A Real-Time IoT-Based Intelligent Health Monitoring Framework with Multi-Sensor Fusion and Automated Anomaly Detection for Continuous Cardiac Assessment

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***Abstract*—Continuous and real-time health monitoring is essential for the early detection of cardiovascular and physiological abnormalities in remote and resource-limited settings. This research aims to develop an intelligent IoT-based framework for multi-sensor health data acquisition, real-time processing, and automated anomaly detection for continuous cardiac and physiological assessment. The proposed system integrates multiple physiological sensors, including heart rate, SpO_2, ECG, blood pressure, and body temperature modules, interfaced with a microcontroller-based edge computing unit for real-time signal processing and decision-making. A rule-based intelligent alert mechanism is implemented to enable automated detection of abnormal conditions and trigger immediate emergency notifications via wireless communication channels including Bluetooth and GSM. Data transmission to cloud-based platforms supports remote monitoring and longitudinal health tracking. The system architecture follows a layered IoT design encompassing sensing, processing, communication, and application layers. Performance was validated through MATLAB-based simulation and experimental testing under multiple activity conditions, achieving accuracies of 92.85% for heart rate, 98.86% for SpO_2, 98.25% for systolic blood pressure, 97.37% for diastolic blood pressure, and 99.7% for body temperature. The results demonstrate that the proposed framework provides a reliable, cost-effective, and scalable solution for continuous remote health monitoring, with significant implications for smart healthcare systems and clinical decision support in IoT environments.**

***Keywords*—Internet of Things (IoT); wearable health monitoring device; biomedical sensors; cardiac monitoring; vital sign measurements**

I. Introduction

In recent years, the global adult population has grown significantly, accompanied by a proportional increase in the prevalence of chronic diseases. This shift has intensified the demand for continuous health monitoring as a fundamental component of modern healthcare systems. Continuous monitoring of key physiological parameters, including heart rate, blood oxygen saturation (SpO_2), blood pressure, and body temperature, enables early detection of abnormalities and supports timely clinical intervention. Cardiovascular diseases remain one of the leading causes of mortality worldwide, underscoring the critical need for reliable real-time health monitoring systems [1, 2, 4, 11].

Recent advancements in wearable technologies have facilitated the development of compact, energy-efficient devices capable of continuous physiological signal acquisition. These devices, typically worn in close contact with the human body, provide real-time and longitudinal insights into an individual's health status. Integration with wireless communication technologies enables seamless transmission of collected data to cloud-based platforms, supporting remote patient monitoring and reducing the necessity for frequent clinical visits. Consequently, such systems play a vital role in alleviating the burden on healthcare infrastructure while promoting the adoption of telemedicine and decentralized healthcare models. Prior studies have demonstrated the effectiveness of wearable health monitoring systems in enhancing healthcare accessibility, improving response time, and enabling proactive disease management [3, 7, 8, 10, 18, 19, 29].

The rising incidence of lifestyle-related disorders further highlights the importance of continuous and non-invasive health monitoring. Persistent tracking of vital parameters facilitates early diagnosis and preventive healthcare, particularly for individuals at high risk of cardiovascular complications and elderly populations requiring continuous supervision. Modern wearable systems are increasingly designed to operate in non-clinical environments, enabling unobtrusive, long-term monitoring without disrupting daily activities. [13, 15, 16, 17].

These systems incorporate embedded biomedical sensors for real time acquisition of physiological data, enabling comprehensive assessment of the user's health condition. Furthermore, the integration of wireless communication protocols and cloud computing infrastructures ensures continuous data streaming, secure storage, and remote accessibility by clinicians and authorized users. Such technological advancements have significantly accelerated the evolution of digital healthcare ecosystems and remote patient monitoring solutions [3, 18, 19, 20, 29].

Fig. 1. Types of wearable health monitoring devices.

Wearable devices are available in diverse form factors, including wristbands, adhesive patches, smart textiles, and belt-mounted systems as shown in Fig. 1. Among these, belt-type wearable devices offer advantages in terms of user comfort, stability of sensor placement, and suitability for continuous daily use. However, many existing systems are limited in their ability to simultaneously monitor multiple physiological parameters, often focusing on a restricted set such as heart rate, physical activity, sleep patterns, and SpO_2 levels. In contrast, multi-sensor systems capable of integrating diverse physiological signals can provide more comprehensive and reliable health assessments. Sensors positioned on or in close proximity to the skin enable continuous, accurate, and real-time measurement of physiological parameters, forming the basis for advanced health monitoring applications. [21, 23, 25]

A. Wearable Health Monitoring

A wearable system integrating multiple sensors enhances the accuracy and reliability of health monitoring by enabling continuous tracking of various physiological parameters. Compared to single-parameter devices, multi-sensor systems provide more comprehensive insights into an individual's health status [14, 18, 26, 28], supporting applications in healthcare, sports performance optimization, clinical monitoring, and remote patient care. In this system, the MAX30100 sensor monitors heart rate and blood oxygen levels, while the LM35D sensor measures body temperature. Microcontrollers such as Arduino and ESP32 process the binary signals, converting them into digital values for straightforward interpretation. Processed data are transmitted via Bluetooth to mobile devices or laptops for further analysis. Continuous data acquisition facilitates real-time monitoring, early detection of abnormalities, and informed decision-making in healthcare. Moreover, the accumulation of long-term health data supports preventive strategies by revealing individual health trends and patterns [3, 29].

B. Challenges/Problems Faced in Using Existing Systems

Despite advances in wearable health technology, current systems face several critical limitations, as illustrated in Fig. 2 and Fig. 3. Many devices monitor only a single physiological parameter, restricting comprehensive assessment of overall health [6, 22]. Measurement accuracy can be compromised by motion artifacts, poor sensor–skin contact, and environmental interference, while frequent battery depletion disrupts continuous monitoring and risks data loss. Moreover, unstable network connectivity and limited integration with cloud-based platforms hinder reliable real-time analysis.

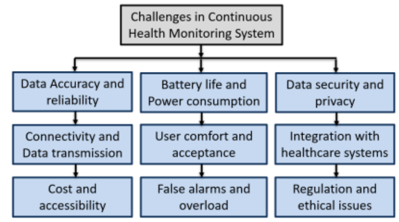

Fig. 2. Challenges in continuous health monitoring system.

To address these challenges, modern wearable systems are designed to track multiple physiological parameters continuously, optimize power consumption for extended operation, and deliver real-time alerts to users and healthcare providers in response to abnormal readings. Together, these advancements enhance the reliability, efficiency, and effectiveness of continuous health monitoring systems. [30, 31]

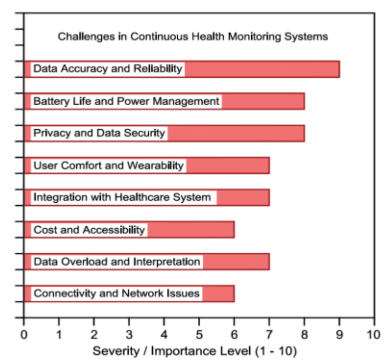

Fig. 3. Level of challenges in continuous health monitoring system.

II. Literature Review

Wearable health monitoring devices have been widely investigated for continuous physiological tracking. Various form factors including smart shirts, belts, skin patches, watches, and rings have been developed to monitor heart rate, SpO_2, ECG, and body temperature. While most systems demonstrate high accuracy (92–98%), they face recurring challenges such as limited battery life, small datasets, restricted testing conditions, motion artefacts, and environmental interference [6, 14, 22, 32]. Wearable belts and smart shirts enable ECG, heart rate, and respiratory monitoring, achieving up to 98% accuracy, but are limited by battery constraints, wash ability, or narrow demographic testing [14, 31, 32, 33]. Smart watches and skin patches allow real-time monitoring of vital signs but are constrained by short-term deployment, adhesive wear, and small datasets [24, 27]. IoT-enabled systems extend functionality through cloud integration and multi-parameter monitoring; however, they depend on wireless connectivity and lack validation in large-scale trials [3, 35]. Ring-based devices offer compact ECG, PPG, and SpO_2 monitoring, yet small sample sizes, hand-placement requirements, and motion artifacts limit generalizability [9, 12, 27]. Table I summarizes representative studies, highlighting device types, monitored parameters, algorithms, accuracy, datasets, and limitations.

TABLE I. SUMMARY OF LITERATURE SURVEY CARRIED OUT IN VARIOUS WEARABLE HEALTH MONITORING DEVICES

Study	Objective	Algorithm	Parameters	Accuracy	Dataset	Limitations
Wearable Belt [32]	Continuous monitoring of ECG, HR, respiration, temperature	ECG filtering & R–R detection	ECG, HR, Respiratory rate, Temperature	N/A	Experimental signals (rest)	Prototype; limited wireless (13.56 MHz); battery & wear ability issues
Smart Shirt [14]	Arrhythmia monitoring with dry ECG electrodes	Wavelet transform, QRS detection, HRV, ML	ECG, HR, HRV, Arrhythmia types	97.5% (rest), 98.2% (arrhythmia)	50 participants, 50 simulated arrhythmia, 500 ECG records	Limited wash cycles; tested only on middle-aged adults
Wearable Watch [24]	Real-time monitoring of HR, SpO_2, temperature	PPG + temperature sensors, microcontroller	HR, SpO_2, Temperature	92–96%	Volunteer validation (no public dataset)	Limited battery life; small display
Skin Patch [27]	Continuous monitoring of ECG, HR, respiration, temperature	ECG filtering, R-peak detection, impedance respiration sensing	ECG, HR, Respiratory rate, Temperature	94–97%	Volunteer recordings (no public datasets)	Battery life; adhesive wear; not tested long-term
IoT System [3,35]	IoT-enabled health monitoring system	Preprocessing, feature extraction, cloud ML	HR, ECG, SpO_2, Respiratory rate, Temperature, Activity	96–98%	Volunteer + benchmark datasets	Wireless dependency; limited battery; no large-scale trials
Smart Ring [12]	Records heart and skin signals	Filters, Pan-Tompkins, t-test	HR, HRV, PRV, SpO_2, Respiratory rate, GSR, PAT	N/A	6 young subjects (rest, sit, stand)	Small sample size; ECG requires both hands
ECG Ring [12]	Finger-based ECG monitoring	Pan-Tompkins (QRS detection)	HR, QRS complexes, ECG waveform	95%	Healthy volunteers (preliminary validation)	Few subjects; early validation stage
Ring Device (ECG+PPG) [27]	Ring-based ECG & PPG cardiovascular monitoring	Filters, ECG & PPG statistical analysis	HR, HRV, PRV, SpO_2, Respiratory rate, GSR	N/A	6 subjects (sit, stand, supine)	Noise issues; small group; ECG requires hand placement
Stress Monitor [5,32]	Cardiovascular and stress monitoring	Filtering, feature extraction, ML	HR, HRV, PPG indices, SpO_2, Respiratory rate, GSR, Stress	85–90% (stress classification)	Human volunteers under stress/rest protocols	Motion artifacts; small dataset; requires larger trials
Finger Ring (ECG+PPG) [9]	Finger-worn ECG-PPG monitoring	Pan-Tompkins (ECG), PPG peak detection	HR, HRV, Pulse arrival time, SpO_2	92–96%	Small group of healthy volunteers	Motion artifacts; small dataset; early-stage prototype

To address these limitations, the proposed Smart Belt integrates multiple sensors into a single, non-intrusive platform for continuous monitoring of heart rate, SpO_2, ECG, and body temperature. Real-time data acquisition with seamless cloud-based transmission enables longitudinal tracking and remote healthcare monitoring. An immediate alert mechanism via a buzzer notifies users and healthcare providers of abnormal vital signs, ensuring timely intervention.

Overall, the Smart Belt provides a scalable, cost-effective, and comprehensive solution, bridging the gap between conventional wearable devices and remote healthcare delivery while overcoming limitations in usability, multi-parameter monitoring, and real-time responsiveness. [36, 37, 38, 39]

III. METHODOLOGY

This research aims to develop a wearable health tracking and cardiac monitoring device for continuous monitoring of individual health. The system comprises multiple components, including a heart rate module, pulse oximeter, ECG sensor, temperature sensors, Arduino UNO, Node MCU (ESP32), power supply board, LCD display, GSM module, and buzzer. Their specifications and roles are described below.

A. Data Acquisition (DAQ)

Fig. 4 shows the components used in the wearable health tracking and cardiac monitoring system. These components work together to enable efficient sensing, processing, and communication. A 12V lithium-ion battery (5000 mAh) provides stable DC voltage, regulated to 5V/12V via a linear or switching power supply board. The ESP32 microcontroller handles wireless transmission via Bluetooth/Wi-Fi.

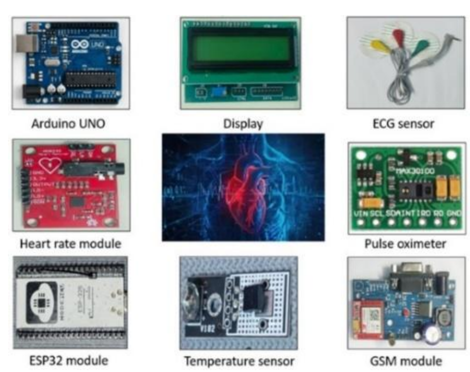

Fig. 4. Components of wearable health tracking and cardiac monitoring.

The HW-827 pulse sensor is an optical PPG sensor operating at 3.3–5V for real-time heart rate detection via analogue output. The MAX30100 pulse oximeter measures heart rate and SpO_2 at 1.8–3.3V. The AD8232 ECG module amplifies and filters ECG signals, operating at 3.3–5V; ECG electrodes use snap leads with Ag/AgCl gel to ensure accurate measurement of systolic and diastolic blood pressure.

A 16×2 LCD module displays real-time health data. Temperature is measured using LM35 and DS18B20 sensors, with the latter transmitting data via the one-wire protocol. The SIM900A GSM module operates at 3.2–4.8V and supports dual-band communication. A piezoelectric buzzer (3–12V) provides audible alerts for abnormal readings. All components are integrated to create a reliable, low-power, and user-friendly wearable system suitable for continuous health monitoring.

B. Sensory Input

The system collects physiological data from heart rate, SpO_2, ECG, and temperature sensors, integrated with the GSM (SIM900A) module. The controller manages and transmits this data to an IoT platform via Node MCU, where it is visualized and analysed. Abnormal readings trigger immediate alerts; if conditions persist, an additional alert is sent to an authorized person. Sensor data undergoes pre-processing on the IoT platform, including acquisition, transmission, visualization, and control. Continuous physiological data is sent via ESP32's Bluetooth/Wi-Fi, processed by the microcontroller, and displayed in real time on the IoT application. Cloud storage maintains longitudinal records, providing authorized users with access to continuous monitoring and control. [40, 41, 42. 44]

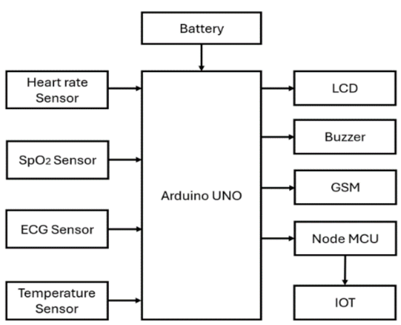

Fig. 5. System architecture diagram of wearable health monitoring system.

Fig. 5 illustrates the system architecture, integrating multiple physiological sensors with Arduino as the central processing unit. Data is displayed on the LCD, and abnormal readings trigger a buzzer alert. Remote monitoring is supported via GSM and ESP32 communication to cloud-based IoT platforms [45].

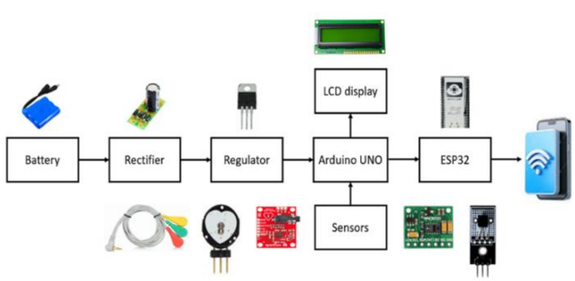

Fig. 6. Proposed system of continuous health tracking and cardiac monitoring system.

Fig. 6 shows the block diagram of the proposed system, where the battery powers the device and a regulator maintains constant voltage (5V/3.3V). Arduino reads sensor data and performs basic processing; ESP32 transmits the processed data to cloud/mobile devices for real time monitoring [46]. Fig. 7 shows the experimental hardware prototype.

Fig. 7. Hardware prototype used for experimental evaluation.

IV. Simulation of Continuous Health Monitoring and Health Status Indication System

The Fig. 8 illustrates the simulation of key physiological parameters, including heart rate, SpO_2 , systolic and diastolic blood pressure, and body temperature, under continuous monitoring. The simulation was implemented in MATLAB 2025 using Simulink, where logical operations serve as status indicators to evaluate sensor inputs and generate alerts [47]. Green represents normal physiological conditions, while red indicates abnormal or critical conditions requiring immediate attention.

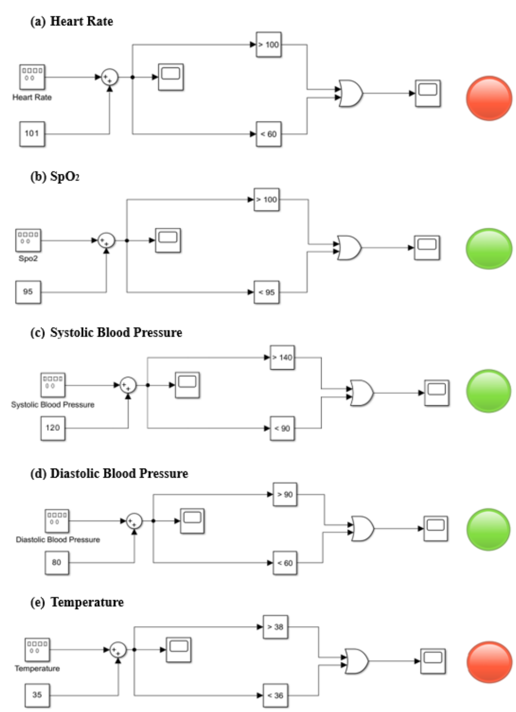

Fig. 8. Simulation of the continuous health monitoring system.

The simulation of the continuous health monitoring system was performed in MATLAB 2025 using Simulink. As shown in Fig. 8, the system continuously monitors heart rate, SpO_2, systolic and diastolic blood pressure, and body temperature. Logical operations serve as status indicators, where green represents normal physiological conditions and red indicates abnormal or critical states requiring immediate attention. Each parameter is processed in real time: heart rate is analysed to detect bradycardia or tachycardia, SpO_2 is monitored to identify hypoxemia, blood pressure is evaluated to detect prehypertension or hypertension, and temperature readings are used to detect hypothermia or fever [48, 49, 50]. The simulation demonstrates the capability of real-time processing of multi-parameter biomedical signals to assess an individual's overall health and generate timely alerts.

TABLE II. OBSERVATIONS OF PHYSIOLOGICAL PARAMETERS IN THE CONTINUOUS HEALTH MONITORING SYSTEM

Parameter	Value	State	Remark
Heart Rate (bpm)	<60	Abnormal (Low)	Bradycardia
	60-100	Normal	Healthy
	>100	Abnormal (High)	Tachycardia
SpO2 (%)	≥95	Normal	Healthy
	90-94	Abnormal (Low)	Mild Hypoxemia
	<90	Abnormal (Very Low)	Severe Hypoxemia
Systolic Blood Pressure (mmHg)	<90	Abnormal (Low)	Hypotension
	90-119	Normal	Healthy
	120-129	Elevated	Prehypertension
	130-139	Abnormal (High)	Hypertension (Stage 1)
	140-179	Abnormal (High)	Hypertension (Stage 2)
	≥180	Abnormal (Very High)	Hypertensive Crisis
	<60	Abnormal (Low)	Hypotension
	60-79	Normal	Healthy
	<80	Elevated	Prehypertension
Diastolic Blood Pressure (mmHg)	80-89	Abnormal (High)	Hypertension (Stage 1)
	90-119	Abnormal (High)	Hypertension (Stage 2)
	≥120	Abnormal (Very High)	Hypertensive Crisis
Temperature (°C)	<35	Abnormal (Low)	Hypothermia
	35-36.4	Slightly Low	Mild Hypothermia
	36.5-37.5	Normal	Healthy
	37.6-38.4	Abnormal (High)	Fever
	38.5–39.5	High	High Fever
	≥40	Critical	Hyperpyrexia

Table II summarizes the observations from the system. Normal body temperature is 36.5–37.5 °C, with deviations indicating hypothermia or fever. Heart rate between 60–100 bpm is normal, while values below 60 bpm suggest bradycardia or hypothyroidism, and values above 100 bpm indicate potential cardiovascular stress. Systolic (90–119 mmHg) and diastolic (60–79 mmHg) pressures are normal, moderate increases indicate Stage 1 hypertension, higher values indicate Stage 2 hypertension, and readings ≥180 mmHg represent hypertensive crisis. SpO_2 levels of 95–100 % are healthy, 90–94 % indicate mild hypoxemia, and below 90 % reflect severe hypoxemia. Overall, the integration of multi-parameter monitoring facilitates early detection of abnormalities, real-time alerts, and continuous health assessment. This highlights the effectiveness of wearable systems in preventive care, remote health supervision, and timely intervention for critical physiological conditions [51, 52].

V. RESULTS AND DISCUSSION

In this research, real time health parameters of three men of same age group was monitored and experimental validation was conducted to monitor key physiological parameters, including heart rate, SpO_2, blood pressure, and body temperature, under three different conditions: rest, walking, and running. The health parameters in real-time for three subjects: Adhithan (21), Ashwin (21), and Veerabathiran (21). Blood pressure is reported as systolic over diastolic values. Heart rate variations for each case study are illustrated in separate graphs, along with individual graphs for SpO_2, systolic blood pressure, diastolic blood pressure, and temperature. The graphs reflect the variations of physiological parameters over time. Mean and standard deviation values were calculated for each parameter using sample standard deviation.

TABLE III. TIME-SERIES ANALYSIS OF MULTI -PARAMETERS UNDER THREE CONDITIONS ACROSS MULTIPLE SUBJECTS

Parameters / Adhithan (21)	Time & Measurement (minutes)														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -1 Heart Rate (BPM) Rest	58	60	57	62	61	59	63	65	64	66	68	67	62	61	60
Case Study -1 SpO2 (%) Rest	97	98	97	99	98	97	98	99	98	99	97	98	96	97	99
Case Study -1 Systolic (mmHg) Rest	116	118	117	119	118	117	118	119	118	117	118	119	118	117	118
Case Study -1 Diastolic (mmHg) Rest	76	78	77	79	78	77	78	79	78	77	78	79	78	77	78
Case Study -1 Temperature (°C) Rest	36.4	36.5	36.4	36.6	36.5	36.4	36.5	36.6	36.4	36.5	36.4	36.6	36.5	36.4	36.5
Parameters / Adhithan (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -1 Heart Rate (BPM) Walk	75	77	78	80	82	79	86	83	91	92	77	84	90	93	97
Case Study -1 SpO2 (%) Walk	97	98	99	98	97	96	98	99	97	98	99	97	98	96	97
Case Study -1 Systolic (mmHg) Walk	122	124	123	125	124	123	124	125	124	123	124	125	124	123	124

Case Study -1 Diastolic (mmHg) Walk	82	84	83	85	84	83	84	85	84	83	84	85	84	83	84
Case Study -1 Temperature (°C) Walk	36.7	36.8	36.9	37	36.9	36.8	36.9	37	36.9	36.8	36.9	37	36.9	36.8	36.9
Parameters / Adhithan (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -1 Heart Rate (BPM) Run	100	103	106	109	111	114	117	115	113	118	116	112	110	108	105
Case Study -1 SpO2 (%) Run	95	96	97	98	97	96	95	97	96	95	95	95	96	97	95
Case Study -1 Systolic (mmHg) Run	134	136	138	139	137	136	138	139	137	136	138	139	137	136	138
Case Study -1 Diastolic (mmHg) Run	86	88	89	90	88	88	89	92	88	88	89	90	88	88	89
Case Study -1 Temperature (°C) Run	37.2	37.2	37.3	37.4	37.3	37.2	37.3	37.4	37.3	37.2	37.3	37.4	37.3	37.2	37.3
Parameters / Ashwin (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -2 Heart Rate (BPM) Rest	54	55	55	58	60	60	62	68	75	78	79	69	69	65	62
Case Study -2 SpO2 (%) Rest	95	96	97	98	99	97	96	98	99	97	96	98	97	95	96
Case Study -2 Systolic (mmHg) Rest	112	113	114	113	112	113	114	113	112	113	114	113	112	113	114
Case Study -2 Diastolic (mmHg) Rest	72	73	74	73	72	73	74	73	72	73	74	73	72	73	74
Case Study -2 Temperature (°C) Rest	36.3	36.4	36.5	36.4	36.3	36.4	36.5	36.4	36.3	36.4	36.5	36.4	36.3	36.4	36.5
Parameters / Ashwin (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -2 Heart Rate (BPM) Walk	78	82	85	80	88	90	84	79	86	92	87	81	89	83	91
Case Study -2 SpO2 (%) Walk	96	97	98	99	98	97	96	98	99	97	98	99	97	96	98
Case Study -2 Systolic (mmHg) Walk	121	122	123	122	121	122	123	122	121	122	123	122	121	122	123
Case Study -2 Diastolic (mmHg) Walk	81	82	83	82	81	82	83	82	81	82	83	82	81	82	83
Case Study -2 Temperature (°C) Walk	36.6	36.7	36.8	36.7	36.6	36.7	36.8	36.7	36.6	36.7	36.8	36.7	36.6	36.7	36.8
Parameters / Ashwin (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -2 Heart Rate (BPM) Run	102	103	105	108	110	112	115	118	116	119	117	113	111	109	107
Case Study -2 SpO2 (%) Run	95	95	96	97	96	95	95	96	97	95	96	95	95	96	95
Case Study -2 Systolic (mmHg) Run	132	135	119	138	136	134	135	136	138	134	135	136	138	134	136
Case Study -2 Diastolic (mmHg) Run	86	88	79	90	89	87	88	89	90	87	88	89	90	87	89
Case Study -2 Temperature (°C) Run	37	37.1	37.2	37.1	37	37.1	37.2	37.1	37	37.1	37.2	37.1	37	37.1	37.2
Parameters / Veerabathiran (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -3 Heart Rate (BPM) Rest	55	55	56	58	60	60	62	68	67	71	75	69	63	57	56
Case Study -3 SpO2 (%) Rest	96	97	98	99	98	97	96	98	99	97	98	96	97	98	99
Case Study -3 Systolic (mmHg) Rest	115	116	117	115	116	117	115	116	117	115	116	117	115	116	117
Case Study -3 Diastolic (mmHg) Rest	74	75	76	74	75	76	74	75	76	74	75	76	74	75	76
Case Study -3 Temperature (°C) Rest	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5
Parameters / Veerabathiran (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -3 Heart Rate (BPM) Walk	76	79	81	84	86	89	88	85	87	90	92	83	86	88	91
Case Study -3 SpO2 (%) Walk	97	98	99	98	97	96	98	99	98	97	98	99	97	98	96
Case Study -3 Systolic (mmHg) Walk	125	126	124	125	126	124	125	126	124	125	126	124	125	126	124
Case Study -3 Diastolic (mmHg) Walk	84	85	83	84	85	83	84	85	83	84	85	83	84	85	83
Case Study -3 Temperature (°C) Walk	36.8	36.9	37	36.9	36.8	36.9	37	36.9	36.8	36.9	37	36.9	36.8	36.9	37

Parameters / Veerabathiran (21)	Time & Measurement (minutes)														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -3 Heart Rate (BPM) Run	101	104	107	109	113	116	119	117	115	118	114	112	110	108	106
Case Study -3 SpO2 (%) Run	95	96	97	96	95	95	96	97	95	96	95	95	96	97	95
Case Study -3 Systolic (mmHg) Run	130	132	134	133	131	132	134	133	131	132	134	133	131	132	134
Case Study -3 Diastolic (mmHg) Run	85	87	88	87	86	87	88	87	86	87	88	87	86	87	88
Case Study -3 Temperature (°C) Run	37.2	37.3	37.4	37.3	37.2	37.3	37.4	37.3	37.2	37.3	37.4	37.3	37.2	37.3	37.4
Parameters / Veerabathiran (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -3 Heart Rate (BPM) Rest	55	55	56	58	60	60	62	68	67	71	75	69	63	57	56
Case Study -3 SpO2 (%) Rest	96	97	98	99	98	97	96	98	99	97	98	96	97	98	99
Case Study -3 Systolic (mmHg) Rest	115	116	117	115	116	117	115	116	117	115	116	117	115	116	117
Case Study -3 Diastolic (mmHg) Rest	74	75	76	74	75	76	74	75	76	74	75	76	74	75	76
Case Study -3 Temperature (°C) Rest	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5	36.6	36.5
Parameters / Veerabathiran (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -3 Heart Rate (BPM) Walk	76	79	81	84	86	89	88	85	87	90	92	83	86	88	91
Case Study -3 SpO2 (%) Walk	97	98	99	98	97	96	98	99	98	97	98	99	97	98	96
Case Study -3 Systolic (mmHg) Walk	125	126	124	125	126	124	125	126	124	125	126	124	125	126	124
Case Study -3 Diastolic (mmHg) Walk	84	85	83	84	85	83	84	85	83	84	85	83	84	85	83
Case Study -3 Temperature (°C) Walk	36.8	36.9	37	36.9	36.8	36.9	37	36.9	36.8	36.9	37	36.9	36.8	36.9	37
Parameters / Veerabathiran (21)	**Time & Measurement (minutes)**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Case Study -3 Heart Rate (BPM) Run	101	104	107	109	113	116	119	117	115	118	114	112	110	108	106
Case Study -3 SpO2 (%) Run	95	96	97	96	95	95	96	97	95	96	95	95	96	97	95
Case Study -3 Systolic (mmHg) Run	130	132	134	133	131	132	134	133	131	132	134	133	131	132	134
Case Study -3 Diastolic (mmHg) Run	85	87	88	87	86	87	88	87	86	87	88	87	86	87	88
Case Study -3 Temperature (°C) Run	37.2	37.3	37.4	37.3	37.2	37.3	37.4	37.3	37.2	37.3	37.4	37.3	37.2	37.3	37.4

The designed wearable system is a multi-parameter sensing platform that integrates heart rate, SpO_2, blood pressure estimation, and temperature monitoring into a single platform. Unlike previous devices, as reported by A. Sardini and M. Serpelloni [32], which are limited to monitoring one or a few physiological parameters at a time, the present system simultaneously tracks multiple physiological signals. This aligns with trends in multimodal wearable healthcare systems highlighted by Kuldeep Mahato et al. [18] and Hongwei Xie et al. [11]. The system demonstrates enhanced operational stability across varying activity conditions, addressing key challenges emphasized by G. Shin et al. [34].

Furthermore, the low cost modular architecture improves scalability and accessibility, mitigating practical limitations discussed by A. A. Ammar and A. A. Al aealaqi [3] and C. Zhang et al. [43]. The system is suitable for seamless long-term remote monitoring in applications such as home health care, elderly support, and preventive cardiovascular screening. The simultaneous measurement of multiple physiological signals provides a broader clinical context than traditional single sensor devices.

However, certain limitations remain. The current model relies on wired interconnections, which may reduce user comfort and long-term wear ability. Blood pressure readings are extrapolated rather than collected with clinical-grade instrumentation, introducing potential estimation variability. Advanced analytical frameworks, such as machine learning-based predictive models, are not yet implemented. Future work could focus on miniaturizing the system, integrating wireless connectivity, and incorporating intelligent data analytics to enhance usability and clinical applicability, making the system more comparable to next-generation wearable health devices.

A. Time-Series Analysis

Table III presents the time-series analysis of multiple physiological parameters across rest, walking, and running conditions for all three subjects. During rest, the overall average heart rate across subjects was 62.98 BPM, indicating stable physiological monitoring. For walking, the overall average heart rate increased to 84.98 BPM, reflecting normal cardiovascular response to moderate activity. During running, the overall average heart rate reached 110.91 BPM. The minimum heart rate observed was 54 BPM (rest), and the maximum was 119 BPM (running). Heart rates above 100 BPM indicate tachycardia, while rates below 60 BPM indicate bradycardia.

The overall average SpO_2 levels were 97.49% at rest, 97.67% during walking, and 95.80% during running. The lowest recorded value was 95% during running, and the highest was 99% during walking and running, reflecting normal oxygen saturation variations. SpO_2 levels below 95% indicate mild hypoxemia, while values below 90% indicate severe hypoxemia. Systolic blood pressure (SBP) averaged 115.98 mmHg at rest, 123.98 mmHg during walking, and 135.07 mmHg during running. The minimum SBP was 112 mmHg (rest), and the maximum was 139 mmHg (run). SBP values outside 90–119 mmHg indicate hypotension or elevated/ pre-hypertensive states. Values above 130 mmHg correspond to Stage 2 hypertension, and values exceeding 140 mmHg indicate a hypertensive crisis. Diastolic blood pressure (DBP) averaged 75.98 mmHg at rest, 83.98 mmHg during walking, and 87.98 mmHg during running. DBP is less variable with activity, ranging from 72–78 mmHg at rest, 80–85 mmHg during walking, and 85–92 mmHg during running. Deviations outside 60–79 mmHg indicate hypotension or prehypertension, while values between 80–89 mmHg indicate Stage 2 hypertension. Body temperature gradually increased with activity, averaging 36.46°C at rest, 36.84°C during walking, and 37.21°C during running. The minimum observed temperature was 36.3°C (rest), and the maximum was 37.4°C (run). Values below 36.5°C indicate mild hypothermia, whereas values above 37.5°C indicate fever.

B. Mean and Standard Deviation

Table IV shows the mean and standard deviation for each parameter across subjects and activity levels. Overall, heart rate variability is low (±5.41–6.12 BPM), with accuracies ranging from 90.65% to 95.12%. SpO_2 shows high stability (±1.02–1.15%), with accuracies above 98.8%. SBP and DBP measurements show minimal dispersion (standard deviations 0.82–2.90 mmHg), with accuracy exceeding 97%. Temperature measurements are highly stable (±0.05–0.13°C), with accuracy above 99.6%.

TABLE IV. MEASUREMENT OF MEAN AND STANDARD DEVIATION OF THREE ADULTS IN THREE CONDITIONS

	Case Study - 1 / Adhithan (21)		**Case Study - 2 / Ashwin (21)**		**Case Study - 3 / Veerabathiran (21)**	
Parameters	***Mean***	***Standard Deviation***	***Mean***	***Standard Deviation***	***Mean***	***Standard Deviation***
Heart Rate (BPM) Rest	62.2	± 3.28	64.6	± 8.38	62.13	± 6.43
SpO2 (%) Rest	97.8	± 0.94	96.93	± 1.22	97.53	± 1.10
Systolic BP (mmHg) Rest	117.8	± 0.86	113	± 0.82	116	± 0.82
Diastolic BP (mmHg) Rest	77.8	± 0.86	73	± 0.82	75	± 0.82
Temperature (°C) Rest	36.48	± 0.08	36.4	± 0.07	36.55	± 0.05
Heart Rate (BPM) Walk	83.6	± 6.77	85	± 4.69	85.67	± 4.87
SpO2 (%) Walk	97.6	± 0.99	97.53	± 1.06	97.6	± 1.06
Systolic BP (mmHg) Walk	123.9	± 0.83	122	± 0.82	125	± 0.82
Diastolic BP (mmHg) Walk	83.9	± 0.83	82	± 0.82	84	± 0.82
Temperature (°C) Walk	36.9	± 0.08	36.7	± 0.07	36.9	± 0.07
Heart Rate (BPM) Run	110.5	± 5.32	110.3	± 5.01	111.2	± 5.45
SpO2 (%) Run	95.93	± 1.10	95.4	± 0.91	95.93	± 1.03
Systolic BP (mmHg) Run	137.3	± 1.25	135.7	± 2.02	132.4	± 1.30
Diastolic BP (mmHg) Run	88.53	± 1.19	87.73	± 2.90	87	± 0.93
Temperature (°C) Run	37.29	± 0.07	37.1	± 0.07	37.3	± 0.08

C. Graphical Analysis

Fig. 9 illustrates heart rate variability across the three case studies under rest, walking, and running conditions over a 15-minute period. All subjects showed a progressive increase in heart rate from rest to walking and then to active conditions. Base levels were maintained between 55–65 BPM, consistent with stable physiological parameters. During walking, heart rate increased moderately to 75–95 BPM, representing a normal cardiovascular response to low physical activity. During sustained running, heart rates ranged from 100–120 BPM, reflecting normal physiological responses to higher workloads.

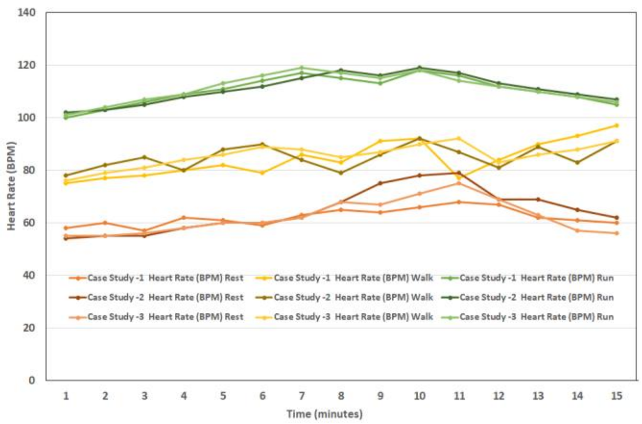

Fig. 9. Overall case study readings of Heart Rate (BPM).

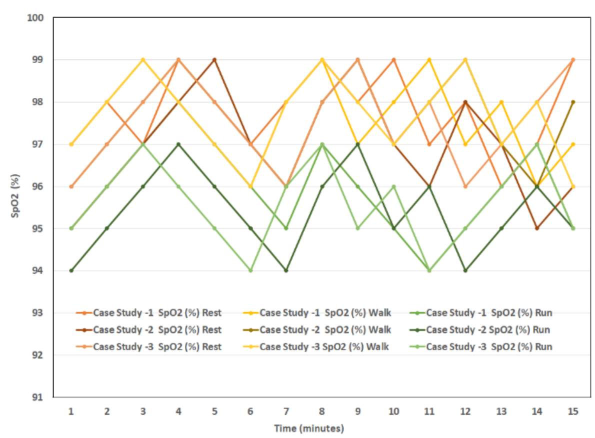

Fig. 10. Overall case study readings of SpO_2 (%).

Fig. 10 shows SpO_2 levels across different activity states. Unlike heart rate, SpO_2 values remained in a narrow range of approximately 94–99%, suggesting stable oxygen saturation regardless of activity. Resting values showed minimal variation, and slight changes during walking and running indicate that physical activity does not significantly affect oxygen saturation in healthy individuals.

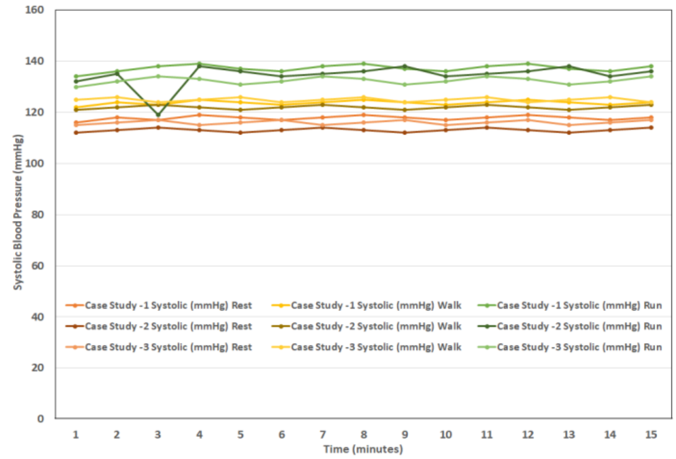

Fig. 11. Overall case study readings of systolic blood pressure (mmHg).

Fig. 11 depicts the evolution of systolic blood pressure (SBP) across activity levels. SBP increases progressively with exercise. At rest, values ranged from 112–118 mmHg, indicative of a stable cardiovascular state. During walking, SBP rose to 120–126 mmHg, reflecting a moderate increase in cardiac output. Running induced further increases to 130–140 mmHg, consistent with physiological demands during higher activity. These results demonstrate the system's accuracy and reliability for continuous cardiovascular monitoring.

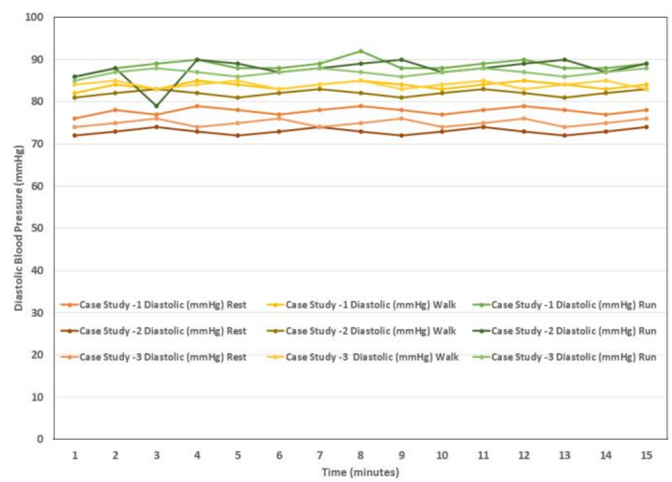

Fig. 12. Overall case study readings of diastolic blood pressure (mmHg).

Fig. 12 presents diastolic blood pressure (DBP) trends. DBP is less sensitive to activity than SBP, indicating more stable vascular behaviour. At rest, DBP ranged from 72–78 mmHg, reflecting baseline vascular resistance. During walking, values increased to 80–85 mmHg, while running produced a modest rise to 85–92 mmHg, consistent with expected physiological responses.

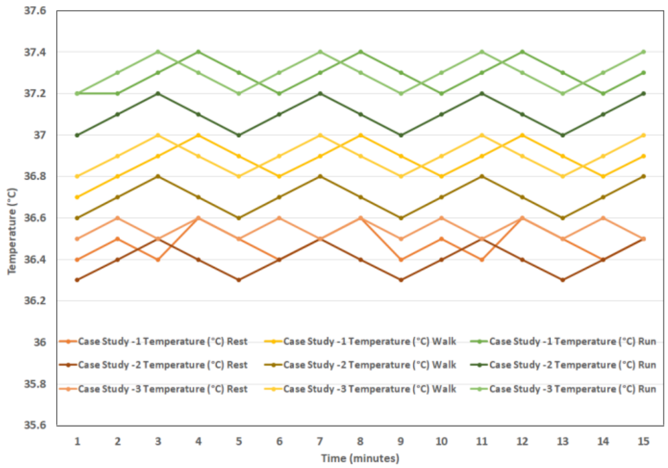

Fig. 13. Overall case study readings of Temperature (°C).

Fig. 13 shows body temperature changes across activity states. Resting temperatures ranged from 36.3–36.6°C. Walking caused a slight increase to 36.6–37.0°C, reflecting mild metabolic activation. Running increased temperatures further to 37.0–37.4°C, consistent with higher metabolic heat production and thermoregulatory adjustments during physical exertion.

To evaluate the significance of physiological changes across activity levels, a one-way ANOVA was performed for heart rate, SpO_2, systolic blood pressure (SBP), diastolic blood pressure (DBP), and body temperature under rest, walking, and running conditions. The analysis was performed at a significance level of $p < 0.05$.

The results showed statistically significant differences across activity levels for heart rate ($p < 0.001$), SpO_2 ($p < 0.001$), SBP ($p < 0.001$), DBP ($p < 0.001$), and body temperature ($p < 0.001$). These findings indicate that the observed changes in the physiological parameters across rest, walking, and running were statistically significant. In particular, heart rate, SBP, DBP, and temperature increased progressively with activity, while SpO_2 showed a comparatively small decrease during running.

Overall, the statistical analysis supports the observed physiological responses and demonstrates that the proposed wearable system can detect changes associated with different activity levels.

VI. Conclusion

The developed wearable health monitoring system demonstrates the feasibility of continuous multi-parameter physiological monitoring using compact, low-cost hardware integrated with an IoT platform. Experimental results confirm the system's capability to accurately monitor heart rate, SpO_2, systolic and diastolic blood pressure, and body temperature under various activity conditions, including rest, walking, and running. The system achieved high accuracy: heart rate 92.85% (error 7.14%), SpO_2 98.86% (error 1.10%), systolic blood pressure 98.25% (error 1.86%), diastolic blood pressure 97.37% (error 2.62%), and temperature 99.7% (error 0.3%). Mean values and standard deviations were consistent with normal physiological ranges. Heart rate increased progressively from rest to walking and running, SBP rose with activity while DBP remained relatively stable, SpO_2 remained within 94–99%, and body temperature increased moderately with activity. These results confirm the system's reliability, stability, and suitability for continuous health monitoring, with wireless communication enabling real-time data transmission and remote observation. The proposed wearable system effectively monitors multiple vital signs with high accuracy across different activity levels, reflecting expected physiological responses. Its compact, low-cost design and IoT integration make it suitable for continuous, real-time health monitoring, supporting preventive healthcare and eldercare applications. The system's stability and reliability highlight its potential for personalized and remote medical monitoring, with future improvements in battery life and predictive analytics further enhancing its clinical utility.

VII. Future Scope

Future work will involve developing a modular version of the continuous health monitoring system in which the sensing modules can be detached and replaced independently. This approach will make the system easier to maintain and allow individual components to be upgraded or modified when required. The current wired connections can also be replaced gradually with low-power wireless technologies such as Bluetooth Low Energy (BLE), providing greater freedom of movement and improved user comfort. Further improvements in battery capacity and the use of predictive analytics may enable longer-term operation and more personalized health monitoring. These developments could improve the practicality, scalability, and reliability of the proposed system for continuous health monitoring applications.

For future investigations in future, the research can be extended to be conducted in a larger and more diverse group of participants, including males and females from different age groups. Testing the system under different environmental conditions and levels of physical activity would also help assess its performance under a wider range of practical situations. Moreover, a larger batch participant would improve the reliability of the results and allow more meaningful statistical comparisons of the physiological changes observed during different activities. Such an expanded study would provide a stronger basis for evaluating the effectiveness and general applicability of the proposed real-time health monitoring system.

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