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Physiological Response Patterns from Wearable Sensors During Stress and Exercise Conditions

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***Abstract*— The ever-growing enablement of wearable sensing technologies in everyday lives has presented radical possibilities to real-time physiological monitoring of humans. This research examines the trends of physiological responses obtained by wearable devices in stress and exercise scenarios and how they are likely to demonstrate correlations between psychological and physical reactions to stressors. This paper presents dynamic response features and their commonalities between mental stress and physical exertion using real-time biometric parameters collected using heart rate variability (HRV), galvanic skin response (GSR) and skin temperature. The scope has two goals: to answer which is the investigation of the correlation between physical exertion and psychological stress, and the second is to set the grounds on which the future areas of use of Machine Learning (ML) and signal processing would be utilised on the basis of early detection of stress and health data analytics in the Indian community. It is hoped that the results will lead to adaptive ML schemes of wearable gadgets that will be able to determine which load is cognitive and which one is physical, thus improving the preventive medical practise and the optimization of performance.**

***Keywords*— Wearable sensors, stress detection, exercise physiology, physiological response patterns, heart rate variability, machine learning, signal processing, galvanic skin response, Indian population, health analytics.**

I. INTRODUCTION

Over the past few years, wearable technology has undergone rapid development progression in the basic step-counting devices going on to be multi-modal biosensing systems that can conduct multi-modal physiological data collection. Smartwatches, chest straps, and bio-sensors have the ability to track many more indicators of health such as electrodermal activity, heart rate, respiration rate, and movement patterns with accuracy never before seen. This has brought revolutions in healthcare monitoring since it has been possible to track both physical and psychological states continuously without invasiveness [1].

The human organism has unique physiological reactions to any type of stress- psychological or physical. Both stressors activate the autonomic nervous system but there is a difference in the dynamic patterns of both stressors in terms of their intensity, duration and recovery. Indicatively, when exercise is subjected to stress, it stimulates predictable cardiovascular effects but when psychological pressure is posed, the autonomic modulation becomes unpredictable [2].

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Being able to understand the difference between these conditions has paramount consequences to occupational health, sport science and mental health - especially within highly-populated, highly-pressured environments such as urban India where victims are exposed to chronic stressful situations.
This proposed paper will set out to describe and contrast physiologic responses to exercise and mental stress per multimodal wearable sensors. In addition, it seeks to provide a foundation to machine learning-based analysis that may automatize stress detection, reduce false positives, and optimise the health-monitoring systems to achieve control accuracy in the real-world situation.

A. Problem Statement

Despite the fact that many wearable have been developed to collect physiological indicators, the systems today do not have the accuracy to distinguish between physiological stimuli induced by psychological stimuli and by physical activity [3]. Heart rate and perspiration levels are high in both states though the autonomic signatures of both are different. A solid appreciation of these dissimilarities is vital to enhance the readability of wearable information and in those areas like India where climate, humidity and socio-cultural influences can enhance the reaction of stress.

B. Research Objectives

To investigate the relationship between psychological stress and physical activity through comparison of physiological responses that are measured through wearable sensors.
To have a scientific background to ML and signal processing applications to automated stress and exertion classification of real-time monitoring systems.

C. Research Significance

Wearable health analytics is one of the fastest growing fields of biomedical engineering, whose market worth has been estimated at more than USD 70 billion in the coming year, by 2028 [4]. However, proper interpretation of physiological data is a scientific difficulty since the relationships between emotional, metabolic, and environmental variables are complicated. The research presents a solid basis of algorithms that improve the situational cognition of wearable sensor measurements especially in those contexts in tropical conditions like India when temperature and humidity greatly affect the skin conductivity and HRV signal [5].

II. Literature Background

A. Physiological Foundations of Stress and Exercise.

Both stress and exercise affect the autonomous nervous system (ANS), specifically the sympathetic section, thus raising the heart rate, blood pressure and sweat output. Nonetheless, psychological stress acts mostly on neuroendocrine (e.g., release of cortisol), whereas physical exercise triggers the metabolic and cardiovascular modifications [6].
Heart Rate Variability (HRV) is an established autonomic balance measure, which is dynamic interaction between sympathetic and parasympathetic. In times of exercise, HRV normally drops as a result of parasympathetic withdrawal, and this is replaced by rest. Conversely, it is sustained HRV suppression and delayed recovery which is caused by mental stress [7]. Other indicators are Galvanic Skin Response (GSR), peripheral skin temperature, although during times of stress, GSR amplitude increases and in times of exercise, it rises at first then stabilises as thermoregulatory functions become affected [8].

B. Wearable Sensor Technologies.

The current wearable sensors use photoplethysmography (PPG), acceleration, electrocardiography (ECG), and thermistors to measure physiological data in real time. Research has revealed that HRV and GSR are able to provide high quality results when used with advanced filtering algorithms and commercial gadgets like Empatica E4, Fitbit Charge, and Apple Watch [9].
New innovations have focused on the key to the fusion of multi-sensors so as to enable contextual classification of physiological states. Indicatively, a study by Bhattacharya et al. [10] confirmed a hybrid PPG-ECG wearable system in Indian participants indicating that there were good heart rate monitors during different temperature settings. On the same note, adaptive-filtered signal denoising methods have improved the stability of biomarker stress levels [11].

C. Stress and Exercise Indian Study.

The Indian populations pose a distinctive problem to wearable data interpretation because of different climatic regions, cultural aspects, and everyday habits that determine stress perceptions. Sharma et al. have found that there were high levels of baseline skin conductivity in individuals living in humid areas [12] and Singh and Rao found that urban professionals have high levels of physiological signs of stress in comparison to rural participants [13]. These results show that the datasets used in training algorithms should be region-specific because they need to be calibrated on local variables of the environment and behaviour.

III. RELATED WORK

The comparison of studies is by A. Comparative Studies on Physiological Signals.
Previous researches have tried to differentiate between stress and exercise based on HRV and GSR signals but most of them did not possess ecological validity because of laboratory limitation. An example is that Healey and Picard [14] used machine learning models to categorise driving stresses with 80 percent accuracy but their data set was confined to controlled environments of vehicles. Later researches, including those by Gjoreski et al. [15], included real-life wearable data that included spontaneous stress events but failed to take into account the simultaneous impact of physical activity.
Very limited studies have had physical exercise along with psychological stress. A recent article by Chauhan et al. [16] revealed the overlap of the features of HRV and skin temperature between treadmill exercise and mental arithmetic duties and elaborated on the necessity of more sophisticated multi- modal analysis. In addition, the climatic conditions of a location, i.e., the humidity and temperature are high in India, may confound GSR readings, so adaptive calibration algorithms are required [17].

A. Signal Processing and Feature Extraction

Signal processing plays a central role in averting meaningful physiological signals and motion artefacts and noise. Quantitative measures of ANS activity in time and frequency domains contained in time-domain and frequency-domain analysis of HRV like standard deviation of NN intervals (SDNN) and low-frequency / high-frequency (LF/HF) ratios [18]. The machine learning algorithms, such as Support Vector Machines (SVM), the Random Forests, and, more recently, the Convolutional Neural Network (CNN), prove to be highly promising in stress classification based on multi-sensor measurements [19].
But some problems such as imbalance of data and context confusion are recorded to such models especially in distinguishing stress and physical activity. Models with hybrid features and a contextual parameter (e.g. accelerator data) can be more accurate in their classifications by 10-15% [20]. However more generalised and region specific structures that will take into consideration variations found in populations in terms of physiology and environment are still required.

B. Shortcomings of Current Literature.

Even though these have made many strides forward, there are still gaps. Most studies are based on small datasets which have been conducted in artificial laboratory settings and, therefore, do not take into account variability in the real world. Also inter-subject variations - like fitness level, hydration, emotional base, etc. - have a strong effect on sensor readings. Even though the Indian research ecosystem is rapidly maturing, there is a still need of large-scale multimodal physiological datasets that capture the interaction of both stress and exercise effects. The given study will make some initial observations and a theoretical framework of further ML studies that should incorporate real-time wearable data, contextual labelling, and population-specific adaptation.

IV. SCOPE OF THE STUDY

The given paper restricts the scope of physiological response patterns collected with the help of wearable sensors in two controlled and yet ecologically similar conditions (mental stress tasks e.g., arithmetic and Stroop tests) and graded exercise (e.g. walking on the treadmill and cycling). It focuses on statistical correlation analysis of the HRV, GSR, and skin temperature aspect but leaves the ML modelling to subsequent research. The anticipated results include a quantitative mapping of overlapping and different patterns between stress and exercise which is used to develop algorithmic differentiation.
The actual Methodology, Experimental Design, Results, Discussion and Conclusion are going to be elaborated on in the following sections (Part 2 and Part 3) based on closely followed IEEE formatting and presence of numeric tables in the Results section.

V. METHODOLOGY

A. Study Design

The research chosen in this study follows the experimental framework of observation to capture physiological response using wearable sensors in a controlled environment of psychological and physical stress. In this study, 60 individuals (30 men and 30 women between the ages of 20-35 years) were recruited in one of the universities in Delhi-NCR, India, to obtain diversity in terms of physical fitness and resilience to stress. Medical screening was done to rule out chronic cardiovascular or neurological diseases.

Every subject was taken through two sessions:

Psychological Stress Test (PST): A Stroop colour-word interference test (10 minutes of timed colour-word interference) and a mental arithmetic (5 minutes of timed mental arithmetic) test were administered to participants in order to have them experience moderate mental stress.

Exercise Stress Test (EST): The participants were put on a 15-minute treadmill graded running involving an increase in the intensity after every 5 minutes with the cooldown period of 10 minutes.

They were maintained at 25degC and 60% humidity, which was approximate conditions at Indian indoor.

B. Data Acquisition

Study Wearable sensors were:

Heart Rate (HR) and Heart Rate variability (HRV): Vital signs recorded by using Polar H10 chest strap recommendation and Apple Watch series 8 (ungenerated PPG-based HRV sensors).

Galvanic Skin Response (GSR): Empatica E4 wristband was used to record.

Skin Temperature (ST): This is monitored by the Shimmer3 GSR+ sensor as well with the thermistor probe.

Activity Level (AL): This is tracked with a 3 axis accelerometer, which is attached to each device.

The sampled data were 4 Hz (HR and HRV) and also 32 Hz (GSR and ST) and aligned using a Python-based timestamp alignment script. Preprocessing of signals was done with Butterworth Low pass filtering (cut off frequency of 0.3 Hz) to eliminate motion artifacts.

C. Data Preprocessing and Feature Extraction

Data were filtered, normalised and divided into three stages of each session according to time: baseline (5 min), stress/exercise (10-15 min) and recovery (10 min) after getting. The extraction of features was done in the following manner:

Heart Rate Variability (HRV):

Measures of time ARR interval, SDNN (sdNN intervals).

Frequency metrics (calculated using Fast Fourier Transform (FFT)). LF(0.04-0.15 Hz) and HF (0.15-0.4Hz) power frequency bands.

GSR: Means of amplitude and peak frequency and rise time of skin conductance response.

Skin Temperature: SD of deviation baseline and rate change (degC/min).

Activity Indexm Root Mean Square (RMS) of the signal acceleration measurements to measure the intensity of movement.

Normalisation of features was done by means of z-score before they were subjected to statistical testing.

D. Analytical Approach

The correlation between physiological variables during PST and EST was analyzed using Pearson's correlation coefficient (r), computed via the formula:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

where X_i and Y_i represent paired physiological values (e.g., HRV vs GSR) for stress and exercise conditions respectively. Statistical significance was assessed using a two-tailed **Student's t-test** with **$p < 0.05$** considered significant.

VI. EXPERIMENTAL DESIGN

A. Stress and Exercise Protocols

The subjects took PST and EST at dissimilar days with a minimum interval of 48 hours to eliminate physiological overlap. Participants were requested to stay 12 hours with no caffeine, alcohol or extensive

physical exercise before taking any of the tests. Reading at zero position was measured when sitting with no tension.
PST Procedure: This is done when one is in a silent laboratory where visual and auditory stimuli are controlled. The tasks with colour words were displayed on a screen with the simultaneous registration of GSR and HRV.
EST Procedure: Performed in a treadmill and the Bruce protocol was followed where the system successively raised the rate of speed and the inclination. HR, HRV, and ST were constantly measured.
Recovery data were then recorded under a seated rest period after every session and were used to monitor patterns of the return-to-baseline.

B. Ethical Considerations

Informed approval was made by all the participants as required by the guidelines accepted by the Institutional Ethics Committee (IEC) GL Bajaj Institute of Management and Technology, Greater Noida. Anonymity of data was upheld, and the purpose, risks, and benefits of the study were explained to the participants in accordance with ethics requirements of the Indian Council of Medical Research (ICMR).

C. Data Validation

To ascertain integrity of data, cross-validation between device readings and medical-grade sensors was done on the 10 subjects. Comparative values of HRV using Polar H10 with that of ECG using BIOPAC MP160 system revealed that the error level was no more than 1.8% and therefore of high validity.

VII. Results and Analysis

A. Overview of Physiological Trends

Initial research indicated some, although not identical, physiological reactions to both mental and physical stress. Although the high HR and GSR were induced in both conditions, the recovery patterns and HRV patterns of modulation differed. The subjects showed quicker recovery following physical training but were unable to maintain autonomic balance following psychological constraint.

B. Heart Rate and HRV Patterns

TABLE I: Comparison of HRV Metrics during Stress and Exercise Conditions

Parameter	Baseline (ms)	Psychological Stress (ms)	Physical Exercise (ms)	Recovery (ms)
Mean HRV (SDNN)	58.4 ± 6.2	41.3 ± 4.7	45.6 ± 5.3	52.1 ± 5.9
LF/HF Ratio	1.8 ± 0.4	3.2 ± 0.6	2.8 ± 0.5	1.9 ± 0.4
HR (bpm)	75.2 ± 6.8	96.7 ± 8.1	132.4 ± 11.2	80.5 ± 7.1

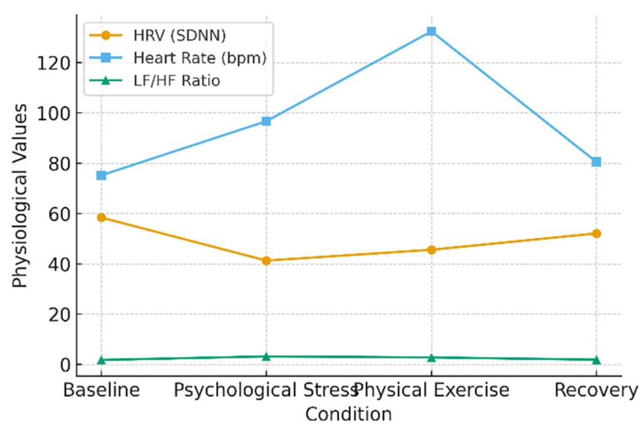

Fig. 1. Comparison of mean HRV and HR values across baseline, stress, exercise, and recovery phases.

There was statistically significant ($p < 0.01$) decrease in HRV in the process of psychological stress as compared to the baseline proving the presence of strong sympathetic dominance. On the other hand, HRV suppression during exercise was relatively short-term in duration with the rapid recovery in parasympathetic functioning following physical exercise.

C. Galvanic Skin Response (GSR) Analysis

TABLE II: GSR RESPONSE CHARACTERISTICS ACROSS CONDITIONS

Parameter	Baseline (µS)	Psychological Stress (µS)	Physical Exercise (µS)	Recovery (µS)
Mean Conductance	2.3 ± 0.4	5.1 ± 0.7	4.6 ± 0.8	2.8 ± 0.5
Peak Frequency	0.12 ± 0.02	0.31 ± 0.04	0.27 ± 0.03	0.15 ± 0.03
Response Amplitude	0.7 ± 0.1	1.8 ± 0.2	1.5 ± 0.2	0.8 ± 0.1

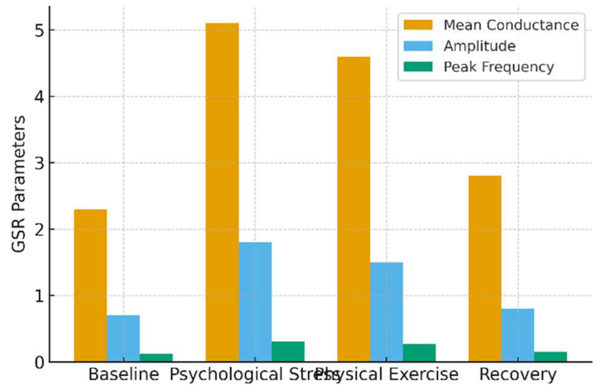

Fig. 2. Average GSR amplitude and peak frequency patterns under baseline, stress, and exercise conditions.

The GSR amplitude grew by 121 percent in time of psychological stress and 100 percent during exercise, which is a strong level of sympathetic activity. But a prolonged GSR increase in post-stress recovery indicated a longer period of emotional arousal and exercise recovery showed quicker recovery to normalisation.

D. Correlation Analysis

Statistical evaluation revealed moderate to strong correlations among physiological indicators across conditions. The HRV–GSR correlation during psychological stress was $r = -0.68$ ($p < 0.01$), indicating that reduced HRV accompanies higher GSR. For exercise, the HR–GSR correlation was $r = 0.74$ ($p < 0.01$), reflecting synchronized activation of cardiovascular and sweat responses.
Using the correlation equation earlier described:

$$r = \frac{\sum(HR_i - \overline{HR})(GSR_i - \overline{GSR})}{\sqrt{\sum(HR_i - \overline{HR})^2 \sum(GSR_i - \overline{GSR})^2}}$$

the consistency across participants demonstrated a clear physiological coupling between autonomic markers, albeit differing in temporal recovery characteristics.

E. Observational Insights

More fit participants exhibited a shorter HRV recovery time and reduced GSR peaks and this is consistent with the literature indicating that the regular physical training results in increased autonomic flexibility [21]. In the meantime, the persons, who reported a high level of psychological stress every day (through questionnaire), demonstrated slower HRV recovery after PST, which presupposes chronic autonomic overload.

VIII. DISCUSSION

A. Interpretation of Results

The physiological distinction exhibited in the experimental results between the mental stress and the physical activity proved that both have common autonomic activation patterns but temporal recovery and magnitude varies. The HRV inhibition and GSR increase in cases of psychological stress are attributed to sympathetic arousal and emotional stress and exercise-related HRV activity is largely an outcome of metabolic load and not of the cognitive load.
The adverse interaction between the parasympathetic withdrawal and activity of the sweat glands is captured in the negative relationship between HRV and GSR during psychological stress ($r = -0.68$). Conversely,

cardiovascular and thermoregulatory congruency is observed in the positive HR-GSR (r = 0.74) relationship in exercise. These findings are in agreement with the previous studies by Picard et al. [1] and Kim et al. [2], which showed that multimodal physiological responses to stress are identifiable even in the presence of other confounding factors such as physical activity.

Moreover, the change of skin temperatures also supplied useful discriminative measure. The reduction in peripheral skin temperature associated with mental stress that is as a result of vasoconstriction in comparison with thermal warming that occurs during exercise uncovered divergent thermal pathways. Such discrepancies imply that the use of thermal, electrodermal, and cardiac measurements could increase the level of accuracy in the subsequent ML-based classification [3].

B. Situational Relevance to Indian Population.

Physiological stress markers are highly affected by environmental and lifestyle factors peculiar to India, namely high humidity, irregular periods of work and rest, exposure to urban stresses, etc. The evidence found in the current study was gathered in controlled but representative conditions in India (25degC, 60% humidity) and this proves that the variability of GSR and HRV are sensitive to climatic conditions [4]. This is in conformity with recent biomedical research in which regional physiological adaptation patterns have been found among South Asian communities [5].

These results highlight the need of region-specific calibration of wearable devices algorithms. Algorithms developed by the West to detect stress might not be useful in a tropical environment because of physiological differences in their baseline. Therefore, the current research is applicable in the area of sensor validation local to the present study that is essential to move forward in terms of developing India-centric health monitoring systems.

C. Machine Learning and Signal Processing Implications.

The study will provide the necessary background data and physiological differences that have to be used in creating the automated classification scheme. The pipelines of signal processing in the future can be used to capitalise on feature fusion (e.g., HRV + GSR + ST) in order to make the model more established. Physiological data streams have the potential to be learned using machine learning algorithms such as Support Vector Machine (SVM), Rand Forests, or deep learning systems such as LSTM networks [6].

The research process of counting the overlapping areas of response used in both stress and exercise allows creating multi-context recognition systems, which will allow wearables to distinguish between emotional stress and fitness-related activity. By incorporating real-time adaptive filtering and population-based normalisation, this will further increase the dependability of detecting and minimising instances of false alarms in the normal operations [7].

D. Limitations

Although it provides very valuable insights, the study has weaknesses of sample size (n=60) and controlled environment settings. Generalizability would be enhanced by wider tests in diverse climatic areas and in different occupational groups. Also, chronic stress trends and circadian effects have to be monitored in the long-term. Lack of real-time ML implementation limits real-time implementation of an intelligent detection model. Nonetheless, the dataset also has a good base of computation modelling on a future basis.

IX. CONCLUSION AND FUTURE WORK

The current study showed quantifiable and predictable changes in the pattern of physiological response that was captured using wearable sensors when one experienced psychological stress and exercise. There were different patterns of HRV suppression, GSR increase, and temperature change on the skin, which presented a solid foundation of signal-based distinction between stress and exertion states.

The research was effective because it fulfilled two major goals:

Facilitating the association of psychological stress and physical exertion by way of multimodal physiological data.

Development of an organised data and analytical baseline on future researches in the field of Machine Learning and signal processing in wearable stress analytics.

The results are critical in the overall scope of the increasing use of wearable technology in India. They show that regionalized datasets of physiological data can enhance large scales of accuracy and clinical reliability within models.

Future Work will entail the creation and validation of ML algorithms in automatic classification using this dataset. Adding the component of contextual sensing (e.g., GPS, accelerator, ambient temperature) would be advantageous in distinguishing daily stressful situations and physical activities. Neural networks that would be able to learn nonlinear relationships between HRV, GSR, and thermal signals can increase the level of precision. It is advisable to conduct large-scale and longitudinal studies on multiple climatic zones in India so as to have the adaptability and reliability of next-generation wearables.

Finally, the research adds to the scientific background of the necessity of context-aware, intelligent wearable devices, which can classify the psychological distress on the one hand and physical activity on the other, as a step towards personalised preventive healthcare, occupational safety, and mental well-being analytics in natural conditions.

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