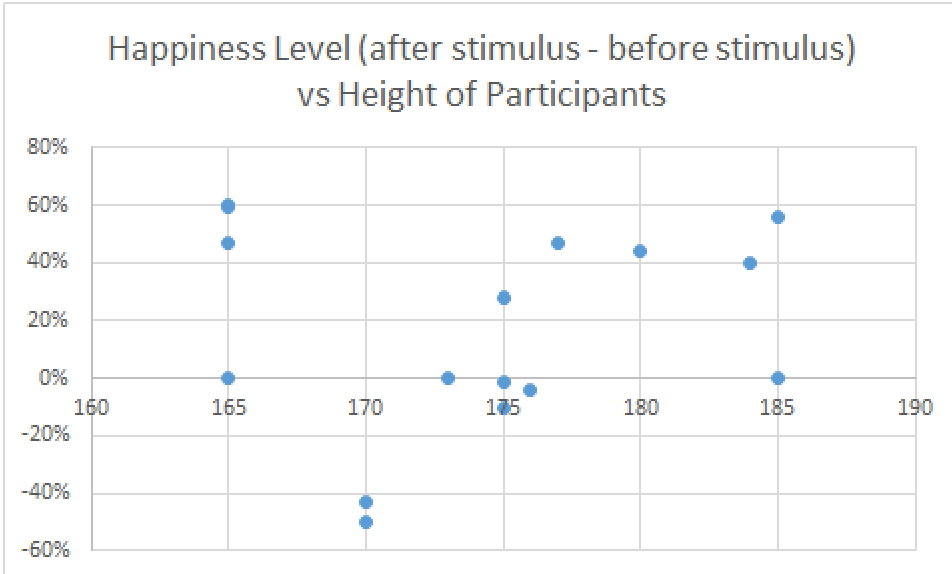

Figure 5–20: Happiness Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Height

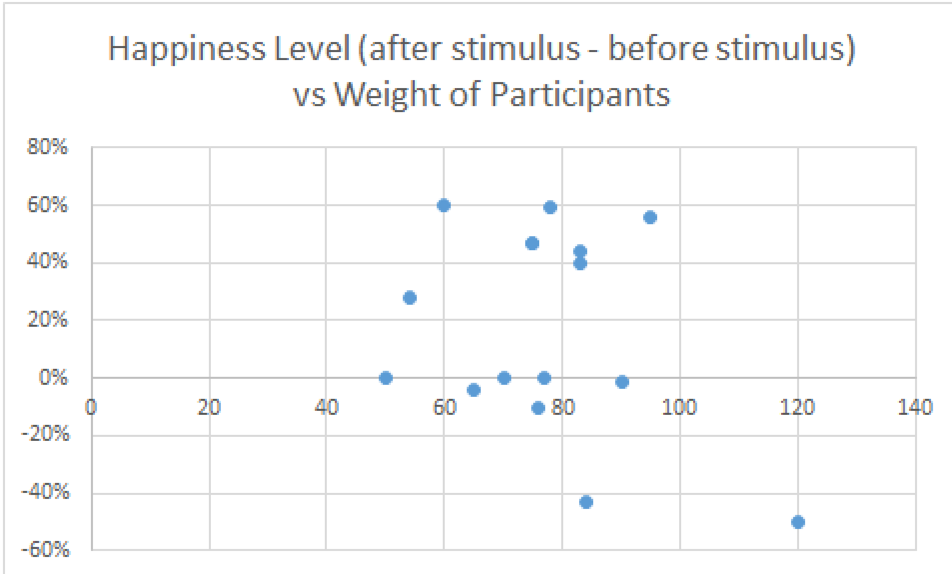

Figure 5–21: Happiness Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Weight

5.5.6 Sadness Level Graphs

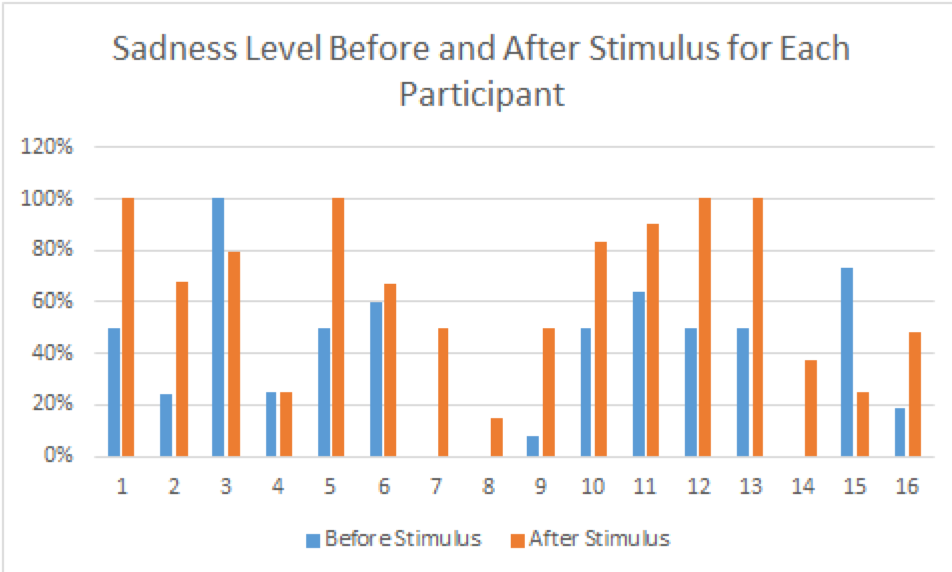

Figure 5–22: Sadness Level Before and After Evoking Stimuli for Each Participant

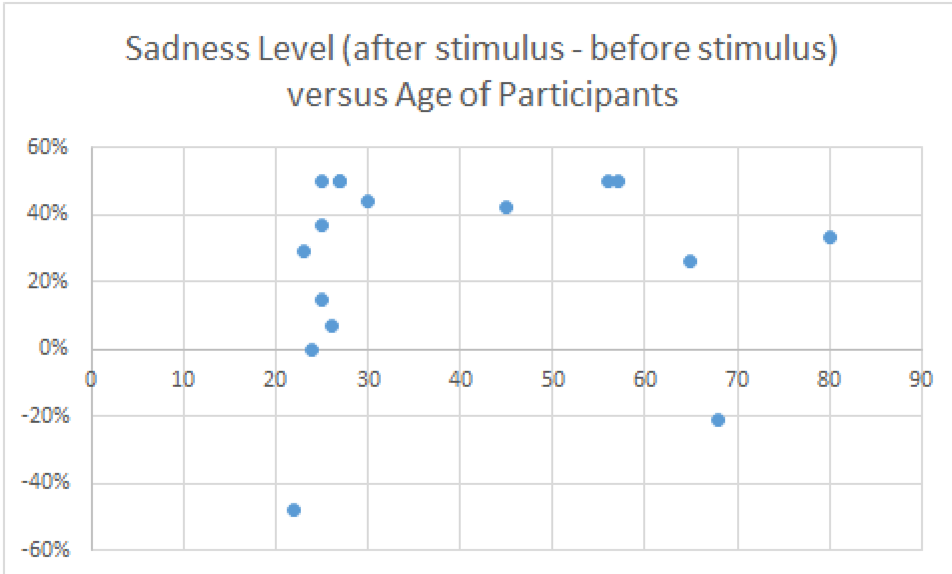

Figure 5–23: Sadness Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Age

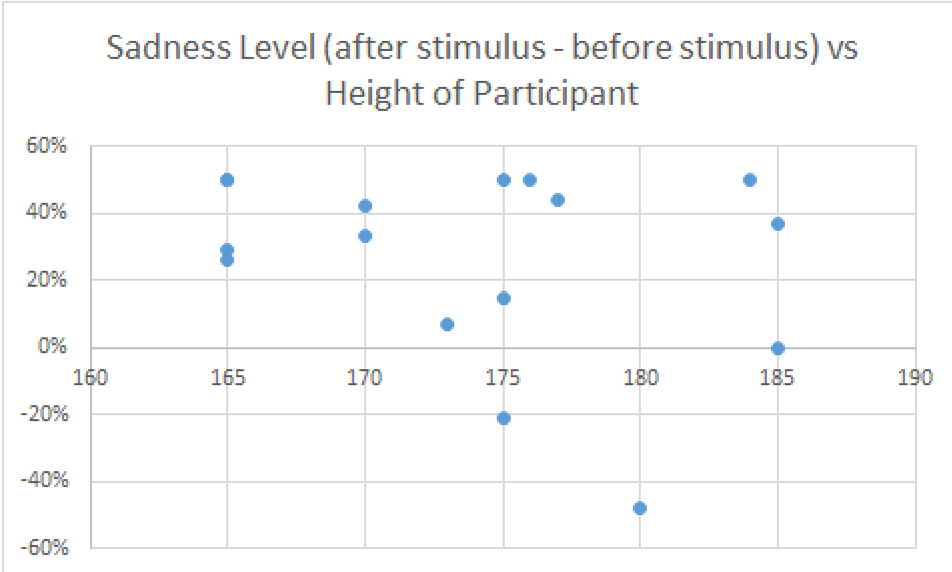

Figure 5–24: Sadness Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Height

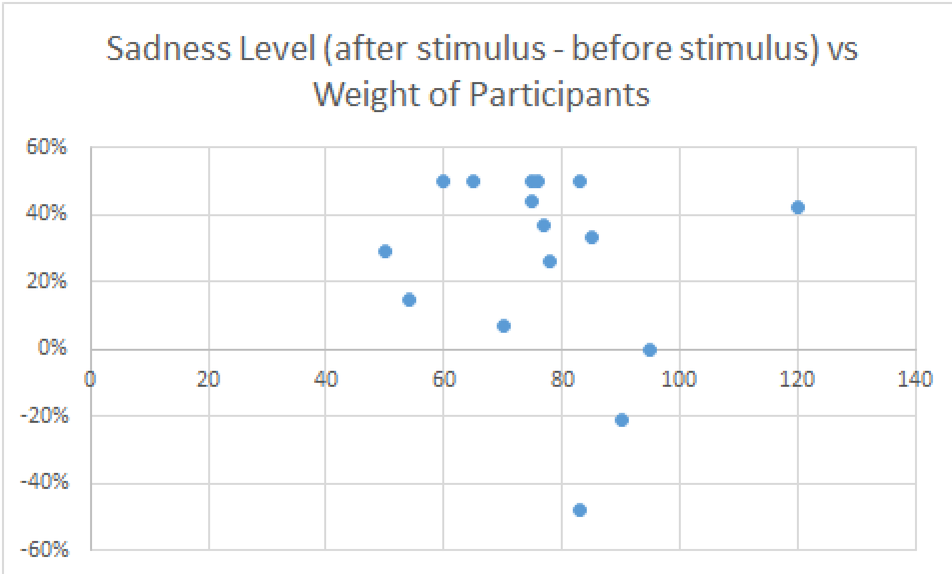

Figure 5–25: Sadness Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Weight

5.5.7 Arousal Level Graphs

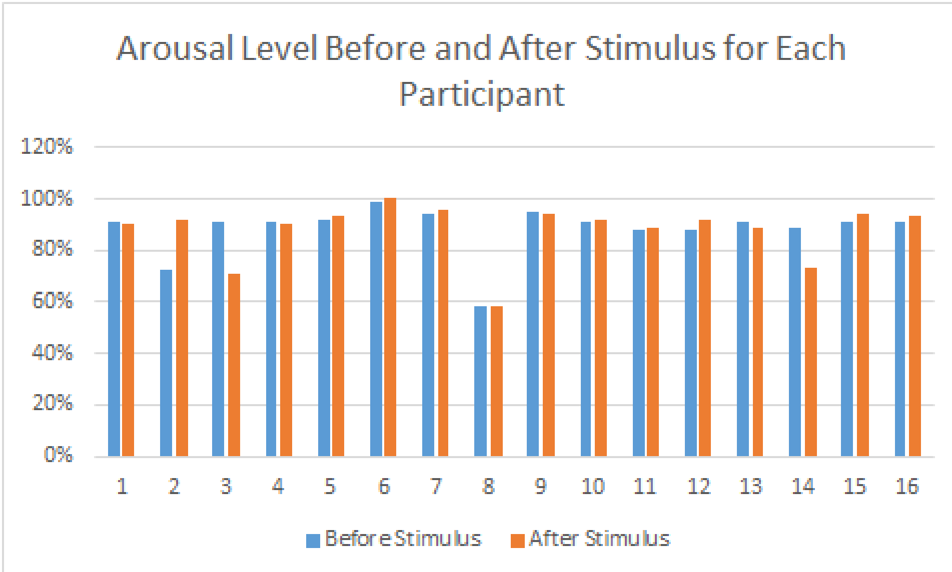

Figure 5–26: Arousal Level Before and After Evoking Stimuli for Each Participant

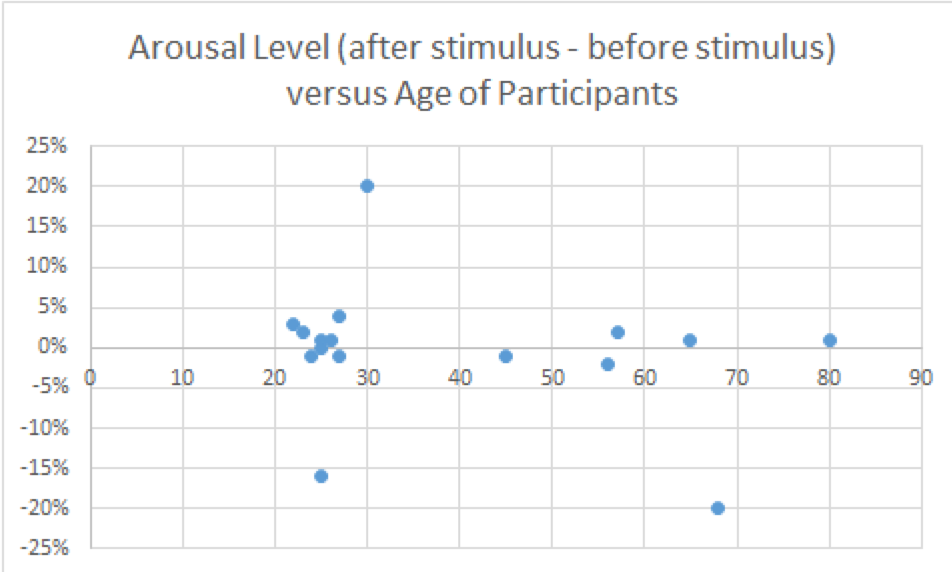

Figure 5–27: Arousal Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Age

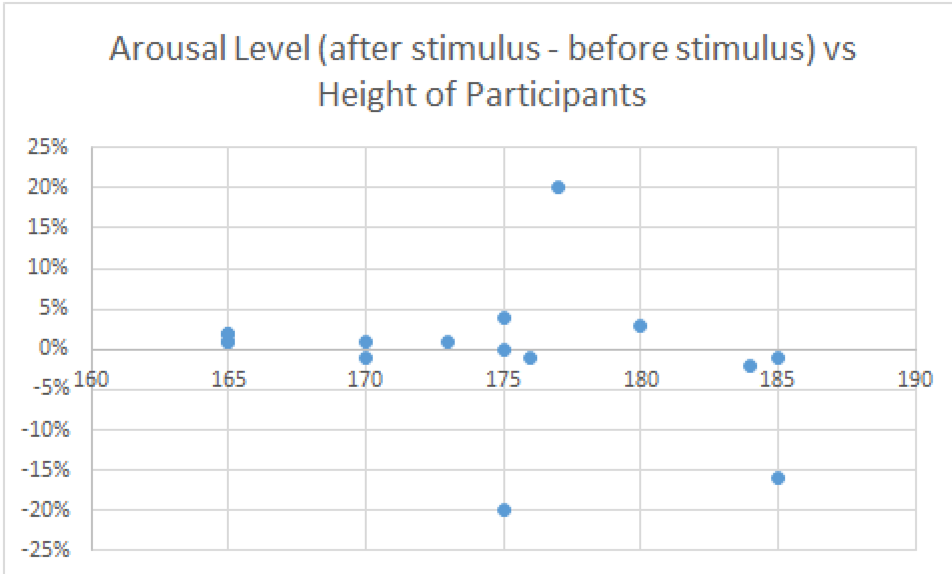

Figure 5–28: Arousal Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Height

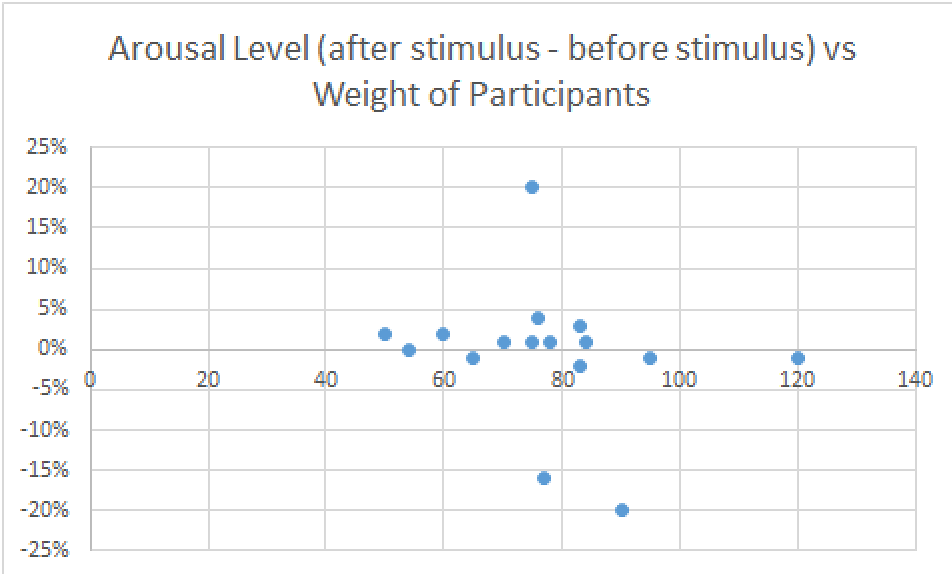

Figure 5–29: Arousal Level (After Evoking Stimuli - Before Evoking Stimuli) for Each Participant versus Their Weight

5.5.8 Memory Performance Level Graphs

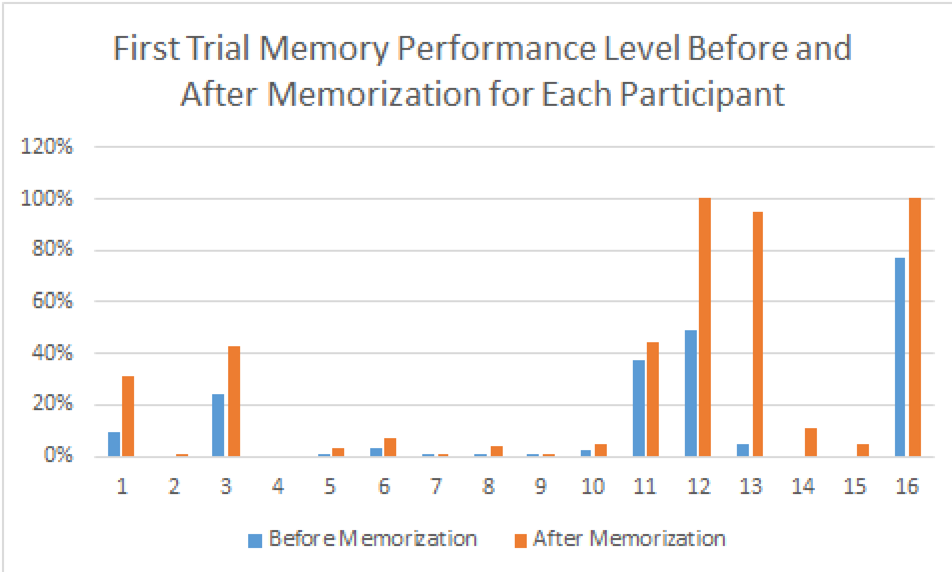

Figure 5–30: First Trial Memory Performance Level Before and After Memorization for Each Participant

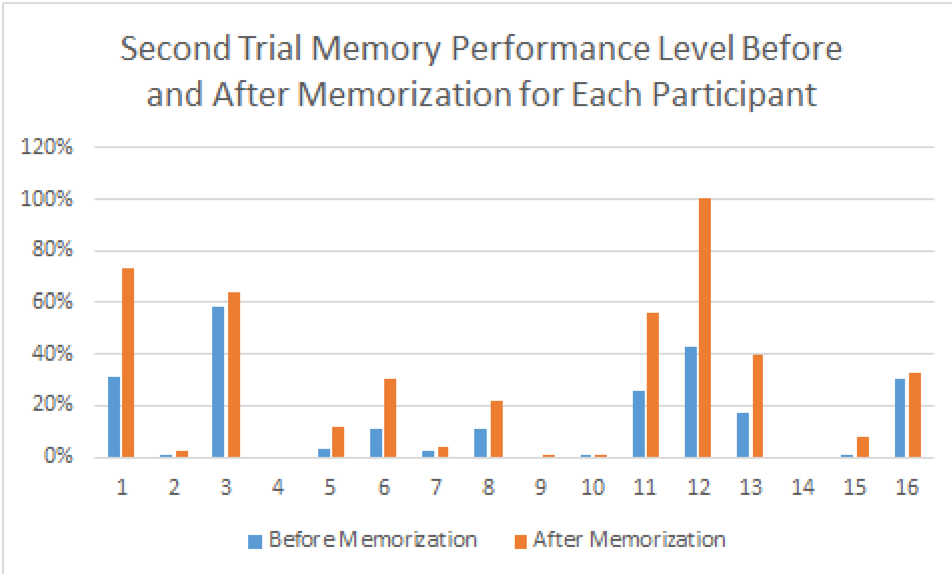

Figure 5–31: Second Trial Memory Performance Level Before and After Memorization for Each Participant

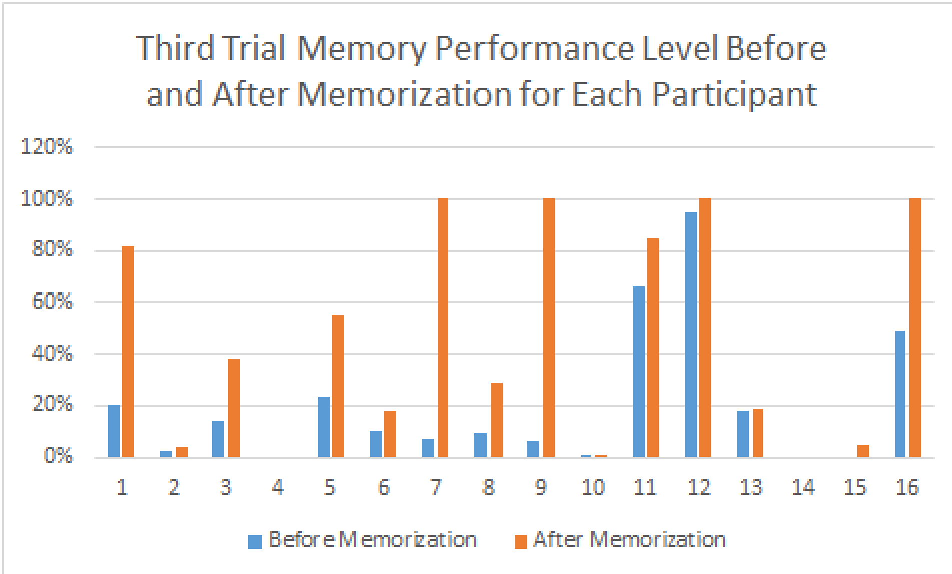

Figure 5–32: Third Trial Memory Performance Level Before and After Memorization for Each Participant

5.6 Discussion

First of all, the relaxation levels before and after evoking the stimulus for each participant have shown that the experiment has been successful at raising the relaxation levels of the participants when being shown the stimulus. About 56% of all participants had a higher relaxation level after the stimulus as compared to before the stimulus. The 44% remaining participants had relaxation levels lower or equal after the stimulus as compared to before the stimulus. Participants were found to have varying reactions when exposed to such stimulus: Some of the 44% may have had other thoughts or emotions during the experiment, and may have been preoccupied with other matters. Some may have felt other emotions such as anxiety or stress during the experiment, thereby negating any effect of the relaxation stimulus on them.

Another problem potentially accounting for the variation in results is the fact that the brain sensor's EEG data had to travel from the brain cortex to the electrodes of the brain sensor. During its travel, the signal may have been attenuated or dampened as a result of traveling through many brain regions before reaching the brain sensor's electrodes. So, the quality of the signal using the method is not optimal, and results in a lower-quality EEG signal. The change in relaxation level (the relaxation level after stimulus minus the relaxation level before stimulus) was plotted against the age of all participants. The graph reveals that almost all participants had a positive or neutral change in relaxation levels and that most participants with the greatest positive changes in relaxation levels (relaxation levels changes higher than 40%) are the younger participants, those aged 22 to 30. The older population, those aged 40 to 80, had the most participants with negative changes (relaxation level changes lower than 10%) in relaxation levels (3 participants aged 50-80). The results reveal that the ability of the participants to relax quickly in response to a conducive stimulus is greater for younger individuals than for older ones. The change in relaxation level was plotted against the height of all participants. The results reveal that the tallest individuals (heights ranging from 175 to 185 cm) had the majority of values corresponding to the highest changes (relaxation change higher than 40%) in relaxation levels (5 individuals with heights ranging from 175 to 185 cm versus 1 individual with a height of 165 cm). The participants with all the values corresponding to negative changes in relaxation levels (values less than -10%) are the shortest individuals (4 individuals with heights ranging from 165 to 175 cm). The results mean that the taller participants are better able to relax quickly than shorter participants.

Second, the engagement levels before and after evoking the stimulus for each participant have shown that the experiment has been successful at raising the engagement levels of the participants. The success rate is about 81%, which is 25% higher than the one of the relaxation mood experiment. The 19% remaining of participants had engagement levels lower or equal after the stimulus as compared to before the stimulus. The same reasons discussed in the relaxation mood experiment could be applied to explain why the 19% of participants had lower or equal engagement levels after evoking the stimulus as compared to before evoking the stimulus. The change in engagement level (engagement level after evoking the stimulus minus the engagement level before evoking the stimulus) was plotted against the age of all participants. The graph reveals that the number of participants with changes in engagement levels which is greater or equal to 30% is greater for the younger population than for the older population (4 individuals aged 20-30 versus 2 individuals aged 40-70). This result indicates that the ability of participants to be engaged quickly in response to a conducive stimulus is greater for the younger population than for the older population. The change in engagement level versus the height of all participants was plotted. The graph reveals that the shorter population (with heights ranging from 165-175 cm) has 3 values with negative changes in engagement levels. The taller population (with heights ranging from 176-185 cm) has only neutral or positive changes in engagement levels. This may indicate that the ability of participants to be engaged quickly is greater for taller individuals than for shorter individuals.

Third, the stress levels before and after evoking the stimulus for each participant have shown that the experiment has been successful at raising the stress levels of the participants. The success rate is about 73%, which is 17% higher than the one of the relaxation mood experiment. The 27% remaining of participants had stress levels lower after the stimulus as compared to before the stimulus. The same reasons discussed in the relaxation mood experiment could be applied to explain why the 27% of participants had lower or equal stress levels after evoking the stimulus as compared to before evoking the stimulus. The change in stress level (stress level after evoking the stimulus minus the stress level before evoking the stimulus) was plotted against the age of all participants. The graph reveals that the number of participants with changes in stress level greater or equal to 40% is greater for the younger population than for the older population (3 individuals aged 20-30 versus 2 individuals aged 40-80). The number of participants with negative changes in stress level (values lower than -20%) is greater for the older population than for the younger population (1 individual aged 27 versus 2 individuals aged 50-70). The results indicate that the ability of participants to be stressed quickly in response to a conducive stimulus is greater for the younger participants than for the older participants. The change in stress level versus the height of all participants was plotted. The graph reveals that the shorter population (with height ranging from 165-175 cm) has 3 values with negative change in stress levels versus 2 values of negative change in stress levels for the taller population. Also, the number of participants with changes in stress levels greater than 40% is greater for the taller population than for the shorter population (3 individuals with heights ranging from 176-185 cm versus 2 individuals with heights ranging from 165-175 cm). The results indicate that the ability of participants to be stressed quickly in response to a conducive stimulus is greater for taller individuals than for shorter individuals. The graph showing the change in stress level against the weight of participants reveals that the majority of individuals with the greatest changes in stress levels (higher or equal to 40%) are those with weights ranging from 80-120 kg. The graph also shows that the individuals with weights ranging from 55-80 kg have all values associated with negative changes in stress levels. The results show us that the ability of participants to be stressed quickly is greater for individuals who weigh more than 80 kg than for individuals who weigh less than 80 kg.

Fourth, the anger levels before and after evoking the stimulus for each participant have shown that the experiment has been successful at raising the anger levels of the participants. The success rate is about 50%, which is 6% lower than the one of the relaxation mood experiment. The 50% remaining of participants had anger levels lower after the stimulus as compared to before the stimulus. The same reasons discussed in the relaxation mood experiment could be applied to explain why the 50% of participants had lower or equal anger levels after evoking the stimulus as compared to before evoking the stimulus. The change in anger level (anger level after evoking the stimulus minus the anger level before evoking the stimulus) was plotted against the age of all participants. The graph reveals that the number of participants with a change in anger level which is greater or equal to 40% is greater for the younger population than for the older population (2 individuals aged 20-30 versus 1 individual aged 65). The number of participants with negative changes in stress levels (values lower than -10%) is greater for the older population than for the younger population (1 individual aged 23 versus 4 individuals aged 45-70). The results indicate that the ability of participants to be angry quickly in response to a conducive stimulus is greater for the younger participants than for the older participants. The change in anger level versus the height of all participants was plotted. The graph reveals that the shorter population (with height ranging from 165-175 cm) has 3 values with negative changes in anger levels (values lower than -10%) versus 1 value of negative change of anger level for the taller population (with height ranging from 176-185 cm). The results indicate that the ability of participants to be stressed quickly in response to a conducive stimulus is greater for taller individuals than for shorter ones. The graph showing the change in anger level versus the weight of participants reveals that the majority of individuals with the greatest change in anger level (higher or equal to 40%) are those with weights ranging from 75-85 kg. The graph also shows that the individuals with weights ranging from 80-120 kg have almost all of the values associated with negative changes in anger levels (1 value for a weight of 60 kg versus 4 values for weights ranging from 80-120 kg). The results show us that the response of participants to events or situations causing anger is lower for individuals who weigh more than 85 kg than for individuals who weigh less than 85 kg.

Fifth, the happiness levels before and after evoking the stimulus for each participant have shown that the experiment has been successful at raising the happiness levels of the participants. The success rate is about 53%, which is 3% lower than the one of the relaxation mood experiment. The 47% remaining of participants had a happiness level lower or equal after the stimulus as compared to before the stimulus.

The same reasons discussed in the relaxation mood experiment could be applied to explain why the 47% of participants had lower or equal happiness levels after evoking the stimulus as compared to before evoking the stimulus. The change in happiness level (happiness level after evoking the stimulus minus the happiness level before evoking the stimulus) was plotted against the age of all participants. The graph reveals that the number of participants with a changes in happiness levels greater or equal to 40% is greater for the younger population than for the older population (4 individuals aged 20-30 versus 3 individuals aged 40-80). The number of participants with negative changes in happiness level (value lower than 0%) is greater for the older population than for the younger population (2 individuals aged 20-30 years old versus 3 individuals aged 40-70). The results indicate that the ability of participants to be happy quickly in response to a conducive stimulus is greater for the younger participants than for the older participants. The change in happiness level versus the height of all participants was plotted. The graph reveals that the shorter population (with heights ranging from 165-175 cm) has 3 values with negative changes in happiness levels versus 1 value of negative change in happiness level for the taller population (with heights ranging from 176-185 cm). The results may indicate that the response of participants to events or situations causing happiness is greater for taller individuals than for shorter individuals.

Sixth, the sadness levels before and after evoking the stimulus for each participant have shown that the experiment has been successful at raising the sadness levels of the participants. The success rate is about 73%, which is 17% higher than the one of the relaxation mood experiment. The 27% remaining of participants had sadness levels lower or equal after the stimulus as compared to before the stimulus. The same reasons discussed in the relaxation mood experiment could be applied to explain why the 27% of participants had lower or equal sadness levels after evoking the stimulus as compared to before evoking the stimulus. The change in sadness level versus the height of all participants was plotted. The graph reveals that the shorter population (with height ranging from 165-175 cm) has 1 value with negative change in sadness level versus 2 values of negative changes in sadness levels for the taller population (with height ranging from 176-185 cm). The graph also reveals that the taller population has less values associated with positive changes in sadness levels (4 values greater than 20%) than the shorter population (6 values greater than 20%). The results indicate that the ability of participants to be sad quickly in response to a conducive stimulus is greater for taller individuals than for shorter individuals. The graph showing the change in sadness level versus the weight of participants reveals that the majority of individuals with the greatest changes in sadness levels (higher or equal to 40%) are those with weights below 80 kg. The graph also shows that the individuals with weights above 80 kg have all the values associated with negative changes in sadness levels (2 values below -20%). The results show us that the response of participants to events or situations causing sadness is smaller for individuals weighing more than 80 kg than for individuals weighing less than 80 kg.

Seventh, the arousal levels before and after evoking the stimulus for each participant have shown that the experiment has been successful at raising the arousal levels of the participants. The success rate is about 56%, which is equal to the one of the relaxation mood experiment. The 44% remaining of participants had arousal levels lower or equal after the stimulus as compared to before the stimulus. The same reasons discussed in the relaxation mood experiment could be applied to explain why the 44% of participants had lower or equal arousal levels after evoking the stimulus as compared to before evoking the stimulus. The change in arousal level (arousal level after evoking the stimulus minus the arousal level before evoking the stimulus) was plotted against the age of all participants. The graph reveals that the number of participants with a change in arousal level which is greater than 0% is greater for the younger population than for the older population (5 individuals aged 20-30 versus 3 individuals aged 40-80). The results indicate that the ability of participants to be aroused quickly in response to a conducive stimulus is greater for the younger participants than for the older participants. The change in arousal level versus the height of all participants was plotted. The graph reveals that the shorter population (with height ranging from 165-175 cm) has 2 values of negative changes in arousal levels versus 4 values of negative changes of arousal levels for the taller population (with height ranging from 176-185 cm). The results may indicate that the response of participants to events or situations causing arousal is greater for shorter individuals than for taller individuals. The graph showing the change in arousal level versus the weight of participants reveals that individuals with weights above 78 kg have less values associated with positive changes in arousal levels (3 values) as compared to individuals with weights below 78 kg (6 values). Also, individuals with weights above or equal to 78 kg have all values associated with negative changes in arousal levels. This implies that participants' response to events or situations causing arousal is lower for participants who weigh more than 78 kg than for participants who weigh less than 78 kg.

The first, second, and third trial memory performance levels before and after memorizing the set of letters for each participant show that our experiment has been successful at raising the memory performance levels of the participants. Almost all participants had higher memory performance levels after memorizing the set of letters as compared to before memorizing the set of letters which is associated with positive memory activity. The success rates of all trials are 81%. The 19% remaining participants for each trial had memory performance levels lower or equal after memorizing the set of letters as compared to before memorizing the set of letters. An explanation of the variation in results is the fact that the brain sensor's EEG data had to travel from the brain cortex to the electrodes of the brain sensor. During its travel, the signal may have been attenuated or dampened as a result of traveling through many brain regions before reaching the brain sensor's electrodes. It is very likely that the more head hair a participant had, the more attenuated or dampened the signal was when reaching the electrodes of the brain sensor.

CHAPTER 6
Conclusion and Future Work

This thesis has presented a system capable of detecting the mood and memory performance of humans. A complete description of this system along with the features it has to offer were discussed in Chapter 5. Chapter 4 focused on giving background information essential for understanding the system's mood and memory performance evaluation features such as EEG, human brain waves, human brain structure, heart rate variability, and BLE sensors. Chapter 6 described the testing procedure and a discussion on all of the experiment results was formed.

This application can be a first step in mental health evaluation, and, as we know, it is up to the patient to take the right decisions so that meaningful changes in health and lifestyle can be made.

To increase the accuracy of mood and memory detection in the future, we could use more external sensors such as skin sensors and infrared sensors (infrared camera to measure body temperature), all of which are connected via Bluetooth Low Energy or another protocol to a smartphone, tablet, or other electronic device. Although mood and memory evaluation from heart and brain sensors is accurate, it does not provide enough information on all body activity such as skin (perspiration), arms and legs (motion), back (posture), and more. The algorithms on mood and memory detection could be more refined and accurate and, when combined with the multiple external sensors, could be used to detect a bigger range of emotions. To evaluate memory, we could use more sophisticated devices such as fMRI (Functional Magnetic Resonance Imaging) and MEG (Magnetoencephalography) to get a better view of brain activity. In order to acquire such devices, experience and funding would be required.

Mood and memory evaluation devices have become very popular with the expansion and improvement of technology. The field of mood detection and memory evaluation can be expected to grow and evolve thanks to researchers and developers who seek to improve quality of life by introducing new devices and systems that help raise awareness of individuals' health and well-being. We hope that our contribution can make difference in many fields of study, especially in computer engineering, biomedicine, mental health and other medical specialties.

Appendix A

The appendix contains testing slides used in my experiment to evaluate the mood and memory performance of adults.

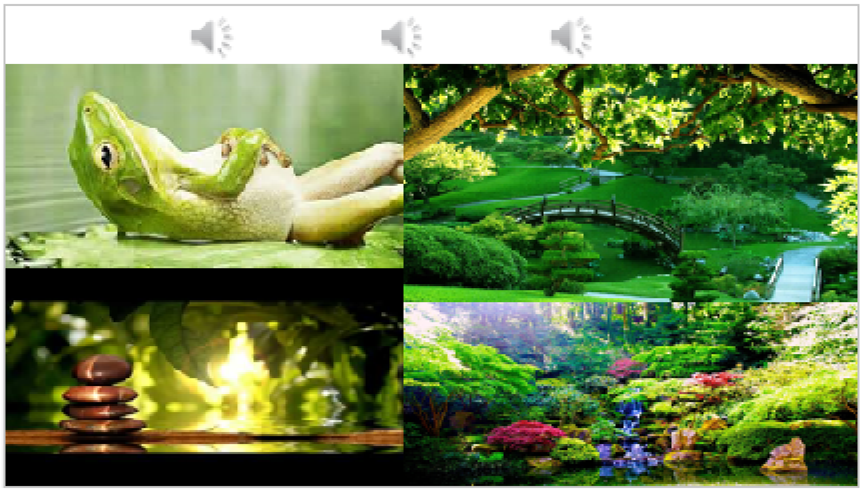

Figure 6–1: Relaxation Test Slide

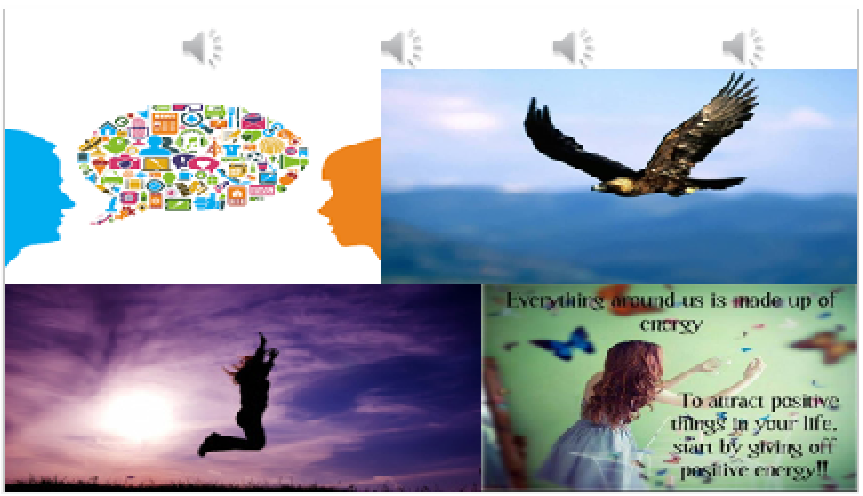

Figure 6–2: Engagement Test Slide

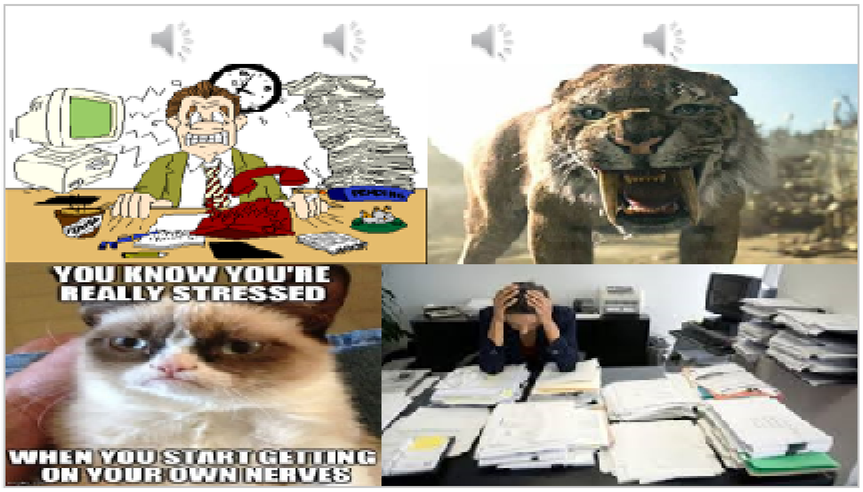

Figure 6–3: Stress Test Slide

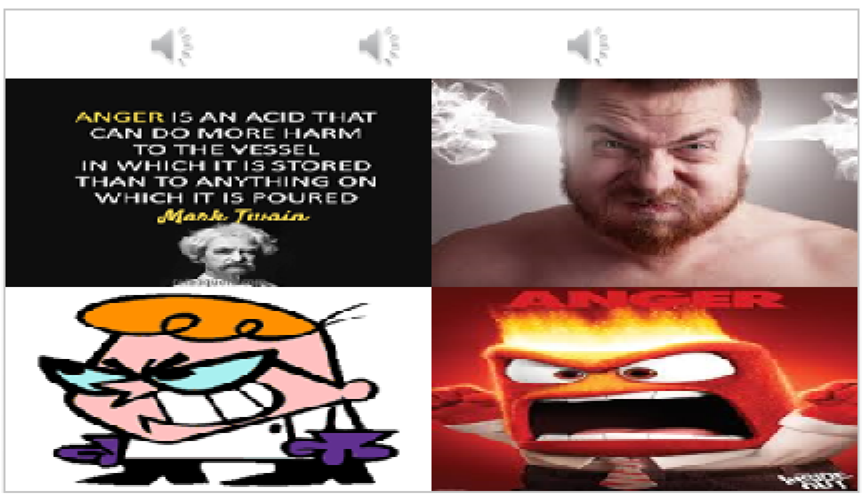

Figure 6–4: Anger Test Slide

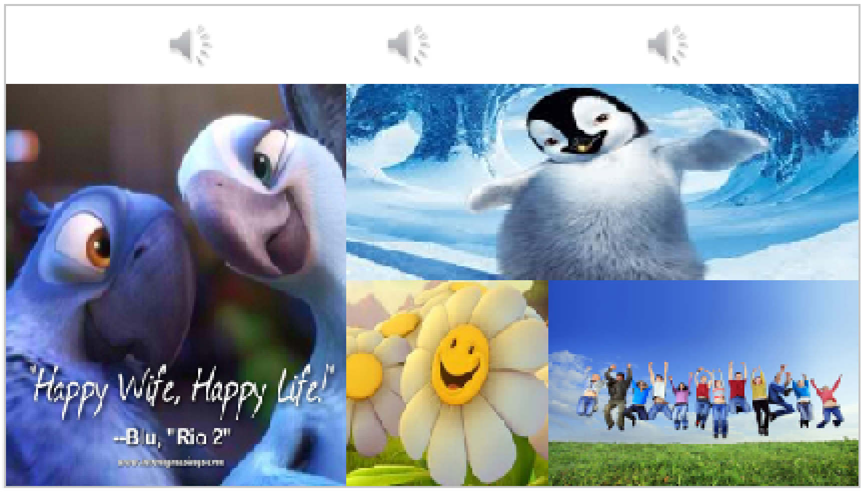

Figure 6–5: Happiness Test Slide

Figure 6–6: Sadness Test Slide

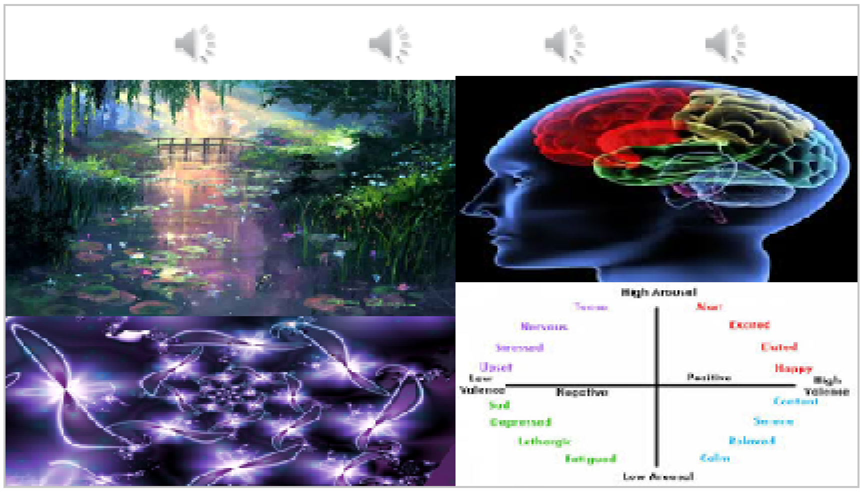

Figure 6–7: Arousal Test Slide

B K V J

Figure 6–8: First Set of Letters

M

Figure 6–9: First Probe

L S C Y R

Figure 6–10: Second Set of Letters

C

Figure 6–11: Second Probe

E Q H D F I

Figure 6–12: Third Set of Letters

J

Figure 6–13: Third Probe

Appendix B

Here is the text of a second, additional Appendix

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