# Wearable Technology for Mental Wellness Monitoring and Feedback

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Submitted in partial fulfilment of the requirements of the Degree of Doctor of Philosophy

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Queen Mary University of London

2023

# Statement of Originality

I, Reham Alhejaili, declare that, to the best of my knowledge, this thesis has been composed solely by myself. I confirm that this thesis has not been submitted, in whole or in part, in any previous application for a degree except were stated otherwise by reference or acknowledgment. The copyright of this thesis rests with the author. No quotation from it is permitted without full acknowledgment.

# Abstract

This thesis investigates the transformative potential of wearable monitoring devices in empowering individuals to make positive lifestyle changes and enhance mental well-being. The primary objective is to assess the efficacy of these devices in addressing mental health issues, with a specific focus on stress and anxiety biomarkers. The research includes a systematic literature review that uniquely emphasizes integrating wearable technology into mental wellness, spanning diverse domains such as electronics, wearable technology, machine learning, and data analysis. This novel systematic literature review encompasses the period from 2010 to 2023, examining the profound impact of the Internet of Things (IoT) across various sectors, particularly healthcare. The thesis extensively explores wearable technologies capable of identifying a broad spectrum of human biomarkers and stress-related indicators, emphasizing their potential benefits for healthcare professionals. Challenges faced by participants and researchers in the practical implementation of wearable technology are addressed through survey analysis, providing substantial evidence for the potential of wearables in bolstering mental health within professional environments. Meticulous data analysis gathering from biosignals captured by wearables investigates the impact of stress factors and anxiety on individuals' mental well-being. The study concludes with a thorough discussion of the findings and their implications. Additionally, integrating Photoplethysmography (PPG) devices is highlighted as a significant advancement in capturing vital biomarkers associated with stress and mental well-being. Through light-based technology, PPG devices monitor blood volume changes in microvascular tissue, providing real-time information on heart rate variability (HRV). This non-invasive approach enables continuous monitoring, offering a dynamic understanding of physiological responses to stressors. The reliability of wearable devices equipped with PPG and Electroencephalography (EEG) sensors is emphasized in capturing differences in subject biomarkers. EEG devices measure brainwave patterns, providing insights into neural activity associated with stress and emotional states. The combination of PPG and EEG data enhances the precision of stress and mental well-being assessments, offering a holistic approach that captures peripheral physiological responses and central nervous system activity. In conclusion, integrating PPG devices with subjective methods and EEG sensors significantly advances stress and mental well-being assessment. This multidimensional approach improves measurement accuracy, laying the foundation for personalized interventions and innovative solutions in mental health care. The thesis also evaluates body sensors and their correlation with medically established gold references, exploring the potential of wearable devices in advancing mental health and well-being.

# Acknowledgments

Let it be known that I want to dedicate this thesis foremost to my incredible parents, whose constant presence and unwavering support have been the guiding light throughout my academic journey. Their boundless compassion, care, dedication, and love have been the foundation upon which I have built my achievements. Words cannot adequately express my gratitude. May God bless them abundantly for their selflessness and make me a source of perpetual joy and pride for them.

I sincerely thank my supervisor for his invaluable assistance and direction, Prof. Akram Alomainy, who paved the way for me to see the importance of laborious effort in my field. The research was an inspiration to me in every aspect. He never stopped addressing my inquiries and assuaging my concerns, even when I was sceptical. Also, I would like to thank my second supervisor Dr. Anne Hsu for her scholarly advice, which helped me to accomplish this task.

Gratitude is also extended to the entire staff at KFSH&RC-J for their generous support. I want to express heartfelt thanks to the neuroscience team at KFSH&RC-J, including Dr. Fawzi Babtain, Dr. Noor Habib, Alaa Sobhi, the supervisor for the neurophysiology lab, and Tariq Khoja, the neurophysiology technologist, for their unwavering encouragement and cooperation throughout my study period.

Finally, I wish to convey my appreciation to my beloved brothers, sister, sisters-in-law, nieces, nephews, friends, colleagues, and all those who kept me in their prayers. Your constant encouragement and positive energy have been a source of immense strength, and I will forever be grateful to each of you from the depths of my heart.

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# List of abbreviations

ACC Anterior cingulate cortex
ANS Autonomic nervous system
BVP Blood volume pulse sensor
CAN Central autonomic network
ECG Electrocardiogram
EDA Electrodermal activity
EEG Electroencephalography
FFT Fast Fourier Transform
fMRI Functional magnetic resonance imaging
HF High frequency
HRV Heart rate variability
IBI Interbeat interval
ICA Independent Component Analysis
LF Low frequency
MRI Magnetic resonance imaging
PET Positron emission tomography
PPG Photoplethysmographic
PSTD Post-traumatic stress disorder
RF Respiration frequency
SC Skin conductance
STFT Short time Fourier transform
TP Total power
VLF Very low frequency
MDD Major depression disorder
GAD7 General anxiety disorder
PSS_10 Predive stress scale
SLR Systematic literature review
SAM Self-assessment manikin
SCWT Stroop colour word test
EMG Electromyogram
QOTS quality-of-life technologies
OECD Organization for Economic Cooperation
VOCs Volatile organic components
PSD power spectral density
(IAPS) photos International Affective Picture System
(AIC) Akaike Information Criterion

(OLS) Ordinary Least Squares regression
(DL) Deep Learning
(RNNs) Recurrent Neural Networks
(GANs) Generative Adversarial Networks
(ML) Machine learning

# Chapter 1

# Introduction

# CHAPTER 1

# Introduction

*In this introductory chapter, the thesis embarks on a profound journey that delves into the core of its research. It begins by exploring the sources of inspiration that drove the pursuit of the chosen research topics, shedding light on significant events, thinkers, and discoveries that influenced the investigation. Understanding the origins of these ideas provides essential context and motivation for scholarly endeavours. Moreover, the chapter emphasizes the invaluable contributions this thesis aims to make within its respective fields of study. As the research findings are unveiled, the thesis seeks to bridge gaps in knowledge, challenge prevailing paradigms, and offer fresh insights that enrich the academic landscape. Beyond advancing discourse, the contributions aspire to address real-world challenges and create meaningful impacts, establishing the research as a vital and relevant contribution to the academic community and beyond.*

The responsiveness of the human body to a demand for modification is known as stress [1]. A fight-or-flight reaction is invoked when there is an approach to a dangerous situation. Normal routine tension does not harm life; however, the fight-or-flight reaction can always be invoked. Continuing this short-term stress for a prolonged time can have long-lasting effects on a person's neurological system. Stress can increase through psychological demands such as expectations to succeed on a high level or future endeavor issues. It is possible to see how competition might lead to threats and increase anxiety.

*Anxiety* is defined as the sensation of unpleasant feelings when faced with actual, potentially threatening circumstances demands biologically; anxiety comprises two subcomponents: somatic and cognitive. Somatic anxiety is a physiological feature characterized by autonomic arousal (e.g., heightened blood pressure, sweating, changes in breath rate and intensity). Cognitive anxiety refers to the behavioural aspect of anxiety, which consists of negative assumptions for success or self-evaluation, worrying, negative self-talk, and disturbed attentional mechanisms. Anxiety is particularly significant in deciding factors between winning or losing. Stress brings physical effects inside the body that are harmful to performance. Researchers found a strong association between life-event tension and individuals' elevated likelihood of injury.

Due to the substantial increase in world population and the financial and resource strains it is adding to healthcare provision, physicians and researchers need to suggest machinery and equipment that could simplify their roles and practices and contribute to providing patient assistance [1]. This would help reduce the level of strain, tension, and anxiety that has increased significantly due to elevated levels of performance and anxiety. Researchers have suggested an updated approach to assist healthcare professionals and doctors in identifying various vital factors and criteria and taking different human body measurements to assess the degree of stress and distress a person might be experiencing [2].

Obstacles and challenges that healthcare workers encounter can be substantially minimized with the implementation of emerging technology and recent developments. The research study focuses on wearable, non-invasive technologies that measure human stress levels utilizing numerous parameters [3]. A study by Martinez et al. has reported a dramatic increase in the number of patients with cognitive load and anxiety in recent years [4]. The study's authors also addressed stress as one of the states that have become epidemiologically more prevalent in most nations worldwide [5]. Wearable sensor-based technologies can sense different parameters of a person, which can be viewed as signs of stress within the individual. These indications, often used for stress and stress detection, are heart rate, pulse rate, pupil dilation, skin temperature, and electrodermal activity in the human body [6]. The research further illustrates that although low stress levels have always benefited the human body, risk factors, challenges, and difficulties should be considered when making choices or doing everyday activities. Continuously experiencing difficult circumstances may impact a person's physiology, cognition, and neurocognitive behaviour. A person under stress may develop chronic conditions, including anxiety, depression, and accelerated aging [7].

The appearance of stress within an individual contributes to additional adverse effects and repercussions on the individual, including anxiety, depression, and panic attacks. However, with the aid of specific technologies that monitor and recognize the physiological and mental changes within a person naturally, it is possible to improve a person's quality of life through the early identification of problems. These devices also help determine the underlying stimuli that cause disruptive behavior and cognitive problems. Healthcare providers should design a management plan for their patients with the help of such a type of detection.

## 1.1 Motivation

This thesis' primary goal is to identify levels of stress, anxiety, or other cognitive loads, and it is possible to observe the effectiveness of several biomarkers in identifying stress levels with the aid of a literature study on this subject. The relationship between heart rate variability (HRV) and brain activity is intriguing in physiological research. As a potential stress and relaxation marker influenced by both the sympathetic and parasympathetic brain systems, HRV has also been referred to as an autonomic function measure that correlates with[8] lifespan In the HRV biofeedback approach, participants learn to match their equipment-led along with respiratory rate and rhythm to increase their HRV, [9] a rise in HRV indicates excellent health [10]– [13].

Because of the high burden of stress and stress-related illness, it is important to recognize appropriate stress control strategies among subjects. Interventions widely used to relieve stress and anxiety include gradual muscle relaxation, listening to soothing and classical music, cognitive-behavioural treatments, and meditation. Abnormal alpha asymmetry, or the relative difference in EEG alpha strength between homologous right and left electrodes [1], has been proposed as a trait predictor of susceptibility to acute stress in electroencephalography (EEG) studies. According to Davidson's approach-withdrawal model, greater left frontal activation is associated with approach-related positive emotion [5].

In contrast, withdrawal-related depressive emotion is associated with proper elevated EEG frontal function and structure. Apart from raising the theta and alpha power of the EEG spectrum, self-regulation, like meditation, may also increase the theta and alpha power of the EEG spectrum. The level of relaxation, visual learning, memory functions, and feelings can all be expressed in alpha waves. The complex association between EEG alpha band activity and heart rate variability has already been investigated, and spectral analysis of the EEG is a valuable tool for determining the contribution of various brain functions over cortical areas through brain states[5].

## 1.2 Research Questions

The proposed research study's goal is to respond to the key questions.

> *How wearable devices can capture biomarkers that aid in detecting and potentially assisting with stress levels and mental well-being?*

The answer to this question holds significant implications, as the utilization of wearable biosensors in real-life experimentation poses numerous challenges concerning the reliability and utility of the measurements for extracting emotions. A sufficient sampling frequency is essential to depict biosensor signals accurately, and precise sensor placement is required to record physiological signals while minimizing ambiguities. Raw signals often exhibit fluctuations due to the individual's physiological state. Even with correct sensor placement and inevitable recording of fluctuations, it becomes imperative to filter the raw sensor signal to eliminate noise, thus enhancing stress detection efficiency. As a preliminary step, evaluating the current State-of-the-Art in Wearable Technology for individuals experiencing stress and anxiety is essential.

***RQ 1*** *What is the current State-of-the-Art in Wearable Technologiesfor persons with stress and anxiety?*

Secondly, we should assess the reliability of wearables devices in capturing the differences in HRV and EEG Signals before, during, and after the stress-induced performance.

***RQ 2*** *what is the reliability of wearables devices in capturing the differences in HRV and EEG bio signals before, during, and after the stress-induced performance?*

After considering the reliability of the wearable biosensors by recording the subject biomarkers for two different types of wearable technologies, we should investigate the relationship between HRV and EEG.

Furthermore, we are exploring the potential of wearable sensors to provide dependable and non-intrusive methods for classifying stress-related illnesses. This involves assessing the viability of measuring Heart Rate Variability (HRV) and Electroencephalogram (EEG) biomarkers as indicators of stress.

***RQ 3*** *Is there a significant correlation between HRV and EEG bio signals derived by using wearables technology in detecting the stress factors in normal healthy subjects?*

Then and after exploring the correlations between HRV and EEG bio signals at the resting stage, we will explore to assess the relationships between HRV and EEG to stress-induced performance.

***RQ 4*** *How strong is the association between HRV and the Multidimensional model to measure emotional stress factors?*

Exploring the potential of Heart Rate Variability (HRV) monitoring and wearable technology holds significant promise in comprehending and effectively managing emotions. This area of study not only opens up promising avenues for future investigations but also paves the way for the development of personalized approaches to assist individuals in managing their emotions effectively.

***RQ 5*** *Will wearable technologies be considered an assistive solution for the subject mental well-being?*

Various approaches have been taken to address these research questions. First, we have conducted a systematic literature review to answer the first research question (RQ 1): What is the current State-of-the-Art in Wearable Technologies to be considered assistive solutions for mental well-being? We have looked at the use of wearable technology in detecting stress biomarkers.

To answer the second and the third research questions (RQ 2&3) regarding the reliability of wearable devices in capturing the differences in HRV and EEG before, during, and after the stress-induced performance, we conducted pilot research study to evaluate the accuracy of wearable sensing technologies. The link between HRV and EEG is produced from wearables and cognitive function utilizing wearables technology.

Additionally, we used data to analyze the relationship between HRV and EEG to respond to the fourth and fifth research questions (RQ 5) related to the association between HRV and EEG function in emotional stress performance.

Finally, we investigated the Sam scale to assess individuals' emotions concerning IAPS image to address the last research question (RQ 5) on the suitability of wearable biosensor devices for evaluating physiological changes associated with subjects' mental well-being concerning stress and anxiety.

## 1.3 Contributions and Thesis structure

Based on the idea that wearable monitoring devices may give people useful information and insights that can help them make good adjustments to their lifestyle and enhance their mental health, this thesis aims to ensure that these devices help provide solutions for mental well-being.

This thesis presents a novel systematic literature review on the use of wearable technology in mental wellness and specifically linked to stress markers. This covers electronics, wearable technology, and healthcare applications. The manuscript presents a systematic review targeting a new area of research with increasing interest. Its crossovers the period the 2010-2023 and emphasizes how the Internet of Things (IoT) has a significant impact on a variety of industries, including healthcare.

The thesis addresses several wearable technologies which can detect numerous human biomarkers, and stress-related biosensors that have had a favourable impact on healthcare professionals. The difficulties that participants and researchers encountered when bringing wearable technology into practice are also addressed in chapter 2. This chapter conclusion is based on an evaluated survey and the findings generally imply that wearable technology has the potential to be extremely crucial for maintaining mental health at work.

The rest of the thesis will present an in-depth investigation of the subject metal wellbeing by using wearable technologies, starting with the inspiration and context that inspired the study. The literature study will examine various sources, including academic publications and research papers, to better comprehend wearable and stress detection technologies. The study will also include a survey analysis to examine how stressed factors affect the subject's mental well-being. The debate will focus on the study's conclusions and consequences.

**Chapter 2: A Review on the use of wearable technologies in providing solutions for mental wellness** to answer RQ 1, In this methodological systematic review analysis, we provide a thorough summary using the studies that have been done so far on the use of wearable technology to assist a subject's wellbeing.

**Chapter 3: Detecting the correlation between HRV and EEG bio signals: A pilot Study.**

Chapter 3 looks through the associations between EEG bio signals and the HRV during stress-induced sessions by using cognitive performance tests in young, healthy participants to detect the autonomic nervous system reactions using wearable sensors. This is done to respond to RQs 2 and 3 and to determine the accuracy of the most modern wearable sensing devices in detecting autonomic nervous system reactions to stress. A study conducted in two distinct geographical regions was tailored to unveil a standardized methodology pertaining to stress and anxiety. The pilot study utilized the CorSense device and Emotiv 14 channels to capture sensory data, which was subsequently presented. The discussion focused on the potential applications of sensor data in evaluating Autonomic Nervous System (ANS) responses. The primary focus of this chapter lies in assessing the accuracy of wearable technology in detecting variations in Heart Rate Variability (HRV) before, during, and after cognitive tasks, leveraging wearable-based technology. Additionally, electroencephalogram (EEG) signal processing was adapted to explore the association between alpha asymmetry and HRV in the context of stress-induced sessions. Furthermore, the investigation extends to determining potential associations between major depression or major anxiety disorders through the analysis of medical questionnaires in conjunction with these physiological signals.

**Chapter 4: Perspective on assessing human emotions by measuring HRV in healthy individuals.** The study explored the potential of HRV as a valuable marker for emotional performance in healthy individuals. The findings indicated a positive weak association between high HRV and improved emotional regulation, suggesting that HRV could predict emotional well-being and resilience. The use of wearable sensors in the study demonstrated the promising role of technology in understanding and managing emotions. Real-time feedback provided by wearable devices equipped with HRV monitoring capabilities could help individuals recognize and manage emotional fluctuations more effectively, benefiting those dealing with stress and anxiety and potentially enhancing overall well-being and quality of life.

Regarding Research Question 4, the chapter provided a study on the use of wearable sensors to assist human emotions concerning stress and anxiety. The results revealed weak positive correlations between specific HRV metrics, such as RMSSD and SDNN, and the subjective emotional valence and arousal ratings. These findings indicate that changes in HRV are linked to concurrent changes in the perception of emotional states, especially unpleasantness, and arousal. Researchers can quantitatively evaluate the relationship between HRV and subjective dynamic ratings using the Pearson correlation coefficient.

Overall, this research sheds light on the potential of HRV monitoring and wearable technology in understanding and managing emotions, offering promising avenues for future investigations, and developing personalized emotion-assistance approaches.

**Chapter 5: Conclusion and future work.** Serves as a culmination of this study, providing a detailed summary of the work conducted throughout the research. The chapter thoroughly synthesizes the findings, outlining the key results and their significance in addressing the research objectives. It delves into the main insights obtained from the data analysis and emphasizes the implications of these findings in the broader context of the research area.

Additionally, this chapter discusses the limitations encountered during the research process. These limitations are carefully examined to acknowledge their potential impact on the study's outcomes and to demonstrate a clear understanding of the boundaries within which the research was conducted. By recognizing these limitations, future researchers can build upon this work and devise strategies to address them, thereby enhancing the validity and reliability of subsequent investigations.

Furthermore, Chapter 5 delineates the scope for future work and research directions that arise from the present study's outcomes. It highlights the unexplored areas and potential avenues for further investigation, inviting future researchers to extend and deepen their knowledge in this field. The identified scope for future work opens opportunities for innovative research endeavours, potentially leading to novel discoveries and advancements in the domain under study. Overall, Chapter 5 provides a comprehensive summary of the work accomplished and lays the foundation for future research to build Upon and contribute to the scholarly discourse in this area.

## 1.4 Publications

**Reham Alhejaili, Akram Alomainy. The Use of Wearable Technology in Providing Assistive Solutions for Mental Well-Being. Sensors. 2023; 23(17):7378. https://doi.org/10.3390/s23177378**

# Chapter2

# Background and Literature Review

# CHAPTER 2

## Background and Literature Review

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*This chapter offers background and methodological literature review focusing on wearable sensor technology and its connection to mental well-being, specifically in stress and anxiety detection. The chapter explores the currently available wearable technologies, their various sensing options, and how these capabilities can be harnessed to capture physiological changes associated with mental well-being. The main objective of the research analysis is to conduct a systematic literature review. To achieve this, extensive exploration of digital sources and academic journals was undertaken, with meticulous attention to detail. Multiple keywords and research phrases were carefully utilized to categorize and identify pertinent publications, journals, and research papers relevant to the study. By adopting this approach, the study aims to synthesize and present a comprehensive overview of the current research in wearable sensor technology and its potential impact on mental well-being, particularly in stress and anxiety detection*.

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### 2.1 Wearable Devices for Biosensing of Human Body Biophysical Data

Prior research has primarily centered on investigating the heart and brain as distinct entities, with various factors contributing to this historical separation. Once regarded as a potential confounding factor in cognitive metric studies, the autonomic nervous system led to experimental designs that emphasized managing excessive alertness to isolate selective attention effects on EEG[14]. Moreover, a prevailing tendency within the medical field for specialists to remain confined to their specific domains also played a role in the divide between heart and brain research [15] . However, recent literature has shifted its focus towards the emerging field of neurocardiology, aiming to unite the heart and brain as interconnected systems. Simultaneously examining the heart and brain holds great promise in providing valuable insights into the intricate interplay of afferent and efferent signals influencing stress responses, as these systems do not operate in isolation[16]. While past investigations have concentrated mainly on exploring the brain-heart relationship in pathological conditions such as stroke, cardiac arrhythmia, and heart failure, there remains a need for further exploration of this interaction in healthy individuals during rest[16]. By investigating this connection under controlled circumstances, we can deepen the comprehension of our bodies' physiological underpinnings and better understand how various diseases might affect them. In healthy individuals' studies, Heart Rate Variability (HRV) is commonly used to assess the autonomic nervous system's functioning, alongside functional brain imaging techniques like fMRI or PET to measure brain activity [17], [18]. Some studies have delved into specific brain regions associated with HRV activity, focusing on High-frequency HRV indicative of the parasympathetic nervous system's activity [19]. Additionally, specific investigations have utilized HRV and electrodermal response measurements to evaluate the sympathetic and parasympathetic nervous systems, revealing brain regions that control and regulate these systems. This underscores the importance of independently studying sympathetic and parasympathetic nervous systems as they engage distinct brain networks [20]. While some research has explored the impact of activities like meditation or video games on the heart-brain connection, only a few studies have explored the correlation between brain wave frequencies and HRV during rest. A noteworthy study examining low-frequency beta brain activity and sympathetic nervous system activity found a significant correlation with low-frequency HRV power, emphasizing the need for further investigations employing separate metrics to assess the sympathetic and parasympathetic nervous systems [21].

The information presented in the following sections incorporates insights and findings from our published journal titled " The Use of Wearable Technology in Providing Assistive Solutions for Mental Well-Being [22]"[1] This publication serves as a foundational reference for the content within these sections, offering an exploration of the role that wearable technology plays in enhancing mental well-being.

## 2.2 Motivation and Background

Body odour helps to detect fear and anxiety in individuals, and specific biomarkers, such as heart rate, skin conductivity, and oxygen saturation, can be used to assess stress and anxiety in patients. Hui and Sherratt [23]evaluated these vital signals and biomarkers to analyze changing mental states and conditions. In contrast, Happy and Routray[24], used image processing to detect emotional- changes by assessing facial expressions, and Li et al. [25] utilized a similar method but added the analysis and assessment of Electroencephalography reports. Using these reports and facial expressions, they were able to determine if there was a connection between changes in facial expressions and changes in brain activity and electrical nerve impulses. EEG assessment is considered one of the most beneficial methods for detecting mental states and conditions, and research studies that utilize this method are the focus of this literature review[26].

### 2.2.1Research Scope

Due to mental health disorders, and complications among patients, there is a greater need for doctors, psychiatrists, psychologists, and healthcare professionals to assist and treat mental issues[27]. Therefore, researchers need to consider existing theories, inventions, and concepts related to wearable devices that can detect cognitive mental parameters in these conditions. This systematic literature review is designed to provide readers and future researchers with knowledge about wearable devices used to monitor and assist with mental well-being, which can be helpful in the future [27]

### 2.2.2 Aims of the Research

The primary focus of this research study is to investigate how wearable devices can capture biomarkers that aid in detecting and potentially assisting with mental well-being. The study aims to conduct a literature review on this topic to observe the effects of different biomarkers in detecting stress levels and their effectiveness. Effective remedies and solutions have been developed based on the type of device used to monitor mental conditions and emotional parameters.

### 2.2.3 Literature Review

### A. Overview

According to a research study conducted by OECD, i.e., Organization for Economic Cooperation and Development, it has been shown that due to the world's rapidly growing population, there is an increased need and demand for further resources in terms of health care providers and practitioners[28]. However, due to the shortage of such professionals, researchers need new innovative technologies and solutions, which can easily measure the patients' physiological and mental health conditions[29]. Such types of emerging technologies are termed as quality-of-life technologies (QOTS). Another research study supported this fact and explained that the misclassification of an acute disease condition as chronic by electrochemical sweat biomarker sensors could cause significant psychological, emotional, and financial stress among patients[30]. In addition to. monitoring the vital and psychological parameters of the patients, some of these innovative technological devices are being researched, which will help elevate and modify the patients' moods and emotional conditions[30]. The following section will outline an explanation of the wearables, sensors, and signal detection biomarkers associated with stress factors and an assessment of emotions and mental well-being.

## B. Machine Learning Methodologies for Identifying Stress Factors in Physiological Data Captured Through Wearable Devices

While current researchers focus on real-life environments, earlier works on stress detection were performed in laboratory environments. The most widely used physiological signals for detecting stress levels include the accelerometer, heart activity (HR), and electrodermal activity (EDA). In laboratory environments, HR and EDA combined are known to have the best performances. Cho *et al.* [31] showed that EEG signals achieved 89% accuracy in a four-class stress classification. However, currently used EEG measuring devices are obtrusive and irrelevant to daily routines. Wearable biosensors are a basic mediator for physiological signal records, and they can be utilized for daily real-life situations, clinical applications, and fundamental exploration studies, as they allow users to continue their regular activities without interruption [32], [33]. Wearable biosensors offer excellent information and data that is adequately portrayed, detailed, timely, relevant, complete, and accurate, and the extracted data retains appropriate related evidence for supporting decision-making processes[34].

Nevertheless, using wearable biosensors in real-life experimentation presents numerous challenges regarding the reliability and usefulness the measurements for extracting emotions. A sufficient sampling frequency is required to depict signals correctly, and the sensor must be placed properly to record physiological signals while avoiding ambiguities accurately. Raw signals normally have many fluctuations due to the oscillations of the human body's physiological status [35], [36]. Even if the sensor has been placed properly and the fluctuations are inevitably recorded, it is necessary to filter the raw sensor signal to remove noise. This would allow for increased efficiency in detecting stress. Several filters, such as Wavelet Decomposition, Wiener filter, Median filter, Butterworth filter, and Kalman filter, can be used for filtering noise. Selecting an ideal filter depends on the type of noise, the features to be extracted, and the nature of the signal.

Lastly, it is worth mentioning that it is inappropriate for investigators to control environmental factors in real-life cases. Therefore, isolating the impact of a stimulus is challenging. However, despite these challenges, several works have tried to detect stress levels using wearable devices, as presented in this systematic literature review (SLR).

Stress-related illnesses have been identified as the second most common type of illness after musculoskeletal illnesses, which may also be caused by stress-related issues[36]. The type of illness a person experiences can sometimes be correlated with the level and type of stress they face, including emotional distress, headaches, low hormone levels, digestive problems, and over-arousal, among others [37]. Excessive alertness can cause severe harm to those with underlying conditions, potentially leading to heart attacks, panic attacks, and even sudden death in some cases. Chronic stress is commonly diagnosed in patients with hypertension, coronary heart disease, irritable bowel syndrome, gastroesophageal reflux disease, and generalized anxiety disorder [36], and depression [38]. Stress can also lead to more downtime for individuals, causing them to experience lower energy levels, which can ultimately affect the economy. The global economy suffers when people experience downtime related to work-related and personal stress [39]. Various studies across the European economy and its workforce indicate that up to half of all working days may be lost due to stress-related downtime [40], [41]. Isolating the impact of a stimulus is challenging. However, regardless of these challenges, several works have tried to detect stress levels with the use of wearable devices, as presented in this SLR.

## C. Exploration of Assistive Solutions for Mental Wellbeing

An ideal scenario would involve the absence of stress or the removal of stress-inducing factors and conditions, but this is rarely achievable. Long-term stress can result in severe consequences and must be treated with care. Since the treatment does not have a fixed endpoint or path to follow, it necessitates constant monitoring and adjustment over a prolonged period, which may span several months or years. It is best to address stress early to reduce its long-term physical and mental consequences [32], such as attitude changes, mood swings, or loss of taste. Although several tools exist to monitor stress-related vital signs, no direct measurement system exists, and we can only treat the symptoms. The medical community may gather and analyze data using smartwatches and portable health monitors, which are novel tools.

The emergence of computer programming, data science, and powerful computers has made it feasible to develop complex algorithms that can provide extensive real-time data used to evaluate a patient's condition. Data science has revolutionized the use of data to address today's challenges and may be applied in a variety of fields[39]. During work or stressful interactions, data may be collected and examined to assess their impact on individuals [34].

## D. Assessment of Emotions

Emotions are considered one of the most essential yet important aspects of everyone's life, which need to be studied by researchers as they are primarily responsible for generating multiple diseases, disorders, and complications among individuals. Wearable technology can detect people's stress levels as they go about their everyday activities and determine the most frequent triggers that put people in stressful situations. However, this approach can also be responsible for causing various stressful conditions and situations for a person [35]. Several studies have shown the effectiveness of wearable technologies and devices in monitoring a person's stress levels. These studies have provided a descriptive report of all the innovative technologies used to monitor stress levels. However, most of these studies only focused on specific articles that provided detailed information about the research questions. They reported that the focus and emphasis of devices primarily relied upon EEG and CPS systems, which can monitor a person's stress levels [36].

All these research studies have been concluded and compiled so in order to analyze some of the significant patterns of evolution for wearable sensor-based devices, which help monitor a person's stress levels. Numerous research articles and experiments discovered among all the studies included in this systematic literature review showed that monitoring wearable devices for stress measurement employed in a controlled environment are also considered inclusion criteria [42]. Special conditions and situations were explained to the participants; under controlled circumstances, the devices monitored and captured stress levels. In such conditions, observing the stress levels in difficult situations becomes challenging. Although multiple stimuli were provided to the participants to monitor their stress levels even in challenging situations, such studies are not considered beneficial, as the methods failed to suggest the results, which might be obtained under normal circumstances and in the everyday lives of individuals[38].

The core objective of modifying wearable devices is to enable them to analyze individuals' stress levels when exposed to their daily routines. This way, we can analyze some of the most common stimuli and why people often find themselves in stressful situations. Moreover, this criterion also helps us to analyze and investigate only such research studies in which real-life examples and testing were performed. This criterion is set to include literature reviews and research from different authors so that the effectiveness of the devices can be observed and analyzed in real-life situations. In most studies, the research is conducted within workplaces, at home, and for elderly patients in nursing homes[39].

## E. Types of Physiological Signals and Markers

Measuring specific vital signals such as heart rate, galvanic skin response (GSR), and body temperature is essential to gauge people's stress levels. These parameters are detected through various methods, including Electrocardiography (ECG), which monitors heart activity and helps analyze changes in heart rate under different conditions and emotional stimuli. Research study suggests that monitoring these parameters can identify significant stimuli responsible for causing stress [43], [44].

It is recommended to perform a photoplethysmography (PPG) to detect changes in blood volume in a chosen artery, which can help identify changes in blood volume. Additionally, monitoring an individual's galvanic skin response (GSR) is crucial as it enables the quantification of variations in skin conductance.

Constant monitoring of stress levels requires performing an electroencephalogram (EEG) on the patient, which records and tracks the brain's electrical activity [31]. Another essential factor is monitoring the patient's respiration rate (RSP), which provides insights into their stress levels. When conducting examinations and tests, it is crucial to identify the patient's preexisting physiological and psychological conditions. This differentiation can determine whether the responses obtained from the tests and examination reports are due to the stress stimuli experienced by the individual or their preexisting medical conditions [45].

## F. Devices Used for the Detection of Stress Levels

Saganowski *et al.* conducted a systematic literature review by analyzing and compiling results and experiments from multiple researchers. The study aimed to detect vital parameters within individuals, including GSR, heart rate, pulse rate, heartbeat intervals, respiratory rate, and body temperature. The study established discrete values for each dimension, such as joy, sadness, stress, calm, happiness, boredom, or neutrality, which were used to identify a person's current mental status and condition. However, the study noted that other dimensions might be observed during analysis and investigation only in research studies where real-life testing and examples have been performed [31].

Various devices, such as Empatica E4, Microsoft Band 2, Samsung Gear S, Body Media Sense Wear Armband, Neurosky Mind Wave, and XYZ Life Bio Clothing, have been selected for monitoring individual vital signs and parameters. These wearables monitor physiological functions like heart rate, breathing rate, and respiratory care, enabling easy analysis of the brain's electrical activities. The study highlights the availability of commercially available and comfortable wearables in the market that can collect physiological signs and signals to monitor participants' stress levels and anxiety conditions[25].

Furthermore, some articles have proposed self-made devices, but their efficacy and effectiveness require further investigation. Each device is responsible for measuring specific sensors and parameters in an individual. The past years have witnessed explosive growth in wearable devices that aim to monitor a broad spectrum of human physiology and behavior, employing diverse sensors and technologies to gather data that sheds light on users' health, well-being, and performance. The Empatica E4 is a versatile wearable tracking PPG, GSR, and BT, dissecting body temperature and skin responses to activities and stimuli. Similarly, the Microsoft Band 2 employs PPG, GSR, and BT sensors, contributing to stress, activity, and emotional monitoring. The Samsung Gear S specializes in heart rate observation via a heart rate sensor, optimizing exercise and cardiovascular health assessment. Meanwhile, the BodyMedia SenseWear Armband employs multiple sensors for comprehensive analysis of vital signs, such as body temperature, skin response, and activity levels. The NeuroSky MindWave employs EEG technology to discern brainwave activity, enabling monitoring of mental states and focus. The XYZ Life Bio Clothing virtually tracks EEG signals to unveil cognitive states and stress levels discretely. These devices exhibit differences in detected signals and primary focuses, catering to physiological metrics. While some, like Empatica E4 and Microsoft Band 2, cover a broad spectrum, others, like Samsung Gear S and BodyMedia SenseWear Armband, concentrate on specific aspects like heart rate and activity. The NeuroSky MindWave and XYZ Life Bio Clothing excel in EEG monitoring, offering insights into brainwave patterns and mental states. Wearables have transformed data acquisition from our bodies and minds, addressing diverse needs from fitness to emotional well-being. As technology advances, these devices are poised to deliver even deeper insights[46].

## G. Self-Assessment of Emotions

Emotions play a dual role, beneficial when they enhance decision-making and motivate appropriate behaviours but potentially detrimental when inappropriate in intensity, frequency, or duration, necessitating emotion regulation to prevent harm to oneself or others. Emotion recognition systems help in this regard. A positive goal, such as reducing sadness or promoting a healthy lifestyle, is essential to regulate emotions effectively. Emotional regulation can be intrinsic, with individuals managing their own emotions. Additionally, emotions have been understood through two main approaches: discrete or categorical emotion states and continuous or dimensional emotion space, with researchers categorizing primary emotions like fear, grief, love, and rage based on intense physiological changes. However, self-report questionnaires' reliability and emotion awareness pose challenges in training supervised machine learning algorithms for emotion recognition. While laboratory experiments establish the ground truth, ecological momentary assessment using self- reports is conducted outside the laboratory, but subjectivity influenced by individual, cultural, and gender factors may affect accuracy. Obtaining frequent real-time self-reports during daily routines proves challenging, leading to delays in labeling and potential information loss. The demand for labeled data for robust models increases reliance on self-reports, which can be time-consuming for participants. Researchers are exploring semi-supervised methods to reduce the need for labeled data and improve emotion recognition research [47].

In a systematic review [48] the authors investigate the relationships between measured signals and emotions using wearable devices. During the study, the top 20 emotions were identified and analyzed. Electrodermal Activity (EDA) emerged as the most frequently adopted signal, measuring 16 emotions. Additionally, Heart Rate (HR) was commonly used to assess "positive," "negative," "engagement," "stress," and "peacefulness" emotions, while Skin Temperature (ST) and pulse measurements were utilized in some instances. Researchers employed five distinct approaches in studying emotions based on data from wearable devices: machine learning, inferential statistics, deriving emotions from physiological values based on previous literature, descriptive statistics, and specialized algorithms. Inferential statistics, such as correlation and analysis of variance, were used to determine statistically significant relationships between physiological signals and emotion measurements.

Moreover, emotions were derived from physiological values based on conclusions from earlier literature. Descriptive statistics were employed to compare educational emotions measured by wearable devices with results obtained from more established approaches. Lastly, specialized algorithms were utilized for specific purposes, such as estimating positive and negative emotions based on heart rate spectral analysis. The review overviews the connections between educational emotions and wearable devices in diverse teaching and learning contexts.

## H. Stimuli

Researchers in previous studies consider multiple stimuli to detect mental stress in individuals. According to a study conducted by Guk et al., different parameters are used to analyze stress levels, and effective videos, music, and sounds are often used to elicit emotional changes in individuals. These stimuli are easy to use and readily available in most databases and research. Videos and audio are selected because they elicit the most response from individuals, and their responses can be detected and monitored spontaneously [34]. Some databases and research articles also use different stimuli that can be applied in real-life experiences and examples, such as playing physical games, solving math problems, learning, and walking around the city. These methods provide a detailed assessment and analysis of individual responses toward everyday activities and regular tasks being performed[49].

## I. Effects of Emotions on Mental Wellbeing

Another set of research studies and literary sources proposed the fact that there is a strong and influential relationship between mental well-being and emotional changes within a person. According to Kumar et al*.,* the emotions that largely influence an individual's mental state can be categorized into six major categories: fear, disgust, joy, anger, sadness, and surprise. However, stress has been recently added to these emotions, which can be defined as a person's mental state, which usually arises when a person has been subjected to unexpected or unbearable circumstances which are out of his capacity to tolerate and handle properly[50].

Guy et al. revealed some assessment methods for individuals regarding their mental well-being or presence of stress or anxiety. The most popular and widely used invasive method has been used by healthcare practitioners, in which blood cortisol levels are being measured and analyzed by physicians, but to modify the detecting strategies and methods, the scientists and researchers have also proposed some of the non-invasive methods. These methods include the detection of brainwaves with the help of EEG electrodes or by assessment of biomedical tools to detect physiological bio signals[51].

## J. Use of EEG Electrodes

Certain devices and equipment have been formulated by different researchers, with the help of which wearable devices can conduct an EEG of a person spontaneously and immediately provide the result to the healthcare professionals or the individual himself [52]. Although EEG Electrodes provide effective results and measurements about an individual's electrical impulses and bearing activities, the method also possesses a major disadvantage. The electrodes which are used for the detection of brain activities are needed to be attached to the scalp of a person, which can sometimes become painful, disturbing, uncomfortable, or inconvenient for the person, therefore despite the accuracy and precision which is being achieved with the help of this method, it cannot be used on a large scale because of its inconvenient monitoring and measuring methods[53]. Instead of EEG electrodes, the most beneficial and advantageous devices, largely preferred for detecting mental well-being, and preferred by healthcare providers, are compound semiconductor (SC) transistors. These are wearable devices, which are responsible for analyzing and monitoring the skin conductivity of a person. But it has also been reported that most of these devices which help detect skin conductivity are not considered for detecting the components and constituents of sweat produced by the human body. The amount of cortisol produced within the sweat of an individual is considered one of the most effective parameters largely used for the detection of stress levels within the person [40]. In addition to the stress hormone cortisol, additional components are also being investigated and examined within the sweat of the human body, which are named volatile organic components (VOCs); different gases are also being released from the human body, and they are sufficient to depict the current mental health and situation of a person[25], [54].

## K. Devices for Mental Wellbeing in Workplaces

Multiple research studies have reported that mental stress is frequently observed in workplaces due to overwhelming challenges and issues faced by individuals. Consequently, appropriate solutions must be provided to employees and staff members to monitor their mental conditions and offer effective remedies as necessary. Heart rate variability, electroencephalographic data, and electrodermal activities are essential to detect mental stress and anxiety and are emphasized in this research study. Li *et al.* [25] have reported that heart rate variability shows the balance and capacity of the autonomic nervous system, which is often used in the workplace to analyse workload and stress development. Bio-signals, such as heart rate variability, are preferred to monitor stress levels within individuals, as discussed below:

### 1.EEG

The objective of using an Electroencephalogram is to detect the blood flow. Electroencephalography (EEG) is a non-invasive method used in neuroimaging; wherein electrical brain activity is measured from the scalp. This technique offers valuable insights into brain functioning by recording the electrical signals neurons generate. It is widely recognized as one of the most commonly used and accessible in vivo neuroimaging methods, owing to its ability to provide real-time data and user-friendly nature. EEG finds applications in various domains, including neuroscience, diagnosing neurological disorders, sleep research, and cognitive studies. It has emerged as a potent tool for comprehending brain activity and has significantly contributed to advancing our knowledge of brain functions and dysfunctions[55]. However, multiple challenges and complications have also been reported by the researchers and the participants of these studies as well. Primarily, the major issue being reported is proper electrode preparation and accurate placement on the scalp are essential for obtaining accurate EEG data. Incorrect placement can lead to poor signal quality and inaccurate results. Participants wearing EEG caps may experience discomfort due to the weight and tightness of the cap, which can affect their natural behavior and potentially influence the recorded signals. [54]. [56]. Despite these issues and challenges, it has been reported that certain wearable devices have also been introduced, in which dry EEG is being conducted, and they have been reported to be providing effective and beneficial results and outcomes in detecting the mental stress of a person[57], [58].

### 2. Electrodermal Activity

Researchers have introduced multiple wearable devices for detecting electrodermal activity (EDA) in individuals, providing accurate and hindrance-free results. EDA is analyzed to determine differences in dermal activities and the individual's constitution, with changes in dermal temperature and cortisol secretion observed in response to stressful conditions. EDA signals are categorized into skin conductance levels (SCL) and skin conductance responses (SCR). SCL is the tonic component and SCR is the component detected in response to a stimulus. The amount of cortisol in sweat and overall dermal temperature are measured in both conditions, as they are expected to increase during stressful situations[59], [60].

## 3. Heart Rate Variability

Assessing heart rate variability has been reported to be a significant component in detecting mental stress levels in individuals. Electrocardiogram (ECG) reports are commonly used to determine the heart rate of an individual, which provides the monitoring measurements of vital signs,vitals like Blood Volume Pulse (BVP), the electrical activity of the heart, and the blood flowing in peripheral vessels. Heart rate variations are calculated and determined with the help of BVP readings. HRV is usually calculated based on high and low-frequency bands, and an increase in the LF and LF/HF ratio has been linked to high anxiety, stress, and anxiousness among individuals. The heart rate variation is usually increased due to overstimulation of the Autonomic Nervous system or activation of emotional distress, which helps determine stress levels within an individual over a specific time interval [57], [61].

## L. Analysis and Summary

The literature review presented in this paper explores various strategies for stress identification using wearable physiological sensors. Differences between the approaches include the study design (laboratory experimentation or real-life environment), methodological approach, and use of varying physiological signals. Two classes of techniques are considered regarding study design: those that utilize laboratory data without investigating the efficiency of the method in a real-life scenario, and those that are established based on real-life data but may have limitations in detecting psychological stresses due to inherent limitations in describing the ground truth. Machine learning algorithms dominate the applied methods in the literature review. Various combinations of physiological signals have been examined, often associated with the spatial qualities of the physical condition, and occasionally upheld by video recordings. The literature review suggests that fewer attempts have been made to combine the two approaches for detecting stress levels in a well-controlled laboratory environment and extend that knowledge to a real-life setting [49]. Nonetheless, there is still a need for procedures that can accurately identify stress in individuals in a real-life context. The identified research challenges resulting from the literature survey and study are detailed in the following section.

# M. Study Design and Framework for Utilizing Wearable Technologies in Enhancing Mental WELLBEING

## M.1 Research Challenges

The literature review presented in the previous sections highlights several strategies for stress identification utilizing wearable physiological sensors. Based on the literature survey, the identified research challenges are detailed in the following section. These challenges aim to assess the use of multi-modal wearable devices in capturing data of various formats to explore assistive solutions for mental well-being, correlate captured wearable data with gold standard and conventional tests, mainly based on face-to-face assessment and questionnaires, and apply machine learning methodology for identifying stress factors in heart rate variability, dermal temperature, and EEG signal measurements on data obtained from wearable devices.

## M.2 Research Objectives

The major objectives of this research study are:

1. To analyze and investigate the most renowned tracking wearable device, which is largely prevalent among patients.

2. To assess the effects of these wearable devices on the mental and psychological aspects of patients.

3. To observe the literary sources and the recent research and modifications about wearable tracking devices.

4. To carry out controlled and open studies applying tested and validated wearable-based measurement settings.

5. To utilize wearable devices for implementing techniques and formulas for measurment.

6. To use wearable devices for achieving methodologies as well as algorithms for measuring mental wellness and feedback.

7. To test the trained model in a real-life scenario where biological signals will be monitored for assembling data on, e.g., heart rate variability, dermal temperature, and EEG signals.

## M.3 Research Hypothesis

Wearable tracking devices help provide solutions for mental wellness based on the belief that these devices can provide individuals with valuable data and insights that can help them make positive changes to their lifestyle and improve their mental health. However, further research is needed to fully understand the potential benefits of wearable tracking devices for mental wellness and to identify the most effective ways to utilize these devices to support mental health.

## M.4 Research Methodology for Systematic Literature Review

The research study for this project primarily utilized an interpretive systematic literature review design. Additionally, quantitative analysis was adopted to analyze the relevant research and results. For this purpose, a questionnaire survey was distributed among the selected participants to acquire their reviews, perceptions, and knowledge of tracking devices. The survey responses were analyzed and observed using an Excel sheet to illustrate the results in the form of graphs, tables, and charts.

The study collected primary data from electronic databases, including MDPI, ACM Digital Library, Science Direct, and WebMD, APA, PMC, and IEEE, which are reliable and authentic sources for research in the information technology field. Some of the citations from selected research articles were also manually searched.

This research study aims to emphasize the importance of monitoring and detecting stress and anxiety levels among individuals for their mental well-being and diagnosis by physicians. The systematic literature review methodology utilized for this study includes case–control studies, open studies, and cohort studies of selected participants and samples. Previous research articles that conducted experiments provide detailed insights and information about the progress, modifications, and further innovations in wearable devices used to detect stress among participants. The study is designed systematically to cover all aspects and research in ascending order of year to properly trace and highlight modifications in wearable devices.

## a. Inclusion Criteria

We only included studies published in English and published between 2010 and 2023 to ensure that the review includes recent advancements in wearable technology for mental well-being. We also included studies that focus on the use of wearable technology for mental well-being, such as stress, anxiety, depression, mood, emotion recognition, and sleep tracking. This criterion is important because the review aims to evaluate the effectiveness of wearable technology in providing assistive solutions for mental well-being. Studies that have utilized quantitative, qualitative, or mixed-method research designs are also included in the review.

## b. Exclusion Criteria

Studies that are not published in the English language or published before the year 2010 were excluded from the review. Additionally, studies that did not focus on wearable technology for mental well-being or did not evaluate the effectiveness of wearable technology for mental well-being were excluded. Finally, animal models or theoretical studies were excluded from the review.

## c. Research Onion

Saunders *et al.* [50] proposed the Research Onion as a method in which different layers and stages of research are utilized and adopted. The Research Onion process provides an improved method to design, plan, and execute each layer of research in a stepwise manner. By utilizing the Research Onion approach, better outcomes and results can be achieved in a properly designed manner[62]

## d. Research Philosophy

The research philosophy adopted for writing this structured literature analysis is the idea of Epistemology [63]. This approach was chosen for certain types of research that require proven experimental analysis to be conducted. The procedure aims to validate the research priorities and theories, since research that was already carried out is primarily used in the analysis.

## e. Research Design

Positivism has been chosen as the research design for this study, but certain strong characteristics of Constructivism and Objectivism may also be employed because the selection is dependent on the research priorities, concerns, and theories. However, considering the specific orientation of this study, positivism was chosen as the preferred research design.

## f. Research Approach

The third layer of the research onion primarily helps classify the method employed during the compilation of multiple datasets. The deductive method is preferred for this research analysis since the hypothesis was formulated and implemented to conduct the systematic literature review. All libraries and academic papers were obtained based on this theory.

## g. Research Strategies

The survey-based methodology using the deductive approach is employed for this review as the method of testing. Besides the thorough examination and review of databases with specific keywords, survey analysis was also conducted for the research report to gather awareness, details, and insights from people about the idea of tracking devices [64].

## h. Research Choice

A multi-method research design was selected for this study, as the related studies and review papers are the databases, which are used and analyzed in this research analysis Accordingly, quantitative research were conducted while analyzing and classifying all related literary sources

[65]. The literary sources were classified, skimmed, and selected using formulas and Excel sheets based on quantitative analysis.

## i. Time Horizon for Research Study

A linear time frame has been chosen for this analysis, as various libraries, literary materials, and academic papers will be researched and evaluated repeatedly over an extended period [66], [67].

## j. Research Analysis and Data Collection

The final layer of the research onion [54] primarily displays the various phases of scientific study and data collection techniques. To assess its reliability, validity, and accuracy, the data collected and accumulated so far were further analyzed.

## k. Sample Size

Almost 100 papers were selected for the research review based on the previously mentioned exclusion and inclusion criteria. However, in our research report, not all research papers were emphasized, and only the most important papers were finalized after extensive skimming and thorough reading of each post. Sixty-one papers were chosen during the skimming process, providing a full understanding of the current literature on wearable tracking devices primarily used for human physical and mental observation.

## l. Sample Ethics

A research survey was administered along with the literary tools for the research project. The participants were recruited through an email with a link to a Google Form to answer some questions. The team aimed for 21 participants—a number proven sufficient for providing information for the proof of concept in previous studies. The participants were healthy postgraduate students at the Queen Mary University of London aged 18 to 45, comprising 47.6% males and 52.4% females. An ethical consent form was given to these participants, emphasizing that all the knowledge and answers gathered from them would be used exclusively for research.

## m. Data Analysis

The data for the study was collected using the Google Forms service, then coded and processed with Microsoft Excel, as well as the Statistical Package for the Social Sciences (SPSS) version 23. The internal validation of the scales was approved during the study.

## n. Demographical Factors

As shown in (Table 1), 21 people participated in the current study including 11(52.4%) females and 10(47.6%) males. Their age was between 18 and 45 years old with an advantage for 25–34 group (81%). They all declared that they are healthy and do not suffer from any chronic disease.

**Table 1** : Demographical Characteristics Of The Participants (N=21)

| **Demographic Factors** | | **Frequency** | **Percent** |
|---|---|---|---|
| **Gender** | Male | 10 | 47.6 |
| | Female | 11 | 52.4 |
| **Age** | 18–24 | 2 | 9.5 |
| | 25–34 | 17 | 81 |
| | 35–44 | 2 | 9.5 |
| **Health Status** | Excellent | 9 | 42.9 |
| | Very Good | 11 | 52.4 |
| | Fine | 1 | 4.8 |

## P. Wearable devices status

As shown in (Table 2), only 38.1% used Wearable devices, and above 60% said they had never used them for friends, family, and doctors.

**Table 2**: status of wearable device

| **Wearable Device Status** | | **Frequency** | **Percent** |
|---|---|---|---|
| **Do you use wearables or not?** | Yes | 8 | 38.1 |
| | No | 13 | 61.9 |
| **Using wearable devices to communicate with: Friends** | Daily | 2 | 9.5 |
| | Several Times a Week | 5 | 23.8 |
| | Never | 14 | 66.7 |
| **Using wearable devices to communicate with: Family** | Daily | 5 | 23.8 |
| | Several Times a Week | 2 | 9.5 |
| | Seldom | 1 | 4.8 |
| | Never | 13 | 61.9 |
| **Using wearable devices to communicate with: Doctors** | Daily | 1 | 4.8 |
| | Once a Month | 2 | 9.5 |
| | Seldom | 4 | 19 |
| | Never | 14 | 66.7 |

## q. Reliability of the study scale

The Pearson correlations were positive and significant ranging from ($r$=0.87, $p$<0.01) to ($r$=0.24, $p$<0.05), and the Cronbach's alpha coefficient achieved great value (α=0.77). So, the scale was valid and reliable (Table 3).

**Table 3**: The perception toward wearable devices, and the relationship with gender and user status

| Statement | Mean | Std. Deviation | r | Gender t/*p* Value | Users t/*p* Value |
|---|---|---|---|---|---|
| 1. Wearable devices motivate me to evaluate my state of mind. | 3.17 | 0.83 | 0.40* | | |
| 2. The feedback given via wearable devices is useful. | 2.92 | 1.24 | 0.69* | | |
| 3. Sharing my data measured with wearable devices encourages me to evaluate my mental wellness. | 2.42 | 1.24 | 0.65* | | |
| 4. I feel happy with a software, which can assess me using wearable devices, which will measure my biomarkers (such as HRV, EEG, skin conductance). | 2.83 | 1.03 | 0.24* | | |
| 5. I feel that tips evaluating the level I reached in my emotional assessment would be conducive to my mental wellness. | 4.00 | 1.13 | 0.87* | | |
| **Overall** | 3.67 | 1.07 | | t = −1.70/0.12 | t = −1.09/0.30 |
| **Cronbach's Alpha** | | 0.77 | | | |

## r. The perception Toward Wearable Devices and the Relationship with Gender and Users

Table 3 displays the mean score for the perception of using a wearable device (3.67 ± 1.07). There was an insignificant difference in the mean score in terms of gender and wearable device users and non-users ($p$ > 0.05).

## s. Purpose of using wearables

As shown in (Table 4), 66.67% indicated they used the wearable to Monitor physical activities, and 52.63% used the daily activities monitor.

**Table 4:** Purpose of using wearable.

| Statement | | Frequency | Percent |
|---|---|---|---|
| **You use wearables to** | Communicate with people | 1 | 11.11 |
| | Monitor physical activities | 6 | 66.67 |
| | Monitor mental wellness | 2 | 22.22 |
| **What kind of feedback would you like to get from your wearables?** | Monitor daily activities | 10 | 52.63 |
| | Advice on how to tackle daily challenges | 1 | 5.26 |
| | Feedback on general wellness | 2 | 10.53 |
| | Improving your wellness in general | 5 | 26.32 |
| | None of the above | 1 | 5.26 |

Regardless of the variety of stressors that may occur, physical reactions to stress are similar [42]. For biological, physiological, sociological, and philosophical stressors, the body's stress response is the same. Stress causes the body to increase heart rate, blood pressure, and muscle tension, as well as increase glucose and serum cholesterol production, while decreasing protein stores, digestive processes, and T-lymphocytes.

There is a lot of evidence that stressful life events and perceived stress are linked to immune system changes. Chronic physiological responses to stress can lead to illness or disability. For example, HRV feedback reflects the activity of both the sympathetic and parasympathetic branches. This it enables the development of strategies to gain voluntary control of emotional regulation. For sports performance, biofeedback training has demonstrated some psychological effects such as the reduction of anxiety and self-control enhancement. It is also a tool for improving the prevention and treatment of overtraining and athletic injuries.

The above results show that wearable devices are assistive in providing health and mental wellness solutions. Because physical activity tracing would reduce the stress stressors that affect the subject’s body. Thus, it would also affect mental activity and would lead to reducing cognitive mental load.

## t. Preliminary Study and Analysis

### t1. Selections and Preparations of Database

Multiple research projects works and theories were identified and included in this research study; however, to form a systematic literature review, a certain pathway/framework was followed for this purpose, which is shown in Figure 1. The systematic literature review was conducted in a specific order, as shown in the chart. Initially, around 150 research articles were considered for the study based on the selected keywords, such as wearable devices, mental health assessment, mental health in the workplace, and advanced wearable technologies. The articles were then screened based on their year of publication, and only those published after 2010 were included to rely on recent research regarding the research topic.

However, the subject's origin was also important to consider, and some theories, history, and background from previous research were included but not relied upon completely. It should be noted that wearable devices have been used to assess physical and biological functions for many years, but their use for mental health assessment has only been introduced recently.

To further investigate the research topic, several research articles were identified based on the selected keywords and year of publication. In addition to this, the authors of these research articles were also selected based on their affiliation with the academic institutes and research centres. The most recent research articles have been focused on getting a more precise and accurate result. The research articles were reviewed and analyzed based on the previously selected variables, which were the use of wearable devices for measuring the vitals of the human body, the use of devices in workplaces, and the effectiveness of these devices. Finally, the selected research articles were summarized, and their findings were compiled to provide an overview of the current research on wearable devices and their use in measuring the mental health of individuals in workplaces. The literature review and research articles included in this paper have revealed that despite the abundance of information, there are still gaps in the research regarding the use and implementation of wearable devices in the workplace These areas require further attention and investigation in future studies.

### t2. Results and Findings

Research studies reported that wearable tracking devices have become essential to constantly measure and monitor the performance, physical activities, behavioural changes, and changes in the mental health patterns of an individual. This is particularly important to monitor the effects of different stimuli on an individual's mental health and well-being. In addition to physical well-being, workplaces and organizations have begun to focus on individuals' mental well-being and health to ensure their productivity and creativity levels remain stable. To further intensify research studies, authors and researchers have considered certain parameters and factors to be investigate and emphasize further for future research.

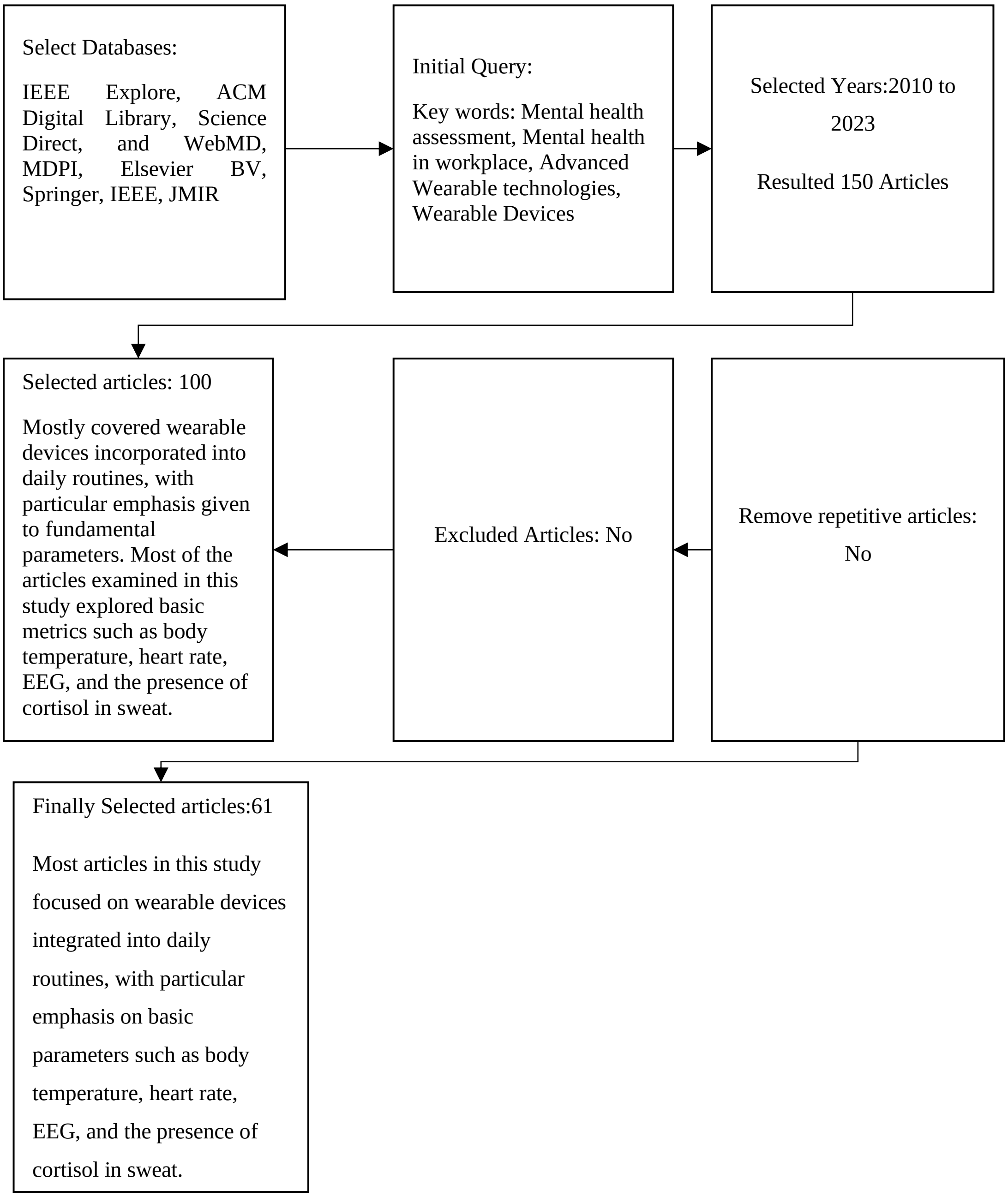



**Figure 1**: **Systematic literature review framework.**

The most common parameters used to analyse mental health are the presence of cortisol in a person's sweat, heart rate, blood pressure, body temperature, and pulse rate. Evaluating these parameters helps identify anxiety and stress among individuals within workplaces. To analyse differences in their biological and mental behaviours towards such stimuli, individuals are also provided with certain stimuli like stressful conditions. Some of these factors include the provision of excessive workload to employees, challenging situations. With the help of research, it was also identified that there are additional terms widely used to assess which type of monitoring, recording, assessment, evaluation, gathering, and measurement of the information of an individual is being performed in terms of their performances, physical or biological behaviours, responses, and environmental data, and the responses and readings are acknowledged for further research.

### 2.2.4 Limitations

Therefore, because the extremely small number of scientific papers and experiments on the subject have been carried out so far, there is not a large amount of information available on various forms of wearable monitoring systems that may be used for the mental analysis of a human being. It is possible to calculate a person's physical vital signs and parameters—and their different variations—using wearable devices, but they are not very significant in measuring human cognitive behaviours.

### 2.2.5 Discussion

The aim of this chapter was to coordinate and conduct a comprehensive systematic literature review, which included a thorough evaluation and study of wearable technologies for detecting mental well-being and human cognitive effectiveness. While some studies have highlighted the use of these technologies in the workplace, there is still a range of challenges in applying these strategies, which need to be investigated by the researchers. In some papers that were included in the research review, it was stated that the total number of these articles was split into two key categories. Numerous academic papers focused on using and evaluating wearable technologies in laboratory environments; no real-life results were included in these research studies. On the contrary, it was also mentioned that a significant number of research papers examined real-life evidence rather than laboratory experimentation so that it is possible to suggest systems and devices that could be conveniently used inside the workplace [29]. Analysis methodologies, which have adapted data from structured environments within the laboratory, are generally inadequate in delivering reliable readings including equipment findings that can be reliably and accurately regarded. On the contrary, it was also stated that methodologies in which real-life data were considered, produced findings with significant specificity and consistency, as they were capable of measuring stress and anxiety within an individual under various environmental conditions. From the study reports, it was also found that it is important to concentrate on the operating process and processes of the technologies being used to keep the results of the findings correct and consistent. Several of the sensor-based portable devices have also been reported in a variety of studies to be highly inadequate and unable to provide reliable data and readings on body temperature, variability of heart rate and human skin performance. These three criteria are important for evaluating a person's stress levels and anxiety disorders, and they largely help provide reliable results [25]. Of these three, the most genuine and important element is the presence of cortisol in the individual’s sweat. The more increased the level of cortisol, the greater the level of physiological arousal. Humans employ multiple devices and equipment to primarily measure these three vital signs. Empatica E4, Microsoft Band 2, Samsung Gear S, Body Media Sense Wear Armband, and Neurosky MindWave are the wireless products, which are often used and considered for this purpose. This occurs especially when the sensors assembled and used in wearable devices are not effective and not of better quality. Inaccurate findings are collected because of errors in the sensors of these wearables, which also leads to errors in the research results. The investigator does not adequately control stress and anxiety levels due to problems with this equipment and the readings collected. To implement an adequate methodology for comprehensive research of wearable devices for diagnosing mental well-being and cognitive awareness, researchers need to concentrate primarily on the four key areas, including a successful study design, recruitment of participants, choice of wearable devices, and techniques for data analysis [68].

Stress is considered one of the major components of mental health, which results in multiple other physical and psychological problems. It has also been reported in numerous research studies that stress management is needed to be considered an important and essential element within workplaces and organizations so that employees could work with increased enthusiasm and motivation [56]. Figure 1 mainly shows some of the important parameters and vitals signals which are needed to be observed and deeply investigated to analyse different types of changes within a person. For example, the help of eyelid movements, changes in facial expressions, spontaneous and abrupt head movements, and pupil dilation are some of the important physical signs which indicate stress or anxiety within an individual. In difficult or complex situations, a person usually performs rapid head movements, or the pupils are dilated. In addition, an abrupt eyelid movement is observed, and most importantly, the individual's facial expressions are rapidly changed [39].

However, the objective of our research study was to analyse the effectiveness of wearable devices for detecting stress levels. Therefore, it has been observed that in most cases, the parameters which are often monitored with the help of devices are GSR, BT, and PPG, and these vitals are monitored by using ECG, EEG, and skin conductance measurement devices. In addition, heart rate variability is also being monitored with the help of these devices, however, body temperature can be simply monitored with the help of a thermometer [35].

Another aspect, which has been proposed, has been reported that to improve the mental well-being of an individual, it is also important to indulge him in physical activity daily, as it largely helps relieve stress to a considerable extent. Several wearable devices are used for this purpose as well, which help in the detection of body weight, obesity level, calorie intake, dietary habits, and other similar parameters of an individual [24]. With the help of these wearable devices, it becomes convenient and feasible for individuals to indulge in some sort of physical activity to promote their mental health and well-being. Patients presenting with serious mental illness tend to lead towards weight gain and obesity, twice as much as normal individuals [56], [57]. Therefore, to keep the body physically fit and healthy, it is essential to keep the psychological conditions of the body intact and stable as well [42].

A statistical research report concluded that more than 300 million people are diagnosed with low or high degrees of stress and anxiety at some stage of their life. The increasing number of people with anxiety and stress is also leading to severe downturns for business organizations and the countries' economies. Depression and anxiety are some of the most common psychological disorders, which have become largely prevalent in the global world [38]. The overall cost being incurred as a result of expenditure on the betterment and treatment of patients with stress and anxiety disorders stands at more than USD 2.5 trillion [69], [70]. Most importantly of all, one of the major problems revealed is the shortage of doctors, physicians, psychiatrists, and healthcare providers, which results in the lack of monitoring of different vital signs and parameters using microelectromechanical, biological, and chemical sensing, as well as electrocardiogram (ECG)-, electromyogram (EMG)-, and electroencephalogram (EEG)-based neural sensing. One of the essential advantages of these wearable devices is that they are considerably easier to use and cheaper than the difficult and complex instruments used in the laboratories of science and health institutions for monitoring the biomarkers of the human body[41].

Several instruments and devices introduced by various companies include ACCU-CHECK by Roche Diagnostics, iSTAT by Abbott, and Lactate Scout by Sport Resource Group. The headquarters of these companies are located as follows: Roche Diagnostics (ACCU-CHECK) in Basel, Switzerland; Abbott (iSTAT) in Abbott Park, Illinois, United States; and Sport Resource Group (Lactate Scout) in Minneapolis, Minnesota, United States. These devices are usually launched and presented on the consumer market for commercial purposes. They are mainly intended to measure the vital signs of athletes and sports individuals, so that their performance and activities can be improved. However, these vital signs can also be used for stress level detection and analysis of anxiety within individuals. It has also been reported that these devices usually take blood samples of an individual for detection of all these vital signs, which is a time-consuming process and considered a huge barrier and challenge for sports companies [69].

## 2.3 Conclusion

This chapter emphasizes the significant positive impact of the Internet of Things (IoT) in various fields, particularly in healthcare, where wearable devices have revolutionized stress evaluation. These devices can detect various parameters, biomarkers, and biosensors, enabling an assessment of stress levels. Among the commonly used wearable devices are ECG, EEG, EMG, PPG, and BT, which facilitate the measurement of Galvanic Skin Conductance, Heart Rate Variability, and body and skin temperature of individuals. An additional facet proposed to improve an individual's mental well-being emphasizes the importance of regular physical activity. Engaging in daily exercise is effective in significantly reducing stress levels. Wearable devices play a vital role in this context, aiding in monitoring various parameters such as body weight, obesity levels, calorie intake, and dietary habits. These devices provide individuals real-time information about their physical health, promoting awareness and encouraging healthier lifestyle choices. As technology evolves, the integration of wearable devices in fostering mental and physical well-being emerges as a promising approach to holistic health management. However, the implementation of wearable devices comes with specific challenges. Participants may need help wearing EEG patches and understanding the intricate workings of these devices. Despite these hurdles, wearable devices have proven to be instrumental in detecting stress and anxiety levels, allowing for the implementing appropriate strategies and a conducive working environment to enhance employee productivity and creativity. The chapter concludes by highlighting the potential of wearable devices in maintaining mental well-being in the workplace. In the subsequent chapter, a pilot study will be explored in-depth, focusing on HRV and EEG bio-signals and their correlation to stress and anxiety.

# Chapter3

# Exploration

CHAPTER 3

# Detecting the correlation between HRV and EEG bio-signals: A pilot Study

*In the following chapter, an exploration was undertaken to explore the efficacy of wearable sensing devices in discerning stress patterns within a cohort of well-regulated individuals. This investigation hinged upon the utilization of two distinct devices: the CoresSense apparatus and the Empotive Epoch 14-channel system. These instruments were instrumental in the measurement of heart rate variability (HRV) and electroencephalogram (EEG) biosignals, thus providing a multifaceted perspective on the subjects' physiological responses. The chapter delves into intricate specifics encompassing the study's design, equipment employed, and the analytical approaches adopted. These components collectively facilitated the assessment of the hypotheses posited in the thesis, all while aligning closely with established research methodologies. By seamlessly integrating technological innovation with scientific rigor, this research avenue illuminates the potential for wearable sensors to decode stress and anxiety markers in controlled and healthy subjects.*

## 3.1. Study Aim and Hypotheses

The following hypotheses were generated to achieve this thesis's objectives:

**Main Hypothesis 1**: Wearable devices reliably capture and show significant differences in HRV patterns before, during, and after stress induce session, with consideration of Alpha Asymmetry.

***Sub-hypothesis 1.0***: The wearable device measurements of HRV and Alpha Asymmetry before and during the stress induce session, will not show any significant differences, suggesting limited reliability in capturing changes induced by mental stress.

***Sub-hypothesis 1.1***: The wearable device measurements of HRV and Alpha Asymmetry before and during the stress induce session will show significant differences, confirming the device's reliability in capturing changes induced by mental stress, and their potential combined role in assessing cognitive challenges.

**Main Hypothesis 2**: Short-term HRV, as measured by wearable devices, in combination with Alpha Asymmetry correlates with cognitive performance on multiple cognitive tests.

***Sub-hypothesis 2.0***: There is no significant correlation between short-term HRV, along with Alpha Asymmetry, measured by the wearable device and cognitive performance, suggesting that this combination may not be indicative of cognitive abilities.

***Sub-hypothesis 2.1***: There is a significant correlation between short-term HRV, along with Alpha Asymmetry, measured by the wearable device and cognitive performance, indicating that the combined metrics can potentially serve as a valuable biomarker for cognitive abilities.

**Main Hypothesis 3**: Demographic factors influence HRV patterns before, during, and after a cognitive stressor.

***Sub-hypothesis 3.0***: There are no significant differences in HRV patterns based on demographic factors (age, gender) before and during the cognitive challenge.

***Sub-hypothesis 3.1***: There are significant differences in HRV patterns based on demographic factors (age, gender) before and during the cognitive challenge, indicating that these factors may impact physiological responses to mental stress.

**Main Hypothesis 4**: There is a significant relationship between frontal cortex asymmetry and the HRV matrix concerning stress and anxiety levels.

***Sub-hypothesis 4-0:*** There is no strong correlation observed between frontal cortex asymmetry and the HRV matrix, indicating their interdependence in the context of stress and anxiety.

***Sub-hypothesis 4-1***: There is strong correlation will be observed between frontal cortex asymmetry and the HRV matrix, indicating their interdependence in the context of stress and anxiety.

## 3.2 Study Design

### 3.2.1 Sampling strategy

The participants in this study were divided into two distinct geographical groups, each allocated to specific design strategies:

First Group: This group comprised twenty participants, equally distributed with 50% males and 50% females, who were drawn from the staff at KFSH-RC in Jeddah. Invitations to participate in the research study were extended to them using the rolling snowball technique.

Second Group: The second group also consisted of twenty participants, with an equal distribution of 50% males and 50% females, who were postgraduate students at QMUL. The determination of the number of subjects was based on prior research findings, and these participants were invited through email.

Each volunteer received comprehensive information regarding the study through an information sheet and consent form (detailed in Appendices A and B). To ensure the integrity of the research, exclusion criteria were employed, requiring participants not to be on long-term medication prescribed for cardiac diseases or mental and cognitive health. Furthermore, participants were required to be in good health and non-smokers.

### 3.2.2 The Ethical guidelines

- The well-being and welfare of the volunteers were consistently upheld throughout the research process.
- Ethical clearance for the study was obtained from the Queen Mary University of London Research Ethics Committee under the reference number QMERC22.150 (**Appendix B**).
- Prior to participating in the study, each participant provided informed consent by signing the consent form.
- Throughout the entirety of the study, the research data was treated with utmost confidentiality, and the researcher obtained explicit agreement from the volunteers before conducting the evaluation. In total, 31 volunteers from KFSH-RC in Jeddah and 20 participants from QMUL were recruited for the study. However, 11 participants from the first group were excluded due to not meeting the specified inclusion criteria.
- The average age of the participants was approximately 30 years old. The participants in the first group were of Semitic ethnicity, while the second group comprised individuals of diverse cultural backgrounds.

## 3.3 Procedure

### 3.3.1 Protocol

Participants were instructed to abstain from consuming coffee and alcohol for up to 12 hours before the study and to ensure they had a restful night's sleep. The experiment was conducted in a controlled laboratory environment, incorporating rigorous measures to mitigate the risks associated with Covid-19 In the laboratory, comprehensive measures are implemented to assess and manage COVID-19 risk, ensuring the safety and well-being of all research participants. These protocols are carefully designed to minimize the potential transmission of COVID-19, encompassing adherence to social distancing guidelines, proper ventilation, and maintaining a clean and sanitized environment.

Furthermore, a critical aspect of risk management involves diligently sanitizing all devices and equipment after each participant's use. This critical practice aims to eliminate potential contaminants, thus reducing the risk of transmission among participants and fostering a hygienic space for subsequent research activities. By strictly adhering to these safety measures, laboratories demonstrate a solid dedication to creating a secure and health-conscious workspace, safeguarding the health of both participants and staff throughout the research process.

Upon arrival, the chosen subjects were requested to complete the questionnaires as part of the data collection process. Followed by the completion of an informed consent form and a demographic questionnaire during the initial visit. To minimize any potential environmental influences, each subject was allowed approximately 3 minutes of rest. During the experiment, the subjects were equipped with Emotive Epoch 14 channel and Coarsens sensors to facilitate data collection. The signals recorded during the study were derived from two biosignal devices, namely CoreSens Heart Rate Variability (HRV) and Electroencephalogram (EEG) Emotive14 channels devices. The study followed a multi-stage protocol to measure Heart Rate Variability (HRV) and Electroencephalography (EEG) to assess stress and anxiety factors. The methodology consisted of the following stages:

1. Baseline Measurement: The measurement procedure began with a period of approximately 5 minutes where participants were instructed to keep their eyes closed. During this phase, baseline measures for HRV and EEG were recorded. Following the baseline measurement, there was a 3-minute rest period.
2. Stroop Colour Test: In the second stage, participants were asked to engage in a Stroop colour test provided by PsyToolkit [71] The Stroop Color and Word Test (SCWT) is a powerful neuropsychological tool that sheds light on the intricate relationship between cognitive processes and stress stimuli. During the test, participants are presented with color words (e.g., "red," "blue") written in incongruent ink colors (e.g., the word "red" written in blue ink). The inherent conflict between the written word and the ink color creates a cognitive challenge, leading to the Stroop Effect. The Stroop Effect has notable physiological implications. As individuals attempt to suppress the automatic response of reading the word, cognitive conflict arises, triggering stress-related responses in the body. The test induces a state of cognitive dissonance, heightening arousal and activating the body's stress response system. Physiologically, the Stroop Color Test elicits increased heart rate, elevated blood pressure, and changes in skin conductance—

all indicative of heightened sympathetic nervous system activity associated with stress. This stress response results from the cognitive demand to inhibit automatic reading, adding a layer of complexity to the traditional understanding of stressors. The recording of HRV and EEG was conducted for a minimum of 5 minutes while participants performed the Stroop colour test. Subsequently, there was a 3-minute rest period.

3. IAPS image and SAM Scale: After the rest period, participants were exposed to an IAPS image provided by the company Milliseconds[72]. Self-Assessment Manikin (SAM) and the International Affective Picture System (IAPS) photos are integral tools in stress measurement, combining subjective self-reports with standardized visual stimuli to comprehensively assess emotional responses. The Self-Assessment Manikin is a widely used instrument for gauging subjective emotional experiences. Participants are presented with a set of graphical manikins representing different affective states, such as pleasure, arousal, and dominance. By selecting the manikin that best represents their emotional state in response to a given stimulus, individuals provide a quick and intuitive self-assessment of their emotional experience. The International Affective Picture System offers a standardized set of images designed to evoke emotional responses. These images span various valence and arousal levels, making them suitable for studying various emotional states, including stress. Participants are exposed to these pictures, and their emotional reactions are assessed using self-report measures like SAM.

Integrating SAM and IAPS in stress measurement allows for a more holistic understanding. Participants not only self-report their emotional experiences using SAM but also react to standardised stimuli with known emotional impact. This combination enables researchers to correlate subjective self-assessment data with objective emotional responses elicited by the IAPS stimuli. The synergy between SAM and IAPS enhances the precision and depth of stress measurement, providing valuable insights into the interplay between subjective emotional experiences and external stimuli. This approach facilitates a more nuanced comprehension of stress, offering researchers and practitioners a well-rounded toolset for investigating and addressing stress in diverse contexts. Concurrently, participants were asked to assess their emotional experience using the Self-Assessment Manikin (SAM) scale. The SAM scale utilizes a wordless graphical approach to evaluate emotions, incorporating three components: dominance, valence, and arousal. The assessment involved participants rating their emotional experience using a 9-point scale integrated with five figures. Following the IAPS image exposure and SAM scale assessment, there was a 3-minute rest period.

4. Post Measurement: Following the rest period, participants underwent a 5-minute recording session for EEG and HRV measures. Subsequently, participants completed two questionnaires: the Perceived Stress Scale (PSS) [73] , and the General Anxiety Disorder-7 (GAD-7) [74]. This multi-stage protocol allowed

for the systematic collection of HRV and EEG data, along with the assessment of stress and anxiety using standardized scales.

## 3.3.2 Hardware and sensor placement

A. The EEG signals were recorded using the Emotive 14-channel system, which utilizes EEG sensors and supports 14 specific channels: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. Additionally, the system incorporates 2 reference channels: CMS/DRL references at P3/P4, with an alternative option for the left/right mastoid process. Furthermore, the Emotive system offers support for various platforms, allowing for versatile usage in different contexts.

| | | |
|---|---|---|
| Windows: 7,8,10; | 8GB | RAM500MB |
| MAC: OS X | 8GB | RAM500MB |
| iOS: 9 or above | iPhone 5+, iPod Touch 6, iPad 3+. | Low Energy |
| Android4.43+ (excluding5.0); | Device with Bluetooth | Low Energy |

**Table 5:**Emotive 14 channels platform

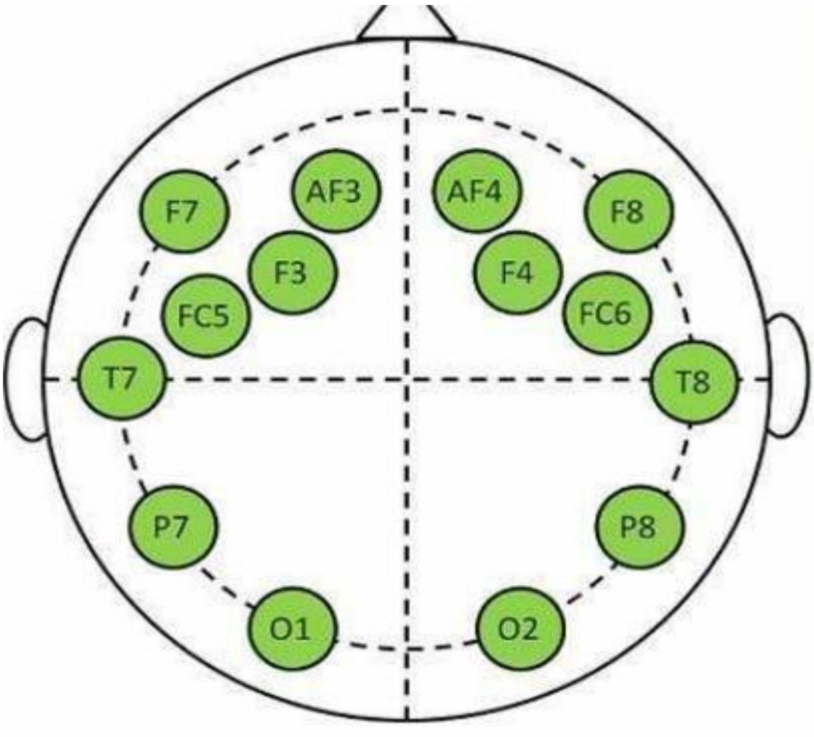



**Figure 2**: **Emotive 14 Channel Placement (taken from source** [75].**)**

B. Coarsens HRV, with proper finger placement, it takes several seconds to automatically detect subjects' pulse after connecting. The CoreSense device continuously measures HRV data through a photoplethysmography (PPG) sensor, which uses light to detect changes in blood volume in the skin's capillaries. This sensor is in contact with the skin on the underside of the device. As blood is pumped through the capillaries, the amount of light absorbed by the skin changes, providing information on changes in blood volume with each heartbeat. The CoreSense device uses advanced algorithms to process the PPG data and calculate HRV metrics, including the standard deviation of normal-to-normal intervals (SDNN), root mean square of successive differences (RMSSD), and low frequency (LF) to high frequency (HF) ratio. These HRV metrics provide information on the variability in time intervals between consecutive heartbeats, reflecting the autonomic nervous system's (ANS) activity, which regulates several physiological functions, including cardiovascular and respiratory control.

### 3.3.3 Methodology Applied

In our study, we established a connection between the demographic characteristics of the participants and the outcomes for both qualitative and quantitative tests. By examining the demographic information of the individuals involved, such as age and gender, we sought to explore potential relationships between these variables and the results obtained from the tests.

We conducted a built-in survey for the qualitative tests to gather subjective data. We carefully examined the responses provided by participants and analyzed them concerning their demographic profiles. This allowed us to identify any patterns, trends, or variations that could be attributed to specific demographic factors.

By linking the demographic information with the qualitative results, we gained insights into how individual characteristics might influence perceptions, opinions, or experiences expressed during the qualitative assessments. The PSS-10 (Perceived Stress Scale-10) and GAD-7 (Generalized Anxiety Disorder-7) questionnaires are widely utilized for assessing psychological well-being. The PSS-10 specifically targets measuring an individual's subjective perception of stress. Comprising ten items, this questionnaire aims to capture individuals' cognitive evaluation of the degree to which their life circumstances are unpredictable, controllable, and overwhelming. Respondents provide ratings on a Likert scale, typically ranging from 0 (indicating the absence of the perceived stress attribute) to 4 (representing a high frequency of the perceived stress attribute). The total scores derived from the PSS-10 questionnaire can span from 0 to 40, with elevated scores indicative of heightened levels of perceived stress.

Conversely, the GAD-7 (Generalized Anxiety Disorder-7) questionnaire serves as a concise screening instrument explicitly designed to evaluate the severity of symptoms associated with generalized anxiety disorder. It consists of a set of seven items that aim to capture the extent of anxiety symptoms experienced by individuals within the preceding two-week period. Each item within the questionnaire is scored on a Likert scale, spanning from 0 (indicating the absence of the specific anxiety symptom) to 3 (representing a high frequency of the anxiety symptom, nearly on a daily basis). The cumulative scores obtained from the GAD-7 questionnaire can vary between 0 and 21, whereby higher scores correspond to more pronounced severity of anxiety symptoms.

Similarly, in the case of quantitative tests, we collected objective HRV and EEG data through measurements via experiments. We then associated the quantitative results with the demographic characteristics of the participants. This enabled us to determine whether there were any significant differences or correlations between specific demographic variables and the numerical outcomes derived from the tests. By examining the relationships between demographics and quantitative test results, we aimed to identify potential influences or associations that might exist.

By linking demographic information with qualitative and quantitative test results, we sought to understand the interplay between individual characteristics and the outcomes of the assessments. This approach allowed us to explore potential factors that could contribute to variations in test performance or responses. Furthermore, it provided valuable insights into how demographics impact the interpretation and generalizability of the findings in our study.

In an experiment, the independent variable is the factor or condition that the researcher controls or manipulates. It is the presumed cause or input variable that is hypothesized to have an impact on the dependent variable. Researchers actively adjust the values or levels of the independent variable during experimental studies to observe its influence on the dependent variable.

On the other hand, the dependent variable represents the outcome or response that is measured or observed in the experiment. It is the affected or output variable, and changes influence its fluctuations in the independent variable. Researchers diligently observe and quantify the variations in the dependent variable to evaluate the impacts of the independent variable. The following is a description reflecting the independent and dependent variables in this study:

1. **Independent variables**: EEG Alpha Asymmetry, HRV matrix.
2. **Dependent variables:** Stress score, and anxiety score.

### 3.3.4 Qualitative Tests

A. Perceived Stress Scale (PSS), which is a 10-item questionnaire resultingin a score of 0-40, gives an overview of a person's perceivable psychological stress. Scores ranging from (0-13) would be considered low stress. Scores rangingfrom (14-26) would be considered moderate stress. Scores ranging from (27-40) would be considered high perceived stress [73]

B. General Anxiety Disorder-7(GAD-7): A score of 10 or greater on the GAD-7 represents a reasonable cut point for identifying cases of GAD. Cut points 5, 10, and15 might be interpreted as representing mild, moderate, and severe levels of anxiety on the GAD-7

### 3.3.5 Quantitative tests

In scientific exploration, a quantitative test entails a meticulously crafted experiment or study wherein numerical data takes certain stages. This method involves the precise collection and thorough analysis of quantitative information. Its fundamental purpose is deriving objective measurements, employing statistical analyses, and harnessing mathematical models to uncover meaningful insights and draw well-founded conclusions.

In the upcoming sections, we will detail the quantitative data acquired by utilizing two cutting-edge devices: the PPG (Photoplethysmography) device and the EEG (Electroencephalogram) wearable.

## 3.4 Data analysis

### 3.4.1 HRV Data Recording and Analysis

The CoreSense + Elite HRV system was utilized to measure heart rate variability (HRV), with simultaneous real-time recording and analysis of the measurements. The photoplethysmography (PPG) signal, which reflects changes in blood volume related to cardiac activity, was employed to identify peak positions like the R-peak positions observed in an electrocardiogram (ECG). By calculating the intervals between these peaks in the PPG signal, HRV can be quantified. HRV has

proven valuable for investigating changes in the Autonomic Nervous System (ANS) and diagnosing heart diseases. Several HRV parameters, such as the high-frequency and low-frequency (HF/LF) power ratio, are associated with the activities of sympathetic and parasympathetic nerves.

The collected data will be subject to analysis using Kubios HRV 2.0 software, which allows for the computation of single-segment power spectra through Fast Fourier Transform (FFT). These power spectra will then be averaged to generate the mean power spectrum. Kubios HRV is a sophisticated and user-friendly software designed specifically for HRV analysis, supporting various input data formats, including electrocardiogram (ECG) and beat-to-beat RR interval data as shown in (figure 2) below. The software incorporates an adaptive QRS detection algorithm and provides tools for artifact correction, trend removal, and analysis sample selection. It efficiently calculates commonly used time-domain and frequency-domain HRV parameters and several nonlinear parameters. In the upcoming section, we will comprehensively explain the HRV parameters within each domain.

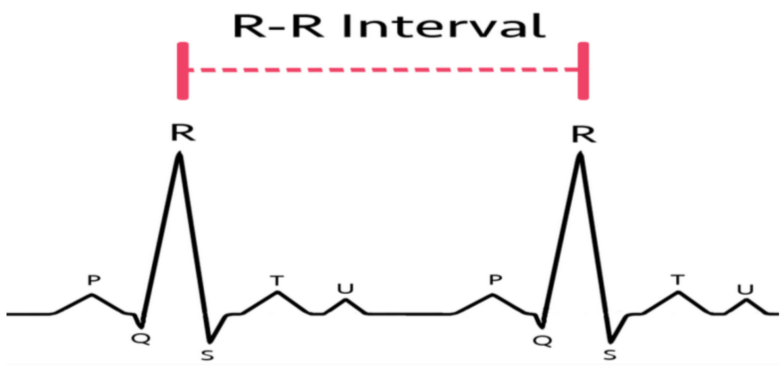



**Figure 3**: This diagram illustrates the dynamic nature of Heart Rate Variability (HRV) by depicting RR intervals. The RR intervals, representing the time intervals between successive heartbeats (R-peaks), are fundamental to HRV analysis. (Source taken from[76])

**Time Domain Analysis**: The QRS complex is essential when examining RR intervals, as it directly corresponds to the depolarization of the ventricles in the heart. The RR interval is the duration between successive R-peaks in an electrocardiogram (ECG) waveform, encompassing the entire cardiac cycle. The

QRS complex represents the depolarization of the ventricles, leading to the contraction of the heart muscles and subsequent ejection of blood. Analyzing the RR intervals with the QRS complex provides valuable information about heart rate variability (HRV), a key indicator of autonomic nervous system activity. Changes in RR intervals, influenced by the QRS complex, offer insights into the dynamic balance between sympathetic and parasympathetic influences on the heart. This analysis is crucial for understanding the adaptability of the cardiovascular system to various physiological and environmental stressors. The QRS complex is central in determining and interpreting RR intervals, significantly assessing cardiac activity and HRV.

The analysis of HRV in the time domain primarily centres around assessing the time intervals between successive heartbeats. This measurement provides insights into the NN (normal-to-normal) time series. These estimates are typically categorized into statistical and geometrical methods. The statistical measures encompass standard deviations of the RR intervals, representing the overall variation within the RR interval series. These time domain measures are significantly affected by changes in both sympathetic and parasympathetic activity, thereby making them mostly nonspecific indicators of autonomic modulation. This approach employs essential HRV metrics as explained in the following table.

**Table 6:**HRV time domain matrix (Reproduced from [77])

| Parameter | Unit | Descriptions |
|---|---|---|
| SDNN | ms | Standard deviation of normal-to normal (NN) intervals |
| PNN50 | % | Percentage of successive RR intervals that differ by more than 50 |
| RMSSD | ms | Root mean square of successive RR intervals differences |
| MeanRR | ms | The average R-R interval duration in a measurement, or the average time between heartbeats |

**Frequency Domain Analysis**: When exploring HRV using frequency domain analysis, a more advanced understanding of the HRV signal is necessary, as it involves estimating the power spectral density (PSD). The PSD characterizes how the signal's power is distributed across different frequencies. The resulting parameters are detailed in Table 7. By quantifying the power present in various frequency bands of the PPG signal, we can gain valuable insights into the activity of the autonomic nervous system and cardiovascular regulation.

**Table 7:**HRV Frequency Domain Matrix (Taken from [78])

HRV frequency-domain measures.

| Parameter | Unit | Description |
|---|---|---|
| ULF power | $ms^2$ | Absolute power of the ultra-low-frequency band (≤0.003 Hz) |
| VLF power | $ms^2$ | Absolute power of the very-low-frequency band (0.0033–0.04 Hz) |
| LF peak | Hz | Peak frequency of the low-frequency band (0.04–0.15 Hz) |
| LF power | $ms^2$ | Absolute power of the low-frequency band (0.04–0.15 Hz) |
| LF power | nu | Relative power of the low-frequency band (0.04–0.15 Hz) in normal units |
| LF power | % | Relative power of the low-frequency band (0.04–0.15 Hz) |
| HF peak | Hz | Peak frequency of the high-frequency band (0.15–0.4 Hz) |
| HF power | $ms^2$ | Absolute power of the high-frequency band (0.15–0.4 Hz) |
| HF power | nu | Relative power of the high-frequency band (0.15–0.4 Hz) in normal units |
| HF power | % | Relative power of the high-frequency band (0.15–0.4 Hz) |
| LF/HF | % | Ratio of LF-to-HF power |

## 3.4.2 HRV Data Analysis outcomes

### 3.4.2.1 Exploring Heart Rate Variability Changes During Different Durations

Stress is an inherent aspect of human life and can have diverse effects depending on the circumstances. While stress can be advantageous in certain situations, prolonged or inappropriate stress responses can negatively affect our well-being. Research indicates that individuals experiencing chronic or repeated stress may display reduced biological stress responses compared to the general population. To understand stress and its implications comprehensively, it is crucial to consider baseline resting levels without any stress when investigating its universality.

Timely intervention is essential for stress that manifests noticeable symptoms, as it can prevent potential declines in mental health and overall well-being. Real-time stress monitoring offers a promising solution by providing immediate biofeedback to individuals, empowering them to take proactive measures to manage stress effectively. The primary aim of this study is to explore whether changes in heart rate variability (HRV) can predict the quality of responses to acute stress and anxiety when individuals are exposed to acute stressors. Specifically, our focus is testing the first main hypothesis that *"Wearable* *devices can reliably capture and demonstrate significant differences in HRV patterns before, during, and after a cognitive challenge*."

To achieve this, the research employs a controlled experimental design where participants experience two types of stress: the Stroop colour test and exposure to IAPS image as stress-induced factors. Physiological measures, including heart rate variability (HRV), are recorded to assess the activity of the autonomic nervous system and the stress hormone response. This investigation provides valuable insights into how individuals process stress and respond to emotionally charged stimuli, as it examines stress responses and stressors using both different stressors the Stroop colour test and stress induced by IAPS image. The study involves exposing participants to emotionally charged stimuli through IAPS image, which evoke both pleasant and unpleasant emotions.

For statistical analyses, we utilized version 4.1.2 of the R software, an open-source programming language and environment specifically designed for statistical computing and graphical representation offers a diverse range of statistical techniques and graphics, making it highly suitable for various data analysis tasks.

To examine the relationship between HRV before, during, and after a STROOP word colour test, we will use a one-way ANOVA. This statistical test allows us to analyse changes in the same set of variables over multiple time points or conditions. In this study, we have HRV measurements before, during, and after the stressor (STROOP Test), which are repeated measurements of the same variable. Prior to running the ANOVA test, we will verify that the data meets the assumptions of normality, homogeneity of variance, and independence, as required by the ANOVA method.

## A.1 Analysis of variance (ANOVA)

The ANOVA test enables the investigation of whether statistically significant disparities exist in the Heart Rate Variability (HRV) values among distinct time points, encompassing pre-test, during the test, and post-test periods. The null hypothesis posits that the mean HRV values remain consistent across the various time points, while the alternative hypothesis contends the presence of at least one discernible difference. ANOVA serves as a statistical tool to scrutinize these hypotheses and ascertain if the observed variations in HRV values are statistically significant. The analysis began with examining SDNN (Standard Deviation of Normal-to-Normal Intervals) as a representative HRV (Heart Rate Variability) parameter from the time domain. To assess the normality of the response variables, the Shapiro-Wilk test and Q-Q plots were utilized. The Shapiro-Wilk test is a statistical method to assess whether a given dataset follows a normal distribution. In statistics, the normal distribution is a bell-shaped, symmetrical curve.

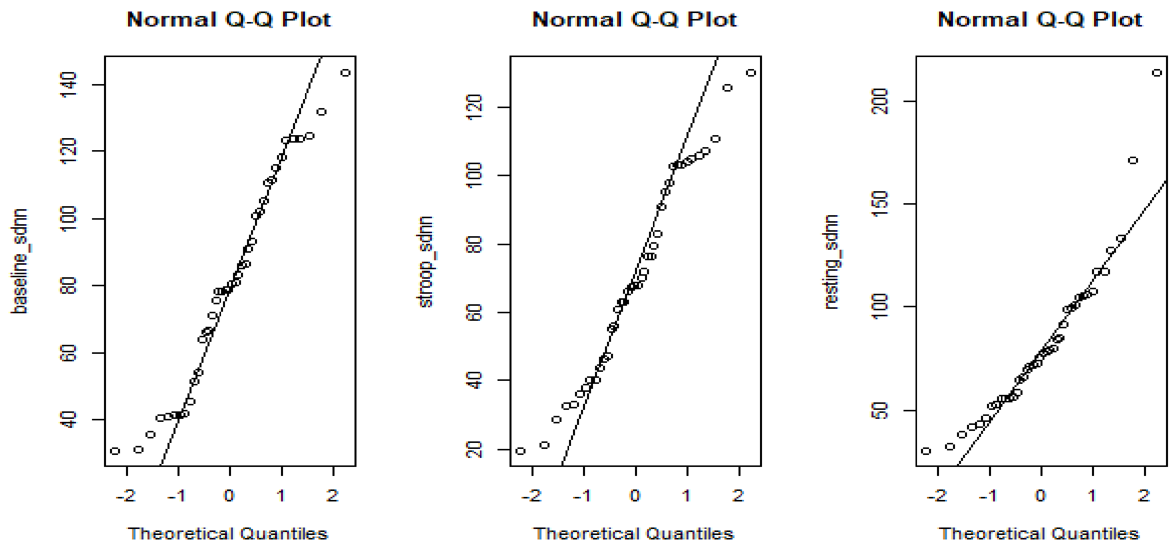



Figure 4:HRV Data (QQPLOT)

characterized by specific properties, such as a mean and standard deviation. The assumption of normality is often crucial in various statistical analyses, as many statistical tests and procedures assume that the data is normally distributed.

The Shapiro-Wilk test computes a test statistic comparing the observed data and the expected values under a normal distribution. The null hypothesis of the test posits that the data is normally distributed. Suppose the p-value associated with the test is below a predetermined significance level (commonly set at 0.05). In that case, the null hypothesis is rejected, indicating that there is evidence to suggest that the data does not follow a normal distribution. Conversely, a higher p-value suggests insufficient evidence to reject the null hypothesis, implying that the data may reasonably be assumed to be normally distributed.

A Q-Q plot is constructed by plotting the quantiles of the observed data on the vertical axis against the quantiles of the expected distribution on the horizontal axis. If the data perfectly follows the expected distribution, the points on the plot will fall along a straight line. Deviations from a straight line indicate departures from the assumed distribution. Q-Q plots provide a visual and effective way to assess the goodness of fit between observed data and theoretical distribution. Additionally, Q-Q plots visually compare the data distribution to an idealized normal distribution. The distribution of data points in the Q-Q plot aligned closely with the diagonal line, indicating approximate normality. This observation was further supported by incorporating a reference line using the qqline() function. Consequently, the Q-Q plot suggests that the SDNN variable follows an approximately normal distribution, albeit with minor deviations in the tails.

## A2. Homogeneity

The Bartlett test was employed to examine the homogeneity of variance, which compares the variances across different groups and assesses their statistical differences. A significant level of 0.05 was used to determine whether the assumption of homogeneity of variance was violated.

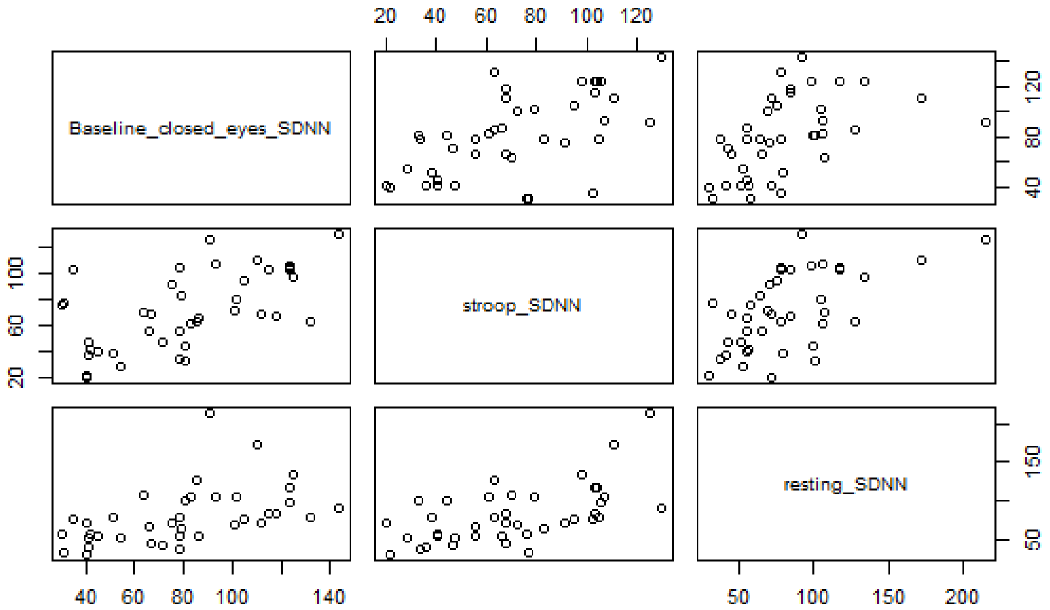



**Figure 5:** HRV Data Analysis Scatterplot

Specifically, the Bartlett test was applied to three groups of data, namely "baseline_sdnn," "stroop_sdnn," and "resting_sdnn." The test statistic utilized was Bartlett's K-squared, with a degree of freedom of 2 due to the three groups. The resulting p-value was calculated as 0.3554. Since the p-value (0.3554) exceeded the significance threshold of 0.05, the null hypothesis was not rejected. These findings suggest that the variances among the three groups were not statistically different, thereby meeting the assumption of homogeneity of variances for the subsequent ANOVA test. Additionally, a scatterplot matrix was employed to assess the independence of the response variables. This graphical representation allowed for the examination of relationships between the response variables and identification of any discernible patterns or trends that might indicate non-independence among the variables.

Once the fulfilment of the assumptions regarding normality, homogeneity of variance, and independence has been ascertained, the ANOVA test can be conducted. With these prerequisites met, the ANOVA analysis can proceed to examine the statistical significance of differences observed among the groups under investigation.

## A.3 Result

The research findings from the one-way ANOVA test using R's linear regression function (lm()) reveal significant differences in the mean values of the SDNN variable before, during, and after exposure to the stressor (p-value < 2e-16). Specifically, the SDNN during the STROOP test deviates from the other time points regarding mean values. A similar ANOVA analysis was applied to all HRV parameters, demonstrating statistical significance for both SDNN (Standard Deviation of NN intervals) and VLF (Very Low Frequency) variables across all time points (before, during, and after the administration of the Stroop test). These HRV variables serve as key indicators of stress levels. Moreover, based on paired t-tests, stroop_sdnn showed a statistically significant decrease compared to both baseline_sdnn and resting_sdnn, further highlighting the distinctiveness of the SDNN during the STROOP test concerning mean values. Consequently, this physiological response involves the release of stress-related hormones, potentially leading to vasoconstriction of blood vessels, increased blood pressure, heightened muscle tension, altered Heart Rate (HR), and reduced heart rate variability (HRV).

These outcomes align with the Sub-hypothesis 1.1, which suggests that the wearable device measurements of HRV before and during the cognitive challenge will demonstrate significant differences, affirming the device's reliability in capturing changes induced by mental stress, and highlighting their potential combined role in assessing cognitive challenges.

In recent research, adopting the CoreSense sensor, utilizing photoplethysmography (PPG), has emerged as a reliable and accurate method for stress assessment. The non-invasive and user-friendly PPG technology allows for real-time data acquisition, enabling efficient stress monitoring and analysis. Utilizing PPG as a stress measurement tool provides valuable insights into an individual's stress response during stress-inducing tasks, such as the Stroop test. This comprehensive evaluation of stress dynamics contributes to precisely understanding stress's impact on physiological responses. In military subjects, heart rate variability (HRV) assessment over 24 hours demonstrated that the standard deviation of normal-to-normal (SDNN) intervals serves as a "gold standard" measure for medical risk stratification within this timeframe [79].

The significant findings related to SDNN and VLF variables during the Stroop test, coupled with the recognition of PPG as a gold standard for stress assessment, underscore the potential of these variables and technological advancements in accurately evaluating individual stress levels. The strong correlation between SDNN and specific frequency bands in HRV, especially the Very Low-Frequency (VLF) bands, emphasizes the importance of understanding the interplay between the autonomic nervous system and HRV components for a comprehensive grasp of heart rate regulation and cardiovascular health. This knowledge has critical implications for analyzing HRV data in diverse research and clinical settings, as the contributions of different frequency bands must be carefully considered under varying measurement conditions.

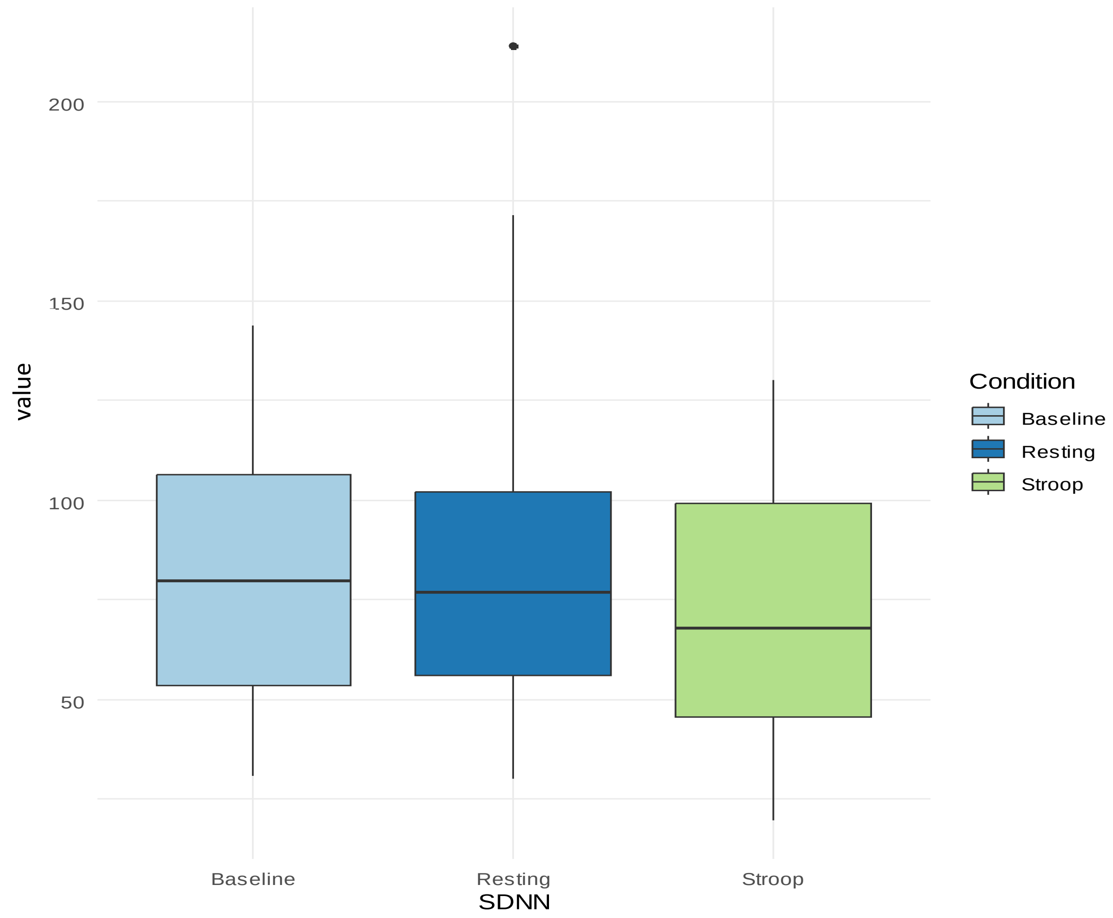



**Figure 6:** SDNN mean value across conditions Result

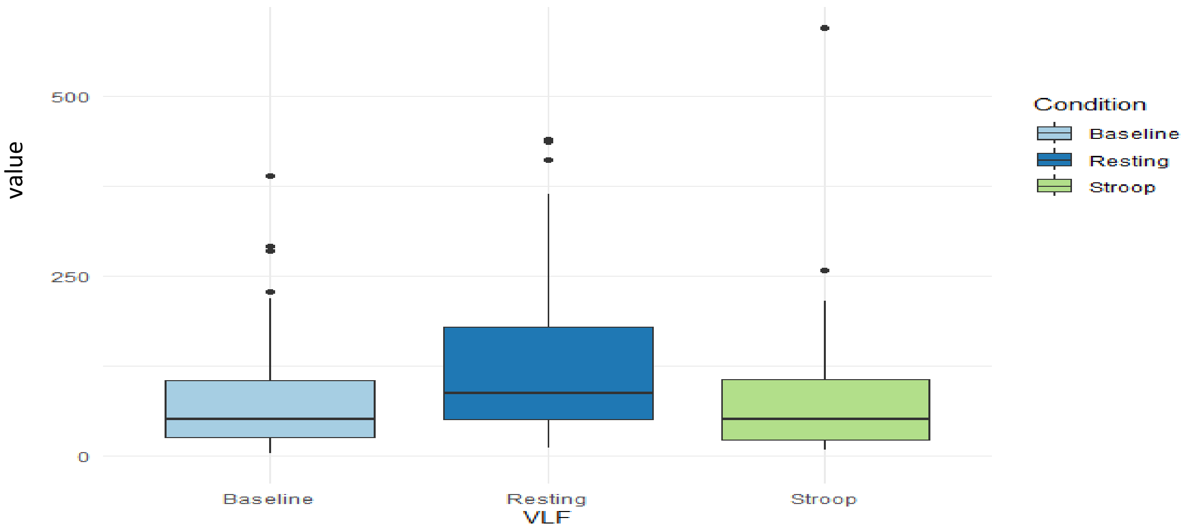



**Figure 7:** VLF mean value across conditions Result

Both (figures 6,7) was generated to depict the SDNN and VLF (Very Low Frequency) values, and it clearly demonstrates a significant difference among the groups. The observed disparity in the SDNN and VLF values is statistically significant, indicating meaningful variations between the groups in terms of this specific variable. The plot serves as visual evidence of the statistical significance of the differences observed in the SDNN and VLF values across the groups.

### 3.4.2.2 Self-Reported Data: Understanding the Power and Limitations of Subjective Information

The study examined the differences in dependent variables (PSS_10 and GAD-7) scores across three groups (baseline, during, and after). The primary objective was to determine if there were statistically significant differences in the measured variables among these groups. Thorough evaluation and comparison of the dependent variables were conducted to identify any notable distinctions among them. The obtained F-value of 12.196, with degrees of freedom (3, 37), indicates that the observed differences in the dependent variables among the three groups are statistically significant, and the p-value of less than 0.001 supports this finding. The intercept term in the analysis was also found to be statistically significant (F-value of 27.312, $p < 0.001$), suggesting overall differences in the dependent variables across all groups, regardless of specific effects. These results imply that the group variable has a significant influence on the combined dependent variables, and further investigation, such as subgroup analyses, may be necessary to gain deeper insights into the specific characteristics and factors contributing to the observed distinctions. The findings pertaining to other variables, namely HF (High Frequency), LF (Low Frequency), and the HF/LF ratio, indicate that there is no statistically significant difference in the mean values of these variables when comparing the three groups under examination. However, it is crucial to acknowledge that these results do not preclude the existence of potential differences between specific pairs of groups or more intricate relationships between the variables and groups. While the mean values across the groups do not exhibit significant distinctions, further analyses or investigations may be required to explore potential nuanced associations or specific between-group differences that may exist. Both upcoming diagrams illustrate the distribution of scores for the subjects in both GAD-7 and PSS-10.

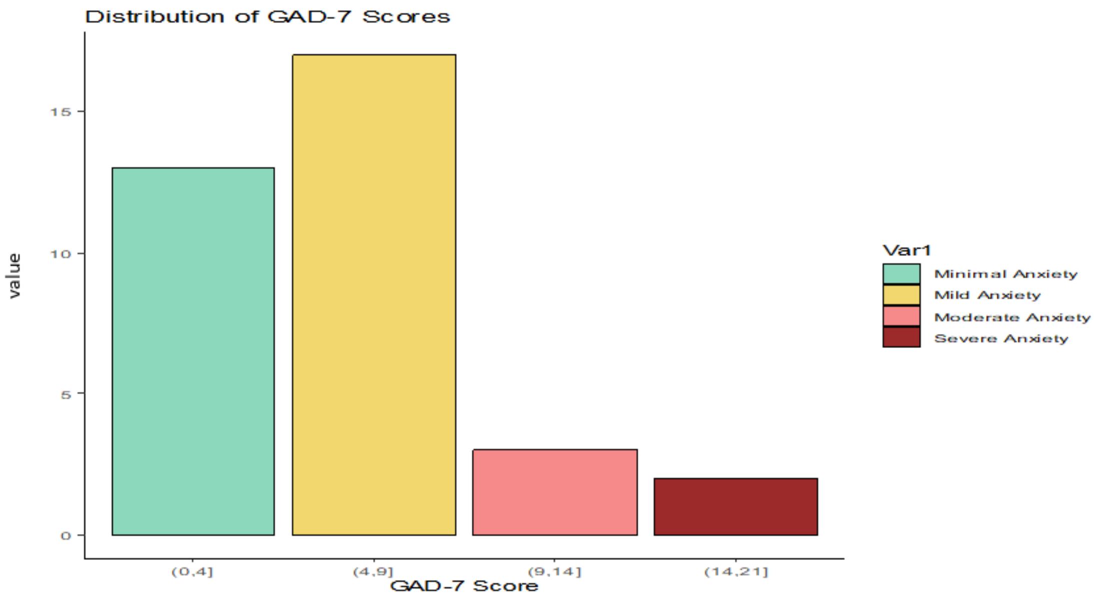
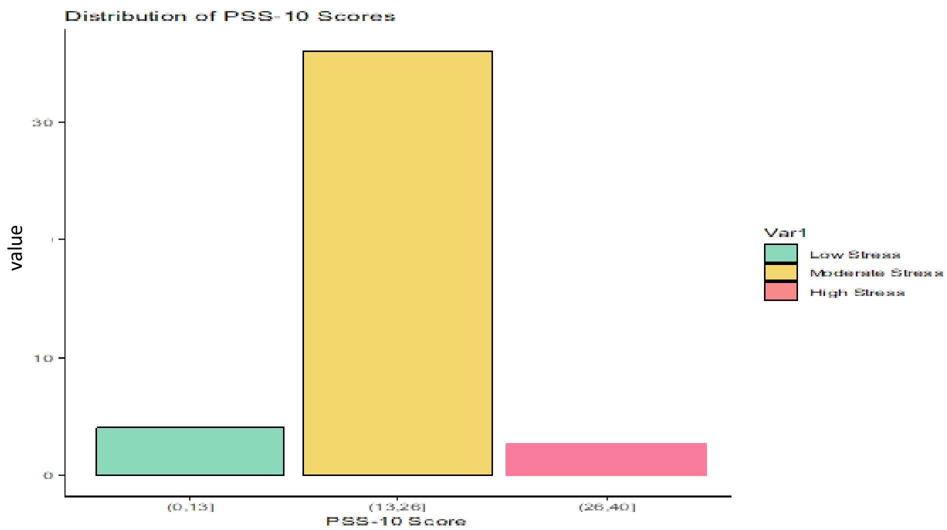



**Figure 8:**GAD7_Score Description




PSS_10 score

**Figure 9:** PSS 10 Score Descriptions

The upcoming section will delineate the subject groups into two divisions. The first group comprises individuals exhibiting minimal to mild anxiety disorders, along with perceived stress scores. The subsequent section will explore the correlation between the subjective questionnaires, focusing on individuals who score high in both categories.

## A. HRV (LF/HF ratio) and GAD-7

In this section, we explore the correlation between HRV parameters and the GAD-7 scores among all subjects. Pearson's correlation analysis was performed on all HRV parameters, revealing a correlation between HRV (LF/HF ratio) during the SAM test and the Generalized Anxiety Disorder (GAD-7) score. The results reveal a sample correlation coefficient of 0.4928868, suggesting a moderate positive correlation between these two variables. The test also reports a t-value of 3.492, with 38 degrees of freedom, and a p-value of 0.001233. The p-value is less than 0.05, which suggests that there is enough evidence to reject the null hypothesis that the true correlation between the two variables is zero. Therefore, we can conclude that there is a statistically significant positive correlation between the HRV (LF/HF ratio) and Generalized Anxiety Disorder assessment variables.

The 95% confidence interval for the correlation coefficient (0.2142773, 0.6973290) suggests that we can be reasonably confident that the true correlation coefficient lies between these two values. This interval does not include zero, which reinforces the conclusion that there is a significant positive correlation between the two variables Overall, the results of this test indicate a moderate positive correlation between the HRV (LF/HF ratio) and Generalized Anxiety Disorder, and the evidence for this correlation is statistically significant. This suggests that there may be a relationship between autonomic nervous system function (as measured by the LF/HF ratio) and generalized anxiety disorder (as measured by the GAD-7 questionnaire).

An increased heart rate is a significant indicator of autonomic nervous system (ANS) activity. The LF/HF ratio plays a crucial role in understanding the ANS function, representing the ratio of low-frequency (LF) power to high-frequency (HF) power in the HRV spectrum. LF power corresponds to both sympathetic and parasympathetic nervous system activity, while HF power predominantly reflects parasympathetic nervous system activity. Therefore, the LF/HF ratio serves as a valuable index of sympathovagal balance, offering insights into the relative dominance of sympathetic and parasympathetic influences on heart function.

Existing research suggests that a higher LF/HF ratio may be associated with increased sympathetic nervous system activity or decreased parasympathetic activity, potentially linked to various physiological and psychological conditions. Anxiety disorders have been identified as potential factors contributing to altered ANS function and an imbalanced LF/HF ratio. Conversely, a lower LF/HF ratio may indicate a more substantial parasympathetic influence, often associated with feelings of relaxation and calmness.

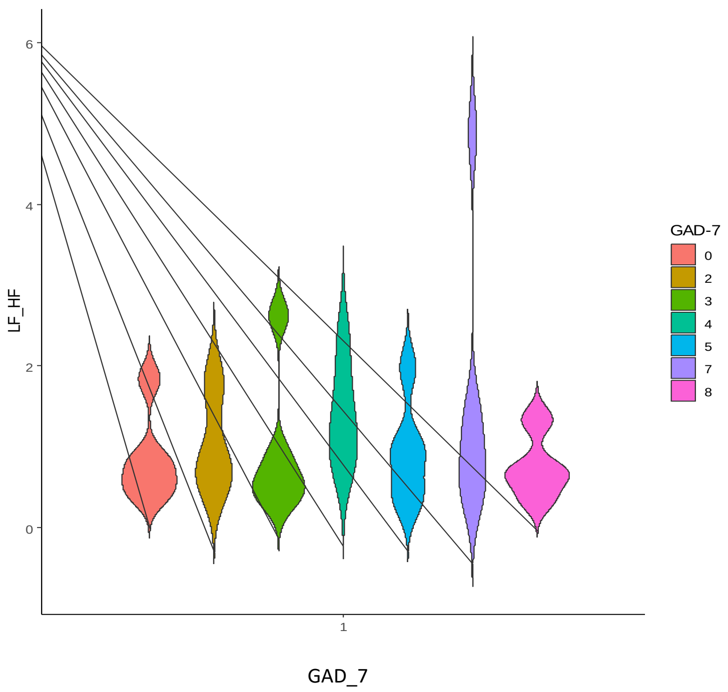



**Figure 10:** The diagram illustrates the mean value distributions of LF/HF ratio in correlation with GAD-7 scores. This representation provides insight into the relationship between HRV parameter (LF/HF ratio) and the corresponding Generalized Anxiety Disorder (GAD-7) scores**.**

## B. HRV(RMSSD) and GAD-7

Moreover, Pearson's correlation analysis between HRV (RMSSD)during SAM test and GAD-7 indicates a negative correlation between the HRV(RMSSD) and GAD-7 (a p-value of 0.04087), and the evidence for this correlation is statistically significant. This suggests that lower levels of heart rate variability (as measured by RMSSD) may be associated with higher levels of generalized anxiety disorder (as measured by the GAD-7 questionnaire). This may suggest that individuals with lower levels of heart rate variability (as measured by RMSSD) have an altered balance between their sympathetic and parasympathetic branches of the ANS. Therefore, the negative correlation between RMSSD and GAD-7 may suggest that this imbalanced autonomic state is associated with higher levels of anxiety symptoms.

Overall, the negative correlation between RMSSD and GAD-7 may be indicative of a link between HRV and ANS activity, and this association may have implications for our understanding and treatment of anxiety disorders.

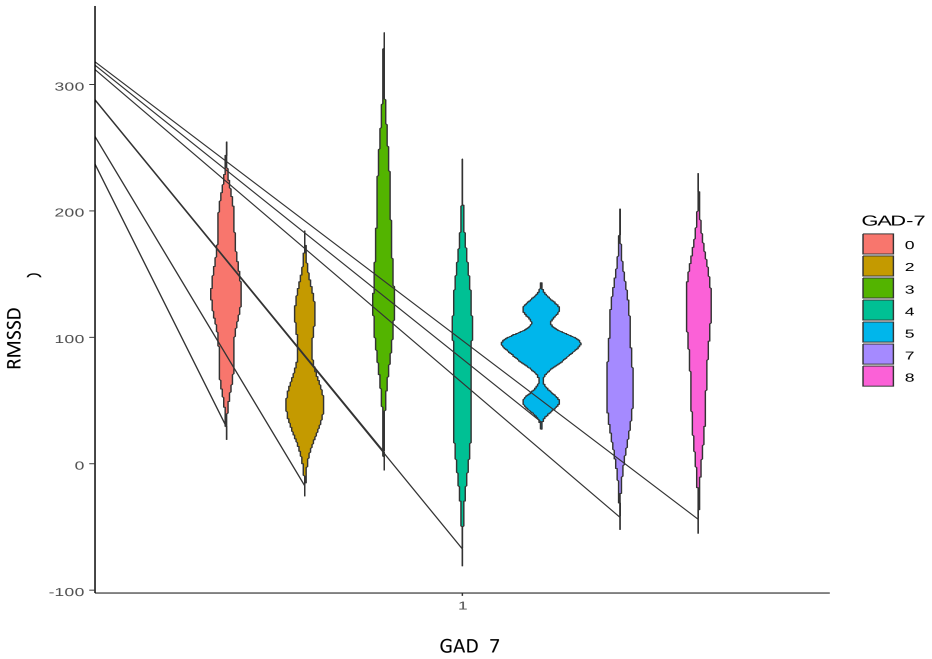



**Figure 11:** The diagram illustrates the mean value distributions of RMSSD in correlation with GAD-7 scores. This representation provides insight into the relationship between HRV parameter (RMSSD) and the corresponding Generalized Anxiety Disorder (GAD-7) scores.

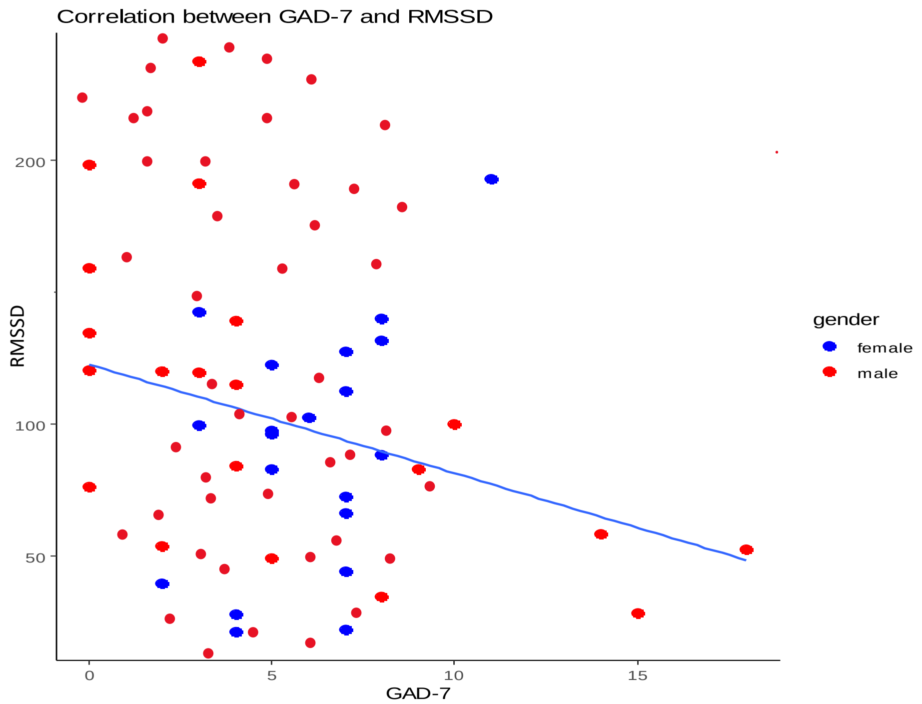



**Figure 12:** Negative correlation between GAD_7 and RMSSD

## C. HRV (LF/HF ratio) and Perceived Stress Scale (PSS-10)

Pearson's correlation analysis between HRV (LF/HF ratio) during SAM test and Perceived Stress Scale (PSS-10) is positive and statistically significant (r = 0.346, p = 0.029). This indicates that higher levels of perceived stress are associated with a higher LF/HF ratio, which is considered an indicator of decreased parasympathetic activity and increased sympathetic activity. Therefore, individuals who perceive higher levels of stress may have a dysregulated autonomic nervous system balance.

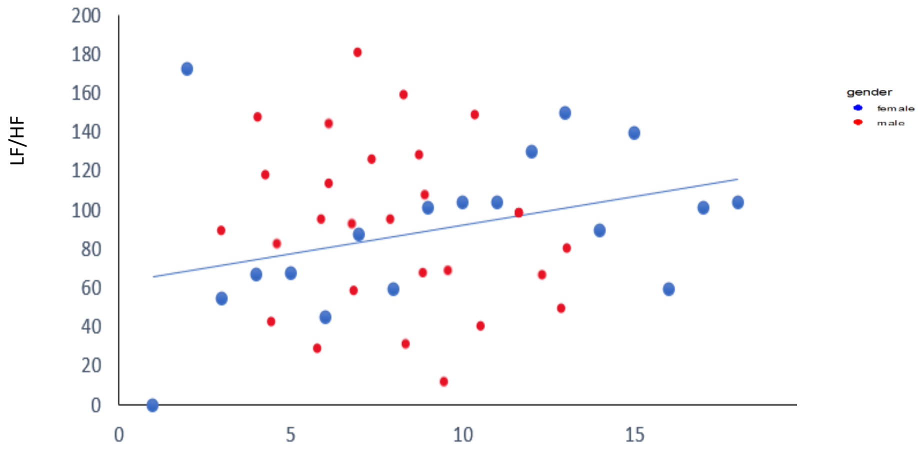



**Figure 13**: Positive correlation between Pss_10 and (LF/HF)

## 3.4.2.3 HRV and its Relationship with Anxiety and Stress: Study across Two Geographical Regions

Understanding the Differences in Stress and Anxiety About Age and Gender through Wearable Device Studies. The examination of stress and anxiety has been a focal point in both medical and psychological research for its profound impact on individual well-being and overall public health. In recent years, the integration of wearable devices into research methodologies has provided a valuable avenue for gaining deeper insights into these psychological states. Particularly, the exploration of how age and gender intersect with stress and anxiety has revealed intriguing nuances in how individuals experience and cope with these emotional states.

1. Age as a Determinant:

Age is a fundamental demographic variable that has demonstrated a significant influence on stress and anxiety levels. Numerous studies utilizing wearable devices have shown that stress and anxiety tend to follow age-related patterns. Younger individuals, such as adolescents and young adults, often report higher levels of stress, which can be attributed to various factors including academic pressures, career aspirations, and societal expectations. Wearable devices, such as heart rate monitors, have enabled continuous monitoring of physiological responses, providing researchers with a more comprehensive understanding of how these stressors manifest in the body.

Conversely, older adults frequently face stressors associated with aging, such as health concerns, financial stability, and caregiving responsibilities. Wearable devices have illuminated how chronic stress can impact the physical health of older individuals, contributing to conditions like hypertension and cardiovascular diseases. By examining age-related differences in stress and anxiety using wearable technology, researchers can tailor interventions and support systems to meet the distinct needs of different age groups [80].

2. Gender as a Moderator:

Gender is another critical dimension in the study of stress and anxiety. Research has consistently indicated that gender plays a significant role in how individuals experience and express these emotions. Wearable devices have been instrumental in capturing physiological and behavioral responses that differ between genders [81].

For instance, studies have shown that women often exhibit a greater degree of physiological reactivity to stressors, including increased heart rate and skin conductance[82]. These gender differences can be attributed to hormonal variations and societal expectations. Wearable devices equipped with biosensors can provide real-time data on these physiological responses, offering insights into gender-specific stress reactions. Moreover, wearable technology has highlighted how gender interacts with other factors, such as age and cultural background, to shape the experience of stress and anxiety. It has become evident that tailored approaches to stress management and mental health support are essential to address these unique intersections.

3. Implications for Research and Interventions:

The utilization of wearable devices in stress and anxiety research has not only expanded our knowledge of these psychological states but also has practical implications. By understanding the differential impact of age and gender, researchers and healthcare professionals can design more effective interventions and preventive strategies. Wearable technology provides a means to track and monitor individual stress responses over time, enabling personalized approaches to stress management.

In summary, the integration of wearable devices into the study of stress and anxiety has illuminated the intricate relationships between age, gender, and emotional well-being. This research not only advances our understanding of these psychological states but also informs targeted interventions and support systems to enhance the mental health and overall quality of life for individuals of all ages and genders.

## A. Age and gender differences

In this section, our focus on subjects with elevated scores in both questionnaires, prompting us to categorize the two sample sets into distinct subgroups. We initiated a correlation analysis between HRV, and scores derived from the PSS-10 and GAD-7 surveys. This methodology facilitated the identification and differentiation of participants within categories associated with heightened stress and anxiety tendencies.

### A.1 PSS10 Questionnaire

Due to the limited representation of only four subjects from the QMUL sample sets scoring high in PSS-10, a Spearman's correlation coefficient was calculated between the Perceived Stress Scale (PSS-10). The resulting correlation coefficient is approximately -0.062, indicating proximity to zero. It suggests a weak negative correlation between the two variables pss10 and (LF) during SAM test. This correlation strength is weak, and the p value is less than 0.5, indicating that the association between PSS_10 and LF is not significant. It is important to note that correlation does not establish causation; therefore, it cannot be concluded that higher perceived stress directly causes changes in LF or vice versa. In summary, the findings indicate a weak positive relationship between PSS_10 and LF.

Further investigation is necessary to gain a more comprehensive understanding of the nature and mechanisms underlying this association.

### A2. GAD_7 Questionnaire

This study investigates the association between anxiety levels, as measured by GAD-7, and HRV parameters. Additionally, it examines gender differences in HRV between participants from QMUL and KFSH. Participants were recruited from QMUL and KFSH, comprising males and females. Anxiety higher levels were assessed using the GAD-7 questionnaire, while HRV was measured through SDNN during SAM test. The sample set for this study include 3 subjects from KFSH and 2 subjects from QMUL.

Pearson's product-moment correlation test was employed to analyse the relationship between GAD-7 scores and HRV. Gender differences were assessed by comparing the mean SDNN values between males and females in each institution.

The Pearson's correlation coefficient between GAD-7 and HRV was calculated to be 0.0604 ($p = 0.7111$). This weak positive correlation suggests that as GAD-7 scores increase, HRV tends to slightly increase. However, the correlation was not statistically significant at the 0.05 level, indicating that the null hypothesis of no correlation between GAD-7 and HRV cannot be rejected.

The results indicate a weak positive correlation between anxiety levels, as measured by GAD-7, and HRV parameters. However, these correlations are not statistically significant, suggesting no strong relationship between the two variables. Furthermore, gender differences in SAM_SDNN were observed, with females generally exhibiting lower SDNN values compared to males in both institutions. However, the clinical implications of these differences require further investigation and to better understand the underlying mechanisms of HRV differences between genders.

Additionally, Pearson's product-moment correlation test between GAD-7 and SAM_RMSSD showed that there is a moderate negative correlation between heart rate variability (SAM_RMSSD) and anxiety levels (gad7). Subjects with higher heart rate variability tend to have lower anxiety levels is a correlation coefficient of 0.0604, with a p-value of 0.7111. This indicates that there is a very weak positive correlation between the two variables, meaning that as GAD-7 scores increase, SAM_RMSSD tends to slightly increase as well. However, this correlation is not statistically significant at the 0.05 level, as the p-value is greater than 0.05. Therefore, we cannot reject the null hypothesis that there is no correlation between GAD-7 and HRV. Overall, the results suggest that there is no strong relationship between anxiety levels (as measured by GAD-7) and SAM_RMSSD.

In summary, this study provides evidence of a weak positive correlation between anxiety levels and HRV parameter, but this correlation lacks statistical significance.

In the upcoming section, we will employ the mean SDNN (standard deviation of normal-to-normal intervals) obtained during the Stroop colour task. This measure emerged as a robust finding, correlating with the established standards outlined in section 3.4.2.1 of this chapter. This section examines the correlation between two geographical groups without considering subjective methods. This study aimed to assess disparities in Heart Rate Variability (HRV) between two distinct geographical regions: QMUL (Queen Mary University of London) and KFSH (King Faisal Specialist Hospital, KSA). The primary objective was to determine whether statistically significant HRV measurement variations exist among individuals from these regions. The HRV data was evaluated and compared to identify any notable differences between the QMUL and KFSH groups. Analyzing the HRV variations within these demographic regions provided valuable insights into potential discrepancies in cardiovascular regulation and autonomic nervous system activity, which may arise due to geographical and cultural diversity. Further investigation is warranted to explore contributing factors, such as lifestyle, environmental influences, and other demographic characteristics, that could impact cardiovascular health and explain the observed differences in HRV between QMUL and KFSH. The mean Stroop_ SDNN value for males in KFSH was honoured to be higher than that of females by -15.22364 units, indicating that females in KFSH generally exhibit lower SDNN values than males. The mean Stroop_SDNN value for females in QMUL was lower by -12.78195 units compared to males. This suggests that female participants in QMUL had significantly lower SDNN values on average than their male counterparts.

The mean Stroop_SDNN difference between males and females in KFSH was found to be -15.22364. This indicates that, on average, females in the KFSH group exhibited lower SDNN values compared to males, with a difference of 15.22364 units.

Similarly, the mean Stroop_ SDNN difference between males and females in QMUL was observed to be -12.78195. This suggests that, on average, female participants in the QMUL group displayed SDNN values that were 12.78195 units lower compared to their male counterparts. These findings highlight the gender-based variations in SDNN measures, indicating that females tend to exhibit lower SDNN values relative to males in both the KFSH and QMUL groups.

To answer the second hypothesis, “*Demographic factors influence HRV patterns before, during, and after a cognitive stressor*.”

In the analysis of SDNN (Standard Deviation of Normal-to-Normal Intervals) between the QMUL (Queen Mary University of London) and KFSH (King Faisal Specialist Hospital) groups, the mean SDNN was calculated for each group and subsequently subtracted from one another. The calculated difference in mean SDNN between the two groups was found to be 10.57245. However, it is crucial to exercise caution and recognize that this numerical value alone does not provide sufficient context to draw robust and meaningful conclusions. Further comprehensive analysis, such as statistical significance testing and exploring the potential implications of this difference, is warranted to ascertain the significance and potential implications of the observed difference in mean SDNN between the QMUL and KFSH groups. The t-test p-value of 0.2667436 means that there is a 26.67% chance of observing a difference in mean SDNN between QMUL and KFSH at least as extreme as the one we observed if the true difference in means is zero. This p-value is relatively high and greater than the commonly used alpha level of 0.05, suggesting that we cannot reject the null hypothesis that there is no significant difference in mean SDNN between QMUL and KFSH. However, further analysis may be needed to determine the significance and implications of this result. We fit an ANCOVA model with stroop_SDNN as the outcome variable, group, and age as the predictors, and calculate the estimated means and standard errors for each group, adjusting for age. The Anova function from the car package will give you the ANOVA table and test for the significance of the difference between the two groups, considering age.

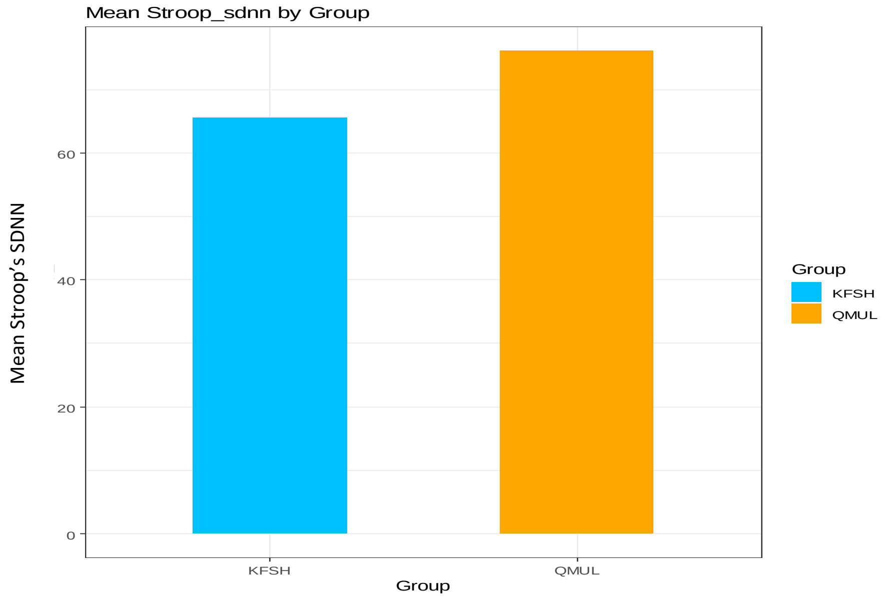



**Figure 14:** This diagram delineates the difference between two demographic groups concerning the mean Stroop_SDNN. The comparison provides a visual representation of the variations in Stroop task related SDNN measurements between the specified demographic groups.

Anova Table (Type II tests)

Response: stroop_SDNN

Sum Sq Df F value Pr(>F)

group 935.9 1 1.4912 0.2299649

Age range 10836.5 2 8.6334 0.0008654 ***

Residuals 22593.3 36

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The ANOVA table shows the results of an ANOVA model where Stroop_SDNN is the outcome variable, group and age range are the predictors. Type II tests are used to assess the significance of each predictor after controlling for the other predictors in the model.

The table indicates that age range has a significant effect on SDNN ($F(2, 36) = 8.6334$, $p = 0.0008654$), but group does not have a significant effect on SDNN ($F(1, 36) = 1.4912$, $p = 0.2299649$).

This suggests that, after controlling for age range, there is no significant difference in SDNN between the QMUL and KFSH groups. However, there is a significant effect of age range on SDNN, meaning that SDNN varies significantly across different age ranges.

The significant p-value for age range ($p = 0.0008654$) indicates that at least one of the age range categories has a different SDNN compared to the others.

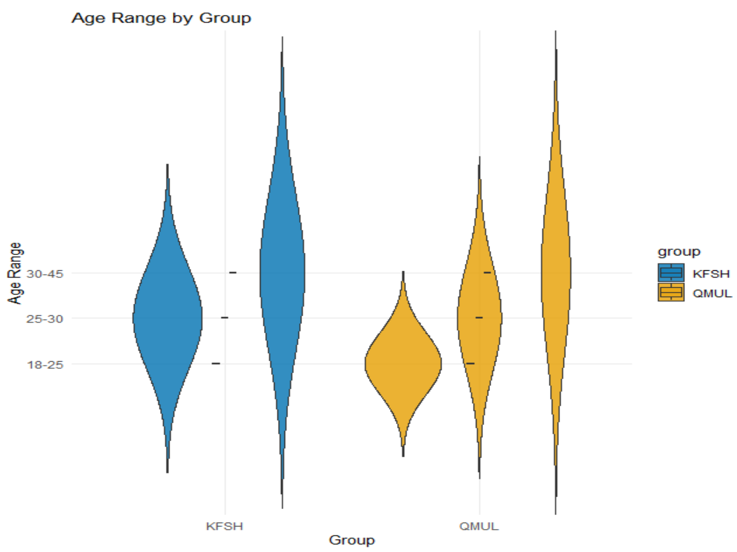



**Figure 15:** The diagram illustrates the age range distribution for Stroop_SDNN within two geographical groups: QMUL (Queen Mary University of London) and KFSH (King Faisal Specialist Hospital, KSA). This representation offers a visual insight into the variation in Stroop task-related SDNN across different age groups in the respective geographical regions.

In summary, statistical significance is a crucial factor in determining the reliability of the observed difference. While the output indicates a numerical difference of 10.57245, it is necessary to determine whether this difference is statistically significant or simply due to restrictions of the sample size and data type used and therefore most relevant to the specific study conducted. Conducting appropriate statistical tests, such as t-tests or ANOVA, will provide insights into the probability of obtaining such a difference if there were no true distinction between the two groups. This analysis enables researchers to determine if the observed difference is likely to represent a genuine disparity in mean SDNN.

In addition to statistical significance, the characteristics of the samples from QMUL and KFSH should be considered. Assessing factors such as sample size, representativeness, and potential sources of bias is important to ensure the generalizability of the findings. A small sample size may limit the reliability of the results, while an unrepresentative or biased sample may lead to erroneous conclusions. Evaluating these sample characteristics helps to determine the extent to which the observed difference in mean SDNN is applicable to the broader population or specific target group.

## B. Machine Learning Prediction Model: OLS Regression and AIC Model Selection

Within the scope of our research, a primary objective was to investigate the association between alpha asymmetry and vagally mediated Heart Rate Variability (HRV) in relation to the severity of depression among a sample of healthy individuals. Our study focused on individuals who had higher scores on both clinical questionnaires, which were instrumental in identifying those with elevated levels of depressive symptoms. Furthermore, the co-occurrence of Major Depressive Disorder (MDD) and an anxiety disorder was typically associated with higher questionnaire scores.

In evaluating the severity of depressive symptoms, we employed a physiological measurement method, supported by clinical experts from the KFSH Neuroscience team who meticulously validated the reliability and validity of the two subjective questionnaires used for this purpose. The diagnosis of comorbid MDD and anxiety disorders was further substantiated by the elevated scores observed on these clinical questionnaires.

It is important to acknowledge that our study had limitations, primarily stemming from a restricted sample size. We had data available for only five individuals, with three of them originating from KFSH and the other two from QMUL, all of whom exhibited a moderate level of anxiety, as assessed by the Generalized Anxiety Disorder questionnaire (anxiety disorder-7 (GAD-7) scale). Additionally, among the subjects, there were four individuals whose Perceived Stress Scale (PSS-10) scores were categorized as high. Notably, these four high-stress subjects were evenly (male and female) divided among those from Queen Mary University of London (QMUL).

In the process of conducting data analysis for this research, Ordinary Least Squares (OLS) regression was employed alongside model selection based on the Akaike Information Criterion (AIC). OLS regression represents a well-established statistical technique used to elucidate the intricate relationship between a dependent variable and one or more independent variables. It achieves this by fitting a linear equation to the observed data, with the primary objective of determining the optimal linear equation through the minimization of the sum of squared differences, also known as residuals, between the predicted and observed values. This process yields coefficients for each independent variable, offering insights into their respective influences on the dependent variable. It is essential to emphasize that OLS regression operates under specific assumptions, including linearity, the presence of normally distributed errors characterized by a mean of zero, constant variance, and the independence of errors. Given its versatility and broad applicability, OLS regression finds extensive utilization across various academic and practical domains.

In stark contrast, the Akaike Information Criterion (AIC) model selection methodology serves as a statistical tool deployed to systematically compare and select the most suitable model from a set of candidate models. The principal aim of AIC is to strike an optimal balance between a model's goodness-of-fit and its inherent complexity. It achieves this by identifying the model that effectively explicates the observed data while penalizing excessive intricacy. This judgment is rendered through the assignment of numerical scores to each candidate model, factoring in essential elements such as the likelihood function and the quantity of parameters integrated into the model structure. Consequently, the model with the lowest AIC score is considered the most suitable, signifying its capacity to provide a robust fit to the data while minimizing the risk of overfitting. It is noteworthy that this approach holds significant relevance and applicability within diverse academic disciplines, including statistics and machine learning. Furthermore, it aids in facilitating informed and prudent decisions concerning model selection and subsequent interpretation of research findings.

In the context of our research investigation, we employed two widely recognized questionnaires, namely the Generalized Anxiety Disorder 7 (GAD-7) and the Perceived Stress Scale (PSS), to evaluate anxiety and stress levels. The GAD-7 is a concise self-report instrument extensively utilized in both clinical and research settings to quantitatively assess the severity of symptoms linked to generalized anxiety disorder. Comprising seven questions, this questionnaire prompts respondents to retrospectively consider their experiences over the preceding two weeks. Responses are graded on a scale ranging from 0 to 3, with higher scores signifying more pronounced symptoms of anxiety. The cumulative score, which varies from 0 to 21, serves to categorize the extent of anxiety, with scores of 5-9 denoting mild anxiety, 10-14 indicating moderate anxiety, and 15 or higher indicative of severe anxiety. Notably, the preponderance of data points within our dataset corresponds to the none or mild anxiety categories, with only a limited number of reflecting instances of moderate anxiety.

In contrast, the Perceived Stress Scale (PSS) is a well-established psychological assessment tool specifically designed to gauge individuals' perceptions of stress levels within their daily lives. Typically comprised of a series of questions, this scale assesses how individuals subjectively perceive the unpredictability, controllability, and burden associated with life's challenges. Respondents assign ratings on a scale typically ranging from 0 to 4, where elevated scores indicate heightened perceived stress levels. During our analytical process, we found it necessary to invert the scores for four specific questions to ensure alignment with the intended structure of the questionnaire. Importantly, within our sample, a subset of participants exhibited PSS scores categorized as high, underscoring the presence of elevated perceived stress levels among specific individuals.

Utilizing the (IPython Notebook) Python library for conducting statistical analysis and model selection through Ordinary Least Squares (OLS) and the Akaike Information Criterion (AIC) is a powerful and interactive approach. IPython Notebook, also known as Jupyter Notebook, provides an integrated environment encompassing code execution, data visualization, and explanatory text, making it an excellent choice for OLS regression and AIC model selection. This approach enhances researchers' ability to document and share their work effectively. OLS regression is a well-established statistical technique for modelling the relationship between a dependent variable and one or more independent variables. Implementing OLS regression in an IPython Notebook follows a structured process.

Conducting AIC model selection within an IPython Notebook streamlines the process and allows for a clear and well-documented rationale behind model selection, enhancing research transparency and reproducibility. The use of the `.ipynb` Python library, or IPython Notebook, for OLS regression and AIC model selection offers an interactive and well-structured approach to statistical analysis. It combines code execution, documentation, and data visualization within a unified environment, making it a valuable tool for researchers and analysts engaged in regression analysis and model selection tasks.

In summary, our methodological approach, encompassing the application of Ordinary Least Squares (OLS) regression, Akaike Information Criterion (AIC) model selection, and the assessment of anxiety and stress levels through the GAD-7 and PSS_10 questionnaires, has played a pivotal role in achieving a nuanced understanding of our dataset and the variables under scrutiny. This comprehensive methodology has facilitated an in-depth analysis of the intricate relationships and influences inherent in the dataset, thereby unveiling crucial patterns and insights central to the objectives of our research.

Consequently, the following section presents the results derived from both the HRV time domain and frequency domain analyses:

**1.MeanRR**

Heart Rate Variability (HRV) serves as a closely interconnected metric with the Autonomic Nervous System (ANS), governing various involuntary bodily functions, notably heart rate regulation. The ANS comprises two key branches: the sympathetic nervous system (SNS), responsible for heightened heart rate during the "fight or flight" response, and the parasympathetic nervous system (PNS), which fosters relaxation and heart rate reduction. HRV's Mean RR metric is rooted in the temporal intervals between successive heartbeats, rendering it a quantitative representation of autonomic activity. Stress and anxiety wield significant influence over HRV, often triggering SNS activation, resulting in escalated heart rate and diminished HRV, as manifested in a reduced Mean RR. Conversely, relaxation instigates PNS predominance, elevating both HRV and Mean RR values. This intricate relationship between HRV and the ANS underscores its pivotal role in elucidating physiological responses to stress and anxiety, thereby proving instrumental in clinical assessments and research endeavors within these domains.

In the context of MeanRR analysis, it was determined that the model incorporating the factors Dataset, Sex, PSS (Perceived Stress Scale), and GAD7 (Generalized Anxiety Disorder 7) provided the optimal fit.

Subsequently, we evaluated the main effects of each of these factors, as well as their interactions. The statistical analysis revealed the following outcomes:

a. Main effects of the factors were observed for Dataset ($t(15, 231) = 2.88$, $p = 0.004$), Sex (male) ($t(15, 231) = 4.32$, $p < 0.001$), GAD7 ($t(15, 231) = 4.38$, $p < 0.001$), and PSS_10 ($t(15, 231) = 4.28$, $p < 0.001$).

b. Additionally, the interaction between Dataset and Sex was found to be statistically significant ($t(15, 231) = 3.38$, $p = 0.006$).

c. Furthermore, all higher-order interactions among these factors were deemed statistically significant, with p-values less than 0. 001.The analysis revealed notable associations and interactions among the considered factors. Particularly, it was observed that males exhibited a stronger negative association with MeanRR within the QM dataset in combination with GAD_7. These findings contribute to a deeper understanding of the relationships between these variables and their implications for the MeanRR measure.

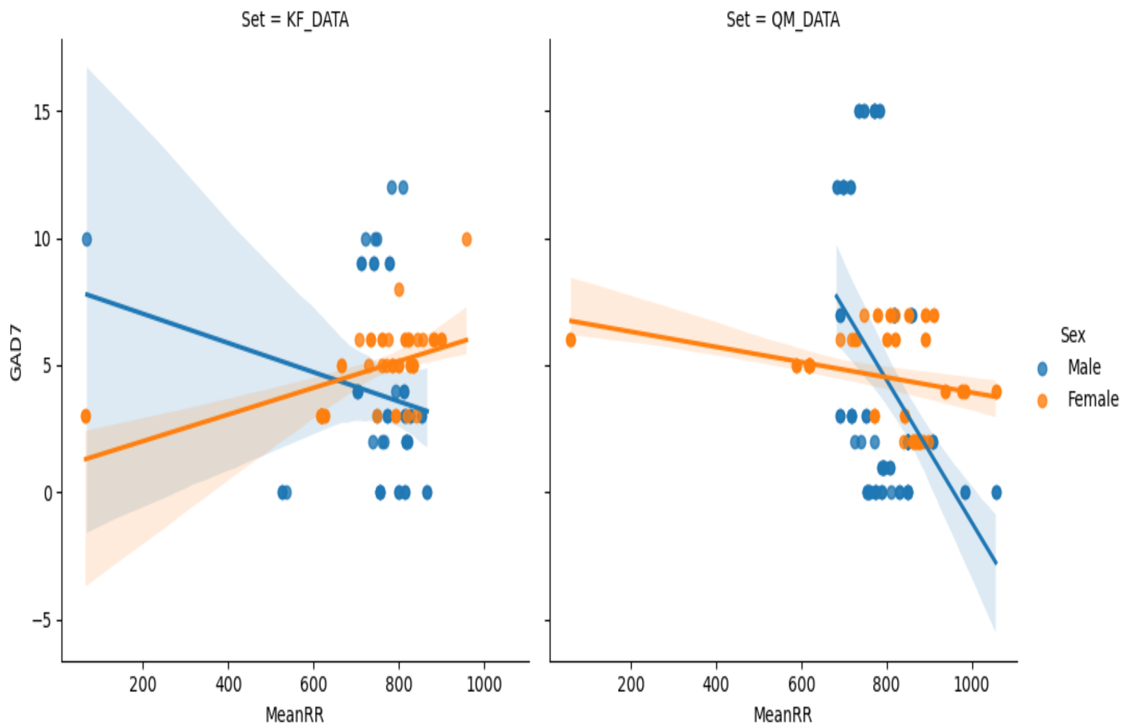



**Figure 16**: The OLS regression model results for GAD7 and the( meanRR )HRV in relation to gender are presented.

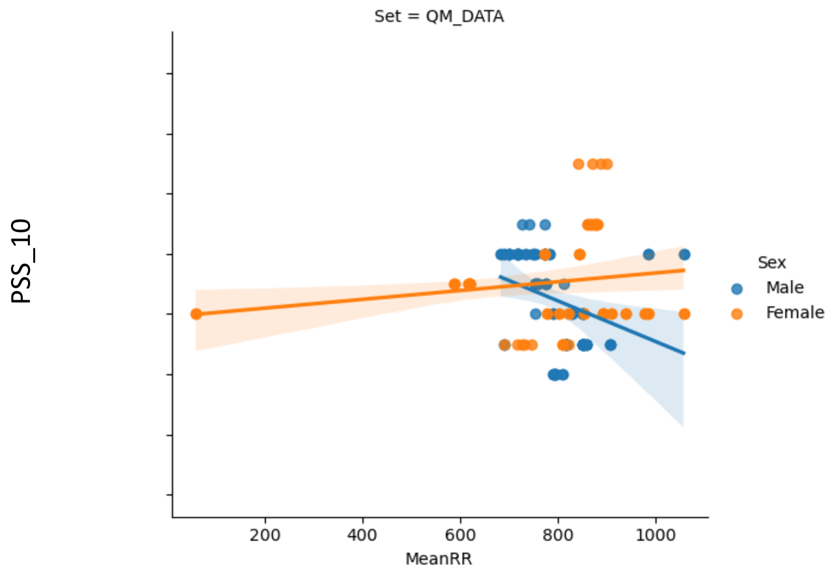



**Figure 17:** The OLS regression model results for PSS_10 and MeanRR HRV in relation to gender are presented.

## 2. RMSSD

Especially within the Heart Rate Variability (HRV) research area, the Root Mean Square of Successive Differences (RMSSD) serves as a pivotal metric for evaluating stress and anxiety. Focusing on the fluctuations in the durations of R-R intervals, as observed through a PPG signal, RMSSD quantifies variations in the time intervals between consecutive heartbeats. Its significance is underscored by its ability to monitor alterations in the parasympathetic nervous system (PNS), a fundamental regulator of the body's responses to stress and anxiety.

A notable advantage of employing RMSSD as a tool for assessing stress and anxiety lies in its capacity to detect changes in PNS activity. The parasympathetic nervous system (PNS) plays a vital role in promoting relaxation and restoring the body to a state of equilibrium after the activation of the sympathetic nervous system (SNS) during stress-induced "fight or flight" responses.

The model encompassing Set, Sex, and PSS_!0 yielded the lowest AIC score, signifying its superior fit. Furthermore, a significant interaction emerged between PSS_10, RMSSD, and Sex, as evidenced by the statistical values ($t(15, 231) = -4.01$, $p < 0.001$), illuminating nuanced relationships within the data. Additionally, a notable main effect of PSS_10 was observed ($t(7, 243) = -3.08$, $p < 0.01$), underscoring its individual significance. Specifically, it was discerned that females exhibited a more pronounced association between PSS_10 and RMSSD only at QMUL sample set and there was no statically significant correlation in the KFSH set. Notably, no statistically significant findings were ascertained concerning GAD_7 within the context of this analysis.

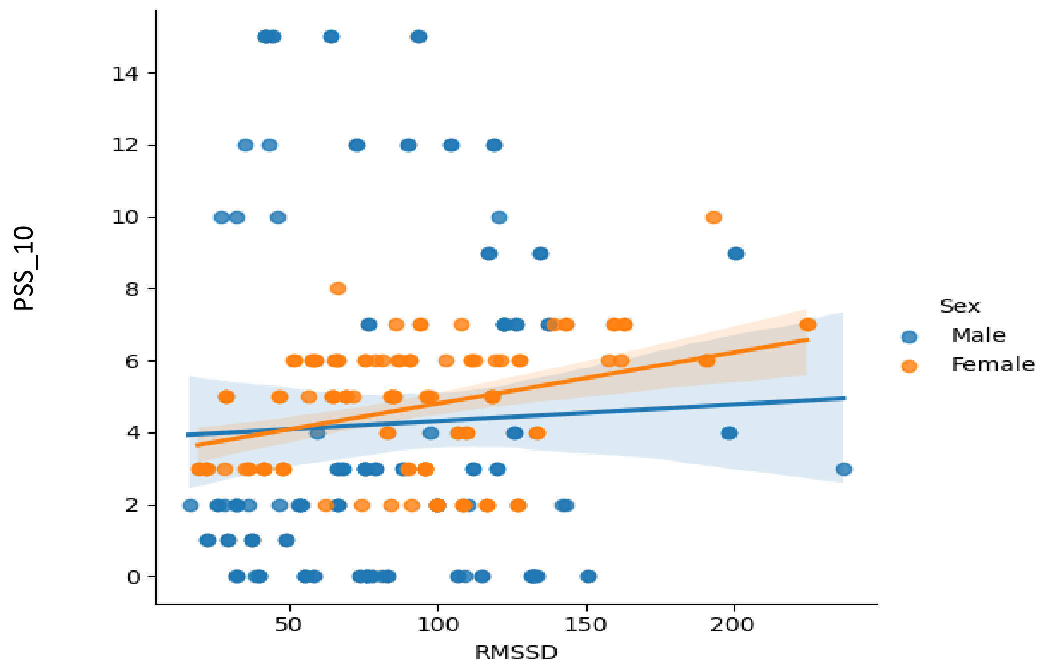



**Figure 18:** The OLS regression model results for PSS_10 and (RMSSD) HRV in relation to gender are presented.

### 3. PNNX

The parameter known as pNNX (proportion of successive NN intervals that differ by more than X milliseconds) within the context of Heart Rate Variability (HRV) analysis offers distinct advantages when it comes to measuring stress and anxiety.

One of the key benefits of employing pNNX as a HRV metric is its sensitivity to subtle changes in autonomic nervous system (ANS) activity. Stress and anxiety exert a direct influence on the ANS, particularly by affecting the balance between its sympathetic (SNS) and parasympathetic (PNS) branches. SNS, often associated with the "fight or flight" response, tends to increase heart rate, and reduce HRV during stressful situations, leading to a lower pNNX value. Conversely, the PNS, responsible for promoting relaxation, tends to enhance HRV and elevate pNNX levels during periods of calmness and reduced stress.

Another advantage of pNNX is its capacity to provide a quantitative and non-invasive measure of stress and anxiety. By analyzing pNNX values, researchers and clinicians can gain valuable insights into an individual's physiological response to stressors. This parameter allows for the assessment of the autonomic balance, with lower pNNX values indicating a dominance of the SNS and higher values reflecting a more prominent role of the PNS.

In the course of this analysis, it became evident that the model encompassing the factors of Dataset, Sex, and Questionnaire demonstrated the most favorable fit when assessing pNNX (t(15, 231)=3.46, p<0.01). our observations revealed noteworthy main effects for each of these factors, specifically Dataset, Sex, and GAD-7 (t(15, 231)=3.91, p<0.01; t(15, 231)=3.33, p<0.01; t(15, 231)=3.88, p<0.01, respectively). It is noteworthy that the most substantial negative association between pNNX and Questionnaire scores was discerned within the QMUL dataset among males. Conversely, females tended to display a positive association, with a more pronounced effect observed in the KF dataset, as visually depicted in the figure below. It is pertinent to highlight that no significant results were ascertained regarding the interaction between pNNX and PSS_10.

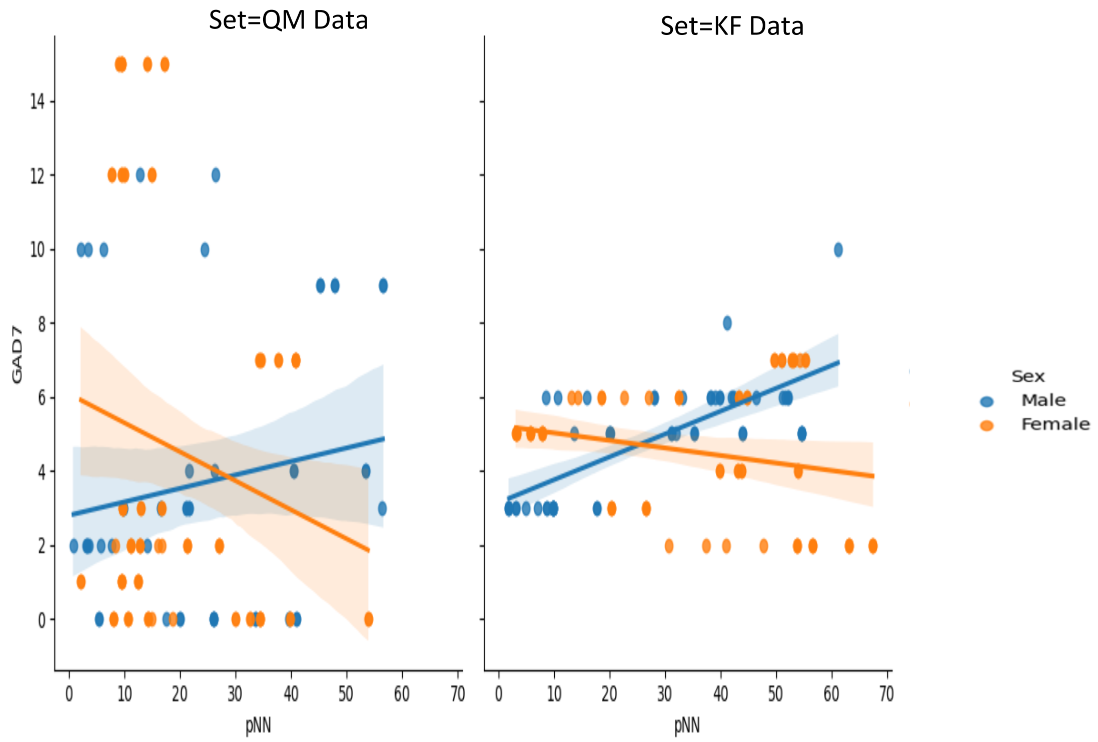



**Figure 19:** The OLS regression model results for Gad_7and (PNNX) HRV in relation to gender are presented.

**4. VLF (absolute peak frequency)**

VLF (Very Low-Frequency) HRV, particularly when considering absolute peak frequency analysis, stands as a valuable parameter in the assessment of stress and anxiety. VLF HRV focuses on the spectral aspects of heart rate variability within a frequency range typically spanning from 0.0033 to 0.04 Hz. This specific frequency band plays a pivotal role in regulating various physiological processes, including the intricate control of the sympathetic and parasympathetic nervous system activities.

During periods characterized by heightened stress and anxiety, it is not uncommon to observe an escalation in sympathetic activity, thereby inducing a discernible shift in the VLF power spectrum. This shift typically manifests as a reduction in VLF power, signifying a prevalence of SNS dominance—a hallmark of the physiological "fight or flight" response. In contrast, during states of relaxation or when individuals experience diminished stress and anxiety, the VLF power spectrum frequently exhibits an augmentation, indicating a more balanced or pronounced parasympathetic influence.

The utility of VLF HRV garners significant attention from both researchers and clinicians owing to its ability to offer profound insights into the autonomic regulation of the cardiovascular system and its adaptability in response to stressors. Through meticulous scrutiny of VLF HRV data, practitioners can gauge the extent of sympathetic and parasympathetic modulation, thereby providing a quantitative measure of the physiological response to stress and anxiety. Moreover, fluctuations in VLF HRV may serve as an early indicator of stress-related health conditions, thus reinforcing its role as a valuable tool for proactive healthcare measures.

Prior to model fitting, we assessed the normality of the data and performed a log transformation to meet the normality assumption. Subsequently, our analysis identified the most appropriate model for explaining variations in Very Low-Frequency (VLF) as a combination of the Sex and GAD-7 variables, supported by the lowest Akaike Information Criterion (AIC) value of 861. Our statistical examination unveiled a significant main effect of Sex ($t(15, 231)=3.56$, $p<0.01$), signifying its notable influence on VLF. Additionally, we observed a statistically significant interaction between Sex and GAD-7 ($t(15, 231)=2.97$, $p<0.01$), underscoring their collective impact on VLF. It is worth noting that the correlation between VLF and GAD-7 Questionnaire scores exhibited a positive association among females and a negative association among males. This observation highlights distinct gender-related patterns in the relationship between VLF and psychological factors.

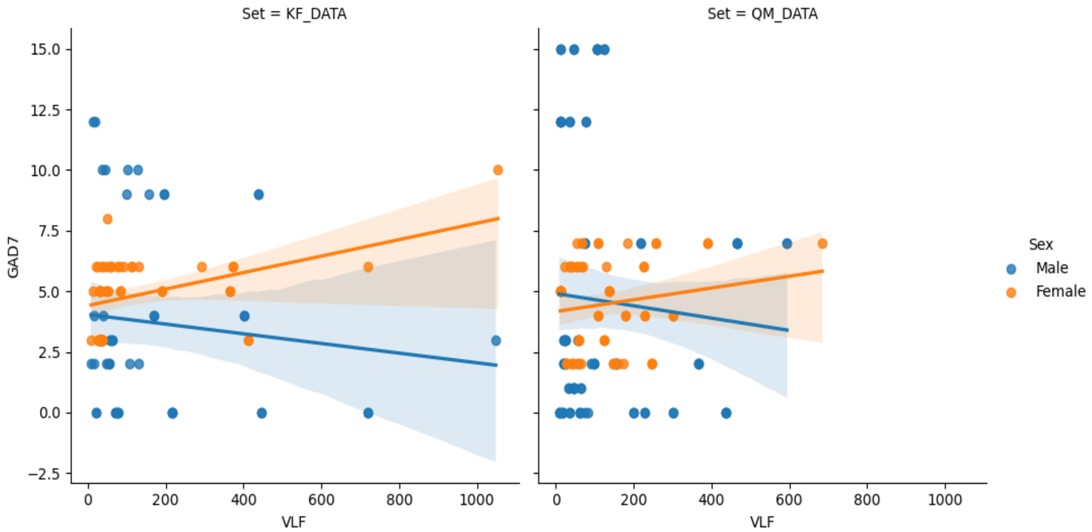



**Figure 20:** The OLS regression model results for GAD-7and (VLF absolute peak frequency)HRV in relation to gender are presented.

### 5. VLF %

VLF% normalization adjusts for variances in VLF power stemming from an individual's overall heart rate variability. This adjustment fosters more meaningful comparisons across a diverse range of individuals, rendering it an invaluable tool for both researchers and clinicians working with heterogeneous populations. Stress and anxiety responses exhibit substantial interindividual variability. Normalized VLF% effectively addresses this variability by delivering a relative measure, thereby facilitating a customized evaluation of stress and anxiety levels tailored to an individual's baseline Heart Rate Variability (HRV). Furthermore, the utility of normalized VLF% extends to monitoring temporal changes in stress and anxiety within an individual. The establishment of a baseline measurement serves as a reference point against which any deviations can be systematically tracked. This tracking capability provides valuable insights into the efficacy of stress management interventions and the progression of stress-related conditions over time.

In clinical contexts, the integration of normalized VLF% can significantly contribute to the diagnosis and management of stress-related disorders such as generalized anxiety disorder, post-traumatic stress disorder, and depression. The provision of a quantitative measure complements traditional clinical assessments, empowering healthcare providers to make well-informed treatment decisions.

Lastly, normalized VLF% operates as an early warning mechanism for individuals susceptible to stress-related health concerns. The detection of deviations from an individual's established baseline can trigger timely interventions by healthcare professionals, potentially averting the exacerbation of stress-related conditions.

Prior to model fitting, the dataset underwent a thorough assessment for normality, following which a logarithmic transformation was applied to ensure adherence to the assumption of normality. When VLF was represented as a percentage scale, the model that incorporated the variables Set, Sex, and Questionnaire demonstrated the best fit, as evidenced by the lowest Akaike Information Criterion (AIC) value of 624. Furthermore, a statistically significant interaction was observed between the variables Set, Sex, and GAD7 ($t(15, 231)=3.71$, $p<0.001$). The utilization of Normalized Very Low-Frequency Percentage Heart Rate Variability (VLF%) as a metric for measuring stress and anxiety offers numerous advantages within research and clinical contexts.

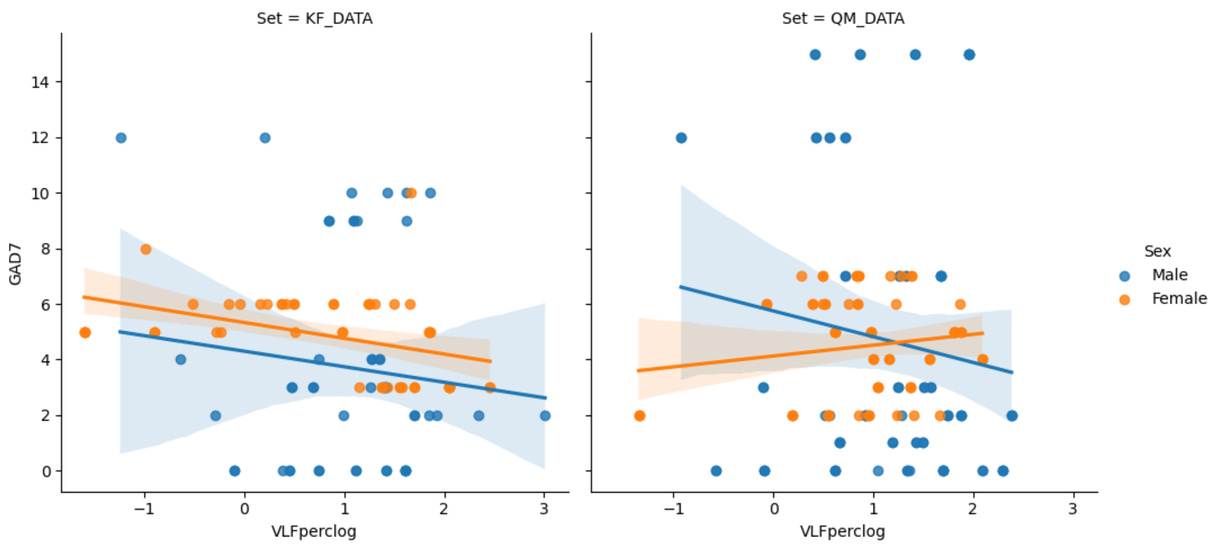



**Figure 21:** The OLS regression model results for GAD-7and (VLF%) HRV in relation to gender are presented.

## 6. LF %

The utilization of normalized Low-Frequency (LF) Heart Rate Variability (HRV) holds a significant role in stress assessment, particularly when investigating its association with the Perceived Stress Scale (PSS-10). LF HRV represents a spectral component situated within the frequency range spanning from 0.04 to 0.15 Hz, often reflecting the activity of both the sympathetic and parasympathetic nervous systems.

When scrutinizing the correspondence between normalized LF HRV and the PSS-10, researchers and clinicians gain valuable insights into the physiological responses of individuals to perceived stress. The process of normalization is critically important in this context, as it accounts for individual variances in overall HRV, consequently amplifying the relevance of comparisons among individuals and facilitating individualized assessments.

Before applying the model, the data underwent a normality inspection and was subsequently subjected to a logarithmic transformation to adhere to the assumption of normality. The outcomes closely resembled those of the absolute LF indicator. The optimal fitting LF model featured Sex and Questionnaire as predictors (AIC=217). Significantly, the interaction between Sex and PSS_10 was observed (t(15, 231)=2.55, p<0.05), as well as the main effect of Sex (t(15, 231)=2.43). Notably, there existed a negative association between questionnaire scores and LF, albeit the magnitude of this association was slightly higher in males. Furthermore, the interaction between Set and PSS statistically significant (t(15, 231)=2.25, p<0.05).

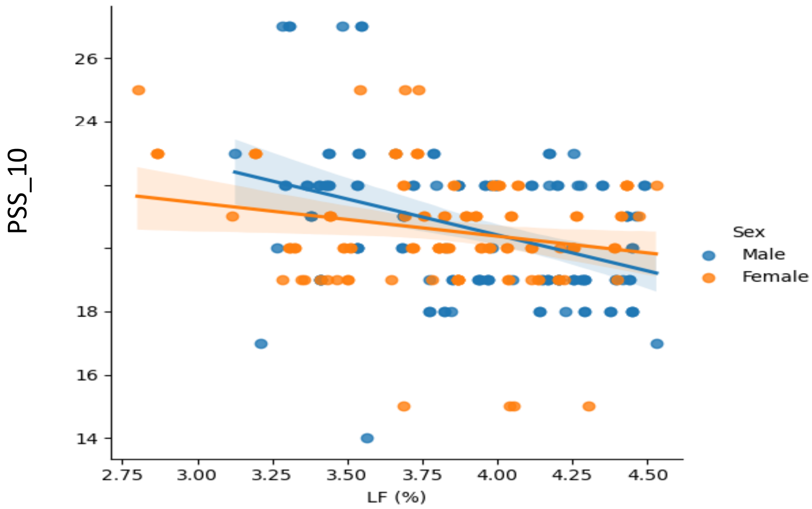



**Figure 22:** The OLS regression model results for PSS_10 and (LF (%)) HRV in relation to gender are presented.

### 7. HF absolute

HF absolute power in HRV analysis is a valuable parameter for evaluating stress and anxiety. Reduced HF power reflects decreased parasympathetic activity, compromised stress recovery, and a more significant physiological response to stressors. Monitoring HF absolute power can provide insights into an individual's stress-related health and guide appropriate interventions to promote relaxation and well-being.

Prior to model fitting, a comprehensive examination of the data was conducted to assess its normality, and subsequently, a logarithmic transformation was applied to align with the assumption of normality. The analysis revealed significant main effects for Sex (t (15, 231) =5.75, p<0.001), Dataset (t (15, 231) =5.74, p<0.001), and GAD7 (t (15, 231) = 5.98, p<0.001). Furthermore, a significant interaction was observed among Sex, Set, and GAD7 (t (15, 231) =5.23, p<0.001). Specifically, the relationship between GAD-7and HF was discerned in females from the KFSH dataset. However, no statistically significant results were found concerning PSS_10.

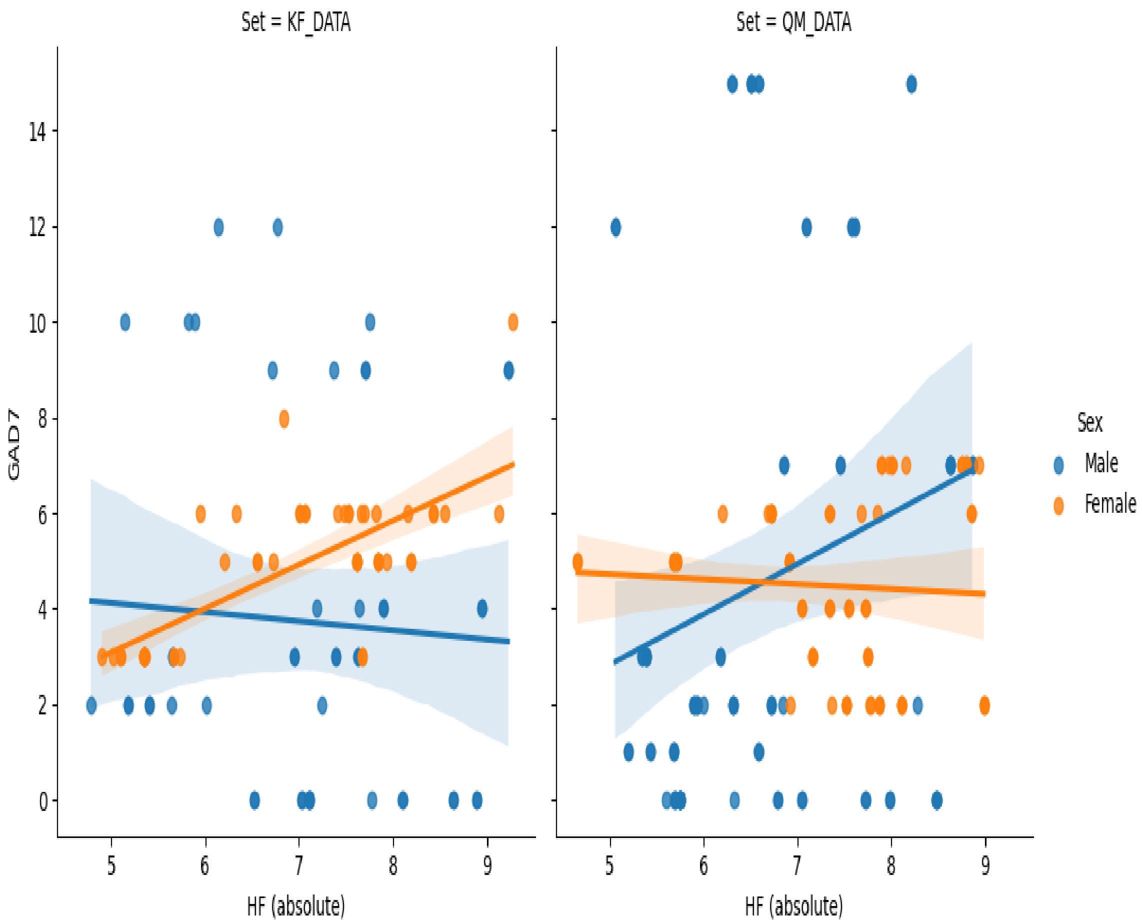



**Figure 23:** The OLS regression model results for GAD_7 and (HF (absolute) )HRV In relation to gender are presented.

**8. LF/HF**

Prior to fitting the model, a thorough assessment of data normality was conducted, and logarithmic transformation was applied to ensure conformity with the assumption of normality. The optimal fitting model was determined to encompass Sex and PSS_10 factors. A significant interaction was observed between Sex and PSS ($t(15, 231)=-2.96$, $p<0.01$), and there was a significant main effect of Sex ($t(15, 231)=-2.83$, $p<0.01$). Specifically, it was noted that the negative association between the Questionnaire and LF/HF was more pronounced in males only at QMUL sample set.

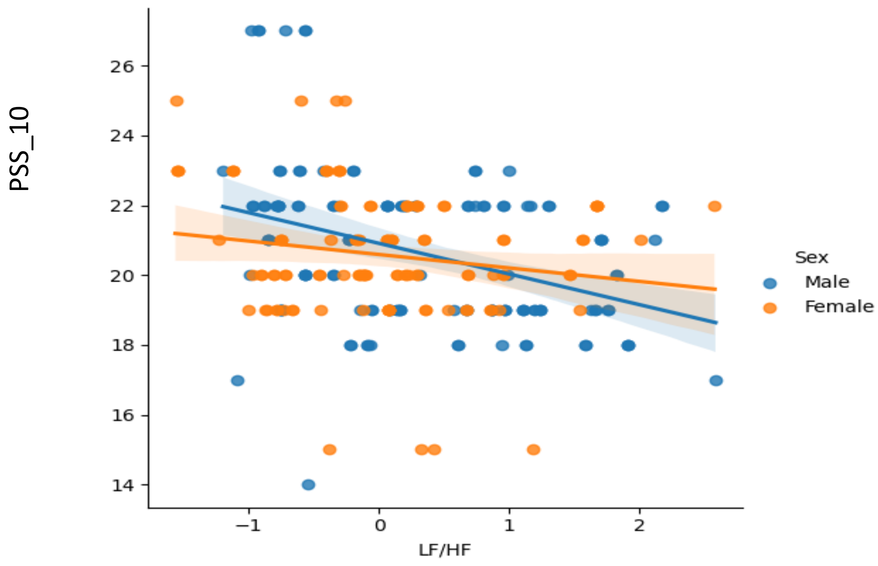



**Figure 24:** The OLS regression model results for PSS_10 (QMUL Set) and (LF/HF) HRV In relation to gender are presented.

The upcoming section will address the prediction model in relation to alpha asymmetry:

1. **Alpha Asymmetry (T7-T8)**

All variables, including Alpha asymmetry were predicted using the OLS regression model that incorporated the dataset, sex, and questionnaire scores. We employed the forward selection method for model building. Prior to executing the regression model, values exceeding or falling below three standard deviations from the mean were excluded. For model selection, we utilized relative AIC (Akaike Information Criterion) scores, which is a common approach for choosing the best-fitting model. The most complex that I fitted consisted of interaction between Dataset * Sex * Questionnaire * Block Type.

In the case of Alpha Asymmetry at T7-T8 locations, we found that the model encompassing Dataset * Sex * PSS * PSS_10 provided the best fit. We observed the main effects of each factor: Dataset, and Sex (t(15, 231)=2.19, p=0.029; t(15, 231)=2.66, p=0.008). Dataset * Sex interaction was significant (t(15, 231)=2.76, p=0.006). Specifically, the QM dataset exhibited a lower mean Alpha asymmetry compared to the KFSH dataset. Males demonstrated higher alpha asymmetry than females. Additionally, higher questionnaire scores were associated with lower Alpha Asymmetry. There was main effect of GAD7 (t(15, 231)=2.76, p=0.006) and significant interaction between GAD_7 and Sex (t(15, 231)=2.55, p=0.011).

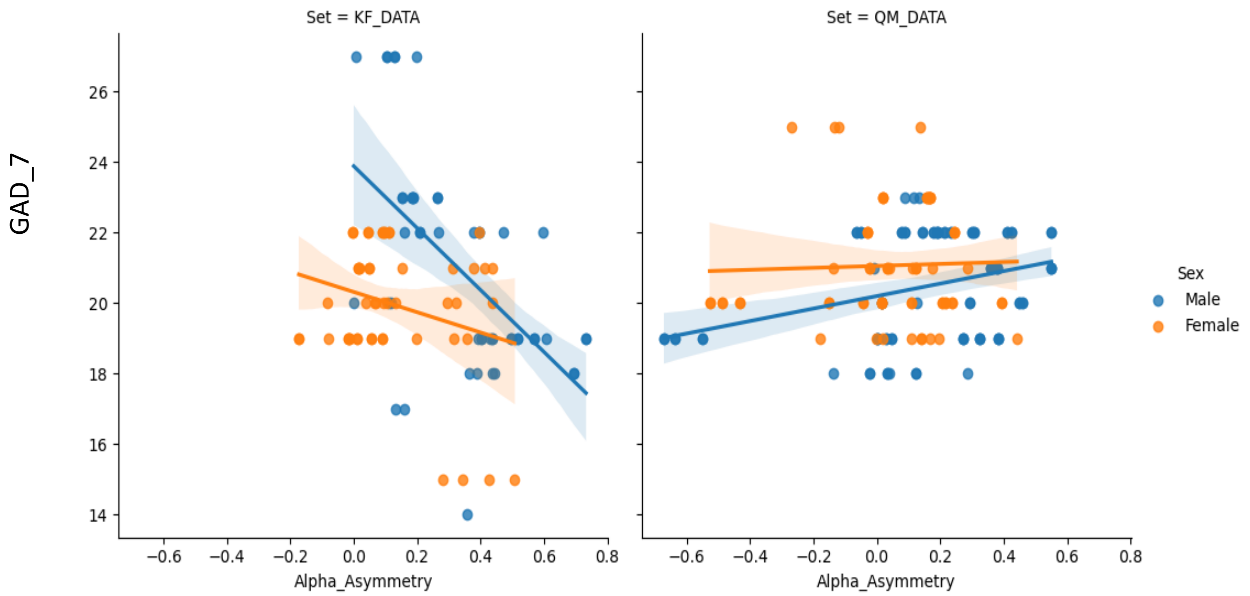



**Figure 25 :** The OLS regression model results for Apla Asymmetry (T7-T8) and GAD_7 In relation to gender are presented.

There was also triple interaction for PSS_10 t(15, 231)=2.57, p=0.011) such that PSS_10 was negatively associated with Alpha Asymmetry in QMUL dataset. This association was stronger for males. There was no association in KFSH dataset.

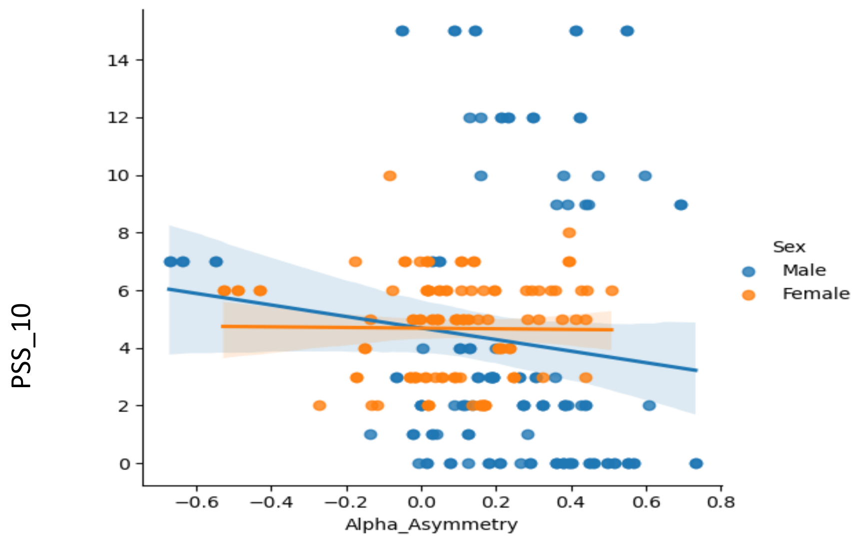



**Figure 26:** The OLS regression model results for Alpha Asymmetry (T7-T8) and PSS_10 In relation to gender are presented.

### 2. Alpha Asymmetry (F3-F4)

In the case of Alpha Asymmetry at F3-F4 locations, I found that the model encompassing Dataset * Sex * PSS * GAD7 provided the best fit. We observed the main effects of each factor: Dataset, and Sex (t(15, 231)=2.88, p=0.004; t(15, 231)=4.32, p<0.001). Dataset * Sex interaction was significant (t(15, 231)=2.76, p=0.006). Specifically, the QM dataset exhibited a lower mean Alpha asymmetry compared to the KF dataset. Males demonstrated higher alpha asymmetry than females. Additionally, higher questionnaire scores were associated with higher Alpha Asymmetry at F3-F4 locations. There was main effect of GAD7 (t(15, 231)=4.73, p<0.001) and significant interaction between GAD7 and Sex (t(15, 231)=4.66, p<0.001). There was higher positive association in the group of males.

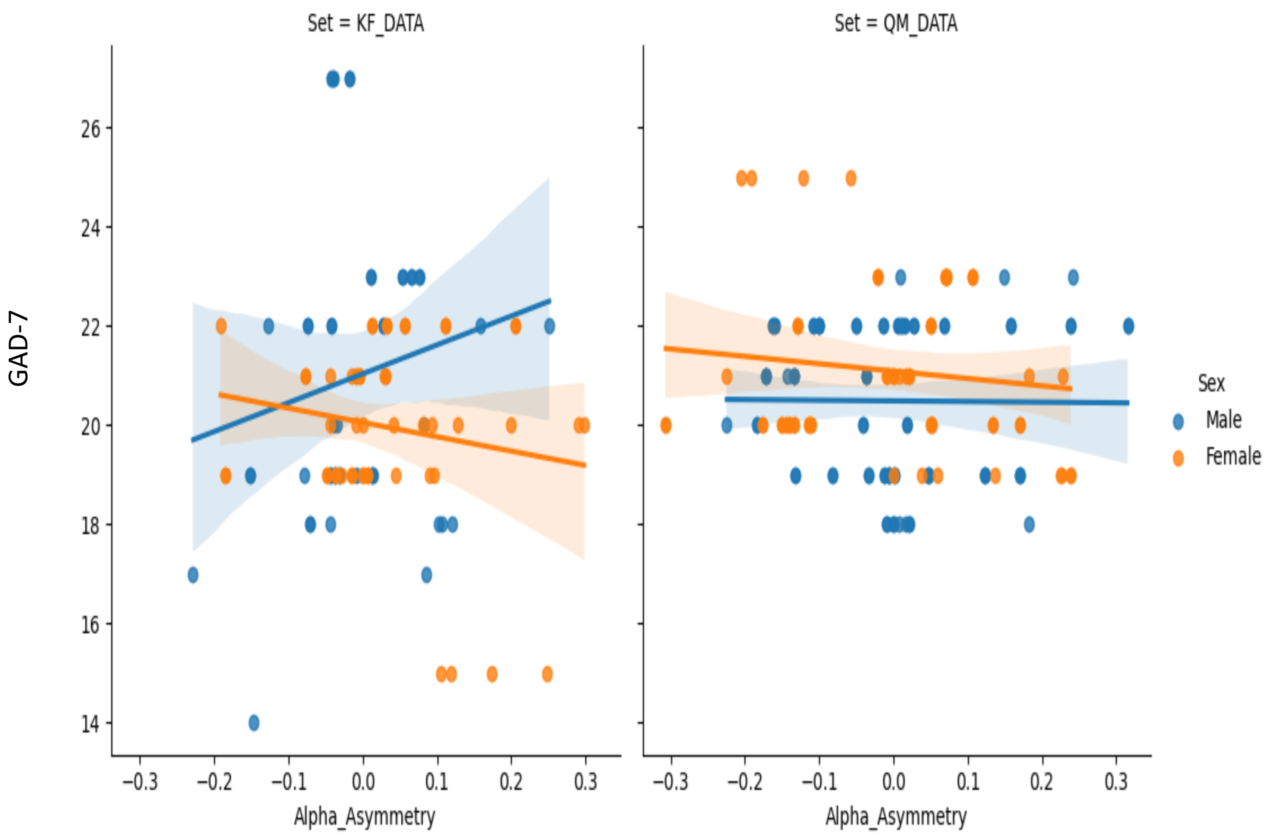



**Figure 27 :** The OLS regression model results for Alpha Asymmetry (T3-T4) and GAD_7In relation to gender are presented.

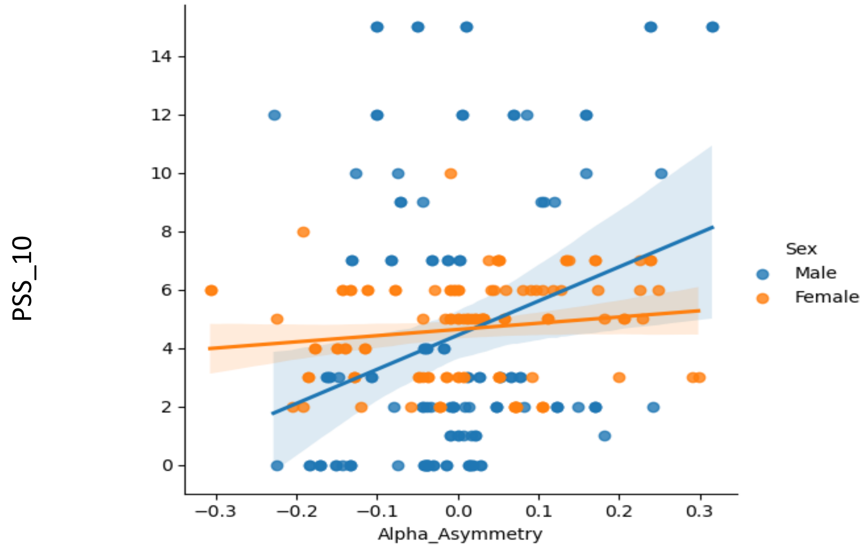



**Figure 28**: The OLS regression model results for Alpha Asymmetry (T3-T4) and PSS_10

In relation to gender are presented.

## 3.4.3 Discussion

### 3.4.3.1 Validity and Reliability of CoreSense PPG Sensing device and Emotive 14 channels EEG.

Numerous studies have demonstrated a strong inverse relationship between HRV and stress levels. Higher stress and anxiety levels are associated with decreased HRV, indicating dominance of sympathetic activity, and reduced parasympathetic activity.

Research has shown that chronic stress can lead to decreased HRV over time, indicative of autonomic dysregulation and an increased risk of cardiovascular disorders. HRV analysis using PPG devices has proven helpful in assessing the acute stress response. Studies have shown that exposure to acute stressors, such as mental or physical stressors, immediately alters HRV parameters. During stress, sympathetic activation reduces HRV, characterized by decreased high-frequency (HF) power and increased low-frequency (LF) power. This sympathovagal imbalance can be effectively captured and quantified using PPG-based HRV measurement.

Several investigations have explored the relationship between HRV and individual resilience to stress. Findings suggest that individuals with higher HRV exhibit greater resilience, indicating a better ability to adapt and recover from stressors.

Higher baseline HRV levels are associated with better-coping mechanisms, emotional regulation, and stress management strategies. PPG devices can facilitate HRV biofeedback interventions aimed at stress reduction. By providing real-time feedback on HRV parameters, individuals can learn to modulate their autonomic response and increase vagal tone, promoting relaxation and stress resilience.

Studies have demonstrated the effectiveness of HRV biofeedback in reducing stress symptoms, improving emotional well-being, and enhancing overall physiological self-regulation. While PPG devices offer a convenient and non-invasive method for HRV measurement, they have certain limitations. Factors like motion artifacts, poor signal quality in certain body locations, and individual variability can affect the accuracy and reliability of HRV measurements. Future research should focus on refining PPG-based HRV measurement techniques, validating their accuracy against gold-standard methods, and exploring the use of advanced signal processing algorithms to enhance data quality and reliability.

To develop a comprehensive understanding of the observed difference in mean SDNN between QMUL and KFSH, further analysis is necessary. It is crucial to explore statistical significance, sample characteristics, and expert insights in order to draw meaningful conclusions.

The findings from the Ordinary Least Squares (OLS) Regression and Akaike Information Criterion (AIC) Model Selection further reinforce the reliability of the wearable biosensing device as an assistive solution for mental well-being. The OLS Regression analysis elucidated the strength and direction of the relationships between HRV parameters, GAD-7 scores, and HRV. This statistical approach allowed for a comprehensive assessment of how these variables interrelate and influence each other.

Moreover, the AIC Model Selection, which identified the best-fitting models, underscores the device's reliability and effectiveness. By indicating which combinations of variables provide the most accurate predictions of HRV and GAD-7 scores, this analysis highlights the device's robustness in assessing mental well-being. It demonstrates that HRV parameters, when integrated with GAD-7 scores and HRV data, can offer a holistic understanding of an individual's psychological state, even in cases where stress symptoms may not be overtly pronounced.

In conclusion, the strong correlations observed between HRV parameters, GAD-7 scores, and HRV in individuals with relatively lower stress levels emphasize the sensitivity and relevance of these metrics for mental well-being assessment. The results from OLS Regression and AIC Model Selection provide further support for the reliability of the wearable biosensing device as an assistive solution in promoting mental well-being. This device offers a valuable means of continuous monitoring and early intervention, contributing to improved mental health outcomes and overall quality of life.

Many of the results obtained from Heart Rate Variability (HRV) parameters in relation to MDD and Anxiety, have shown strong correlations with both HRV and GAD-7 scores. This observation is particularly noteworthy because most of the study subjects did not exhibit acute symptoms on the Perceived Stress Scale (PSS-10). Despite the absence of severe stress symptoms in the study cohort, the HRV metrics still demonstrated significant associations with GAD-7 scores, indicating that CoreSense PPG device to measure HRV parameters are sensitive markers of psychological well-being even in individuals with relatively lower stress levels.

This study interaction remained significant on both alpha asymmetry and HRV. However, these patterns did not apply to patients' participants, and HRV did not moderate the effect for frontal sites or other frequency bands in both groups. Nevertheless, significant disparities in frontal and parietal asymmetries were evident higher sores on both PSS_10 And GAD_7 for healthy individuals. In contrast, those with reduced right parietal activity and decreased HRV may be more vulnerable to depression[83].

However, the study has limitations, relatively small sample size, uncontrolled factors like cardiovascular training, and the absence of specific anxiety domain measurements. Moreover, the study relied on a single short-term HRV measurement, which situational factors can influence. Future research with larger samples and longer study timelines including rigorous controls is needed to validate these findings further. Despite these limitations, this study represents an important initial step in exploring the connection between alpha asymmetry and HRV, suggesting a potential biomarker for MDD and general anxiety disorder.

### 3.4.3.2 Limitations

The relationship between stress, anxiety, Heart Rate Variability (HRV) and EEG intricate and marked by individual disparities. We delve into the intricacies of this connection:

1. Diverse Individual Responses: Stress and anxiety elicit highly personalized reactions. While some individuals may experience substantial alterations in their HRV parameters due to stress and anxiety, others may perceive minimal or imperceptible changes. This diversity results from various factors, including genetic predisposition, past life experiences, coping strategies, and overall health. Collectively, these factors influence how the autonomic nervous system responds to psychological stressors.

2. Impact of Baseline: The extent to which anxiety and stress influence metrics is critically influenced by an individual's baseline. This baseline represents their typical autonomic nervous system activity in non-stressful circumstances. Individuals with higher baseline HRV often exhibit greater resilience and adaptability in response to stress. Conversely, those with lower baseline HRV may display increased susceptibility to pronounced HRV variations under stressful conditions.

3. Significance of Duration and Severity: The duration and severity of anxiety and stress episodes are pivotal factors. Short-term, acute stressors frequently induce transient HRV fluctuations that return to baseline once the stressor dissipates. Conversely, chronic, or severe anxiety and stress can lead to sustained alterations in HRV metrics.

4. Impact of Stress and anxiety Coping Strategies: The management of anxiety and stress significantly influences. Effective stress-reduction techniques, such as mindfulness meditation and regular exercise, have demonstrated positive effects on HRV, mitigating the adverse impact of anxiety and stress. Conversely, maladaptive coping mechanisms, such as excessive caffeine consumption or inadequate sleep, may exacerbate HRV fluctuations.

5. Clinical Considerations: While HRV parameters offer valuable insights into autonomic nervous system function, their interpretation should be situated within a broader clinical context. A comprehensive evaluation of an individual's stress and anxiety-related health necessitates clinical assessments, consideration of medical history, and incorporation of additional physiological measures such as blood pressure and cortisol levels.

6. Potential for Tailored Interventions: Acknowledging the individualized nature of the relationship between stress, anxiety, EEG and HRV, healthcare professionals can customize stress management interventions. Tailored approaches that account for an individual's baseline HRV, coping strategies, and specific stressors hold the potential to be more effective in enhancing both psychological well-being and HRV.

7. Causality Interpretation: Interpreting causality from correlations between alpha asymmetry and psychological variables can be intricate. It is crucial to acknowledge that these correlations do not inherently signify a causal relationship. Future research should delve deeper into the underlying mechanisms to elucidate these connections.

8. Individual Variability: Considerable individual variability in alpha asymmetry is a significant challenge, making it arduous to draw definitive conclusions. Factors such as medication use, comorbid conditions, and individual differences can substantially influence alpha asymmetry patterns. The precision and

consistency of EEG measurements are pivotal for reliable results. Factors such as electrode placement, skin impedance, and equipment variations can introduce measurement errors. To ensure dependable results, maintaining standardized and rigorous measurement procedures is imperative.

The investigation into EEG alpha asymmetry offers valuable insights into the correlation between brain activity and psychological factors. However, it is crucial to recognize several limitations that necessitate consideration. Many EEG and HRV studies grapple with limited sample sizes, which can constrain the generalizability of their findings. These small samples may not adequately represent the broader population. Future research should strive to include larger and more diverse samples to enhance the robustness of results. One limitation pertains to the generalizability of findings. The sample composition, including factors like age, gender, and clinical diagnoses, may be somewhat narrow and not wholly reflective of the diversity within the general population. Researchers should aim to work with more diverse and inclusive samples in subsequent studies.

Additionally, EEG studies often transpire in controlled laboratory environments that may not authentically replicate real-world conditions. As a result, individuals may exhibit different alpha asymmetry patterns in everyday life, influenced by various uncontrolled factors. This divergence can challenge the external validity of the findings.

The variability of EEG alpha asymmetry across different electrode sites underscores the need for comprehensive analysis. While many studies focus on a select few sites, diverse results can emerge when considering a broader range of electrode locations. Therefore, a more holistic assessment of multiple electrode sites may yield a more accurate understanding of brain activity.

Finally, while research on EEG alpha asymmetry has enriched our comprehension of the interplay between brain activity and psychological variables, these limitations warrant attention. Addressing these constraints in future studies is paramount for refining the quality and applicability of research in this field, ultimately advancing our understanding of the role of alpha asymmetry in psychology and neuroscience.

Moreover, the interplay between GAD-7 scores, PSS-10 scores, EEG alpha asymmetry and HRV metrics is complex and subject to individual variations. Healthcare providers must recognize and consider these distinctions when evaluating and addressing concerns related to anxiety and stress. By adopting a personalized and comprehensive approach to stress management, healthcare professionals can better assist individuals in improving their overall well-being and autonomic nervous system function. Furthermore, research focusing on utilizing PPG (Photoplethysmography) devices for HRV measurement in stress assessment has yielded valuable insights into the relationship between HRV and stress levels. These findings demonstrate the potential of PPG-based HRV monitoring in measuring acute stress reactivity, identifying individual resilience, and facilitating interventions for stress reduction. Despite certain limitations, ongoing advancements in technology and techniques present promising opportunities for further research and the application of PPG devices in stress monitoring and promoting mental well-being.

### 3.4.4 EEG Data Recording and Analysis

Throughout the EEG data collection process, obtaining a minimum of 5 minutes of data for each stage was essential, as indicated in (section 3.3.1.). This was accomplished by utilizing the Emotive EPOC 14-channel neuroheadset tool in combination with the Emotive testbench software for precise measurements. Once that data acquisition phase was completed, the recorded EEG data underwent additional processing using the MATLAB EEGLAB toolbox to extract meaningful insights and patterns. The data processing involved several steps carried out through an in-house, fully automated pipeline, which is outlined below:

1. Loading the Dataset: The raw EEG dataset was loaded into the EEGLAB software for further processing.

The EEG processing pipeline comprised the following steps:

1. Searching for EDF files within the "raw" folder.
2. Identifying the current block (baseline, Stroop, Sam, and resting) from the filename.
3. Reading the EDF data.
4. Applying a bandpass filter ranging from 1 to 35 Hz.
5. Isolating the F3 and F4 electrode channels.
6. Converting the data into microvolt (uV) units.
7. Reading the sampling frequency and setting the window size to 2 times the sampling frequency.
8. Calculating the Power Spectral Density (PSD) for each channel.
9. Calculating the band power for the following frequency bands:
    - Delta: 0.2 – 3 Hz
    - Theta: 3 – 8 Hz
    - Alpha: 8 – 13 Hz
    - Beta: 13 – 30 Hz
    - Gamma: 30 – 64 Hz
10. Converting the F3 and F4 band power values to a percentage (%).
11. Creating F3 and F4 band power tables.
12. Calculating the alpha band asymmetry measure as follows: Convert F3, F4, T7, and T8 band power to % units.
13. Create F3, F4, T7, and T8 band power tables.

14. Calculate F3-F4 and T7-T8 alpha band asymmetry measure as:

(F4 alpha power – F3 alpha power) / (F4 alpha power + F3 alpha power)

(T8 alpha power – T7 alpha power) / (T8 alpha power + T7 alpha power)

#### 3.4.4.1 EEG Data Outcome

In this study, separate one-way repeated measures ANOVA models were conducted to compare various EEG measures across four different conditions: baseline, Stroop, Sam, and resting conditions. Repeated Measures ANOVA is the preferred statistical tool when working with a single group of participants, subjecting them to multiple measurements on the same dependent variable across varying conditions or at distinct time intervals. The underlying design principle of Repeated Measures ANOVA hinges on the premise that the observations within each participant are inherently linked, making it particularly suitable for assessing and scrutinizing differences between these conditions or time points, ultimately enabling a more comprehensive understanding of the data under examination. The significance level (alpha) was predetermined and set at 0.05, indicating that any p-value less than or equal to 0.05 would be considered statistically significant.

In the context of our research, we utilized the Python library to conduct repeated measures of ANOVA. We initiated the process by installing the necessary Python library pandas using pip and carefully structured our dataset to represent repeated measurements on subjects and groups. We imported the panda's library in our Python script and utilized the AnovaRM. We loaded the data into a Pandas DataFrame, and a formula specifying the dependent variable, subject/group identifier, and within-subject factor(s) was created using the AnovaRM class to execute repeated measures ANOVA.

The following EEG measures were investigated:

1. F3 Alpha
2. F3 Beta
3. F4 Alpha
4. F4 Beta
5. Alpha Asymmetry

The EEG alpha asymmetry, an intriguing neural marker, offers valuable insights into the relationship between brain activity and stress factors. This neuroscientific measure examines the asymmetrical distribution of alpha brainwave activity, specifically in the frontal cortex, as an indicator of emotional and cognitive states. Studies have suggested that an imbalance in alpha power between the left and suitable frontal regions is associated with stress experiences. When confronted with stressors, individuals may exhibit changes in EEG alpha asymmetry, reflecting alterations in emotional processing and cognitive engagement. Increased suitable frontal alpha activity is often linked to negative affectivity and heightened stress responses, while greater left frontal alpha activity is associated with positive affectivity and emotional regulation. Monitoring EEG alpha asymmetry thus provides a unique window into the neural dynamics underlying stress reactions. Understanding the interplay between EEG alpha asymmetry and stress factors is essential for unraveling the complexities of the brain's response to stress. This neuroscientific perspective enhances our understanding of the neural mechanisms involved in stress processing, paving the way for more targeted interventions and personalized strategies to manage stress and promote mental well-being[84].

The ANOVA tests were used to examine whether there were significant differences in these EEG measures across the different experimental conditions (Baseline, Stroop test, Sam test, and Resting conditions). The results of the ANOVA repeated measurement tests are as follows:

The significance level was set priori to 0.05. Post-hoc comparisons consisted of running paired t tests with one step Bonferroni correction of p-values.

a. <u>ANOVA repeated measurement tests that did not reach statistical significance:</u>

- Anova comparing F3 and T7 alpha asymmetry across conditions did not show any statistically significant differences. In other words, there were no significant variations in alpha asymmetry among the different conditions studied.

b. <u>ANOVA repeated measurement tests that reached statistical significance:</u>

- The Anova comparing F3 Alpha across conditions reached statistical significance. This indicates that there were significant differences in the alpha brainwave activity at the F3 electrode site across the different experimental conditions.
- The Anova comparing F3 Beta across conditions also reached statistical significance, suggesting significant differences in beta brainwave activity at the F3 electrode site among the various conditions.
- Similarly, the Anova comparing F4 Alpha across conditions reached statistical significance, indicating significant differences in the alpha brainwave activity at the F4 electrode site across the different conditions.

- The Anova comparing F4 Beta across conditions also reached statistical significance, revealing significant differences in beta brainwave activity at the F4 electrode site across the various conditions. To provide a comprehensive understanding of the significant post-hoc differences relative to the baseline for all EEG models, Table 9 presents a summary of these findings. The table likely includes specific pairwise comparisons between each experimental condition and the baseline condition for each EEG measure that showed statistically significant differences in the ANOVA tests. Overall, the significant results in the ANOVA tests for specific EEG measures (F3 Alpha, F3 Beta, F4 Alpha, and F4 Beta) suggest that these brainwave activities were influenced by the different experimental conditions. However, alpha asymmetry, which compares the differences in alpha activity between the brain's left and right hemispheres, did not show significant variations across the conditions. Researchers and readers should interpret these findings with consideration of the study's design, sample size, and the chosen significance level. The presented post-hoc differences in Table 9 can provide further insights into the specific effects of each experimental condition on the EEG measures, helping to understand the relationships between brainwave activity and the studied conditions.

**Table 8**:Effects of stress on EEG features during (Rest, SAM, Stroop)

| Feature | Baseline | Rest | SAM | Stroop |
|---|---|---|---|---|
| F3 Alpha | 25.061 ± 3.15 | **9.998 ± 0.955** | **6.871 ± 0.459** | **6.146 ± 0.458** |
| B3 Beta | 11.67 ± 1.018 | 12.413 ±1.306 | 11.317 ± 0.98 | **8.279 ± 0.83** |
| F4 Alpha | 24.506 ± 3.044 | **10.417 ±1.004** | **7.172 ± 0.493** | **6.266 ± 0.492** |
| F4 Beta | 11.392 ± 1.178 | 11.599 ± .072 | 11.218 ± 0.952 | 7.992 ± 0.717 |
| T7 Alpha | 15.952 ± 2.468 | **8.145 ± 0.64** | **6.735 ± 0.559** | **6.7 ±0.544** |
| T7Beta | 12.478 ± 1.65 | **17.613 ±1.718** | 17.129 ± 1.736 | 16.391 ± 1.908 |
| T8 Alpha | 22.26 ± 2.473 | **12.774 ± 1.41** | **8.466 ± 0.638** | **9.31 ± 0.764** |
| T8 Beta | 13.858 ± 1.178 | 16.854 ±1.392 | **18.135± 1.662** | **17.943 ± 1.631** |
| T3 Alpha Asymmetry | 0.009 ±0.032 | 0.019 ± 0.024 | 0.021 ± 0.02 | 0.011 ± 0.021 |
| T7 Alpha Asymmetry | 0.223 ± 0.04 | 0.176 ± 0.041 | 0.139 ± 0.039 | 0.0158 ± 0.035 |

Significant post-hoc differences are bolded for comparisons to baseline at a p-corr < 0.05

The subsequent following barplots depict the variations across conditions for ANOVA models that have demonstrated statistical significance:

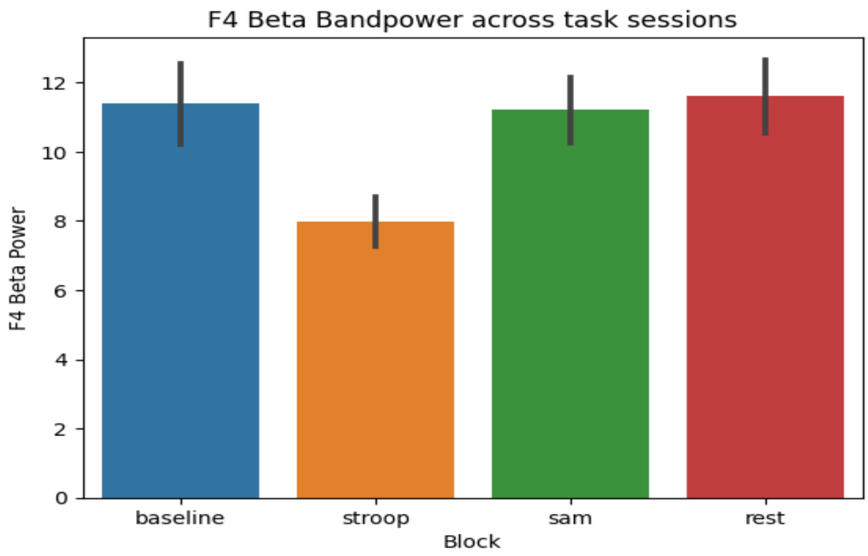



**Figure 29:**F4 Beta band power across tasks.

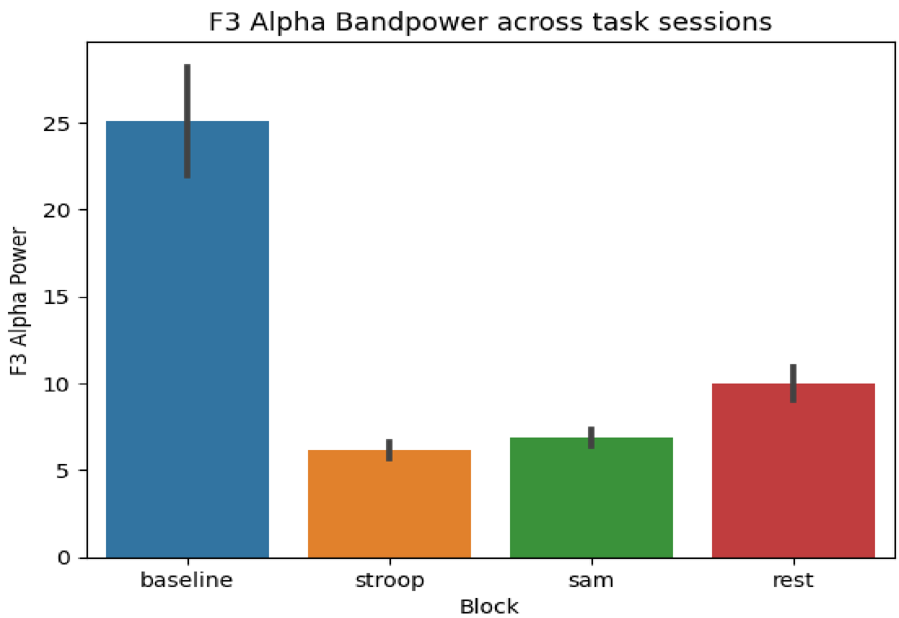



**Figure 30:** F3Alpha band power across tasks

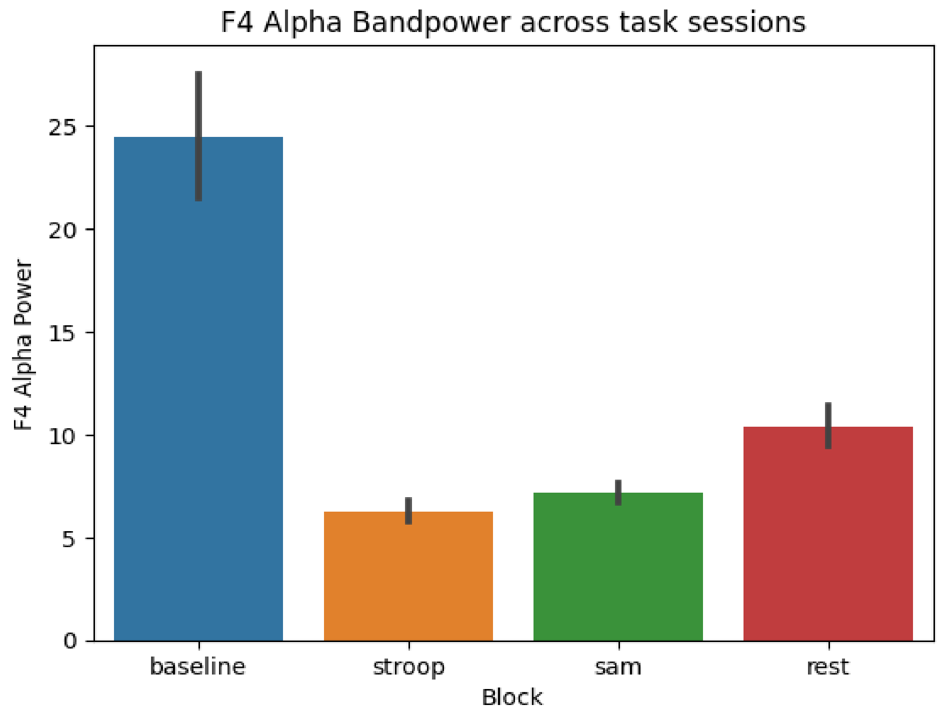



**Figure 31**:F4 Alpha band power across tasks

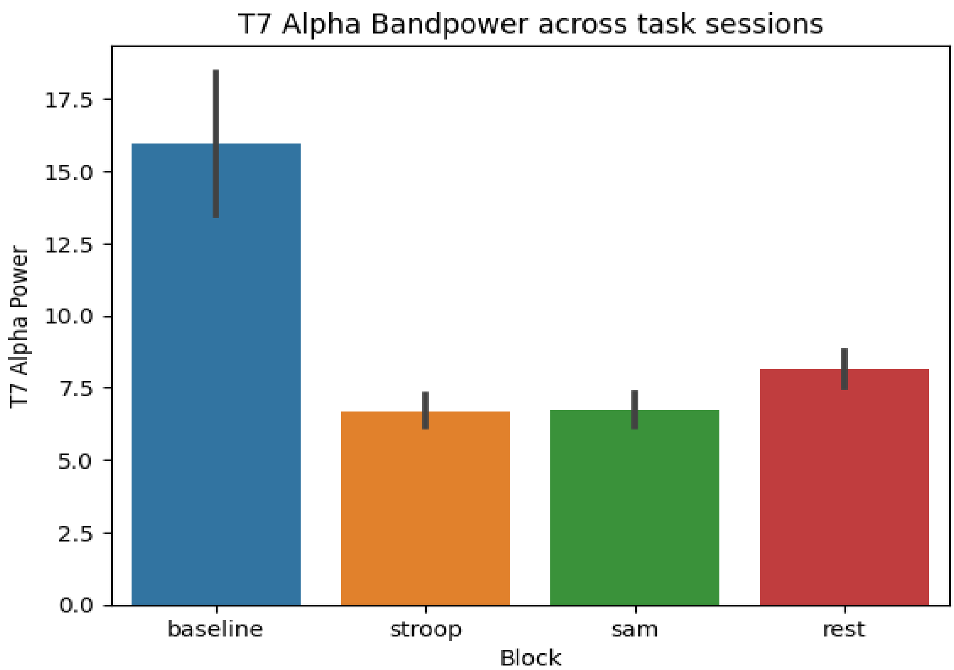



**Figure 32:**T7 Alpha band power across tasks

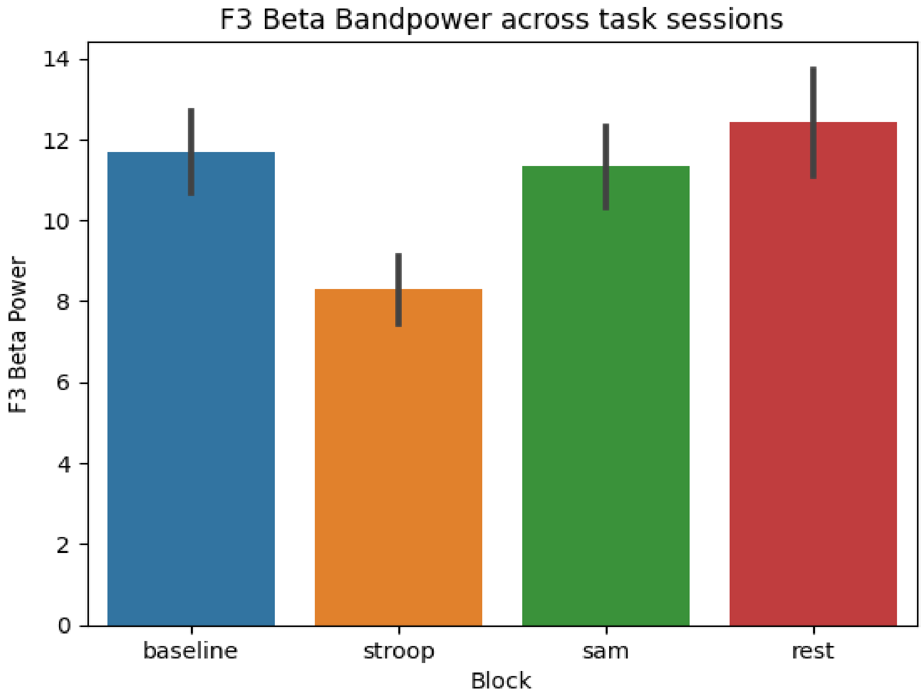



**Figure 33**: F3 BETA band power across tasks

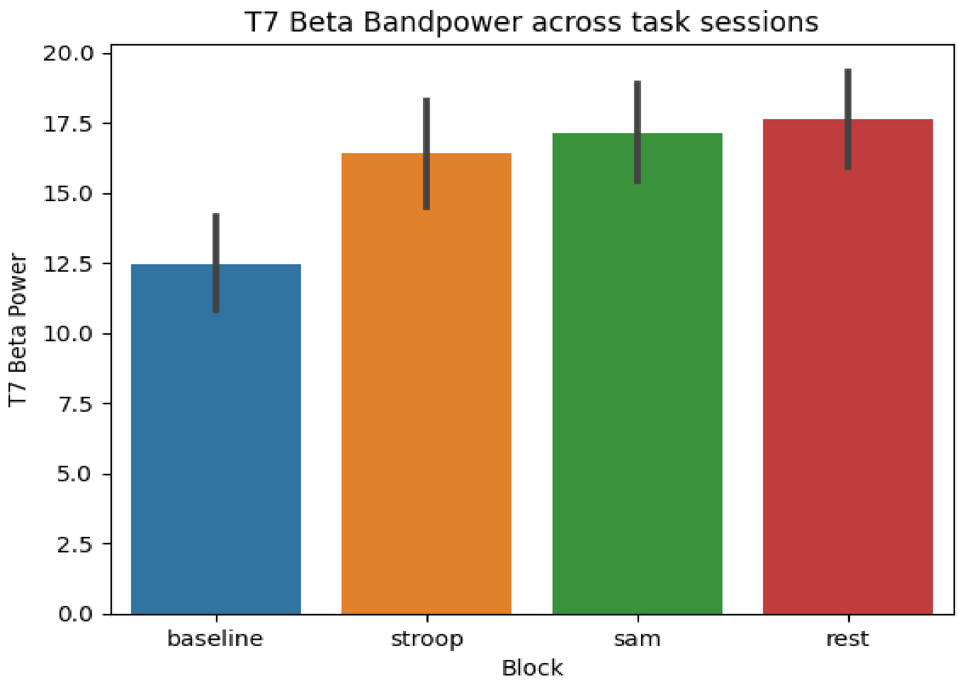



**Figure 34:**T7 Beta Band power across tasks

### 3.4.4.2 Particulars and Limitations of EEG Data Studies and Analysis

Electroencephalography (EEG) is a widely employed technique for measuring and recording the electrical activity in the brain. It plays a crucial role in various disciplines, including neuroscience, psychology, and clinical diagnostics, providing valuable information about brain function. Nevertheless, it is essential to acknowledge that EEG recordings are subject to limitations, and the occurrence of artifacts can substantially impact the quality and reliable interpretation of the acquired EEG data.

One common type of artifact in EEG recordings is muscular activity. Muscles in the face, jaw, and neck can generate electrical signals that contaminate the EEG signal, obscuring the underlying brain activity. These artifacts can be caused by movements, tension, or even subtle muscle contractions during everyday activities like swallowing or facial expressions. To mitigate the impact of muscular artifacts, participants are typically instructed to remain as still and relaxed as possible during recording sessions. Electromyography (EMG) can also monitor and identify muscular artifacts, allowing researchers to differentiate them from genuine brain signals. Signal processing techniques can also be applied to remove or minimize muscular artifacts, enhancing the accuracy of the EEG data.

Another source of artifacts in EEG recordings is electrical interference from external sources. Environmental factors such as power lines, electrical devices, and poor grounding can introduce unwanted electrical noise into the EEG signal. This noise can obscure the subtle electrical activity of the brain, making it challenging to extract meaningful information. Proper shielding and grounding of the recording equipment are essential to address this issue. High-quality EEG systems often incorporate advanced filters that can reduce electrical interference, ensuring a cleaner signal for analysis. Additionally, careful placement of the recording equipment, away from potential sources of interference, can minimize artifacts caused by electrical noise. Electrode artifacts pose a significant concern in EEG recordings, as they can arise from various factors such as electrode impedance mismatch, inadequate skin preparation, or poor electrode contact. When the impedance values of electrodes are excessively high or inconsistent, it can lead to a decline in signal quality and even data loss. To address electrode artifacts, it is essential to establish a solid electrode-skin connection. This involves thorough skin preparation, including cleansing and exfoliating the scalp to eliminate dead skin cells, oils, and other substances that may hinder proper electrode contact. Continuous monitoring of electrode impedance throughout the recording session can effectively identify and promptly resolve any impedance-related issues.

Moreover, eye movements and blinks introduce artifacts in EEG recordings called ocular artifacts. These artifacts stem from the electrical activity generated by eye muscles and the movement of the eyeballs. Ocular artifacts significantly contaminate the EEG signal, making it challenging to differentiate them from genuine brain activity. Techniques such as electrooculography (EOG) can monitor eye movements and blinks separately, providing a distinct measure of ocular artifacts. To enhance the accuracy of the EEG data, signal processing methods like independent component analysis (ICA) can be utilized to isolate ocular artifacts from the underlying brain activity, facilitating improved interpretation of the EEG recordings.

In summary, EEG electrodes are vital for capturing electrical brain activity, but they are susceptible to various artifacts that can affect the quality and interpretation of the recorded data. Muscular activity, electrical interference, electrode-related issues, and ocular artifacts are familiar sources of artifacts in EEG recordings. To minimize the impact of these artifacts, researchers should provide clear instructions to participants, ensure proper equipment setup and skin preparation, monitor impedance values, and employ appropriate signal processing techniques. By addressing these challenges, researchers can enhance the reliability and validity of EEG measurements, leading to a better understanding of brain function and improved applications in research and clinical settings.

#### 3.4.4.3 The correlation between HRV and EEG

In section 3.4.2.1, a One-Way ANOVA analysis was conducted to assess the differences among various conditions in HRV parameters, including LF, HF, LF/HF, MeanRR, pNN50, and rMSSD. The results indicated that, despite the observed trends aligning with expectations, there were no significant differences ($p > 0.05$) in these parameters. However, it's noteworthy that significant differences were observed in the case of SDNN, which was a key focus of that specific study.

The concept of statistical significance plays a pivotal role in determining the credibility of observed differences. While numerical distinctions may be evident, it is imperative to establish whether these differences are statistically significant or merely the result of random chance. Employing appropriate statistical tests, such as t-tests or ANOVA, can shed light on the likelihood of encountering such disparities.

For this study at this section, an ANOVA with repeated measures was employed, which is particularly useful when comparing the means of three or more groups with the same participants in each group. This repeated-measures approach is advantageous as it tends to yield smaller p-values compared to a standard ANOVA. The strength of the repeated-measures test lies in its ability to distinguish between variability among subjects and variability within subjects. Notably, this method was applied in the present section.

The separate one-way repeated measures ANOVA models conducted to compare various physiological variables across four different conditions: baseline, Stroop test, Sam test, and resting conditions. The significance level (alpha) was predetermined at 0.05, indicating that p-values equal to or less than 0.05 were considered statistically significant. To address multiple comparisons, we performed post-hoc analyses using paired t-tests with a one-step Bonferroni correction applied to the p-values.

The ANOVA results for the different physiological variables across the conditions are as follows:

1. SDNN (Standard Deviation of NN intervals) ANOVA: The analysis comparing SDNN across conditions did not show statistically significant differences. In other words, there were no significant variations in the variability of NN intervals (a measure of heart rate variability) among the different conditions under investigation.
2. LF/HF (Low-Frequency to High-Frequency ratio) ANOVA: Similarly, the comparison of LF/HF ratio across conditions did not reveal statistically significant results. The LF/HF ratio is often used as an indicator of sympathovagal balance in heart rate variability analysis, but in this study, it did not display significant differences between the conditions.
3. RMSSD (Root Mean Square of Successive Differences) ANOVA: In contrast, the ANOVA comparing RMSSD across conditions did reach statistical significance. This suggests that there were significant differences in the parasympathetic nervous system activity, as reflected by the RMSSD measure of heart rate variability, among the various conditions studied.
4. pNNXX (%) ANOVA: The ANOVA comparing pNNXX (%) across conditions also reached statistical significance. pNNXX represents the proportion of NN intervals that differ by more than a certain threshold value, and its significance indicates variations in heart rate variability across the conditions.
5. LF (Low-Frequency power) ANOVA: The ANOVA comparing LF across conditions reached statistical significance, indicating significant differences in the low-frequency component of heart rate variability among the various conditions.
6. HF (High-Frequency power) ANOVA: Similar to the LF analysis, the ANOVA comparing HF across conditions also reached statistical significance, revealing significant differences in the high-frequency component of heart rate variability across the different conditions.

Overall, the ANOVA tests that reached statistical significance (PNNXX, RMSSD, LF, and HF) suggest that specific conditions had a notable impact on certain aspects of heart rate variability. On the other hand, the ANOVA tests that did not reach statistical significance (SDNN and LF/HF) indicate that these particular conditions did not lead to significant differences in overall heart rate variability and sympathovagal balance.

We must interpret the significance of these findings in the context of the study's design, sample size, and methodology. The one-step Bonferroni correction helped address the issue of multiple comparisons, reducing the risk of false positives. However, it is essential to consider the possibility of false negatives (Type II errors) when interpreting the results. Further research and replication of the study may be necessary to validate these findings and provide a more comprehensive understanding of the relationships between the physiological variables and the experimental conditions. For further details on post-hoc differences relative to baseline for all HRV models, please refer to the accompanying table.

**Table 9:**Effect of stress on HRV features during rest, Sam, and Stroop task.

| Feature | Baseline | Rest | SAM | Stroop |
|---|---|---|---|---|
| SDNN | 100.461 ± 21.349 | 82.216 ± 5.868 | 88.475 ± 7.013 | 70.796 ± 4.706 |
| RMSSD | 77.325 ± 6.031 | 89.281 ± 6.681 | **99.606 ± 8.187** | 83.441 ± 6.14 |
| PNNXX (%) | 29.167 ± 3.045 | 27.369 ± 2.81 | 29.828 ± 2.852 | **23.661 ± 2.733** |
| LF | 60.732 ± 3.905 | 53.446 ± 2.79 | **45.694 ± 2.576** | 60.732 ± 3.905 |
| HF | 39.222 ± 3.901 | 46.461 ± 2.782 | **53.434 ± 2.337** | 39.222 ± 3.901 |
| LF/HF | 3.374 ± 0.576 | 1.638 ± 0.235 | 340.788 ± 339.7 | 3.374 ± 0.576 |

Significant post-hoc differences are bolded for comparisons to baseline at a p-corr < 0.05

The accompanying barplots present the disparities observed across conditions for ANOVA models that have yielded statistically significant outcomes:

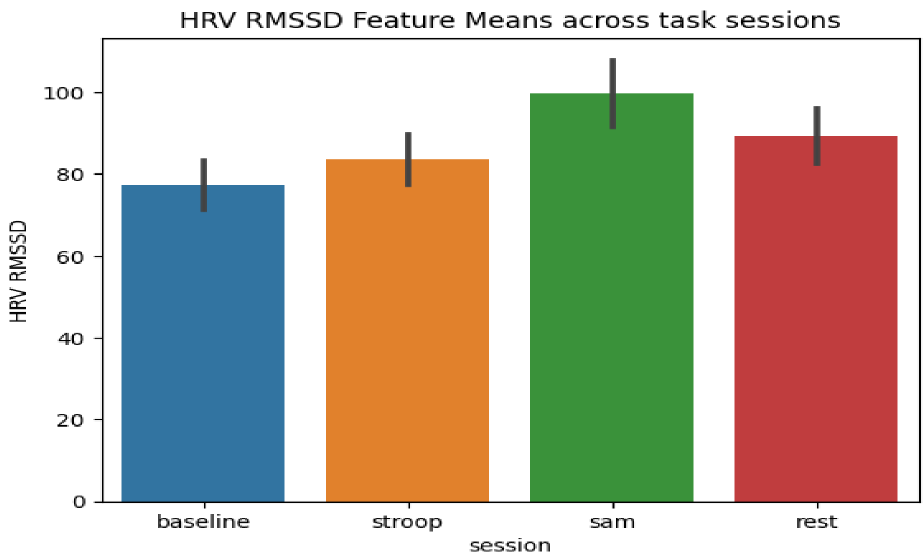



**Figure 35:** HRV (RMSSD) Means value across tasks.

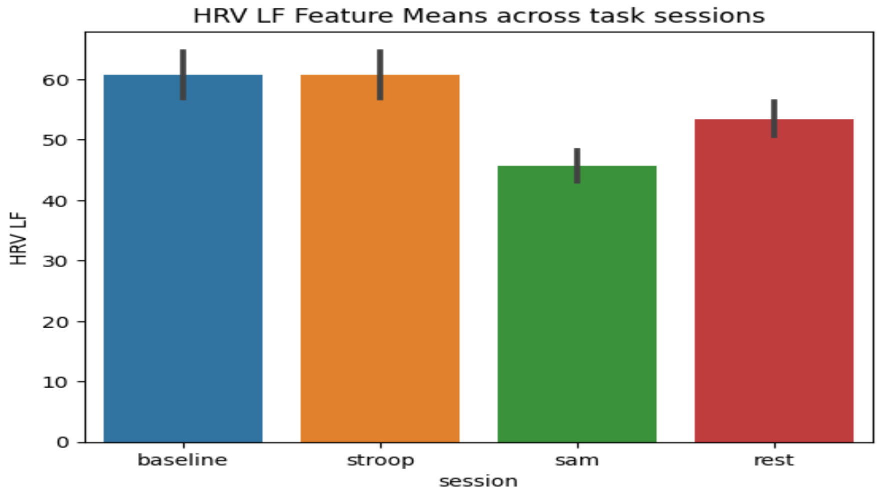



**Figure 36:**HRV(LF) Means value across tasks.

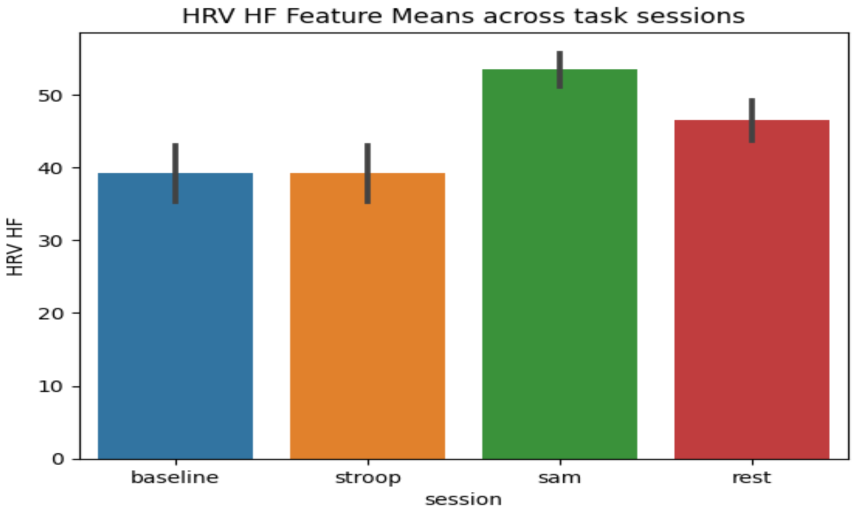



**Figure 37**: HRV(HF) Means value across tasks.

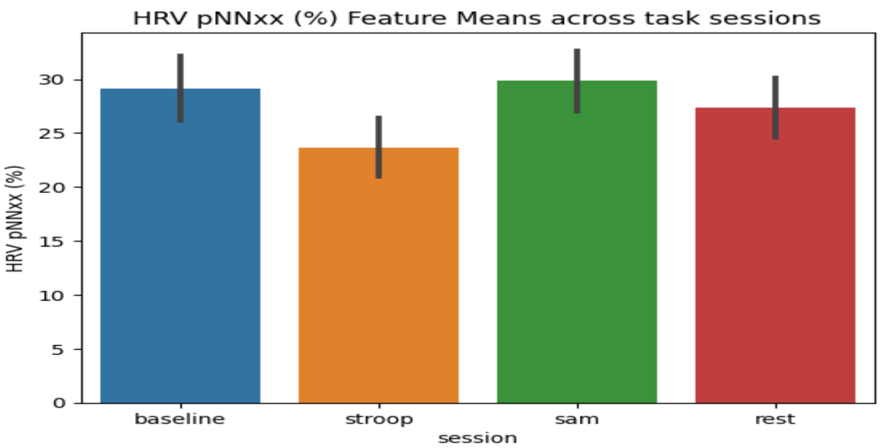



**Figure 38:**HRV (PNNXX) Means value across tasks.

#### 3.4.4.4 Outcomes

Data from the HRV and EEG sessions were merged. This analysis excluded the same individuals described in the initial EEG and HRV sections. Pearson correlation: Repeated measures correlations were computed for the features described in the table below. No significant correlations were identified between HRV and EEG biosignals. The following table provides a summary of the observed correlations.

**Table 10:** Repeated Measures Pearson Correlations Between HRV and EEG Features

| EEG Feature | HRV Feature | r | Pval | CI 95% | Power |
|---|---|---|---|---|---|
| F3 Alpha | LF | 0.029 | 0.771 | [-0.16, 0 22] | 0.06 |
| F3 Alpha | HF | 0.058 | 0.552 | [ -0.25, 0 13] | 0.091 |
| F3 Alpha | RMSSD | 0.011 | 0.911 | [-0.18, 0.2] | 0.051 |
| F3 Alpha | PNXX | 0.005 | 0.691 | [ -0.19, 0.2] | 0.05 |
| T7 Alpha | LF | 0.002 | 0.981 | [ -0.19, 0 19] | 0.05 |
| T7 Alpha | RMSSD | 0.005 | 0.84 | [ -0.19, 0 19] | 0.054 |
| T7 Alpha | HF | 0.002 | 0.56 | [ -0.29, 0 16] | 0.07 |
| T7 Alpha | PNXX | 0.008 | 0.78 | [ -0.16, 0.1] | 0.04 |
| T8 Alpha | RMSSD | 0.003 | 0.64 | [ -0.17, 0. 27] | 0.02 |
| T8 Alpha | LF | 0.039 | 0.42 | [ -0.18, 0.29] | 0.01 |
| T8 Alpha | HF | 0.029 | 0.28 | [ -0.19, 0 .12] | 0.034 |
| T8 Alpha | PNXX | 0.023 | 0.18 | [ -0.16, 0 23] | 0.087 |
| T8 Beta | RMSSD | 0.054 | 0.42 | [ -0.17, 0 18] | 0.004 |
| T8 Beta | LF | 0.012 | 0.15 | [ -0.15, 0.2] | 0.03 |
| T8 Beta | HF | 0.024 | 0.29 | [ -0.16, 0 .3] | 0.058 |
| T8 Beta | PNXX | 0.06 | 0.26 | [ -0.13, 0 .20] | 0.07 |
| F4 Alpha | LF | 0.09 | 0.53 | [ -0.16, 0. 2] | 0.02 |
| F4 Alpha | HF | 0.015 | 0.84 | [ -0.12, 0 1.9] | 0.097 |
| F4 Alpha | RMSSD | 0.019 | 0.31 | [ -0.15, 0 .18] | 0.049 |
| F4 Alpha | PNXX | 0.012 | 0.92 | [ -0.18, 0 .24] | 0.014 |
| F3 Beta | PNXX | 0.04 | 0.12 | [ -0.19, 0 .22] | 0.006 |

Significant correlations are bolded at a $p < 0.05$

## 3.5 Critical Discussion and Conclusions

In conclusion, our study has determined that there is no significant correlation between Heart Rate Variability (HRV) and Electroencephalogram (EEG) measurements in the context of stress-induced sessions, despite the presence of notable variations in the parameters of each device related to stress factors. Furthermore, our findings also indicate that there are no statistically significant differences in stress measurement between the two geographical regions under investigation.

Overall, the utilization of HRV as measures of stress using CoreSense HRV monitor by EliteHRV offers valuable tools for stress assessment and management. These objective measurements, coupled with continuous monitoring and personalized interventions, support individuals in their journey towards improved stress management and overall well-being. Measuring Heart Rate Variability (HRV) using

Photoplethysmography (PPG) signals is subject to various influencing factors. These factors include movement artifacts, ambient light, and skin conditions, all of which can impact the quality and reliability of the PPG signal. Therefore, it is crucial to ensure consistent and reliable signal quality to obtain accurate HRV measurements. The accuracy and reliability of Heart Rate Variability (HRV) and Electroencephalogram (EEG) wearable devices can vary significantly among different Photoplethysmography (PPG) devices. These variations arise from a combination of factors, including sensor quality, sampling rate, and signal processing algorithms employed by the devices. As a result, the validity of the HRV and EEG measurements obtained from these wearables is contingent on the technical specifications and performance characteristics.

Additionally, participant cooperation and adherence to instructions during data collection are vital in obtaining high-quality HRV and EEG data. Any movements, talking, or engagement in activities that influence HRV can introduce noise and significantly affect the results. Therefore, it is essential to establish clear protocols and guidelines for participants to follow during data collection to minimize such potential sources of interference. Moreover, it should be noted that individual characteristics, such as age, gender, physical fitness, and underlying health conditions, can influence HRV measurements. These factors can introduce variability in HRV patterns, and researchers should consider them when interpreting the results.

Our study ventured into the intricate field of bio signal measurements, with the specific aim of unraveling the potential correlation between Heart Rate Variability (HRV) and Electroencephalogram (EEG) signals when used as indicators for stress assessment. Following an exhaustive process of data collection, thorough analysis, and an interpretation, our investigation yielded a compelling finding: there exists no statistically significant correlation between HRV and EEG bio-signals in the context of gauging stress levels.

This discovery carries substantial implications as it underscores the intricacy of stress assessment and the multifaceted nature of the human body's responses to stress-inducing stimuli. While HRV and EEG have each carved their niche as invaluable tools in independent stress research, our study suggests that their combined application, at least within the confines of this specific study, does not manifest a quantifiable relationship. This sheds light on the necessity to explore diverse facets of stress assessment, discerning under which circumstances these bio-signals may or may not intersect.

Importantly, it is crucial to emphasize that our findings by no means diminish the individual utility of HRV and EEG in the scope of stress study. Each of these bio-signals offers distinct insights into varied aspects of the body's reaction to stressors, even though their convergence in this context remains elusive. These results propel us toward further exploration and beckon for a nuanced approach to stress assessment, one that acknowledges the intricate and multifaceted nature of this complex phenomenon.

Our study was meticulously guided by an assessment of sample requirements, a fundamental aspect that reinforced the robustness and credibility of our research outcomes. Numerous critical facets were thoughtfully considered to align with the precise requisites of our investigation. As we move forward, we recommend a diligent focus on the adequacy of the sample size, emphasizing the pursuit of a larger and more diverse sample to augment the statistical power of our research, ultimately enabling the generation of conclusions with broader relevance. Furthermore, our commitment to data quality remained unwavering, exemplified by the implementation of rigorous data collection and measurement procedures, including the utilization of standardized instruments and the training of data collection. This dedication was instrumental in safeguarding the precision and reliability of our dataset. The delineation of precise inclusion and exclusion criteria also played a pivotal role, ensuring that our sample comprised individuals possessing the predefined characteristics and variables of interest. This strategic step enabled us to concentrate our research efforts on the specific population under investigation. The selection of the most appropriate sampling methodology was intimately connected to our research design, adapting to align seamlessly with our research objectives. Additionally, we underscored the importance of embracing diversity within our sample, actively seeking to encompass a wide spectrum of demographic variables such as age, gender, and geographical location. By recognizing and addressing potential sources of variation, we endeavoured to produce findings that could be more broadly applied and offer valuable insights to the field of study.

The study utilized wearable HRV and EEG devices to assess stress levels, aligning measurements with gold medical references and focusing on individuals with elevated scores on the SPSS-10 and GAD-7 clinical questionnaires. Employing advanced techniques like OLS Regression and AIC Model Selection Methodology, the analysis revealed distinctive patterns in the QM dataset, indicating a lower mean Alpha asymmetry than the KF dataset. Notable gender differences were observed, with males exhibiting higher alpha asymmetry than females. Within the KF dataset, the main effect of GAD7 highlighted the significant impact of anxiety levels on alpha asymmetry, and the identified interaction between GAD7 and Sex unveiled a nuanced relationship, notably showcasing a higher positive association in the male subgroup. These findings offer substantial insights into the intricate interplay between anxiety, gender dynamics, and alpha asymmetry, advancing our understanding of the neurophysiological correlates of stress measured by wearable EEG devices across diverse demographic groups. In essence, our meticulously structured sample requirements provided a sturdy foundation for our research, aiming to elevate the levels of validity, reliability, and generalizability of our findings, with the goal of contributing substantive insights to our area of research. In summary, our study contributes valuable knowledge to the broader domain of stress assessment and the intricate interplay between physiological and neurological responses within the field of mental wellness research.

The forthcoming chapter illuminates the exploration of emotional perceived stress and the fascinating of biomarkers that can be captured through the ingenious utilization of wearable and thoughtful subjective questionnaires.

# Chapter 4

# Perception of Assisting Human Emotions

**CHAPTER 4**

# Perception of Assisting Human Emotions

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*This chapter provides an exposition regarding perceived emotional stress. As delineated by the American Psychological Association (APA), this variant of stress materializes as individuals respond to potent and adverse stress-inducing stimuli, often concomitant with emotions such as anxiety, fear, frustration, perceived threats, or sadness. Through adept and judicious assessment of emotions, we accrue invaluable discernments into the cognitive and emotional conditions of individuals. This, in consequence, enhances our understanding of human behavior, the complexities inherent in decision-making processes, and the holistic state of well-being.*

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## 4.1 Overview and Related Work

### 4.1.1 Multidimensional Assessment of Perceived Stress and Emotional States

Perceived stress is fundamental in human experiences, exerting substantial influence on emotional responses and overall psychological well-being. This chapter adopts a comprehensive approach by integrating subjective and objective methods to capture and evaluate perceived stress.

Subjective methods pertain to the individual's self-perceptions and experiences, reflecting their evaluations and feelings concerning stress. These methods involve human-based assessments, where individuals provide self-reports about their stress levels and related experiences.

In contrast, objective methods are complementary by providing additional insights into perceived stress by measuring physiological responses.

Stress is a multifaceted and intricate phenomenon with profound implications for both physical and mental health. It encompasses various dimensions, including exposure to stress-inducing events, individual perceptions of stress, and physiological responses to stressors. Extensive research consistently underscores the strong correlation between stress and a broad spectrum of physical and mental health issues. This recognition has fostered a widespread consensus among interdisciplinary scholars and practitioners regarding the imperative to delve into the multifaceted relationship between stress and health. To attain a comprehensive comprehension of stress, it becomes indispensable to scrutinize three fundamental domains that constitute the core of stress research.

Firstly, stress often emanates from external factors, encompassing elements such as work-related pressures, financial hardships, interpersonal conflicts, or traumatic life occurrences. The initial phase of understanding stress entails identifying the presence and nature of these environmental stressors, laying the foundation for comprehending their impact on individuals.

Secondly, individuals experiencing stressors invariably undergo a spectrum of psychological and biological responses. These responses are highly diverse and can significantly influence emotional well-being, cognitive functions, and even physical health. A profound exploration of these reactions is pivotal for gaining insights into the intricate nature of stress.

Furthermore, stress exhibits variations in terms of its duration and persistence. It can manifest as acute stress arising from brief and intense events or chronic stress, extending over extended timeframes. An understanding of the duration and chronicity of stress is pivotal since it greatly influences its consequences on health. Chronic stress can exert profound and enduring impacts on both the body and the mind.

To comprehensively investigate stress, researchers employ a multitude of methodologies and tools, which encompass self-report measures, biomarkers, and digital biomarkers. Self-report measures serve as indispensable instruments for capturing the subjective experiences of individuals in response to stress. These assessments empower individuals to articulate and evaluate the severity and duration of their psychological reactions to stressors, providing valuable insights into the personalized perception of stress.

In contrast, biomarkers provide objective and quantifiable measurements of stress, furnishing a deeper understanding of the biological responses to both acute and chronic stress. These biomarkers encompass a range of physiological indicators, such as cortisol levels, heart rate variability (HRV), and immune system markers, which enable a more precise quantification of the physiological impacts of stress.

As we cast our gaze toward the future of stress and health research, a multidimensional approach that amalgamates insights from all three methodological groups—self-reports, biomarkers, and digital biomarkers—is pivotal. This triangulated approach bestows a more comprehensive and nuanced understanding of stress, allowing for a deeper insight into its effects on individuals. Through the amalgamation of subjective experiences with objective biological data and real-time physiological measurements, researchers can foster a more holistic perspective on stress. This, in turn, can lay the groundwork for the formulation of more efficacious strategies for managing, intervening in, and preventing stress. In this context, the multidimensional perspective underscores the significance of interdisciplinary collaboration as an indispensable tool in unravelling the intricacies of stress and its profound repercussions on human health.

By combining subjective and objective methods, a holistic and nuanced examination of perceived stress is achieved, leading to a deeper comprehension of its impact on individuals' emotional states and psychological well-being. Self-report questionnaires are valuable tools for capturing individuals' perceived stress levels, allowing participants to evaluate their stress experiences using Likert or numerical scales subjectively. Concurrently, physiological measures, such as heart rate variability (HRV), blood pressure, skin conductance, and cortisol levels, provide objective insights into stress responses, contributing to a deeper understanding of perceived stress from a physiological standpoint[85].

Psychophysiological assessments integrate physiological and psychological data, yielding profound insights into emotional responses and the complex relationship between perceived stress and autonomic nervous system activity. Observing and analyzing behavioural expressions, including facial expressions and body language, facilitates real-time assessments of emotional responses, adding valuable context to understanding perceived stress in various situations[85].

Incorporating the Ecological Momentary Assessment (EMA) further enhances understanding of emotions and stress in real-world settings. EMA involves participants reporting their emotional states multiple times throughout the day, offering contextually relevant information on perceived stress and emotional fluctuations in natural environments[86].

By employing diverse assessment methods, researchers and practitioners can gain valuable insights into individuals' emotional experiences, leading to targeted interventions and support strategies for stress management and mental health promotion. The multidimensional assessment of emotions, particularly perceived stress, contributes to a more holistic understanding of human emotional responses, enabling a better grasp of the factors influencing well-being and paving the way for effective interventions to enhance overall mental health.

### 4.1.2 Emotion Models

Recent research has revealed intriguing connections between HRV signals and emotions. Assessing individual emotions and internal states can be challenging, but self-evaluation reports such as the Self-Assessment Manikin (SAM) provide a valuable tool for evaluating emotions. SAM utilizes three independent and bipolar dimensions, namely pleasure-displeasure, degree of arousal, and dominance-submissiveness, visually presented to the person through pictures. This method offers an alternative to more complex psychological evaluations by medical professionals, as it allows individuals to express their emotions directly. However, caution is required to ensure the authenticity and accuracy of the information provided by the person using the SAM report, as some individuals may face difficulties or lack truthfulness in expressing themselves [87].

Emotions are complex and involve interconnected changes in various components, including cognitive processing, subjective experiences, action inclinations, physiological changes, and motor expressions. It is essential to differentiate between emotions in terms of physiological changes and subjective experiences. The scientific community has broadly approached defining emotions from two perspectives: the dimensional model and the discrete model. The dimensional model focuses on essential emotional dimensions, such as valence and arousal, to describe emotions. Valence refers to the positive or negative quality of emotions, while arousal represents their intensity. This perspective is considered beneficial in interpreting neuroimaging data related to emotions.

Traditionally, the locations paradigm has dominated efforts to identify the neurological basis of emotional perception. This perspective posits that distinct emotions are generated by unique brain centres. According to this view, each emotion is associated with specific brain activation patterns, and particular brain regions exhibit increased activity during the experience of certain emotions. For instance, fear and sadness are believed to be controlled by separate neural regions, each having its distinct neural pattern [87].

In contrast, the dimensional model proposes that emotions can be described by a few fundamental dimensions. The consensus among researchers is that valence and arousal are crucial dimensions necessary to characterize emotions [88]. This approach simplifies the interpretation of neuroimaging data and has gained popularity in emotional psychometric studies. However, there is ongoing debate regarding the ideal number of dimensions required to fully describe emotions.

Overall, the integration of HRV data with self-report questionnaires offers a comprehensive understanding of emotions, particularly perceived stress. This multidimensional assessment provides valuable insights into emotional responses and their neural underpinnings, contributing to a more holistic understanding of human emotional experiences and well-being [89].

## 4.2 Study design

This section presents a detailed description of the protocol employed in Chapter 2, specifically focusing on Stage 3, which involved the IAPS image and SAM Scale assessment. Following the previous rest period, participants were exposed to an IAPS image provided by the company Milliseconds [69].

The methodology involved capturing HRV data using a Photoplethysmography (PPG) device, paired with the implementation of the SAM (Self-Assessment Manikin) scale as a validated tool for assessing emotional stress. The SAM scale adopts a non-verbal graphical approach, evaluating emotions based on three fundamental components: dominance, valence, and arousal. Participants were instructed to rate their emotional experience on a 9-point scale, complemented by five visual figures representing distinct emotional states. Using a graphical representation, this SAM subjective method aimed to provide participants with a user-friendly means of effectively expressing and quantifying their emotional responses.

After the SAM scale assessment, participants underwent exposure to images from the International Affective Picture System (IAPS). Following this emotional stimulus, participants were granted a 3-minute rest period. This interlude served as a brief recovery period and an opportunity for potential emotional regulation before proceeding with further study procedures. This approach aimed to capture and understand emotional responses through both physiological measures (HRV data from PPG devices) and subjective self-reporting (SAM scale), ensuring a thorough exploration of emotional states in the experimental setting. The combined use of HRV and the SAM scale offered an understanding of emotional perceived stress. It provided a versatile and accessible means for participants to communicate their emotional states during the experimental process. At the rest period, participants were allowed to recuperate and ensure an appropriate baseline before proceeding to subsequent stages of the measurement protocol.

### 4.2.1Participants

The experimental cohort consisted of 40 healthy participants aged 18 to 45, with gender distribution achieving parity, comprising 50% male and 50% female individuals.

### 4.2.2 HRV Analysis

### A1. Standard Deviations

The initial steps in establishing the Pearson correlation entail the computation of the standard deviation for each variable and the covariance between them. The standard deviation serves as a statistical measure, quantifying the extent to which data points are dispersed within each individual variable. On the other hand, the covariance elucidates the nature of the relationship existing between the two variables. Table11, below grouped all participants into Male and Female Categorized the data by target type into unpleasant and pleasant photos based on the image file names in the target column. Calculated the mean (and standard deviations) ratings for each subgroup. 3 ratings ^ 4 subgroups = 12 means calculated.

Table12, Followed the same procedure as in without grouping by sex. This resulted in 6 means (3 ratings * 2 groups = 6 cells).

**Table 11:** SAM ratings grouped by sex and target photo type.

| Sex | Photo Type | Valence | Arousal | Dominance |
|---|---|---|---|---|
| F | Pleasant | 3.62 ± 1.04 | 3.66 ± 1.51 | 4.36 ± 0.77 |
| | Unpleasant | 2.55 ± 1.40 | 2.75 ± 1.38 | 1.99 ± 1.07 |
| M | Pleasant | 3.79 ± 1.12 | 3.51 ± 1.49 | 4.33 ± 0.81 |
| | Unpleasant | 2.55 ± 1.24 | 2.51 ± 1.36 | 1.85 ± 0.92 |

Note: All values are mean ± standard deviation.

**Table 12:** SAM ratings grouped by target photo type.

| Photo Type | Valence | Arousal | Dominance |
|---|---|---|---|
| Pleasant | 3.71 ± 1.08 | 3.59 ± 1.50 | 4.34 ± 0.79 |
| Unpleasant | 2.55 ± 1.32 | 2.63 ± 1.37 | 1.92 ± 1.00 |

Note: All values are mean ± standard deviation.

## A2. Pearson Correlation

Researchers and analysts extensively employ the Pearson correlation coefficient to ascertain the extent of the relationship between two variables and can be utilized to make predictions or infer causal relationships between them. In this study, we selected three matrices from the time domain to assess the reflection of subject emotions in association with IAPS image, using the SAM scale as the measurement tool.

**Table 13**: Correlation between MeanRR and SAM ratings in each photograph category

| | Unpleasant Group | Pleasant Group |
|---|---|---|
| Valence | 0.025 | -0.049 |
| Arousal | 0.100 | 0.019 |
| Dominance | 0.087 | **-0.144** |

**Table 13**: Correlation between MeanRR and SAM ratings in each photograph category

| | Unpleasant Group | Pleasant Group |
|---|---|---|
| Integrated Index | -0.020 | -0.019 |

Note: Bold values represent Pearson correlations with $p<0.1$.

In this study, the statistical analysis encompassed the computation of the Pearson correlation coefficient to examine the association between HRV meanRR and SAM ratings for pleasant and unpleasant photos, categorized based on three emotional dimensions, as elucidated in Table 13. The resulting correlation coefficient of -0.144 indicates a weak negative correlation. This implies that fluctuations in HRV meanRR are connected to corresponding changes in SAM ratings, particularly concerning pleasant photos in the dominance dimension.

Researchers and analysts relied upon the Pearson correlation coefficient to evaluate the strength and direction of the relationship between HRV meanRR and SAM ratings. Positive correlations suggest a consistent emotional response, where alterations in HRV meanRR align with SAM ratings. Conversely, negative correlations indicate an inverse relationship, where modifications in HRV meanRR are associated with opposite changes in SAM ratings.

**Table 14 :** Correlation between SDNN and SAM ratings in each photograph category

| | Unpleasant Group | Pleasant Group |
|---|---|---|
| Valence | **0.161** | -0.093 |
| Arousal | -0.032 | **-0.152** |
| Dominance | 0.005 | -0.087 |
| Integrated Index | **0.214** | **-0.155** |

Note: Bold values represent Pearson correlations with $p<0.1$.

Based on the statistical analysis presented in Table 14, it is commonly acknowledged that a weak negative correlation typically falls within the range of -0.1 to -0.3. In the current study, when investigating the association between HRV SDNN (Standard Deviation of Normal-to-Normal intervals) and SAM ratings for photos categorized based on the valence dimension, a distinct weak positive correlation of 0.161 is observed, specifically for unpleasant photos.

The observed pattern indicates that variations in HRV SDNN are connected to concurrent changes in SAM ratings, reflecting the perception of unpleasantness. An increase or decrease in HRV SDNN corresponds to a corresponding increase or decrease in the perceived level of unpleasantness, as indicated by the SAM ratings.

Additionally, in the analysis of the relationship between SDNN and SAM ratings for photos categorized as pleasant based on arousal, a weak negative correlation is identified. This suggests that fluctuations in SDNN are associated with corresponding changes in arousal levels, as reflected by the SAM ratings.

**Table 15**: Correlation between RMSSD and SAM ratings in each photograph category

| | Unpleasant Group | Pleasant Group |
|---|---|---|
| Valence | **0.209** | -0.112 |
| Arousal | 0.009 | -0.123 |
| Dominance | 0.016 | -0.109 |
| Integrated Index | **0.239** | **-0.166** |

Note: Bold values represent Pearson correlations with $p<0.1$.

The conventional understanding designates a weak positive correlation as a coefficient falling within the range of 0.1 to 0.3, while a moderate positive correlation encompasses values from 0.3 to 0.5, and a strong positive correlation span from 0.5 to 1.0.

Considering the findings presented in Table 15, it becomes evident that a weak positive correlation is present between RMSSD (Root Mean Square of Successive Differences) and the Unpleasant Group SAM rating within the valance domain.

### 4.2.3 HRV Data Results and Discussion

Assessing human emotions is a multifaceted undertaking that has garnered considerable interest across several disciplines, encompassing psychology, neuroscience, and human-computer interaction. Among the various approaches to measuring emotions, using the Self-Assessment Manikin (SAM) scale, as elucidated in Figure 21 below, in conjunction with Heart Rate Variability (HRV) data, stands out as a prominent perspective. This integrated approach offers valuable insights into its advantages and limitations in emotion assessment.

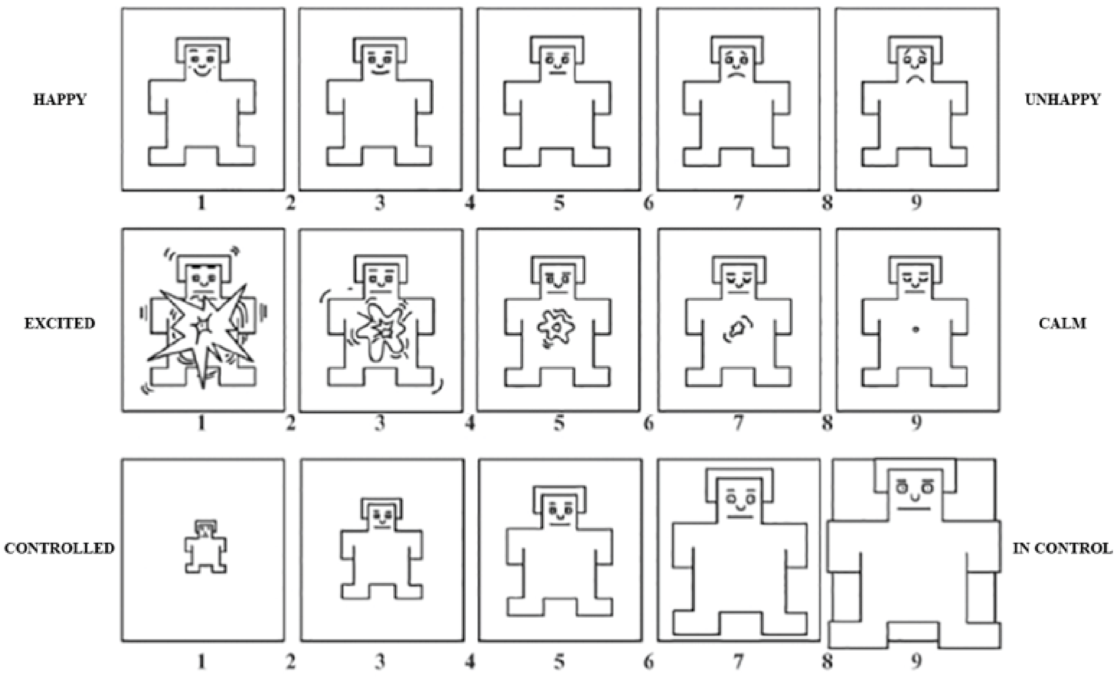


**Figure 39:** Self-Assessment Manikin (Resource taken from [90])

The Self-Assessment Manikin (SAM) scale is extensively utilized as a self-report instrument that enables individuals to assess their emotional experiences across multiple dimensions, including Valence (indicating whether the elicited emotion is positive or negative), Arousal (measuring the level of activation associated with the emotion), and Dominance (reflecting the extent to which the participant feels in control of the emotion). Through the application of this scale, researchers are empowered to gather subjective data related to an individual's emotional state, thus facilitating the acquisition of valuable insights into their affective experiences. Consequently, the SAM scale assumes a pivotal role as an indispensable tool in comprehending how individuals perceive and articulate their emotions, significantly enhancing our understanding of emotional responses and subjective feelings.

On the other hand, Heart Rate Variability (HRV) is a physiological measure that reflects the fluctuations in time intervals between successive heartbeats. HRV has been correlated with the functioning of the autonomic nervous system and has exhibited potential as an objective indicator of emotional states. Alterations in HRV patterns have been associated with various emotional states, such as an increase in HRV during positive emotions and a decrease in HRV during negative emotions.

Integrating the SAM scale with HRV data presents a comprehensive approach to assessing human emotions. Researchers can develop a more holistic understanding of emotional experiences by combining subjective self-reports with objective physiological measurements. This amalgamation allows for data triangulation, potentially enhancing the reliability and validity of emotion assessments.

Moreover, the SAM scale offers a contextual and nuanced perspective to HRV data by encompassing the multidimensional aspects of emotions. While HRV provides valuable insights into autonomic responses, it may not fully capture the specific dimensions of valence and arousal that the SAM scale measures. The integration of these two approaches facilitates bridging the gap between subjective experiences and physiological responses, thereby providing a more comprehensive portrayal of emotions. However, it is essential to acknowledge the limitations of this combined approach. Self-report measures, such as the SAM scale, rely on individuals accurately and honestly reporting their emotional experiences, which can be influenced by factors such as memory biases, social desirability, and individual differences in introspection. Additionally, HRV measurements can be influenced by various physiological and environmental factors, as mentioned earlier.

Moreover, interpreting the relationship between SAM scale ratings and HRV data can be challenging. While changes in HRV have been associated with different emotional states, individual variations, and contextual factors can influence these relationships. Furthermore, the mechanisms underlying the link between emotions and HRV are still under investigation, and the field is continuously evolving.

## 4.3 Conclusions

In conclusion, combining the SAM scale with HRV data provides a valuable approach to assessing human emotions. This integrated approach offers the advantage of capturing both subjective experiences and objective physiological responses, enhancing our understanding of emotional processes. However, it is essential to consider the limitations and challenges associated with self-report measures and HRV measurements when utilizing this combined approach. Continued research and advancements in methodology will further refine the integration of subjective and objective measures, leading to a more comprehensive assessment of human emotions.

# Chapter 5

# Conclusions and Future Work

# CHAPTER 5

# Conclusions and Future Work

*This chapter is the final section of this thesis, offering a summary and synthesis of the study's main findings, insights, and implications. It provides an opportunity to revisit the research objectives and questions, reflect on the research process, and draw meaningful conclusions based on the results. It aims to provide closure to the research endeavor, highlighting the significance and contributions of the study within the broader academic field. It also offers a platform to discuss the limitations of the research, propose avenues for future research, and present practical implications and recommendations stemming from the study's outcomes.*

## 5.1 Summary of contributions

The summary of contributions underscores the novelty of the methodological systematic review presented in this study. This review is an exceptional and distinct approach to assessing and consolidating the existing literature on a specific field or topic. The study's rigorous and systematic methods contribute significantly to the enhancement and progress of research methodologies within the field.

This innovative methodological systematic review offers a comprehensive and well-organized overview of the available literature, facilitating a critical analysis and synthesis of the evidence. As a result, it serves as a valuable resource for researchers, practitioners, and policymakers who seek to delve deeper into the subject matter under investigation.

The systematics literature review study's implementation of this novel systematic review methodology constitutes a substantial contribution to the scholarly community, bringing forth a wealth of insights and knowledge to those who further explore the topic.

The systematic review's methodology, including the search strategy, inclusion and exclusion criteria, data extraction, and synthesis methods, adds to the methodological repertoire of systematic review techniques and enhances the rigor and reliability of future research in the field. Overall, this study's novel methodological systematic review significantly contributes to the methodological advancements and knowledge base within the relevant academic discipline.

The study's integration of PPG devices, utilizing light-based technology for HRV monitoring, showcases a dynamic understanding of an individual's physiological responses to stressors. The correlation of subjective data with PPG-derived biomarkers represents mental well-being. The reliability of wearables equipped with PPG and EEG sensors is evident in capturing significant differences in subject biomarkers, offering a holistic approach that includes both peripheral physiological responses and central nervous system activity.

Coarsens (PPG) device stand out for their proficiency in capturing precise physiological signals, offering dependable indicators of stress levels. Their capability for continuous monitoring provides a dynamic insight into stress responses throughout various phases—before, during, and after exposure to stressors. Leveraging the data from PPG devices enables a personalized approach to stress management, allowing interventions to be tailored to individual needs for heightened efficacy. Functioning as a bridge between controlled laboratory settings and real-world scenarios, PPG devices facilitate a more nuanced understanding of stress dynamics. Moreover, PPG technology plays a pivotal role in contributing to the development of interventions that enhance mental well-being, unravelling the intricacies of stress responses and paving the way for more effective strategies.

This synergistic use of CorSense (PPG) and Emotive_14 channels (EEG) devices improve the precision of stress assessments, allowing continuous monitoring in real-world scenarios. The integrated approach opens avenues for personalized interventions based on real-time data, contributing to the development of effective strategies for stress management and mental health support. In conclusion, the study's multidimensional approach, combining PPG devices, subjective methods, and EEG sensors, marks a substantial advancement in stress and mental well-being assessment, laying the groundwork for personalized interventions and innovative solutions in mental health care. The evaluation of body sensor devices further emphasizes their potential correlation with medically established gold references, providing a will established understanding of their utility in mental health assessment.

The outcomes of our study provide valuable insights into the existing body of literature investigating the relationship between alpha asymmetry and HRV, as evaluated by both EEG and PPG devices, and major depressive disorder (MDD) as well as general anxiety disorder (GAD). Our research is aligned with the dynamic fields of neuroscience and cardiovascular health, enriching the understanding of potential correlations between alpha asymmetry and HRV in the context of these psychiatric conditions. To fortify the robustness of our evidence, it is recommended to supplement our study by engaging with a broader spectrum of subjects. This inclusive approach, extending beyond healthy individuals, will not only enhance the depth of our findings but also increase the applicability of our research. Such a complete strategy ensures a nuanced and up-to-date grasp of the current state of knowledge on this subject.

This thesis holds paramount significance in advancing mental well-being assessment through innovative wearable devices, particularly biosensors. By leveraging Heart Rate Variability (HRV) bio signals and Electroencephalography (EEG) data, the research introduces a non-intrusive and continuous real-time approach to monitoring stress and anxiety factors. Wearable devices capturing HRV signals objectively measure physiological responses, focusing on autonomic nervous system activity and emotional regulation. The incorporation of EEG measurements further enhances precision by directly assessing brain activity associated with stress and anxiety.

## 5.2 Research limitations

Selecting the most appropriate analytical techniques method relies on specific research goals, dataset characteristics, and desired model interpretability. Researchers must carefully consider these factors to determine the optimal methodological approach for their stress and anxiety assessment study.

Investigating the combined effect of alpha asymmetry and HRV with other physiological measures, such as cortisol levels or skin conductance, could offer a deep understanding of the underlying physiological mechanisms associated with stress and emotional responses [91].

In addition, intervention studies targeting specific factors known to influence alpha asymmetry and HRV, such as mindfulness practices or biofeedback training, could help determine whether changes in these measures lead to improvements in stress management and emotional regulation[92] .

Moreover, the sample size utilized in research must be considered. A small sample size reduces statistical power, undermining the reliability and generalizability of findings. To address this limitation, future work should prioritize more extensive and diverse samples, ensuring a more accurate population representation. Furthermore, conducting multicenter or multisite studies involving participants from various demographics can improve external validity. By addressing sample size limitations and including diverse samples, researchers can strengthen their findings' statistical power and reliability, facilitating a more comprehensive understanding of the research topic[93].

## 5.3 Scope for Future Work

Further areas of research are essential to enhance the validity and reliability of the proposed approach for assessing cognitive behaviours using wearable monitoring technologies. This can involve conducting studies that compare results from different wearable devices, validating measurement accuracy, and establishing a stronger correlation between physical vitals and cognitive states. By addressing these limitations and engaging in additional research, the field can advance in comprehending wearable monitoring technologies and their potential for assessing mental states. This progress can lead to improved applications, enhanced user experiences, and increased validity in real-world settings.

### 5.3.1 Some Study Design Strategies

An area for future studies is to delve into the details of analysing EEG data to identify patterns associated with stress, as well as analysing SAM scale responses to determine changes in perceived stress levels. intricate relationship between physiological responses and perceived stress remains an active area of investigation within the field of neuroscience. To proposes a comprehensive framework for future studies aimed at elucidating the patterns associated with stress perception through the concurrent analysis of EEG data and SAM (Self-Assessment Manikin) scale responses. By focusing on Event-Related Potential (ERP) components, the temporal alignment of EEG patterns with SAM scores, and the averaging of EEG epochs, this research aims to provide a nuanced understanding of how neural activity corresponds to perceived stress levels across various time points during stress-inducing events [94].

Another area that remains relatively unexplored is the examination of partial correlations between HRV and these cognitive tasks, particularly after accounting for neuronal oscillations. This avenue of research could yield valuable insights into the specific contributions of HRV concerning cognitive performance when neuronal factors are statistically controlled [95].

Moreover, replicating the current study using different cognitive tasks offers an opportunity to examine how task-specific characteristics influence the interconnections between the central nervous system (CNS) and the autonomic nervous system (ANS). Depending on the nature of the cognitive task, the potential variations in these interconnections could provide a deeper understanding of the complex relationship between HRV, cognitive function, and the underlying neural mechanisms. To better understand how individuals respond to different stimuli, future studies can extend the conditions of test perception to encompass more diverse sensory fields. For example, incorporating tests that combine auditory stimuli with visual or tactile sense stimuli can offer valuable insights into how individuals process and react to multi-sensory inputs[96].

Conducting longitudinal studies for real-world application. These advancements can lead to more accurate and practical solutions for monitoring and managing individuals' mental and cognitive well-being [97].

In addition, the possibility of remote monitoring without geographical restrictions through the IoT system. Future works can focus on expanding the reach of the monitoring system by implementing wireless connectivity and cloud-based storage, enabling real-time data transmission and analysis from various locations.

### 5.3.2 Advancing Analytical Methods: The Power of Machine Learning (ML) Models for Enhanced Precision and Efficiency

Researchers require access to large and diverse datasets to enhance stress detection efficiency and accuracy using HRV and EEG data. Utilizing representative data from various populations and stress-inducing scenarios enables fine-tuning and generalization of Machine learning (ML) models to different individuals and contexts. While the potential of ML in stress detection is promising, challenges still need to be addressed. The interpretability and explain ability of ML models concerning HRV and EEG data must be carefully considered to gain trust and acceptance from users and healthcare professionals[98].

Recurrent Neural Networks (RNNs) are well-suited for processing time-dependent EEG signals, capturing long-term dependencies that facilitate HRV-EEG pattern correlations over time. Long Short-Term Memory (LSTM) Networks, a type of RNN, offer better retention and propagation of information across extended time intervals, making them suitable for capturing the temporal dynamics in HRV and EEG data[99].

Attention Mechanisms integrated into DL models focus on specific HRV and EEG data segments relevant to stress detection, enhancing correlations by directing attention to critical features. As unsupervised learning models, Autoencoders extract salient features from combined HRV and EEG data, promoting stronger correlations by identifying stress-related variations.

Generative Adversarial Networks (GANs) synthesize realistic data samples resembling stress-related patterns, improving the correlation between HRV and EEG data. Transfer Learning, involving pretraining neural networks on large datasets and fine-tuning on smaller target datasets, enables leveraging learned representations to enhance correlations between HRV and EEG data[100].

# Appendix

# Appendix A

The following pages contain material used during the systematic literature review study (Chapter 2). The material comprises:

1. Ethics approval letter

2. Consent form (sample export)

3.Participant Information Sheet

4.Participant Questionnaire

**Queen Mary, University of London**
Room W117
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**Queen Mary Ethics of Research Committee**
Hazel Covill
Research Ethics FacilitatorTel: +44 (0) 20 7882 7915
Email: research-ethics@qmul.ac.uk
c/o Dr Akram Alomainy
School of Electronic Engineering andComputer Science
Queen Mary University of LondonMile End Road
LondonE1 4NS
United Kingdom
To Whom in May Concern:

**RE: QMERC20.106 – The use of wearable technology in providing assistivesolutions for cognitive and mental wellbeing.**

I can confirm that Reham Alhejaili has completed a Research Ethics Application with regard to the above study.

The result of which was the conclusion that the proposed work does not present any ethical concerns; is low risk; and thus does not require the scrutiny of the full Research Ethics Committee.

Yours faithfully
Mantalena Sotiriadou – Research Ethics Facilitator
Patron: Her Majesty the Queen
Incorporated by Royal Charter as Queen Maryand Westfield College, University of London

Consent Form

**Title of Research Study: THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSISTIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS**

**Principal Investigator:** Dr. Akram Alomainy

**Queen Mary Ethics of Research Committee Ref:** [**RE: QMERC20.106**].

Thank you for your interest in this research.

Should you wish to participate in the study, please consider the following statements. Before signing the consent form, you should initial all or any of the statements that you agree with. Your signature confirms that you are willing to participate in this research, however, you are reminded that you are free to withdraw your participation at any time.

| **Statement** | **Please initial box** |
|---|---|
| 1. I confirm that I have read the Participant Information Sheet dated7/12/2020; Version 1.0: 01 October 2020; or it has been read to me. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. | |
| 2. I understand that my participation is voluntary and that I am free to stop taking part in the study at any time without giving any reason and without my rights being affected. But if you filled in survey and sent it to us then you can't be withdrawal of data after completion the survey because the data will be stored in fully anonymised form. | |
| 3. I understand that my data will be accessed by the supervisor and the investigator. | |
| 4. I understand that my data will be securely stored in password-protected hard drive and in accordance with the data protection guidelines of the Queen Mary University of London until the graduating of the researcher in fully anonymized form. | |
| 5. I understand that I can access the information I have provided and request the destruction of that information at any time prior to the end of this year 2023. I understand that following to that date I will not be able to request the withdrawal of the information I have provided. | |

| | |
|---|---|
| 6. I understand that the researcher will not identify me in any publications and other study outputs using personal information obtained from this study. | |
| 7. I understand that the information collected about me will be used to support other research in the future. | |
| 8. I agree to be contacted about other research studies in the future. | |
| 9. I agree to take part in the above study. | |

Participants should read Queen Mary's privacy notice for research participants which contains important information about your personal data and your rights in this respect. If you have any questions relating to data protection, please contact Data Protection Officer, Queens' Building, Mile End Road, London, E1 4NS or data-protection@qmul.ac.uk or 020 7882 7596.

________________ ______________ _______________________________

Participant name Date Signature

___________________ ________________ __________________________________

Name of person Date Signature

taking consent

I Reham Alhejaili, confirm that I have carefully explained the nature, demands and any foreseeable risks (where applicable) of the proposed research to the participant and provided a copy of this form.

**Principal Investigator (or Supervisor for student projects)**

Akram Alomainy

a.alomainy@qmul.ac.uk

**Student Investigator (if applicable)**

Reham Alhejaili

r.a.s.alhejaili@qmul.ac.uk

QMERC Consent Form template; Version 1.0: 01 October 2020

## Participant Information Sheet

**Study title: THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSISTIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS**

**Version number and date**

0.1 30.10.2020

**Researcher's name**

Reham Alhejaili supervised by Dr. Akram Alomainy

**Queen Mary Ethics of Research Committee reference number:**

[Insert reference number allocated to your study by the Research Ethics Facilitators]

**Invitation paragraph**

We would like to invite you to be part of this research study if you would like to. You should only agree to take part if you want to, it is entirely up to you. If you choose not to take part, there will not be any disadvantages for you, and you will hear no more about it.

Please read the following information carefully before you decide to take part; this will tell you why the research is being done and what you will be asked to do if you take part. Please ask if there is anything that is not clear or if you would like more information.

If you decide to take part, you will be asked to sign the consent form to say that you agree.

You are still free to withdraw at any time and without giving a reason. But if you filled in the survey and sent it to us then you can't withdraw data after completing the survey because the data will be stored in a fully anonymized form.

**What is the purpose of the study and what would taking part involve?**

The purpose of this study is to validate that wearable tracking devices are normally assistive in providing solutions for cognitive and emotional wellness. There will be a questionnaire consisting of 3 general questions that will have sub-questions and will take approximately 10-15 minutes. It covers topics such as your general opinion on Wearable Devices, stress perception in general technological support for cognitive and emotional wellness management.

**Preparation**:

We acquire you to fill out a pre-study consent and then the questionnaire. This questionnaire contains questions about your demographics (age, gender), and your opinion about the wearable tracking devices.

**Study**:

If you decide to take part, the researcher will arrange it via email.

**Baseline Recording**: You will be asked to finish the questionnaire before the end date which is 1st February until 20th of February 2021.

**Time Commitment**

The study will last around 10 to 15 Minutes including an introduction and filling out 2 forms the consent form and the questionnaire.

**Why am I being invited?**

You are being invited to participate in this research study because you are healthy and aged range between 22-35 years.

**Do I have to take part?**

This participant information sheet has been written to help you decide if you would like to take part. It is entirely up to you, you should only agree to take part if you want to. If you do decide to take part you will be free to withdraw at any time without needing to provide a reason, and with no penalties or detrimental effects. You must understand that the information collected about them will be used to support other research in the future. Also, you must agree to be contacted about other research studies in the future.

**What are the possible benefits of taking part?**

Taking part in the study will support this Ph.D. research that aims to further our understanding of the general opinion on Wearable Devices, stress perception in general technological support for cognitive and emotional wellness management.

**What are the possible disadvantages and risks of taking part?**

We don’t anticipate having any risks by participating in this experiment.

**Expenses and payments**

This study is unpaid.

**What information about me will you be collecting?**

We will be collecting data by evaluating the answers in the questionnaire.

**How will my data be stored and who will have access to it?**

Your data will be kept strictly confidential and will be stored in a fully anonymized format. You will not be able to be identified or identifiable in any reports or publications. Any data collected about you will be stored on google Forms and only the Supervisor and the researcher will be able to access it.

Data Protection Policy

Information/Data Governance Policy – DG14 – Storage of information

• **When and how will my data be destroyed?**

Your data will be erased from google forms upon graduating with the Ph.D. degree after 3 years.

• **How will my data be used and shared?**

The results of this study will be part of the Ph.D. thesis that is connected to this research project. Results will be mentioned in a future conference or journal paper publication. All data is stored locally in an anonymized form and will not be accessible for or shared with others.

Research Data Access and Management Policy

• **Under what legal basis are you collecting this information?**

Queen Mary University of London **processes personal data** for research purposes in accordance with the lawful basis of 'public task'.

• Please read Queen Mary's privacy notice for research participants containing **important information about your personal data and your rights** in this respect.

• **If you have any questions** relating to data protection, please contact Queen Mary's Data Protection Officer, Queens' Building, Mile End Road, London, E1 4NS or data-protection@qmul.ac.uk or 020 7882 7596.

• **What will happen if I want to withdraw from this study?**

You can withdraw from this study at any time without providing a reason. Withdrawing will have no disadvantages for you, and you will hear no more about this study. Your data will only be submitted if you complete the study.

Your data will be saved entirely anonymized and is not possible to link the data to a particular person. For this reason, it is however not possible to delete the data entry of a specific person.

• **What should I do if I have concerns about this study?**

If you have any concerns about the manner in which the study was conducted, in the first instance, please contact the researcher(s) responsible for the study Dr. Akram Alomainy (a.alomainy@qmul.ac.uk ) and also you can contact the Ph.D. student named: Reham Alhejaili r.a.s.alhejailii@qmul.ac.uk

• If you have a complaint that you feel you cannot discuss with the researchers then you should contact the Research Ethics Facilitators by e-mail: research-ethics@qmul.ac.uk.

- When contacting the Research Ethics Facilitators, please provide details of the study title, description of the study and QMERC reference number (where possible), the researcher(s) involved, and details of the complaint you wish to make.
- **Who can I contact if I have any questions about this study?**

Dr. Akram Alomainy

a.alomainy@qmul.ac.uk

Reham Alhejaili

r.a.s.alhejailii@qmul.ac.uk

## Surveys and Data Collection

Study title: **THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSISTIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS**

The questionnaire consists of 3 general questions that will have sub-questions and it will take approximately 10-15 minutes. It covers topics such as your general opinion on Wearable Devices, stress perception in general technological support for cognitive andmental wellness management.

### Demographics

**What is your gender:**

1.Female

2. Male

3.Other

4. No answer

**What is your age:**

1. 18 – 24

2. 25 - 34

3. 35 - 44

4. 45 - 54

5. 55+

### General Questions:

**Health statutes:**

1.Excellent

2.very good

3. Fine

4. Bad

You use wearable devices to communicate with:

**Friends:**

**1.** Daily

**2.** several times a week

3.once a month

4.Seldom

5.Never

**Family:**

**1.**Daily

**2.** several times a week

**3.**once a month

**4.** Seldom

**5.**Never

**Doctors:**

**1.**Daily

**2.**several times a week

**3.**once a month

**4.**Seldom

**5.**Never

Please do not select more than 1 answer(s) per row.

| | Strongly consider | consider | neutral | Not consider | Strongly not consider |
|---|---|---|---|---|---|
| 1 Wearable device motivate me to evaluate my state of mind | | | | | |
| 2. The feedback given via wearable devices is useful. | | | | | |
| 3. Sharing my data measured with wearable devices encourages me to evaluate my mental wellness. | | | | | |
| 4. I feel happy with a software, which can assess me using wearable devices, which will measure my biomarkers (such as HRV, EEG, skin conductance). | | | | | |
| 5.I feel that tips evaluating the level I reached in my emotional assessment would be conducive to my mental wellness. | | | | | |

Any other comments: …………………….

# Appendix B

The following pages contain material used during the pilot study (Chapter 3 and Chapter4).

The material comprises:

1. Two ethics approval letters
2. Participant Information Sheet
3. Consent form (sample export)
4. Participant Questionnaire
5. Two surveys (perceived stress score) and (GAD-7 anxiety)

Queen Mary University of London

Queen Mary Ethics of Research Committee

Joint Research Management OfficeDept. W

69-89 Mile End RdLondon | E1 4UJ

Research Ethics Facilitators

Tel: +44 (0)20 7882 7915 / 6947

Email: research-ethics@qmul.ac.uk

10 May 2022

Dr Akram Alomainy

Reader in Antennas and Applied Electromagnetics School of Electronic Engineering and Computer ScienceQueen Mary University of London

cc: Reham Alhejaili

RE: QMERC22.150 - The use of wearable technology in providing assistive solutionsfor cognitive and mental wellbeing

Having received a Research Ethics Application for the study detailed above, the proposed work has been deemed low-risk and will not require the scrutiny of the full Queen Mary Ethicsof Research Committee. It has been reviewed by the Research Ethics Facilitator(s) and I ampleased to inform you that, based on the information provided, this application has now been**approved**.

Date of Approval: 10 May 2022

Approval End Date: 9 May 2025

The application was approved subject to the following conditions:

Extensions and Amendments: If you propose to make an amendment to the research after approval or extend the study beyond the date of the approval expiry date given above, the Research Ethics Facilitators (research-ethics@qmul.ac.uk) should be contacted. The Facilitators will provide guidance about the notification required, the type of amendment and the process to be followed for further approval.

Adverse Events:

In case of any unexpected or adverse events or deviations from the proposed protocol as perthe original QMERC application, please contact the Research Ethics Facilitators at research-ethics@qmul.ac.uk within 5 days of the event.

Covid-19:

Researchers should exercise extra care and precautions when conducting research at this time. There are ethical issues that are of heightened importance to consider when conducting research with human participants.

Researchers are responsible for checking the local and national governmental advice and forbeing aware of any necessary restrictions that may impact their study. In particular, researchthat involves overseas travel or face-to-face research must regularly check for updates and follow the latest guidance.

We wish you the best for your research.Yours faithfully,

Melissa Bliss

Research Ethics Facilitator, on behalf of the Queen Mary Ethics of Research Committee.

Queen Mary Ethics of Research Committee

Joint Research Management OfficeDept. W

69-89 Mile End RdLondon | E1 4UJ

Research Ethics Facilitators

Tel: +44 (0)20 7882 7915 / 6947

Email: research-ethics@qmul.ac.uk

7th February 2022

Dr Alkram Alomainy

School of Electronic Engineering and Computer ScienceQueen Mary University of London

Reham Alhejaili Dear Dr Alomainy

RE: QMERC20.536- The use of wearable technology in providing assistive solutionsfor cognitive and mental wellbeing

Having received a Research Ethics Application for the study detailed above, the proposed work has been deemed low-risk and will not require the scrutiny of the full Queen Mary Ethicsof Research Committee. It has been reviewed by the Research Ethics Facilitator(s) and I ampleased to inform you that, based on the information provided, this application has now been approved.

**Date of Approval: 29th November 2021**

Approval End Date: 28th November 2024

The application was approved subject to the following conditions:

Extensions and Amendments:

If you propose to make an amendment to the research after approval or extend the study beyond the date of the approval expiry date given above, the Research Ethics Facilitators (research-ethics@qmul.ac.uk) should be contacted. The Facilitators will provide guidance about the notification required, the type of amendment and the process to be followed for further approval.

Adverse Events:

In case of any unexpected or adverse events or deviations from the proposed protocol as perthe original QMERC application, please contact the Research Ethics Facilitators at research-ethics@qmul.ac.uk within 5 days of the event.

Covid-19:

Researchers should exercise extra care and precautions when conducting research at this time. There are ethical issues that are of heightened importance to consider when conducting research with human participants.

Researchers are responsible for checking the local and national governmental advice and forbeing aware of any necessary restrictions that may impact their study. In particular, researchthat involves overseas travel or face-to-face research must regularly check for updates and follow the latest guidance.

We wish you the best for your research.Yours faithfully,

Hazel Covill

Research Ethics Facilitator, on behalf of the Queen Mary Ethics of Research Committee.

# THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSITIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS

**Type of project application:** Interventional studies
**Study Number:** IRB 2021-77
**Expected start date:** 19/09/2021
**Expected end date:** 30/09/2022


**Abstract:**

The whole planet's population has rapidly expanded on a broad scale and has forced individuals throughout the world to confront several dangers and challenges. The number of citizens in many nations has also been explicitly seen to increase to a considerable extent. The number of doctors, hospital services and experts has dropped considerably [1]. In many instances, doctors and investigators need to propose specific machines and devices that would make their jobs and practices easier and help in various ways to the supply of patient support and aid. Due the high degree of performance, it was also recorded stress, tension and anxiety levels have also been elevated to a larger extent. The purpose of this research is to provide enhanced and up-to-date techniques that support doctors, identify distinct essential elements, criteria and take various measures and assessments of a human body to evaluate stress and distress.


**Detailed description:**

**5.2.4 Methodology:**

**1. Participants and study design**

We will recruit healthy 20 volunteers to participate at the KFSH-RC Jeddah with age range of 18 to 50. They must be 50% male and 50% female. We would capture their BMI and they must ask to avoid smoking and caffeine intake 6 h prior to the measurement.

Participants will be fully informed about the experimental procedure and will be invited to participate. All subjects provided written informed consent and the protocol will approved by the Ethics Committee.

The Experimental will be Setup in a lab. We will Covid-19 risk management. During the initial visit, subject who were selected according to the inclusion criteria, completed an informed consent, a demographic questionnaire. After filling in the questionnaires.

Each subject will be given approximate 5 minute of rest to control for environmental effect. They will be equipped with Emotive Epoch 14 channel and Coresens sensor rest with eyes closed for about 3 minutes. After that time baseline measures of HRV, EEG and EDA will be collected for at least 3-minutes in while watching an IPAS photo and they will use the SAM The SAM is a nonverbal pictorial technique assessment of emotions in which each affective dimension of valence, arousal and dominance is represented by 5 figures inserted in a 9-point scale After, Post recording of the following measures were done. The participant will fill in 2 questionnaires Perceived Stress Scale (PSS) and General Anxiety Disorder-7(GAD-7). We will follow the process as at (Figure1) below chart

## Official Documents

Participant-Information-Sheet--v1.0---01-October-2020.docx

Participant Questionnaire.docx

RehamAlhejaili_ProtocolApproval_Alomainy (1).pdf

RehamAlhejaili_StudyInvitation_Alomainy (1).pdf

certificate.pdf

Consent Form.docx

LAYOUT FOR PILOT STUDY.docx

ترجمه_اختبار_القلق.docx

ترجمة_معلومات _الفرد.docx

ترجمة_قياس_التوتر.docx

PSS-10.docx

pss_scoring_and_information (1).docx

tiis-calvo (2).pdf

fnhum-07-00414.pdf

### Principal Investigator

HABIB, NOOR, J1504588

### Co-Investigators

ALAA , SUBHI - J96874 - NEUROPHYSIOLOGY LABORATORY (Sec)-J (Active)

## Ethics Reviews

Ethics Review for: THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSITIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS, IRB 2021-77 Interventional studies 20/09/2021
Ethics Review for: THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSITIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS, IRB 2021-77
Interventional studies 20/09/2021

## Keywords

Cognitive wellness
Emotional wellness
WEARABLE TECHNOLOGY

## REC / IRB Approval date

20/09/2021

## Ethics Review/IRB Memo to PI

Thank you for your submission of the above-mentioned research to the Institutional Review Board. The protocol was reviewed and discussed in the board's meeting on **20 September 2021** and the study was found very good and approval is granted.

**In addition, please note that its prohibited to share any data with the collaborative centers before the submission of the final original signed copies of the Collaborative Agreement to the Research Center Department.**

On behalf of the Board, I am pleased to inform you that the above-noted research proposal has been granted scientific and ethical approvals for **(6)** months starting **20 September 2021**. You are requested to kindly submit the AEs, SAEs Report and MRNs list for the enrolled participants from KFSHR-J for the Compliance Assurance Office in the Research Center along with the next progress report please by **20 February 2022** to ensure continuous approvals. The approvals shall be automatically suspended on **20 March 2022** pending submission of the progress report.

Please note the following guidance in the conduct of this research project:

1. Kindly notify the Board of any change in the protocol, SAEs, termination or completion of the research project, during the said six-month period.
2. This research project shall be timely monitored by the Assurance & Compliance Section of the Research Centre in order to ensure that research is carried out according to the approved protocol and in line with the applicable institutional policies and international guidelines.
3. You and your team are required to abide by the rules and regulation of the Kingdom in regard to the conduct of research as well as the IRB and international policies on human subject protection and confidentiality rights.
4. Personally identifying data should only be collected when necessary for research.
5. Data should be stored securely so that only a few authorized users are permitted to access the database.
6. Secondary disclosures of personally identifiable data are not allowed.
7. The use of the collected data requires IRB clearance/approvals.
8. Any serious adverse event that might occur during the conduct of this study should be reported to the Board within forty-eight (48) hours.

King Faisal Specialist Hospital & Research Centre
Institutional Review Board
لجنة أخلاقيات البحوث

Research Centre
Hawazin Abdulbagi
IRB Processing Office
H.A.

9. Kindly make sure that three (3) original Informed Consent Forms (ICFs) are signed accordingly, i.e., one (1) for the study file, one (1) for the participant or legal guardian (in case patient is a minor), and one for the Medical Record file of the participant.
10. For any clinical trial sponsored by other than a Saudi Government Agency, you need to ensure that the sponsor has registered the trial and obtained the approval of SFDA

We wish you every success in the conduct of this research project.

NCB/KACST Reg.# H-002-J-009

مستشفى الملك فيصل التخصصي ومركز الأبحاث
King Faisal Specialist Hospital & Research Centre
Gen. Org. مؤسسة عامة
Jeddah جدة
Institutional Review Board
لجنة أخلاقيات البحوث

Research Centre
Hawazin Abdulbagi
IRB Processing Office

H.A.

# Participant Information Sheet

**Study title: THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSITIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS**

**Version number and date**0.1 29.10.2020

Researcher's name: Reham Alhejaili supervised by Dr. Akram Alomainy

Queen Mary Ethics of Research Committee reference number: [Insert reference number allocated to your study by the Research Ethics Facilitators]

Invitation paragraph

We would like to invite you to be part of this research study, if you would like to. You should only agree to take part if you want to, it is entirely up to you. If you choose not to take part, there will not be any disadvantages for you, and you will hear no more about it.

Please read the following information carefully before you decide to take part; this will tell you why the research is being done and what you will be asked to do if you take part. Please ask if there is anything that is not clear or if you would like more information.

If you decide to take part, you will be asked to sign the consent form to say that you agree. You are still free to withdraw at any time and without giving a reason.

What is the purpose of the study and what would taking part involve?

The purpose of this study is to validate that wearable tracking devices are normally assistive inproviding solutions for cognitive and emotional wellness.

We will recruit healthy 20 volunteers to participate with age range of 18 to 50. They must be 50% male and 50% female. We would capture their BMI and they must ask to avoid smoking and caffeine intake 6 h prior to the measurement. Participants will be fully informed about the experimental procedure and will be invited to participate. All subjects provided written informed consent and the protocol will approved by the Ethics Committee. The Experimental will be set up in a lab. We will Covid-19 risk management. During the initial visit, a subject who were selected according to the inclusion criteria will be completed informed consent, demographic questionnaire.

Each subject will be given approximate 5 minutes of rest to control for environmental effects. They were equipped with Emotive Epoch 14 channel and Coresens sensor and GSK. They will be asked to rest with eyes closed for about 5 minutes. After that time baseline measures of HRV, EEG and GSK we collected for at least 5-minutes while starting by solving a Stroop test provided by PsyToolkit and then they rest for about 6 min.

After that, they were watching an IPAS photo companies with Sam scale. They will use the SAM scale during watching the IPAS photos which is a nonverbal pictorial technique assessment of emotions in which each affective dimension of valence, arousal and dominance is represented by 5 figures inserted in a 9-point scale. We will do 5 min Post recording for EEG, HRV and GSK.

Finally, the participant will be asked to fill in 2 questionnaires called Perceived Stress Scale (PSS) and General Anxiety Disorder-7(G7). The qualitative data were collected by using google form. All collected data were stored on a hard disk

Preparation:

We require you to fill out a pre-study consent and then the questionnaire. This questionnaire contains questions about your demographics (age, gender), and your opinion about the wearable tracking devices.

Study:

If you decide to take part, the researcher will arrange via the email.

**Baseline Recording**: You will be asked to finish the questionnaire before the end date which is 30 of July, 2022.

Time Commitment

The study will last around an hour including introduction and filling out 2 forms the consent formand the questionnaires.

Why BEING AM I invited?

You are being invited to participate in this research study because you are healthy and agedrange between 18-50 years.

Do I have to take part?

This participant information sheet has been written to help you decide if you would like to take part. It is entirely up to you; you should only agree to take part if you want to. If you do decide to take partyou will be free to withdraw at any time without needing to provide a reason, and with no penalties or detrimental effects.

What are the possible benefits of taking part?

Taking part in the study will support this PhD research that aims to further our understanding of the general opinion on Wearable Devices, stress perception in general technological support for cognitive and emotional wellness management.

What are the possible disadvantages and risks of taking part?

We don't anticipate having any risks by participating in this experiment.

Expenses and payments

This study is unpaid.

What information about me will you be collecting?

We will be collecting data by evaluating the answers in the questionnaire.

How will my data be stored and who will have access to it?

Your data will be kept strictly confidential and will be stored in fully anonymized format. Youwill not be able to be identified or identifiable in any reports or publications. Any data collected about you will be stored on a password-protected hard drive and only the researcher will be able to access it.

Data Protection Policy

Information/Data Governance Policy – DG14 – Storage of information

When and how will my data be destroyed?

Your data will be erased through hard drive formatting upon graduating with PhD degree.

How will my data be used and shared?

The results of this study will be part of the PhD thesis that is connected to this research project.Results will be mentioned in a future conference or journal paper publication. All data is storedlocally in an anonymised form and will not be accessible for or shared with  others.

Research Data Access and Management Policy

Under what legal basis are you collecting this information?

Queen Mary University of London **processes personal data** for research purposesin accordance with the lawful basis of 'public task'.

Please read Queen Mary’s privacy notice for research participants containing

**important information about your personal data and your rights** in this respect.

**If you have any questions** relating to data protection, please contact Queen Mary’sData Protection Officer, Queens’ Building, Mile End Road, London, E1 4NS or data-

protection@qmul.ac.uk or 020 7882 7596.

What will happen if I want to withdraw from this study?

You can withdraw from this study at any time without providing a reason. Withdrawing will have no disadvantage for you, and you will hear no more about this study. Your data will onlybe submitted if you complete the study.

Your data will be saved entirely anonymised and is not possible to link the data to a particularperson. For this reason, it is however not possible to delete the data entry of a specific person.

What should I do if I have concerns about this study?

If you have any concerns about the manner in which the study was conducted, in the first instance, please contact the researcher(s) responsible for the study Dr. Akram Alomainy(a.alomainy@qmul.ac.uk ) .

If you have a complaint which you feel you cannot discuss with the researchers then you should contact the Research Ethics Facilitators by e-mail: research- ethics@qmul.ac.uk. When contacting the Research Ethics Facilitators, please provide details of the study title, description of the study and QMERC reference number (where possible), the researcher(s) involved, and details of the complaint you wish to make.

Who can I contact if I have any questions about this study?

Dr. Akram Alomainy

a.alomainy@qmul.ac.uk

Reham Alhejaili

r.a.s.alhejailii@qmul.ac.uk

# Consent Form

**Title of Research Study:** THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSISTIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS

Principal Investigator: Dr. Akram Alomainy

Queen Mary Ethics of Research Committee Ref: [Insert the reference number allocated to your research ethics application by the Research Ethics Facilitator].

Thank you for your interest in this research.

Should you wish to participate in the study, please consider the following statements. Before signing the consent form, you should initial all or any of the statements that you agree with. Your signature confirms that you are willing to participate in this research, however, you are reminded that you are free to withdraw your participation at any time.

| Statement | Please initial box |
|---|---|
| 1. I confirm that I have read the Participant Information, or it has been read to me. I have had the opportunity to consider the information, ask questions, and have these answered satisfactorily. | |
| 2. I understand that my participation is voluntary and that I am free to stop taking part in the study at any time without giving any reason and without my rights being affected. | |
| 3. I understand that my data will be accessed by the investigator. | |

| | |
|---|---|
| 4. I understand that my data will be securely stored on a password protected hard drive and in accordance with the data protection guidelines of the Queen Mary University of London until the graduating of the researcher in fully anonymized form. | |
| 5. I understand that I can access the information I have provided and request the destruction of that information at any time before the end of the year 2022. I understand that following that date I will not be able to request the withdrawal of the information I have provided. | |
| 6. I understand that the researcher will not identify me in any publications and other study outputs using personal information obtained from this study. | |
| 7. I understand that the information collected about me will be used to support other research in the future. | |
| 8. I agree to be contacted about other research studies in the future. | |
| 9. I agree to take part in the above study. | |

Participants should read Queen Mary's privacy notice for research participants which contains important information about your personal data and your rights in this respect. If you have any questions relating to data protection, please contact Data Protection Officer, Queens' Building, Mile End Road, London, E1 4NS or data-protection@qmul.ac.uk or 020 7882 7596.

__________________ _______________ __________________________________

Participant name Date Signature

__________________ _______________ __________________________________

Name of person Date Signature

taking consent

I Reham Alhejaili, confirm that I have carefully explained the nature, demands, and any foreseeable risks (where applicable) of the proposed research to the participant and provided a copy of this form.

Principal Investigator (or Supervisor for student projects)

Akram Alomainy

a.alomainy@qmul.ac.uk

Student Investigator (if applicable)

Reham Alhejaili

r.a.s.alhejaili@qmul.ac.uk

# A. Perceived Stress Scale- 10 Items

The questions in this scale ask you about your feelings and thoughts during the last month. In eachcase, please indicate with a check how often you felt or thought a certain way.

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| never | almost never | sometimes | fairly often | very often |

1. In the last month, how often have you been upset because of something that happened unexpectedly?
2. In the last month, how often have you felt that you were unable to control the important things in your life?
3. In the last month, how often have you felt nervous and "stressed"?
4. In the last month, how often have you felt confident about your ability to handle your personal problems?
5. In the last month, how often have you felt that things were going your way?
6. In the last month, how often have you found that you could not cope with all the things thatyou had to do?
7. In the last month, how often have you been able to control irritations in your life?
8. In the last month, how often have you felt that you were on top of things?
9. *In the last month, how often have you been angered because of things that were outside ofyour control?*
10. In the last month, how often have you felt difficulties were piling up so high that you couldnot overcome them

## B. GAD-7 Anxiety

| Over the last two weeks, how often have you been bothered by the following problems? | Not at all | Several days | More than half the days | Nearly every day |
|---|---|---|---|---|
| 1. Feeling nervous, anxious, or on edge | 0 | 1 | 2 | 3 |
| 2.Not being able to stop or controlworrying | 0 | 1 | 2 | 3 |
| 3.Worrying too much about differentthings | 0 | 1 | 2 | 3 |
| 4. Trouble relaxing | 0 | 1 | 2 | 3 |
| 5. Being so restless that it is hard to sitstill | 0 | 1 | 2 | 3 |
| 6. Becoming easily annoyed or irritable | 0 | 1 | 2 | 3 |
| 7. Feeling afraid, as if something awfulmight happen | 0 | 1 | 2 | 3 |

Column totals ________ +______+ ________ +______=

Total score

If you checked any problems, how difficult have they made it for you to do your work, take care.

| Not difficult At all | Somewhat difficult | Very difficult | Extremely difficult |
|---|---|---|---|

Source: Primary Care Evaluation of Mental Disorders Patient Health Questionnaire (PRIME-MD- PHQ).

The PHQ was developed by Drs. Robert L. Spitzer, Janet B.W. Williams, Kurt Kroenke, andcolleagues. For research information, contact Dr. Spitzer at ris8@columbia.edu. PRIME-MD® is a trademark of Pfizer Inc. 

Scoring GAD-7 Anxiety Severity:

This is calculated by assigning scores of 0, 1, 2, and 3 to the response categories, respectively,of "notat all," "several days," "more than half the days," and "nearly every day."

GAD-7 total score for the seven items ranges from 0 to 21.

0–4: minimal anxiety

5–9: mild anxiety

10–14: moderate anxiety

15–21: severe anxiety

# C. Demographical Survey and Data Collection

**Study title:** THE USE OF WEARABLE TECHNOLOGY IN PROVIDING ASSISTIVE SOLUTIONS FOR COGNITIVE AND EMOTIONAL WELLNESS

**Questions**

1. What is your age?
2. What is your gender?
   - Female
   - Male
   - prefers not to say.

3 Have you consumed any caffeine beverages in the past two hours?

- [ ] Yes
- [ ] No

4. Have you consumed any alcoholic beverages in the past 24 hours?

- [ ] Yes
- [ ] No

5. Do you usually smoke? If yes, please report the number of cigarettes.

- [ ] Yes
- [ ] No

you smoke on a daily basis……………….

6. Have you smoked in the past two hours?

- [ ] Yes
- [ ] No

7. Have you been clinically diagnosed anyCognitive disease?

- [ ] Yes
- [ ] No

If yes, please specify………….

8.Do you have any history of heart disease?If yes, please specify………

- [ ] Yes
- [ ] No

# Bibliography

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