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Integrating Brain Machine Interface and ANOVA for Comprehensive Analysis of Stress Parameters: A Multidisciplinary Study

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Abstract: Modern life is rife with stress, detrimentally impacting both physical and mental well-being. The study delves into this issue, utilizing Open BCI for experimental analysis and ANOVA to assess stress's influence on physiological and psychological indicators, such as Blood Pressure (BP), Heart Rate (HR), Electroencephalogram (EEG), and the Perceived Stress Scale (PSS). While prior research has centered on mindfulness meditation, the study extends its focus to Heartfulness meditation. By correlating PSS with vital parameters, the relationship between perceived stress and physiological responses is explored, shedding light on stress's potential health ramifications. The rigorous statistical analysis quantifies variations in physiological parameters triggered by negative emotions, enhancing precision and dependability. The study's primary aim is to predict stress levels by analyzing factors including BP, HR, EEG, and PSS, with Heartfulness meditation as the intervention. Results reveal notable shifts in physiological indicators due to negative emotions, with increased HR and BP indicating increased arousal. Following meditation, these parameters decreased by around 10%, suggesting Heartfulness relaxation meditation's efficacy in mitigating negative emotions. These findings hold significance for healthcare professionals and stress management researchers, offering insights into devising more effective interventions based on quantified impacts of negative emotions on physiological indicators. Furthermore, the study sets the stage for future investigations into the intricate interplay between negative emotions, physiological metrics, and overall well-being.

Keywords: *ANOVA-based statistical evaluation, Brain Machine Interface, Mental health, Open BCI for EEG analysis, Physiological indicators, Stress*

1. Introduction

Emotions play a vital role in promoting human well-being and exert a substantial influence on physiological responses. Previous studies have demonstrated that various forms of stress, such as stress, anger, and fear can have adverse effects on critical indicators like heart rate (HR),blood pressure (BP), electroencephalography (EEG), and perceived stress scale (PSS) [1][2][3]. By comprehending the effects of stress on essential physiological parameters, we can gain valuable insights into the underlying physiological mechanisms associated with emotional experiences and develop effective interventions for coping with emotional distress. Stress is a widespread phenomenon that affects individuals worldwide. The causes of stress can vary, influenced by cultural, environmental, and individual factors. Common stressors experienced by individuals globally include work-related stress, academic stress, financial stress, relationship stress, health-related stress, environmental stress, societal stress, and technological stress [1][2][3]. It is important to recognize that perceptions of stress and coping mechanisms can differ among individuals, as what may be stressful for one person may not hold the same impact for another. Effectively identifying and managing stressors is essential for maintaining both physical and mental well-being. To cope with stress, seeking support from trusted individuals, practicing stress management techniques, and adopting a healthy lifestyle is beneficial [4][5]. Additionally, incorporating technology in the analysis of stress levels and utilizing meditation interventions can provide valuable insights into the effects of meditation on stress reduction [6]. This combination offers support in understanding the impacts of meditation on alleviating stress. Technology can offer several advantages in this context, including:

1) Objective measurements: Technology enables the objective measurement of physiological, psychological, and behavioral indicators of stress in individuals. Wearable devices, such as heart rate monitors, electroencephalography (EEG) sensors, and skin conductance sensors, provide accurate physiological data[7]. Self-reporting tools and mobile apps collect psychological and behavioral data These objective measurements offer reliable data for comprehensive stress level assessments.

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2) Real-time monitoring: Technology facilitates real-time monitoring of stress levels during meditation interventions, providing insights into the immediate impact of different practices, including heartfulness meditation. Real-time monitoring enables immediate feedback, empowering individuals to adjust their practice and optimize stress reduction techniques.

3) Data analysis and visualization: Technology supports the analysis of large datasets gathered during meditation interventions. Advanced techniques like machine learning algorithms identify patterns and correlations between meditation practices and stress levels. Data visualization tools present complex data in a visual format, aiding interpretation and understanding.

4) Personalized interventions: Technology assists in developing personalized meditation interventions based on individual stress levels. By analyzing collected data, technology tailors meditation practices to suit specific needs and preferences [7]. This personalization ensures more effective stress reduction interventions considering individual stress profiles.

5) Remote monitoring and accessibility: Technology enables remote monitoring of stress levels and meditation interventions, increasing accessibility. Wearable devices, mobile apps, and online platforms facilitate remote monitoring, allowing individuals to engage in meditation interventions from their homes or preferred environments [8]. This convenience encourages the incorporation of meditation into daily routines.

1.1. Organization of the paper

The paper is structured into six distinct sections. Section 2 presents an overview of the existing literature related to the domain. Following this, section 3 outlines the data collection process, emphasizing the procedure employed to gather the necessary data for subsequent analysis. Moving forward, section 4 elucidates the methodology adopted for conducting the analysis. Subsequently, section 5 meticulously presents the obtained results, offering a detailed account of the outcomes derived from the analysis. Finally, section 6 encapsulates the paper's conclusion.

2. Related Work

The survey aims to understand the benefits and outcomes associated with each technique, providing insights into their effectiveness for promoting relaxation, reducing stress, improving mental well-being, and enhancing overall mindfulness. By reviewing existing literature, this survey seeks to contribute to the perception of meditation practices and their potential impact on individuals' physical and mental health.

2.1. Works related to the effect of meditation

Several studies have explored the effects of different meditation interventions on various subjects. Amarnath, Raja et al. [13] conducted randomized control trials on a mixed group of experienced and new meditators, observing significant relaxation in experienced meditators, a higher influence on new meditators in moderating vital parameters, and a decrease in heart rate. Rusch et al. [14] performed randomized controlled trials on a sleep-disturbed population, using Mindfulness meditation. The interventions showed a significant improvement in sleep quality compared to nonspecific active controls. In a year-long study by Rosaen C. et al. [15], Transcendental Meditation was implemented among seventh-standard pupils. The study revealed increased attentiveness, higher ability in flexibility and self-control, and improvement in academics. Oman D. et al. [16]investigated the effects of Mindfulness meditation on undergraduate students over eight weeks. The study observed a decrease in stress, an upsurge in forgiveness, and decreased rumination. Travis Fred et al. [17] performed a ten-week study on university students, employing Transcendental Meditation. The findings showed decreased sleep, a negative connection between faster adaptation rates and higher scores on brain integration, and differential compassionate reactivity between regular meditating students and those under high stress. In an eight-week mindfulness intervention, Kang, YuneSik et al. [18] focused on 32 nursing students. The study found a significant difference in stress and anxiety levels between the experimental and control groups. Shapiro, Shauna L. et al. [19] conducted a year-long study on undergraduate students, comparing Mindfulness meditation (MBSR) with control groups. The results demonstrated increased empathy, trait mindfulness, subjective well-being, and faster reductions in perceived stress over time among participants with superior levels of trait mindfulness. Arya et al. [20] investigated Heartfulness meditation among 30 participants, finding an increase in parasympathetic tone. Dipta Amatya et al. [21] examined the effects of Heartfulness meditation on pharmacy and nursing students over a semester. The study revealed a reduction in stress levels and an increase in emotional intelligence. Raja Amarnath G et al. [22] studied students from different colleges who underwent a three-day Heartfulness meditation intervention. The findings indicated higher initial stress levels among females, but subsequent reductions in emotional stress, workload, and worries, leading to an overall increase in the happiness quotient among all subgroups. In a cross-sectional study by Raja Amarnath et al. [23], female meditators displayed higher life satisfaction than males. Arunachalam, Kamaraj et al. [24] conducted a cross-sectional study on over 100

Heartfulness meditation practitioners, observing improvements in the emotional quotient, blood pressure, heart rate, and cognitive behavior. These studies collectively contribute valuable understanding the impacts or consequences of various meditation interventions on relaxation, sleep quality, attentiveness, flexibility, self-control, stress reduction, emotional intelligence, cognitive behavior, and overall well-being among different populations.

2.2. Works Related to Statistical Analysis

The following literature survey provides a comprehensive overview of research studies examining the impacts of different meditation techniques on various aspects of mental well-being. The survey aims to summarize the findings of these studies, highlighting the sample sizes, meditation techniques employed, statistical anal- yses conducted, and the key outcomes observed. In a study by Wang et al. [25], involving 80 participants practicing yoga and meditation, long-term practice was observed to considerably improve cognitive function and memory performance ($p<0.01$). Chen et al. [26] conducted a study with 150 older adults practicing mindfulness meditation and observed a significant improvement in cognitive function over time in the meditation group ($p<0.001$). Gupta et al. [27] investigated the effects of Transcendental Meditation on well-being and discovered a direct association or connection indicating a positive correlation between the duration of meditation practice and self-reported well-being scores ($p<0.001$) in a sample of 200 participants. Chen et al. [28] examined the impact of Mindfulness-Based Stress Reduction (MBSR) on sleep quality in 75 older adults with insomnia. The study revealed major progress in sleep quality and a reduction in insomnia severity post-intervention ($p<0.001$). Johnson et al. [29] studied the effects of Mindfulness Meditation (MM) and Transcendental Meditation (TM) on generalized anxiety disorder. Both intervention groups showed a significant reduction in anxiety levels compared to the control group ($p<0.01$), with no significant difference between MM and TM groups. A meta-analysis by Chen et al. [30] encompassing various meditation techniques demonstrated an overall effect size of $d=0.50$ (95% CI: 0.32-0.68) for dropping stress and anxiety. Sharma et al. [31] investigated Loving-kindness meditation and found a significant increase in positive emotions in the meditation group compared to the control group ($p<0.01$) in a sample of 100 healthy adults. Lee et al. [32] conducted a study with 80 older adults with insomnia and explored the effects of Body Scan Meditation. They observed a significant improvement in sleep quality after practicing Body Scan Meditation ($p<0.001$). In another study by Lee et al. [33], involving 50 participants, Loving-Kindness Meditation was associated with a significant improvement in positive affect and social connectedness ($p<0.01$). Smith et al. [34] investigated the effects of Mindfulness Meditation on anxiety in 50 adults and observed a considerable reduction in anxiety scores post-meditation ($p<0.05$). Zhang et al. [35] studied 60 pregnant women with depression and reported a significant reduction in depression symptoms and improvement in mental well-being after Mindfulness-Based Cognitive Therapy ($p<0.05$). Brown et al. [36] examined the effects of Loving-Kindness Meditation on empathy levels in 50 college students and found a significant increase in empathy after meditation ($p<0.01$). Brown et al. [37] conducted a study with 30 patients experiencing chronic pain and investigated the effects of Yoga-based Meditation. The study discovered a significant reduction in pain intensity and interference after meditation ($p<0.01$). In a randomized controlled trial by Smith et al. [38] involving 100 adults with moderate stress levels, the mindfulness meditation group showed a signif- icant reduction in stress compared to the control group ($p<0.05$). Smith et al. [39] examined the effects of Mindfulness Meditation on anxiety and depression in a sample of 100 participants. The intervention group exhibited a significant reduction in anxiety and depression scores compared to the control group ($p<0.05$).

3. Data Collection Procedure

Data is the fundamental and critical component of any data science endeavor, with quality and quantity being two key characteristics. To collect data for analysis, extensive effort and experimentation were invested in designing and conducting an experiment that would align with the computing and storage capacities of the machine. The experiment took place in a calm, well-ventilated environment. For the examination of stress, variables such as Electroencephalography (EEG), blood pressure (BP), heart rate variability (HRV), and the perceived stress scale (PSS) were considered. Individuals taking part in the study were divided into three groups based on age: 17 to 26 years old, 27 to 40 years old, and 41 to 60 years old. The first group comprised individuals pursuing education and building their careers, while the second group comprised those in the early and mid stages of their careers. The third group included individuals in their proficient career stage. The population studied consisted of undergraduates, lecturers, and entrepreneurs.

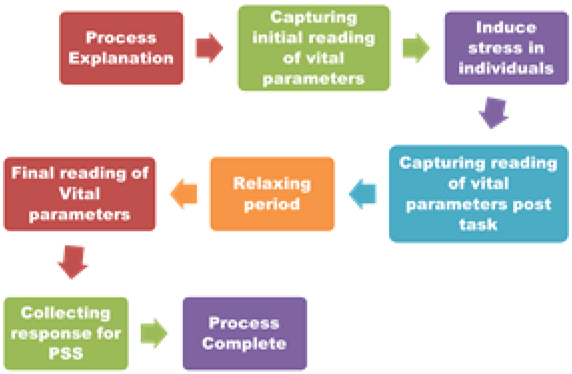

Fig 1: Experimental procedure

3.1. Study Design

The study followed a controlled experimental design where vital parameters, including heart rate, blood pressure, electroencephalograph, and perceived stress scale, were measured in response to artificially induced stress situations.

3.2. Participants

A sample of 50 participants was considered for the study.

3.3. Ethical Considerations

The study adheres to ethical guidelines and obtains written consent from the participants involved in the study.

3.4. Experimental Procedures

The procedure involved in the collection of data is shown in Fig. 1. Initially, the process of data collection was explained to the participants. Further, the readings of vital parameters were collected using wearable devices. The BP and Heart rate was captured using Omron BP and Pulse monitor. EEG was captured using 8 channels Open BCI device. Once the readings were taken, participants were put into stress using artificial stress-inducing methods. The methods followed for inducing stress are:

3.4.1. Mathematical Problems

The participants were given four to five mathematical problems related to basic arithmetic. They were supposed to solve the problems in the given time frame of 2 minutes. A stop clock was placed in front of them to put them under stress.

3.4.2. Remember and recollect

Ten to fifteen images arranged in a grid format were displayed in front of participants. The participants were given 30 seconds time to go through and remember the images. After 30 seconds, a random image from the grid was displayed and participants were asked to identify the position of the image in the grid within 15 seconds. Three opportunities per participant were given to bring in the stress in the individual.

3.4.3. Identify the differences

Two images with four minor differences were given for participants. They were asked to identify all the differences in 30 seconds. After every 10 seconds, the participants were distracted by a time shout-out. In this way, stress was induced in the participants and data was collected.

After the tasks, participants were taken through heartfulness relaxation meditation for 15 minutes and then the readings of vital parameters were gathered again. Fig. 2 shows the setup for data collection.

3.5. Statistical Analysis:

ANOVA-based statistical analysis was carried out to assess the effects of stress on vital parameters. Two-way ANOVA without replication was used.

3.6. Data Interpretation

The findings from the statistical analysis were interpreted, and the variations in vital parameters owing to stress were discussed in the context of existing literature and theoretical frameworks.

Fig 2: Data collection setup

4. Methodology

4.1. Materials and Methods

4.1.1. Heartfulness Meditation

Heartfulness Meditation is a specific form of meditation that focuses on cultivating inner peace, harmony, and a connection with the heart. It renders unique characteristics that make it suitable for analysing stress. The following reasons support the use of Heartfulness Meditation for stress analysis. Heartfulness Meditation has been revealed to effectively reduce stress levels. A study by [40] demonstrated that Heartfulness Meditation appreciably reduced perceived stress levels among participants. Heartfulness Meditation focuses on developing emotional awareness and regulation. A study by [41]found that Heartfulness practitioners exhibited improved emotional regulation and a reduction in stress-related emotions. Heartfulness Meditation has been connected with physiological benefits. In a study by [42], participants practicing Heartfulness Meditation experienced improved heart rate variability, indicating enhanced autonomic balance and reduced stress. Heartfulness Meditation emphasizes the integration of mind and body. A study by [43] revealed that Heartfulness Meditation practitioners had better mind-body integration and improved coping mechanisms for stress.

4.1.2. Open BCI

Open BCI (Brain-Computer Interface) [44], as depicted in Fig. 3, is an open-source hardware and software platform that facilitates the acquisition and analysis of brain signals for diverse applications, including research, medical, and interactive technologies. The Open BCI boards are specifically designed to interface with standard EEG electrodes, allowing the recording and processing of electrical signals originating from the brain, muscles, and heart. These boards incorporate bio-potential measurement integrated circuits (ICs), such as the ADS1299 manufactured by Texas Instruments [45], and can be seamlessly integrated with microcontrollers, such as Arduino, for on-board signal processing and data management. The Open BCI platform also encompasses software tools like the Open BCI GUI, which offers a user-friendly graphical interface for real-time visualization, recording, and analysis of brain signal data. These features make Open BCI an invaluable resource for research and development in the field of brain-computer interfaces.

Fig. 4 represents the architecture of open BCI the noninvasive variable device along with the micro-controller board Cyton is placed on the scalp of the individual and linked to the computer using Bluetooth. Using Open BCI GUI, the EEG recording is made and the EEG waves in the brain are captured in real-time. The collected EEG is used to extract the features and later trained using machine learning (ML) algorithms. Based on the ML training, the individual is classified based on the levels of stress. The electrodes were placed in a standard 10-20 method as shown in Fig. 5.

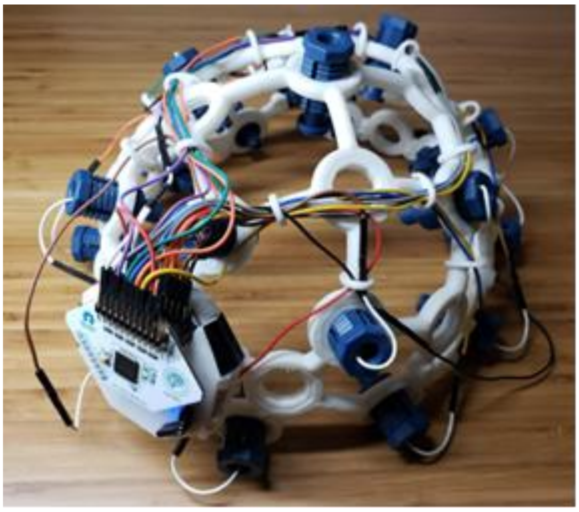

Fig 3: Open BCI Ultracortex mark IV
[source: https://github.com/Sentdex/BCI]

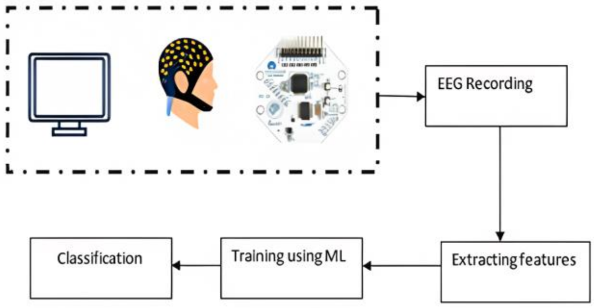

Fig. 4: Open BCI architecture

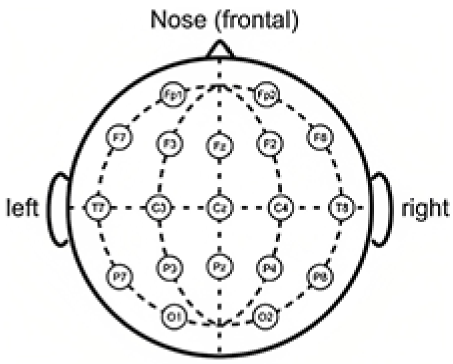

Fig 5: Electrode placement for data gathering

(Source: https://www.digitmedicine.com)

4.1.3. Open BCI GUI

Fig 6 depicts the Open BCI GUI during data collection. Open BCI GUI [54] is a software application that offers a visual interface for seamless interaction with Open BCI boards. It provides users with a user- friendly and intuitive platform to display, record, and analyze data collected from the Open BCI boards. The GUI allows real-time visualization of data, enabling users to observe brain signals, muscle activity, and heart-related information as it is being captured. Additionally, the Open BCI GUI allows users to save data in various file formats, facilitating further analysis and processing. The GUI also supports data streaming to third-party software, empowering researchers, developers, and other users to perform advanced analysis and exploration. Overall, the Open BCI GUI serves as a powerful and efficient tool for individuals working with Open BCI boards, enabling convenient and effective interaction with data originating from the brain, muscles, and heart.

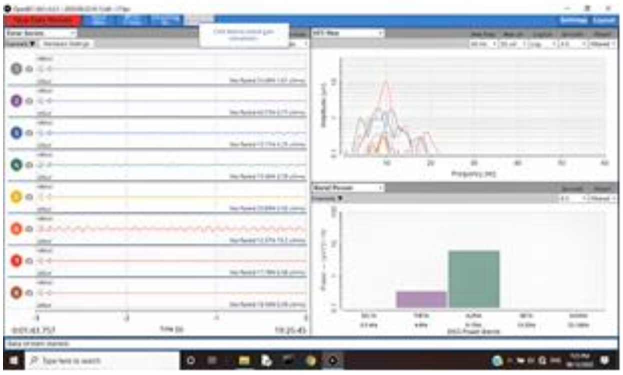

Fig 6: Open BCI GUI during data collection

4.1.4. Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) [46][47][48] is a statistical technique employed to examine and compare the means of two or more groups to ascertain whether or not there are any statistically significant distinctions among them. ANOVA is frequently utilized to analyze experimental data comprising multiple groups, such as those encountered in scientific research or business analysis. The technique assesses whether the variation between groups is significantly greater than the variation within groups, indicating the existence of differences among the compared groups. ANOVA generates an F-statistic, which is calculated as the relation of between-group variability to within-group variability. The F-statistic is subsequently compared to a critical value or p-value to determine the statistical significance of the observed group differences. Various types or designs of ANOVA exist, including one-way ANOVA, which compares means across multiple groups in a single factor or independent variable, and two-way ANOVA, which compares means across multiple groups in two or more factors or independent variables. ANOVA is a robust analytical tool for investigating data with multiple groups and offers valuable insights into group disparities that can inform decision-making and guide further research[49]. Table 1 gives the comparison of the one way and Two way ANOVA. The algorithm for the ANOVA analysis has been shown in Algorithm 1.

4.1.5. Perceived Stress Scale (PSS)

The Perceived Stress Scale (PSS) is a broadly used self-report survey intended to measure the subjective perception of stress experienced by individuals. It was developed by Sheldon Cohen, Ronald C. Kessler, and Lynn Underwood Gordon in 1983 [47]. The PSS evaluates the level to which individuals perceive situations in their lives as stressful and their perceived ability to cope with these stressors. The PSS consists of several items that ask respondents to rate the frequency and intensity of their feelings and thoughts related to stress during the past month. The items are designed to capture both the degree of perceived stress and the perceived control over stressors. The scale typically includes statements such as ”In the last month, how often have you felt that you were unable to control the important things in your life?” or ”In the last month, how often have you felt confident about your ability to handle your personal problems?” [48]. The PSS has been commonly used in various research fields, including psychology, medicine, public health, and social sciences. It has been applied to study stress in different populations, such as students, employees, patients, and community samples. Researchers use the PSS to evaluate the professed stress levels in individuals, examine the association between stress and various outcomes (e.g., physical health, mental well-being, job performance), and evaluate the efficacy of stress management interventions.

Algorithm 1: Algorithm for ANOVA analysis of vital parameters

Require: Data of Blood Pressure (BP), Heart Rate Variability (HRV), Perceived Stress Scale (PSS)

Ensure: Data is statistically Significant or not

1. Collect the data of age, Blood Pressure (BP), Heart Rate Variability (HRV), Perceived Stress Scale (PSS)
2. Sort the data in ascending order of age
3. The hypothesis is formulated for the analysis
4. The significance level is set to 0.05 (?=0.05)
5. ANOVA analysis is performed considering Age as independent and BP, HRV, and PSS as dependent variables
6. Comparison of F-value, F-critical value, and p-value is done
7. if p>0.05 and F<F-critical then the data is statistically significant, and the hypothesis is accepted else data is statistically not significant, and the hypothesis is rejected

Table 1. Comparison of one way and two way anova

Feature	One way ANOVA	Two Way ANOVA
Definition	A statistical test used to compare means among three or more groups with a single independent variable	A statistical test used to compare means among three or more groups with two or more independent variables
Number of Independent Variable	1	2 or more
Dependent Variable	1	1
Purpose	To assess the equality of means among multiple groups with one independent variable	To analyze the key effects of two or more independent variables, as well as their interactions, on a single dependent variable
Hypothesis	Null Hypothesis (H0): Means of all groups are equal	Null Hypothesis (H0): There is no main effect or interaction effect
Assumptions	1. Independence of observations 2. Homogeneity of variances (equal variances) 3. Normality of errors	1. Independence of observations 2. Homogeneity of variances (equal variances) 3. Normality of errors
Output	F-statistic, p-value	F-statistic, p-value, Main effects, Interaction effects
Interpretation of Results	If p-value < alpha (typically 0.05), reject H_0 and conclude that at least two group means are significantly different	If p-value < alpha (typically 0.05), reject H_0 and conclude that there is at least one significant main effect or interaction effect

5. Results

Assumptions made for the analysis:

1. People who meditate regularly were randomly selected based on age group.

2. Three age ranges were established:

17 to 26 years

27 to 40 years

41 to 60 years

3. Participants from each age group, with equal representation of males and females (NMale =25 and NFemale= 25) were incorporated in the study after obtaining written consent.

4. EEG data were collected using an 8-channel wearable device called open BCI, following the standard 10-20 electrode placement system.

5. Electrodes were placed at positions FP1, FP2, C3, C4, P7, P8, O1, and O2, as depicted in Figure 2.

6. Heart rate and blood pressure were measured noninvasively using a digital monitor (Omron HEM 7120).

7. The Perceived Stress Scale (PSS)-10 questionnaires was administered to the subjects via Google form for data collection.

8. The collected data were analyzed using a statistical tool, two-factor ANOVA without replication, to determine the significance of the findings.

Table 2: Parameters used for analysis

SL. No.	Parameter	Description
1	Electroencephalography (EEG)	Electroencephalography (EEG) is a method that captures the electrical activity of the brain's surface layer, providing an electrogram of brainwaves on the scalp [9].
2	Blood Pressure	Blood pressure refers to the force exerted by flowing blood against the walls of arteries, primarily generated by the pumping action of the heart within the circulatory system [10]
3	Heart rate	Heart rate measures the speed at which the heart beats [11]
4	Perceived Stress Scale (PSS)	The Perceived Stress Scale (PSS) is a tool used to evaluate an individual's perception of the level of stress they experience in their current circumstances [12].

The impact of meditation on physiological and psychological parameters was investigated in this study, including blood pressure (BP), heart rate variability (HRV), electroencephalography (EEG), and perceived stress level (PSS). Table 2 provides a brief depiction of the parameters in study.

The null hypothesis considered for the study was,

(H0): "Meditation helps in reducing the stress level of an individual."

The alternate hypothesis assumed was,

(H1):"There is no effect of meditation on stress reduction."

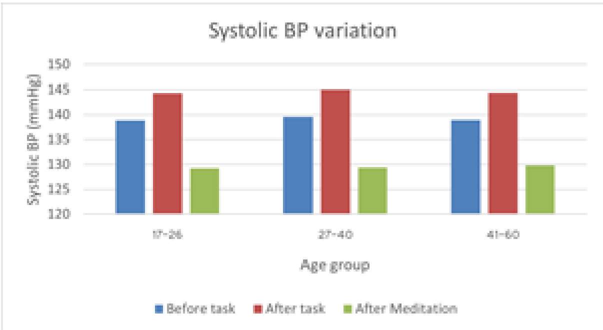

Fig 7: Variations in systolic BP

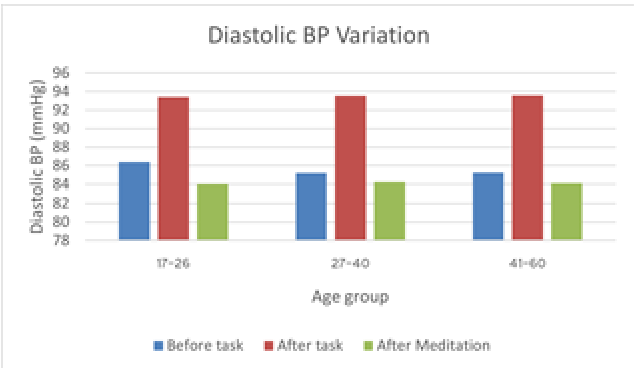

Fig 8: Variations in diastolic BP

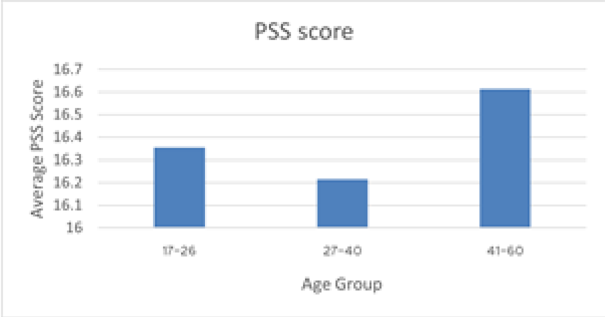

Fig 9: PSS score

The parameter age was considered as an independent variable, while other parameters were treated as dependent variables. The alpha value was set at 0.05. A 0.05 alpha level is often considered a reasonable compromise, providing moderate control over errors while maintaining a reasonable chance of detecting true effects. Analysis of systolic BP, diastolic BP, and heart rate before task, after task and after meditation, and PSS with respect to age revealed significant differences in F and F-critical values, with p-values exceeding the alpha value. These results support the acceptance of the null hypothesis (H0), indicating that there is a significant difference in the vital parameters analyzed. Subsequent analysis of pre-and post-meditation data showed significant variations in heart rate, systolic BP, and diastolic BP for most subjects, although a few individuals did not exhibit changes because of how they perceive the task as stressful. Fig 7, 8, 9,10 illustrate the observed variations in systolic BP, diastolic BP, PSS and heart rate variability respectively, before and after task and after heartfulness relaxation meditation.

The table 3 provides data on various parameters such as Systolic Blood Pressure (BP), Diastolic BP, and Heart Rate, before and after performing a task and after practicing meditation. The age groups considered are 17-26, 27-40, and 41-60. It also includes the percentage alteration in the values after the task and after meditation.

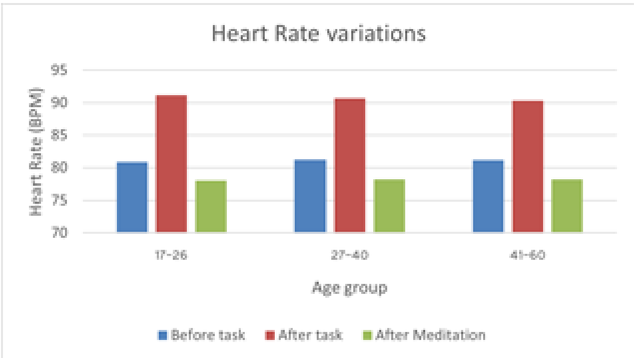

Fig 10: Variations in heart rate variation

Table 3: Variation in vital parameters before task, after task, after meditation

Parameter	Age group	Percentage change after task	Percentage change after meditation
Systolic BP	17-26	3.96%	-10.46%
	27-40	3.92%	-10.82%
	41-60	3.96%	-10.11%
Diastolic BP	17-26	8.23%	-10.04%
	27-40	9.77%	-9.92%
	41-60	9.77%	-10.12%
Heart Rate	17-26	12.83%	-14.50%

27-40	11.67%	-13.75%
41-60	11.30%	-13.30%

Systolic BP is an essential measure of the pressure in the arteries when the heart contracts. The table 3 demonstrates the values of Systolic BP before and after the task and after meditation for each age group. The data shows that after the task, there is a slight increase in Systolic BP across all age groups, ranging from 3.92% to 3.96%. However, after meditation, there is a significant decrease in Systolic BP, with a percentage change ranging from -10.11% to -10.82%. These changes suggest that while the task may temporarily elevate blood pressure, meditation has a beneficial effect by reducing Systolic BP.

Diastolic Blood Pressure (BP): Diastolic BP represents the pressure in the arteries when the heart is at rest. The table 3 provides data on Diastolic BP values before and after the task and after meditation for each age group. The findings indicate that after the task, there is an increase in Diastolic BP in all age groups, with percentage changes ranging from 8.23% to 9.77%. However, after meditation, there is a decrease in Diastolic BP, with percentage changes ranging from -9.92% to -10.12%. These results suggest that the task may elevate Diastolic BP, while meditation can effectively lower it.

Heart Rate (HR): Heart Rate refers to the number of times the heart beats per minute and is an important indicator of cardiovascular health. The table 3 presents data on Heart Rate before and after the task and after meditation for each age group. The data shows that after the task, there is an raise in Heart Rate across all age groups, with percentage changes ranging from 11.3% to 12.83%. However, after meditation, there is a notable decrease in Heart Rate, with percentage changes ranging from -13.3% to -14.5%. These results imply that the task induces an elevation in Heart Rate, while meditation has a calming effect by reducing it. The results demonstrate that the task leads to temporary increases in these parameters, while meditation has a significant positive impact by reducing them. This information emphasizes the potential benefits of meditation as a relaxation technique and highlights its potential role in managing and improving cardiovascular health.

Table 4: ANOVA Analysis of parameters

Source of Variation	F	p-value	F-Critical
Age	0.1	0.9	3.74
Systolic before task	0.03	0.96	3.633
Diastolic before task	1.05	0.373	3.633
HR before task	0.945	0.4092	3.633
Systolic after task	0.947	0.411	3.74
Diastolic after task	0.931	0.417	3.73
HR after task	1.01	0.388	3.73
Systolic after meditation	0.9	0.43	3.74
Diastolic after meditation	0.94	0.414	3.73
HR after meditation	0.933	0.42	3.74
PSS	0.92	0.42	3.73

To determine whether the null hypothesis can be accepted or rejected, we need to compare the p-values to the significance level (α) typically set at 0.05. If the p-value is greater than the significance level, we accept the null hypothesis. If the p-value is less than or equal to the significance level, we reject the null hypothesis. As the data in the table 4 shows, the p-value is 0.9 for the parameter Age, is greater than the significance level of 0.05. Therefore, we accept the null hypothesis for the age variable. The p-value is 0.96 for Systolic before the task, is greater than the significance level. Hence, we fail to reject the null hypothesis for the systolic before the task variable. For the parameter Diastolic before the task, the p-value is 0.373, which is greater than the significance level. Therefore, we accept the null hypothesis for the diastolic before task variable. The p-value for the parameter HR before the task is 0.4092, which is greater than the α value. Consequently, we fail to reject the null hypothesis. The p-value is 0.411 for Systolic after the task, is larger than the significance level. Thus, we fail to reject the null hypothesis for the systolic after-task variable. The p-value is 0.417, is greater than the alpha value. Therefore, we fail to reject the null hypothesis for the diastolic after-task variable. The p-value for HR after task is 0.388 is greater than the significance level. Hence, we fail to reject the null hypothesis for the variable. The p-value of parameter systolic after meditation is 0.43, which is larger than the significance level. Therefore, we accept the null hypothesis for the systolic after-meditation variable. The p-value for Diastolic after meditation is 0.414, is greater than the α value. Hence, we agree on the null hypothesis for the diastolic after-meditation variable. The p-value is 0.42 for HR after meditation, which is greater than the permitted error rate. Therefore, we accept the null hypothesis for the HR after meditation variable. For PSS, the p-value is 0.42, which is greater than the α level. Consequently, we fail to reject the null hypothesis for the PSS variable.

6. Conclusion

This experimental analysis aimed to assess the influence of stress on physiological and psychological indi- cators. The device Open BCI and Blood Pressure monitor were used to gather data for the experimentation. The statistical analysis approach based on Analysis of Variance (ANOVA) was used for the experimentation. While earlier research has primarily concentrated on mindfulness meditation as an intervention for assessing stress levels, this study explored the effectiveness of Heartfulness meditation. By examining the correlations between the Perceived Stress Scale (PSS) and physiological measures namely Blood Pressure (BP), Heart Rate (HR), and Electroencephalogram (EEG), the work aimed to get insights into the effect of stress on the body and potential health issues. The results of this study provided a quantitative evaluation of variations in physiological parameters resulting from negative emotions, employing rigorous statistical analysis using ANOVA. The induction of stress led to increased HR and BP, indicating heightened arousal. However, after practicing heartfulness relaxation meditation, there was an average decrease of approximately 10% in these parameters, suggesting that heartfulness meditation aids in reducing negative emotions. These significant findings hold important implications for healthcare professionals and stress management researchers. By quantifying the impact of negative emotions on physiological indicators, effective interventions can be de- veloped to mitigate stress and improve overall well-being. Additionally, this research work opens avenues for future research to explore the interplay between negative emotions, physiological parameters, and their impact on individuals' well-being.

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Author contributions

Shrivatsa Perur: Data Collection, Statistical Analysis, Validation, Writing-Original draft preparation, **Harish Kenchannvar:** Conceptualization, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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