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Developing an intelligent IoT-enabled wearable multimodal biosensing device and cloud-based digital dashboard for real-time and comprehensive health, physiological, emotional, and cognitive monitoring using multi-sensor fusion technologies

Rayan H. Assaad [a,*], Mohsen Mohammadi [a], Oscar Poudel [a]

[a] Smart Construction and Intelligent Infrastructure Systems (SCIIS) lab, John A. Reif, Jr. Department of Civil and Environmental Engineering, New Jersey Institute of Technology, Newark, NJ 07102, United States

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ABSTRACT

A variety of biosensors have been recently introduced as wearable devices to collect physiological data, with applications ranging from personalized medicine and point-of-care diagnostics to home and fitness monitoring, among others, garnering substantial interest. This interest has been fueled by the increasing demand for ubiquitous, continuous, and pervasive vital signs monitoring, coupled with advancements in biosensor technology and IoT-enabled capabilities. Existing research studies have only relied on a limited number of health- and physiological-related indicators (thus, do not offer a comprehensive health monitoring and assessment system) due to the technical difficulties to integrate multiple sensors. In fact, the issues of multimodality, heterogeneity, and complexity of data as well as the interoperability among sensors make it challenging to seamlessly integrate multiple sensors into one system. This study overcame these technical challenges by leveraging multi-sensor fusion capabilities to develop an intelligent, IoT-enabled wearable multi-modal biosensing device and cloud-based digital dashboard for real-time, comprehensive health, physiological, emotional, and cognitive monitoring. First, 18 different health- and physiological-related indicators were identified. Second, 14 different sensors were used to acquire the entire data for the 18 different indicators using a hardware sensing system designed using four ESP32 microcontroller boards integrated with Wi-Fi and Bluetooth connectivity by fusing the various data from the 14 different sensors. Third, the designed system was developed as a wearable device that can be installed on the hip as well as the right and left feet using 3D printed parts. Fourth, a web-based digital dashboard was created onan edge computing server that was hosted on a microprocessor to instantly publish the data, and a graphical user interface (GUI) was developed to provide intuitive and real-time visualization of the various health-related indicators using the Django and JavaScript-based React.js web development frameworks. The accuracy of the developed IoT-enabled biosensing system was tested and validated by benchmarking and comparing the obtained results from the proposed system with those aquired from various commercially used sensors. The validation outcomes reflected that the proposed system achieved an accuracy of more than 90 % for most of the 18 considered indicators and an accuracy greater than 85 % for all indicators. This study adds to the body of knowledge by being the first research capable of reporting the following 18 indicators into a single biosensing system in real-time: Electrocardiogram (ECG or EKG), Electroencephalogram (EEG), Electrooculogram (EOG), Electromyography (EMG), Photoplethysmography (PPG), heart rate (HR), heart rate variability (HRV), respiratory rate (RR), skin temperature (ST), skin humidity (SH), blood glucose level (BGL), blood pressure (BP), oxygen saturation (SpO2), body weight pressure (BWP), body motion (BM), electrodermal activity (EDA), galvanic skin response (GSR), and skin conductance responses (SCR). The proposed system provides rich information on various vital signs and could be used for a wide window of applications, including monitoring and assessing health status; emotional and arousal status; mental and cognitive status; behavioral, physical, and attention status; and physiological status. The developed system is not specific to a particular industry but rather

* Corresponding author.
E-mail addresses: rayan.hassane.assaad@njit.edu (R.H. Assaad), mm2758@njit.edu (M. Mohammadi), op72@njit.edu (O. Poudel).

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could be used for any sector of interest. This paper lays the ground to significant advancements in wearable sensor technology, data visualization techniques, and health monitoring practices.

1. Introduction

The current trend in healthcare leans towards early disease detection as a cost-effective strategy, reducing the financial burden of treating fully developed diseases [1,57]. This proactive approach also yields improved health outcomes. Wearable biosensors have emerged as a key player in this paradigm shift. Their high specificity, portability, fast detection capabilities, affordability, low power consumption, and real-time data availability integrated with Internet of Things (IoT) capabilities make them ideal for wearable applications [50]. These devices play a pivotal role in gathering vital information continuously and non-invasively 21,3.

Wearable technology encompasses a broad spectrum of devices. On one end, there are consumer-grade wearables designed for entertainment or fitness tracking. On the other end, there are research-grade and medical-grade wearables that adhere to the skin or body, tracking physiological health data [12,22]. These devices can collect data round-the-clock, in various environments, while users go about their daily routines at home or work [13]. Wearable devices can provide valuable insights into physiological, emotional, health, and illness states. They empower individuals to self-monitor without the need for costly equipment or professional medical staff [11,20]. Furthermore, the non-invasive nature of wearable technologies makes them highly beneficial for continuous health monitoring and early disease diagnostics. They also facilitate patient access to clinical information, promoting greater health awareness and compliance in a convenient and cost-effective manner [73].

In recent years, a variety of wearable biosensors have been introduced as wearable devices to collect physiological data, with applications ranging from personalized medicine and point-of-care diagnostics to home and fitness monitoring [50]. These devices, which include shirts [17], necklaces [5], lenses [37], headbands [19], smart wristbands [65], smartwatches [2], shoes [35], eyeglasses [6], wristbands [26], and patches [56], have garnered significant interest. This interest has been fueled not only by the growing demand for ubiquitous, continuous, and pervasive vital sign monitoring in the wearable technology market but also by advancements in biosensor technology, IoT-enabled capabilities, and Wireless Sensor Networks (WSNs) communications [15,47]. The global wearable technology market, valued at over \$1.131 billion at the end of 2023, is projected to reach \$4.891 billion by the end of 2033 [71]. Pervasive health monitoring applications are the fastest-growing segment in the wearable technology market, driven by the pressing need to monitor chronic diseases and aging populations [51,53].

Modern wearable devices have evolved beyond simple fitness tracking, such as daily step counts. With the advancements in sensors fusion in developing multimodal sensing devices [9], it is currently possible to monitor critical physiological indicators, such as Electrocardiogram (ECG) to measure the electrical activity of the heart [64]; Photoplethysmography (PPG) to detect blood volume changes in the microvascular bed of tissue [36]; Electromyography (EMG) to assess the health of muscles [74]; Electroencephalogram (EEG) to evaluate the electrical activity in the brain [16]; Electrooculogram (EOG) to measure the resting potential of the retina [54]; Respiratory Rate (RR) [52]; Skin Temperature (ST) [18]; Heart Rate (HR) [43]; Heart Rate Variability (HRV) to evaluate the variation in the time interval between consecutive heartbeats [69]; Skin Humidity (SH) [7]; Blood Glucose Level (BGL) [48]; Blood Pressure (BP) [60]; oxygen saturation (SpO2) [70]; Body Motion (BM) measurement [38]; Body Weight Pressure (BWP) on feet to detect the weight distribution during activities and detect abnormal gait patterns [40]; and additional emotional arousal health-related information such as Electrodermal Activity (EDA) to identify the emotional status [49]; Galvanic Skin Response (GSR) to evaluate the cognitive status [34]; and Skin Conductance Responses (SCR) to determine the emotion and attention status [52].

An electrocardiogram (ECG or EKG) is a medical test that measures the electrical activity of the heart over a period of time. Photoplethysmography (PPG) is a non-invasive optical technique used to measure changes in blood volume in microvascular tissues; it detects variations in light absorption by blood vessels as they expand and contract with each heartbeat. Electromyography (EMG) is a diagnostic procedure that assesses the electrical activity of muscles. An electroencephalogram (EEG) is a diagnostic test that measures the electrical activity of the brain. An electrooculogram (EOG) is a diagnostic test that measures the electrical potential difference between the front and back of the eye, which reflects eye movement and position. Respiratory rate (RR) is the number of breaths a person takes per minute; it is a vital sign that reflects respiratory health and overall physiological status. Skin temperature (ST) refers to the temperature of the surface of the skin, which can provide insights into a person's overall thermal state and health. Heart rate (HR) is the number of times the heart beats per minute (bpm). It is a vital sign that indicates the efficiency of the heart's pumping action and overall cardiovascular health. Heart rate variability (HRV) is the measure of the variation in time intervals between consecutive heartbeats; it reflects the autonomic nervous system's regulation of the heart, providing insights into cardiovascular health and overall well-being. Skin humidity (SH) refers to the moisture level present on the surface of the skin; it is an important factor in assessing skin hydration and overall skin health. Blood glucose level (BGL) refers to the concentration of glucose (sugar) present in the bloodstream at a given time; it is a critical measure for assessing metabolic health and is especially important for managing diabetes. Blood pressure (BP) is the force exerted by circulating blood against the walls of blood vessels, primarily arteries; it is a vital sign that helps assess cardiovascular health. Oxygen saturation (SpO2) is the percentage of hemoglobin in the blood that is saturated with oxygen; it indicates how effectively oxygen is being transported throughout the body and helps in indicating respiratory or circulatory issues. Body motion (BM) refers to the movement and activity of the body, encompassing various types of physical movements; it is important for assessing physical activity levels, understanding biomechanics, and evaluating health and fitness. Body Weight Pressure (BWP) on feet refers to the distribution of an individual's weight across the foot when standing, walking, or engaging in other activities; this pressure affects how forces are transmitted through the feet and can influence balance, stability, and overall gait, and it is important for understanding foot mechanics, identifying areas of excessive pressure that may lead to discomfort or injury. Electrodermal activity (EDA) refers to the change in electrical conductance of the skin, which is influenced by sweat gland activity and can indicate physiological arousal; changes in EDA can reflect emotional states, stress levels, and overall sympathetic nervous system activity. Galvanic skin response (GSR) is a measure of the electrical conductance of the skin, which varies with changes in moisture levels due to sweating. It is commonly used to assess physiological arousal associated with emotional and psychological states. Skin conductance responses (SCR) refer to the changes in the electrical conductance of the skin that occur in response to stimuli, such as emotional arousal, stress, or excitement; SCR is a component of EDA.

The integration of biosensors with IoT capabilities and WSNs offers numerous advantages in the development of multimodal sensing devices [27,29,46]. These devices can collect a wide range of physiological indicators, providing a comprehensive view of an individual's health status [59]. The collected data can be analyzed and visualized through a user-friendly IoT-enabled Graphical User Interface (GUI), making it easy for individuals to understand and monitor their health status. This comprehensive health monitoring system can help individuals take proactive measures towards maintaining their health, facilitate timely intervention by healthcare professionals when necessary, and ultimately improve the overall quality of healthcare services [61]. Moreover, these health monitoring systems have broad applicability across various industry sectors. For instance, these systems can be used to monitor workers' health and performance in the construction, underground mining, chemical, and logistic industries [28]. This enables tasks to be carried out more safely and efficiently, thereby enhancing productivity while ensuring the well-being of workers [66]. By providing real-time health status and alerting for any potential health risks, these systems can significantly contribute to creating a safer and healthier work environment [76].

Despite the numerous studies that have attempted to collect various physiological indicators, several gaps persist. First, most previous studies have relied on commercially available biosensors to collect some health monitoring-related indicators. However, these available devices measure, collect, and analyze data on limited number of health monitoring-related indicators (and thus do not offer a comprehensive and accurate biological and physiological assessment) mainly due to the technical difficulties to integrate multiple sensors into a single device. In fact, due to the issues of multimodality, heterogeneity, and complexity of data, the interoperability among sensors with various measurements, sampling rates, and technical requirements makes it very challenging to seamlessly integrate multiple sensors into one device. In other words, these available devices are specialized to measure, collect, and analyze data on specific indicators (e.g., EEG, or ECG, or EDA, etc.) rather than providing a comprehensive data collection and assessment on all of the possible health monitoring-related indicators into a single device or system. Thus, necessitating the use of various commercial devices which creates issues in fusing the multi-modal data from the various sensors and devices, complicates the data collection process, and increased the deployment cost. Also, access to raw data from these existing commercial devices is often restricted as they are not open source. Additionally, the reliability of their results may be questionable in some cases, especially for consumer-grade commercial devices, due to the lack of transparency in the raw data analysis process as they do not provide the user with the capability to access and/or modify the data analysis algorithms. Furthermore, these devices are often very expensive and thus are not cost-effective for comprehensive health monitoring assessments and evaluations.

To address these critical knowledge gaps, this paper introduces an intelligent IoT-enabled multimodal wearable biosensing system for real-time comprehensive health and physiological monitoring using sensor fusion capabilities and relying on open source and affordable components. By integrating sensor fusion with IoT capabilities and WSNs, this system aims to provide a more reliable, cost-effective, and comprehensive solution for real-time health monitoring and assessment. This innovative approach not only enhances the functionality and reliability of wearable health monitoring systems but also paves the way for a new era of proactive and personalized healthcare.

2. Goal and objectives

The primary objective of this research is to develop an intelligent and comprehensive multimodal health monitoring system by integrating sensor fusion, WSNs, and IoT capabilities. This system enables real-time collection and visualization of comprehensive biological and physiological indicators. The specific objectives are: 1) identifying a comprehensive list of health-monitoring indicators to be integrated into the proposed health monitoring system; these indicators will serve as essential measures of an individual's well-being, and corresponding sensors suitable for collected data on and capturing these indicators will be selected based on their accuracy, reliability, and practicality; 2) designing and implementing a sensor fusion IoT-based sensing device that seamlessly integrates data from various sensors, accommodating the heterogeneity, multimodality, and complexity of the collected information to provide a holistic view of an individual's health status in real-time; 3) creating a user-friendly GUI platform for real-time data analysis, management, storage and visualization, where users have the flexibility to access the results from any device connected to the internet; these clear and intuitive visualizations will enhance the usability and effectiveness of the system.

This study aims to address several critical aspects of health monitoring. By providing the ability to track and visualize extensive physiological indicators, the proposed system offers a more comprehensive understanding of an individual's health. Also, the integration of sensor fusion techniques ensures accurate and timely data collection. Moreover, the user-friendly GUI platform promotes accessibility and encourages proactive engagement with health information. Furthermore, successful implementation of this research can lead to substantial improvements in individual well-being across various industries and contexts. Ultimately, this innovative approach not only enhances the functionality and reliability of wearable health monitoring systems but also lays the groundwork for personalized and proactive healthcare practices.

3. Background information and knowledge gap

This section reviews the previous relevant literature and identifies the gaps present in the existing body of knowledge that this paper addresses.

3.1. Related research studies on health monitoring systems

In recent years, wearable devices have evolved beyond mere fitness trackers, transcending simple step-counting functionalities. These modern wearables now delve into crucial physiological considerations, providing a holistic approach to health monitoring [63]. Researchers and developers have harnessed the potential of wearable technology to capture a wide range of physiological indicators. These research efforts can be categorized into two groups. The first group includes research studies that have used and/or developed multimodal sensing devices to collect physiological indicators without utilizing a GUI or a platform to visualize the collected data second, while the second group includes research studies that attempted to develop a platform for real-time visualization of the collected data.

In terms of the first group of research studies, they include research efforts that used or developed multimodal health monitoring device for collecting certain or specific (rather than comprehensive) physiological indicators without considering a visualization platform. For instance, the influence of human movement on emotion recognition and health states was investigated by collecting physiological indicators such as EMG, ECG, HR, and ST and emotional arousal indicators such as EDA through a specialized commercial multi-sensor platform (i.e., Biosignalplux) [74]. Furthermore,a multimodal sensing device that integrates three biosensors on a wrist was used as a wearable health monitoring system to collect PPG and ECG [36,64]. Additionally, a wearable multimodal bio-sensing system integrated into a headset with capabilities to collect PPG, EEG, BM, and GSR data was used to track the HR and HRV [54]. Moreover, in another study, physiological indicators such as HR, ST, and GSR were collected, and deep learning facial emotion recognition was applied to identify emotion recognition and health states [10]. In addition, a healthcare wearable device to track heart health status was developed based on collecting heart-related physiological indicators such as ECG, HR, and BM through three biosensors and integrating them onto a belt [31]. In another study, the effect of sedentary motion and micro-motion (e.g., typing) on HR was investigated by collecting PPG, ECG, and HR through a proposed wearable device attached to the upper arm [14]. Additionally, to track behavioral and emotional arousal symptoms of dementia, a wearable wristband was developed to collect PPG, BM, ST, and EDA data, and a personalized machine learning method was utilized to classify the presence of dementia symptoms [30]. Furthermore, PPG and ST data from physiological indicators and EDA data from emotional arousal indicators were collected to propose a construction workers' risk perceptions model based on these collected data and the use of classification machine learning algorithms [42]. Moreover, a noninvasive method for assessing workers' physical demands was introduced based on collecting PPG, EDA, and ST data from workers while they perform regular tasks in the field, thus, estimating the rate of energy expenditure, and applying Gaussian kernel support vector machine to predict different physical-intensity levels [33]. Previous studies also considered collecting physiological, emotional, and cognitive arousal indicators to track the stress levels of the workers [16,32,49], perceived risk [42], workers' fatigue [7], workers' physiological activity [43,69], safety training of workers [62], environmental distress [38], and the effect of different learning scenarios [70].

The second group of studies included research efforts that utilized a visualization platform to display the collected data from the used biosensors. For example, a wearable monitoring system was developed based on collecting ECG, GSR, SCR, HR, and HRV data, and displaying results on console screens while participants were engaged in mental performance [52]. Additionally, an approach for monitoring and tracking in-home, fine-grained activity recognition was proposed based on collecting BM data (i.e., accelerometer and gyroscope data) and ambient temperature, humidity, and atmospheric pressure and visualizing the collected data through a developed GUI [18]. Moreover, a wearable stress monitoring system was proposed based on gathering EEG, ECG, EMG, HR, and ST data from wearable biosensors, utilizing WSN communication to transmit collected data, and developing a user interface to visualize the raw data and quantified stress credibility index [75]. In addition, an IoT-based BP and ST monitoring device with a web-based visualization interface was developed based on quantifying systolic and diastolic pressure from an air pressure sensor attached to a manual blood pressure cuff and a temperature sensor [60]. In another example of utilizing a web-based user interface for visualization of collected data, a healthcare monitoring system was developed based on collecting ECG, HR, ST, BM, and BP data from an integrated commercial biosensor and enabling WSNs for data transmission [55]. In another study, to track foot deformation, inadequate rotation, or improper balance, a foot weight pressure distribution monitoring system with an IoT-based application for smartphones was developed based on using commercial smart shoe insoles integrated with built-in pressure sensors laminated [40]. Furthermore, a physiological computing toolkit was designed to collect PPG, GSR, EDA, and RR data and visualize real-time processed data through a web-based user interface [34]. More recently, a noninvasive approach for estimating the BGL was developed based on calculating a metabolic index from oxy- and deoxyhemoglobin signals resulting from PPG data and visualizing the results through a smartwatch-based prototype [48]. In another example of noninvasive approaches for estimating the BGL, a breath analysis model was proposed based on identifying the concentration of three gases (i.e., alcohol, acetone, and propane) in exhaled and their correlation with BGL [4,45].

3.2. Knowledge gaps

The comprehensive review of pertinent literature and studies reveals that, despite significant progress in the field of wearable bio-sensing health monitoring and assessment systems, there are still notable gaps. Table 1 provides a detailed summary of previous related research studies and compares them with the proposed approach in this paper, which helps in better highlighting the knowledge gaps and underscoring the novelty of the proposed wearable multimodal bio-sensing health

Table 1
Summary of previous studies in wearable multimodal bio-sensing health monitoring and assessment systems.

Reference	Biological and/or physiological indicators considered in each research study																		GUI
	ECG	EMG	EOG	EEG	BM	PPG	BGL	BWP	HR	HRV	SpO2	RR	ST	SH	EDA	GSR	SCR	BP	
[52]	✓	-	-	-	-	-	-	-	✓	-	-	✓	-	-	-	✓	✓	-	✓
[18]	-	-	-	-	✓	-	-	-	-	-	-	-	✓	-	-	-	-	-	✓
[36]	✓	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-
[70]	-	-	-	-	-	-	-	-	✓	-	✓	✓	✓	-	-	✓	-	-	-
[7]	-	-	-	✓	-	-	-	-	✓	-	-	-	-	✓	-	-	-	-	-
[43]	-	-	-	-	-	-	-	-	✓	✓	-	-	-	-	-	-	-	-	-
[74]	✓	✓	-	✓	-	✓	-	-	-	-	-	✓	✓	-	✓	-	-	-	-
[54]	-	-	-	✓	✓	✓	-	-	✓	✓	-	-	-	-	-	✓	-	-	-
[33]	-	-	-	-	-	✓	-	-	-	-	-	-	✓	-	✓	-	-	-	-
[32]	-	-	-	-	-	✓	-	-	-	-	-	-	✓	-	✓	-	-	-	-
[58]	✓	-	-	-	-	-	-	-	✓	-	✓	✓	✓	-	-	-	-	-	✓
[39]	-	-	✓	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[38]	-	-	-	-	✓	-	-	-	✓	-	-	-	-	-	✓	-	-	-	-
[64]	✓	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	-	-	-
[45]	-	-	-	-	-	-	✓	-		-	-	-	-	-	-	-	-	-	✓
[10]	-	-	-	-	-	✓	-	-	✓	-	-	-	✓	-	-	✓	-	-	-
[31]	✓	-	-	-	✓	-	-	-	✓	-	-	-	-	-	-	-	-	-	-
[16]	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	✓	-	-	-	-
[42]	-	-	-	-	-	✓	-	-	-	-	-	-	✓	-	✓	-	-	-	-
[69]	-	-	-	-	-	-	-	-	-	✓	-	-	-	-	-	-	-	-	-
[49]	-	-	-	-	-	✓	-	-	-	-	-	-	-	-	✓	-	-	-	-
[14]	✓	-	-	-	-	✓	-	-	✓	-	-	-	-	-	-	-	-	-	-
[30]	-	-	-	-	✓	-	-	-	✓	-	-	-	✓	-	✓	-	-	-	-
[75]	✓	-	-	✓	-	-	-	-	✓	-	-	-	✓	-	-	-	-	-	✓
[60]	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	-	-	-	✓	✓
[55]	✓	-	-	✓	-	-	-	-	✓	-	-	-	✓	-	-	-	-	✓	✓
[4]	-	-	-	-	-	-	✓	-	-	-	-	-		-	-	-	-	-	✓
[72]	-	-	✓	✓	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[34]	-	-	-	-	-	✓	-	-	-	-	-	✓	-	-	✓	✓	-	-	✓
[62]	-	-	-	✓	-	✓	-	-	-	-	-	-	-	-	✓	-	-	-	-
[40]	-	-	-	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	✓
[48]	-	-	-	-	-	-	✓	-	-	-	-	-	-	-	-	-	-	-	✓
This Study	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

monitoring and assessment system in this paper.

Table 1 indicates that a comprehensive health and physiological monitoring system requires complicated sensing capabilities and integrating data on various health-related indicators, which is a very hard task to achieve as it requires the fusion of a high number of sensors and combining heterogeneity, multimodality data with different formats and requirements. Therefore, the majority of existing research studies have focused on collecting data on basic or fundamental or specific health-related aspects, while disregarding other important indicators. While these studies have contributed valuable insights, they lack the comprehensiveness required for a reliable health monitoring and assessment system. The more sensors there are, the harder it is to fuse them to a single IoT-enabled health device as many challenges emerge with the heterogeneity, multimodality, and complexity of various data from the various sensors. These challenges exist due to the fact that the sensors have different measurements, formats, resolutions, sampling rates, calibration requirements, error models, and spatio-temporal alignments. Setting different sensors to seamlessly communicate with one another in real time is significantly challenging in the sensor fusion field [67].

Table 1 also indicated that the number of health and/or physiological-related indicators collected from biosensing systems in previous studies generally ranges between 1 and 7. In contrast, the proposed approach in this paper provides a comprehensive health and physiological monitoring and assessment based on 18 indicators by integrating 14 different biosensors using open-source components and sensors. Further, Table 1 illustrates that the majority of existing studies have relied on the collection of ECG, PPG, and HR data for the development of a multimodal healthcare monitoring system through utilizing plug-and-play biosensors. While these studies have contributed valuable insights into health monitoring, their primary focus has been very specific on tracking heart-related behaviors. This focus has resulted in a lack of comprehensive and other vital health sign monitoring and assessment.

Another gap identified in previous studies is the lack of a user-friendly GUI capable of visualizing different health-related indicators with varying quantification approaches, sample rates, and time delays. Some of these indicators (such as ECG, EEG, EOG, EMG, and PPG) need to be transmitted in real-time, while other indicators (like HR, HRV, BP, and BGL) require appropriate delays for quantification. As Table 1 shows, the development of a visualization platform to display collected data has not kept pace with the increase in the number of monitored health-related indicators (e.g., see [70] and [74] in Table 1).

To address these critical knowledge gaps, this paper develops a research grade IoT-enabled multimodal wearable bio-sensing system compromised of both a device and a GUI-based dashboard for real-time health monitoring. This system provides comprehensive tracking of physiological symptoms using sensor fusion technologies. This approach represents a significant advancement in the field and offers a promising solution to the identified gaps in the literature.

It is important to note that to the authors' best knowledge, this is the first time an intelligent multimodal IoT-enabled health monitoring system of this level of comprehensiveness is being developed/proposed. This pioneering work opens a new era in the field of wearable bio-sensing health monitoring and assessment systems. The proposed system's ability to collect more than 18 indicators by integrating 14 biosensors is unprecedented. This level of comprehensive monitoring can provide a more holistic view of an individual's health and performance, making it a significant advancement in the field. This underscores the novelty and potential impact of this study in the realm of health monitoring systems.

4. Methodology

To achieve the goal and objectives of this paper, an integrated research framework has been implemented, as shown in Fig. 1.

4.1. Multimodal sensing and signal acquisition and fusion

In this phase, several critical processes were undertaken, each contributing to the development of a comprehensive health monitoring system. These processes are detailed in the subsequent subsections.

Initially, the necessary physiological indicators for comprehensive health monitoring were identified; and reliable, open-source, and cost-effective sensors capable of collecting the identified indicators were selected. Afterwards, a multimodal sensing device, enabled by IoT and capable of fusing various sensor data, was designed. This device is primarily responsible for signal acquisition. The developed multimodal sensing device transmits the collected data from the biosensors to an edge server, where further processing and real-time analysis are conducted. This systematic approach ensures the robustness and efficiency of the health monitoring system as detailed in the next subsections.

4.1.1. Identification of Health-related Indicators

To comprehensively monitor health physiological indicators, a comprehensive literature review was conducted to identify potential indicators to be used for monitoring various vital health-related signs. Table 2 shows the various identified indicators and the associated reference(s). Ultimately, 18 key indicators were determined as illustrated in Table 2.

4.1.2. Development of a multimodal sensing device

After identifying the various health-related indicators, a multimodal sensing device was designed/developed to collect and integrate the data for each indicator. First, the needed wearable sensors for collecting these 18 health-related indicators were identified. Specific features were considered when selecting the sensors and designing the multimodal sensing device, including measurement sensitivity, response speed, reception accuracy, drive circuit complexity, lifespan, and cost. The selected sensors for each indicator along with their position on the body and data acquisition/communication methods are detailed in Fig. 2.

As depicted in Fig. 2, EEG, EOG, ECG, and EMG signals were collected through three electrodes (e.g., IN+, IN-, and REF for each indicator) that were connected to an analog-front-end (AFE) biosensor signal acquisition board that can be paired with any microcontroller unit (MCU) or single-board computer (SBC) with an analog-to-digital converter (ADC) such as ESP32 (which is a series of low-cost, low-power system on a chip microcontrollers with integrated Wi-Fi and dual-mode Bluetooth) or any Arduino board. In this paper, the AFE boards were paired with ESP32 by connecting the VCC and GND pins of the AFE board to the 5 volts and GND pins of the ESP32 microcontroller. In addition, the output pin of the AFE boards was connected to the ADC pin of the ESP32 microcontroller. The ESP32 microcontroller is responsible for collecting and pre-processing the data such as on-sensor signal processing to reduce data transfer rates and the computational burden before sending it to the edge computing server.

As for the HR and HRV indicators, they were measured through signals acquisition from the ECG sensor.

As for the RR indicator, it was measured by developing a belt respiration sensor. The developed respiration sensor includes a chest strap with a conductive rubber curd, as shown in Fig. 3. The changes in resistance of the conductive rubber cord due to stretches of expansion of the chest when breathing were used to measure RR [77] (i.e., when the conductive rubber stretches, its resistance increases).

As illustrated in Fig. 3, one end of the conductive rubber cord was connected to the 5-volt pin of the ESP32 microcontroller, another end was connected to one side of a 4.7 KΩ resistance and the GND pin of the ESP32 microcontroller, and the other side was connected to an ADC of the ESP32 microcontroller.

As for the BP indicator, it was measured based on quantifying the systolic and diastolic pressure of blood. Systolic pressure occurs when the ventricles contract and eject blood into the arteries, while diastolic pressure occurs when the ventricles relax and fill with blood from the

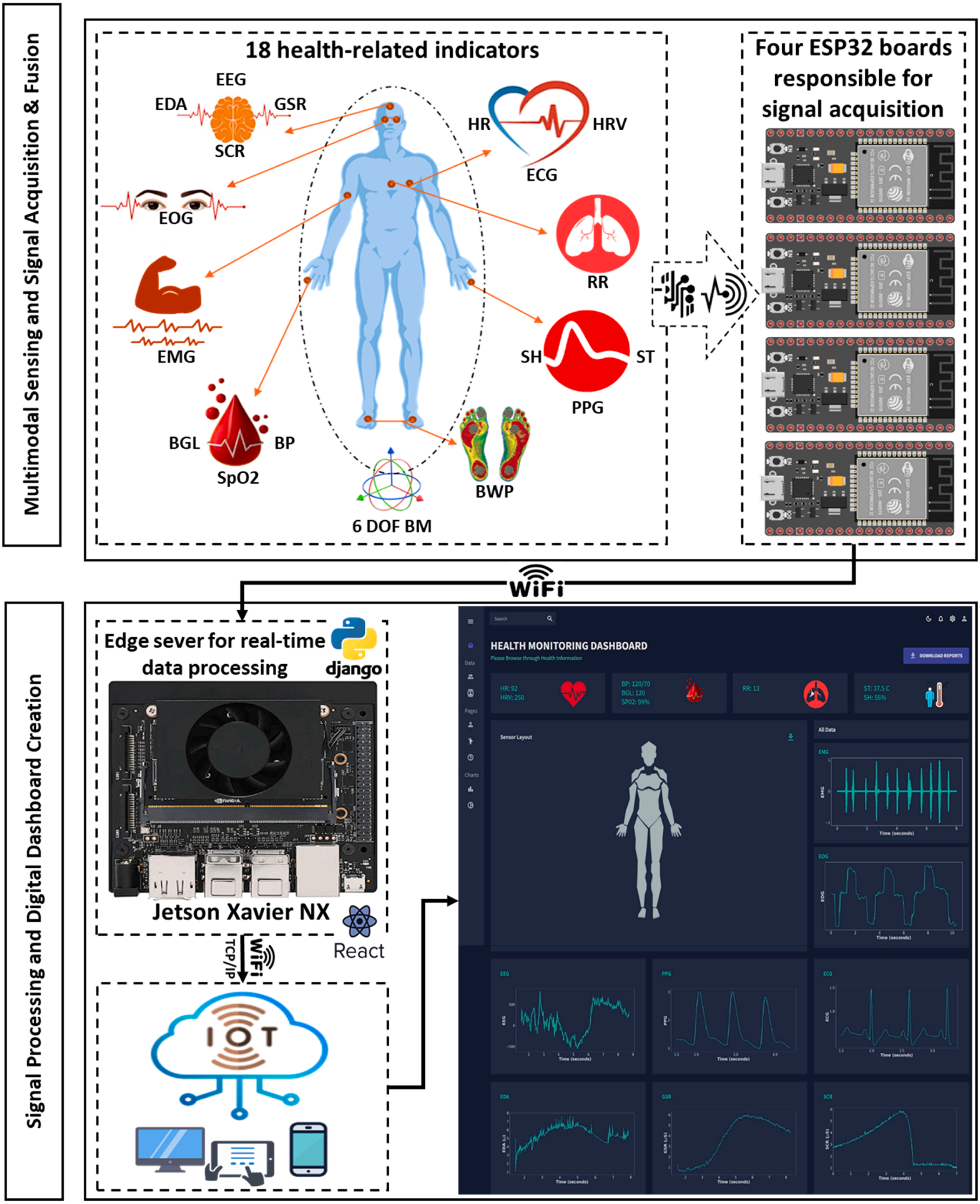

Fig. 1. Summary of the research methodology.

Table 2
List of health-related indicators considered in this paper.

Indicator	References
ECG	[14,31,36,52,55,58,64,75,74]
EEG	[7,74,54,39,16,75,55,72,62]
EOG	[39,72]
EMG	[74]
PPG	[10,14,33,32,34,36,42,49,54,62,64,74]
HR	[7,10,14,30,31,38,43,52,54,55,58,70,75]
HRV	[43,54,69]
RR	[34,52,58,70,74]
ST	[10,18,30,33,32,42,55,58,60,70,75,74]
SH	[7]
BGL	[24,45,4,48]
BP	[55,60]
SpO2	[58,70]
BWP	[40]
BM	[18,30,31,38,54]
EDA	[16,30,33,32,34,38,42,49,62,74]
GSR	[10,34,52,54,70]
SCR	[52]

As depicted in Table 2, 18 indicators were identified to comprehensively monitor and analyze the human body's vital signs including biological, psychological, and emotional arousal indicators.

atria [60]. Measuring the BP indicator was conducted based on integrating a pressure sensor sensitive to low pressure with a manual blood pressure cuff as shown in Fig. 4. The pressure sensor was connected to the ESP32 microcontroller, and when the user uses the manual cuff pump to apply pressure to 40 KPa (i.e., 300 mmHg) and slowly release the pressure, the sensor can detect the systolic and diastolic pressure of blood based on the correlation between the changes of the sensor output voltage and PB value [60].

As depicted in Fig. 4, the VCC and GND pins of the pressure sensor were connected to the 5-voltage and GND pins of the ESP32 microcontroller. Furthermore, the data communication between the pressure sensor and the ESP32 microcontroller was conducted through Inter-Integrated Circuit (IIC) serial communication protocol by connecting the serial data line (SDA) pin and serial clock line (SCL) pin of the pressure sensor and the ESP32 microcontroller.

As for the BGL, it was measured by developing a non-invasive breath analyzer sensor that collects the concertation of the acetone gas with exhaled breath and quantifies the BGL based on its correlation with acetone concertation [4,45]. To do so, an MQ138 gas sensor with high sensitivity to acetone was selected and connected to the ESP32 microcontroller as shown in Fig. 5.

As shown in Fig. 5, the VCC and GND pins of the MQ138 were connected to the 5-volts and GND pins of the ESP32 microcontroller. Moreover, the digital output pin of MQ138 was connected to a digital pin of the ESP32 microcontroller. The acetone concentration with breath exhaled was quantified based on Equation 3 as follows [24].

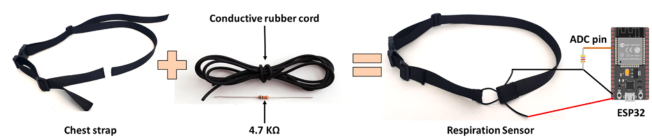

Fig. 3. The developed respiration sensor to measure the RR indicator.

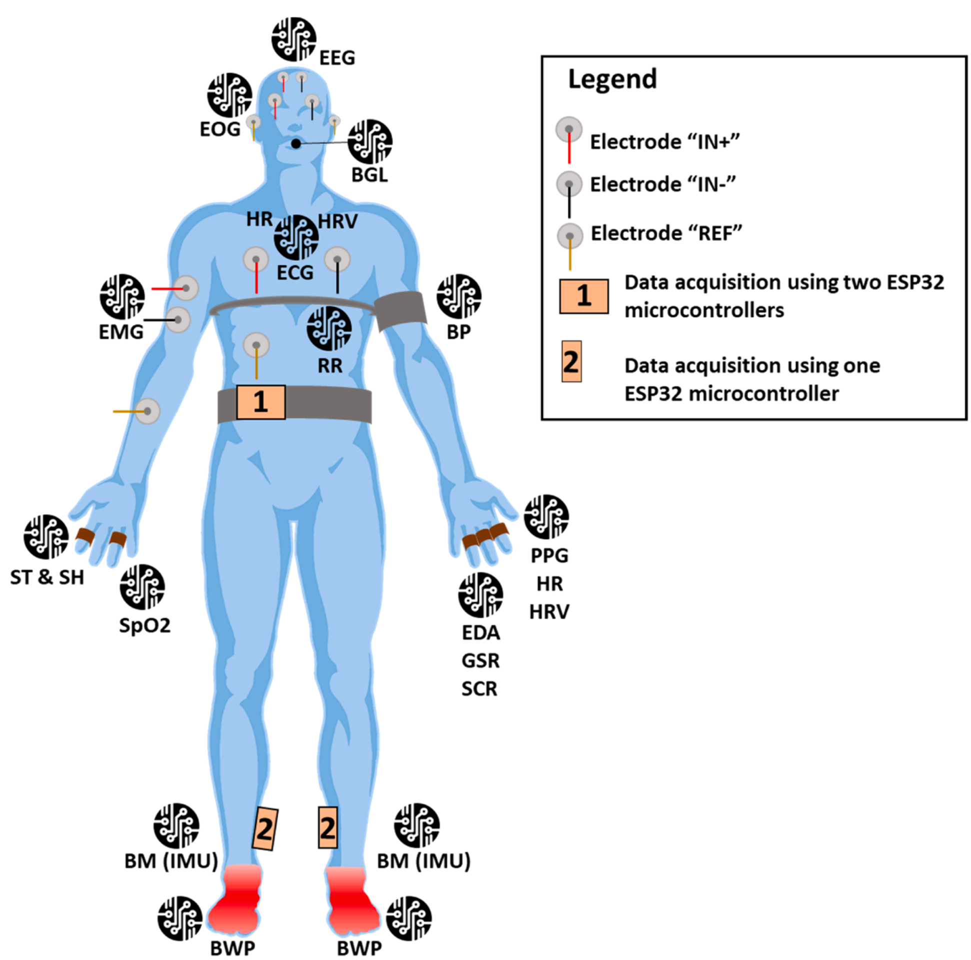

Fig. 2. The selected sensors for each indicator along with their position on the body.

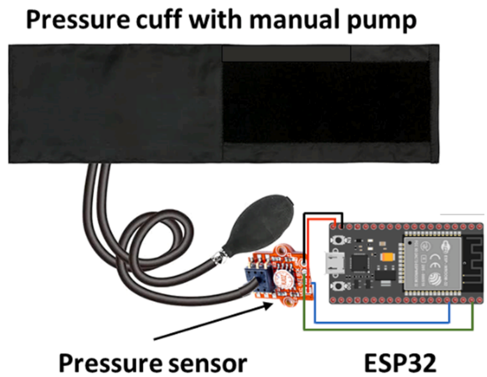

Fig. 4. The developed blood pressure sensor to measure the BP indicator.

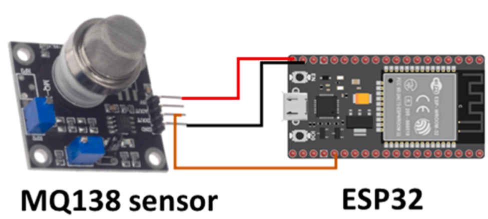

Fig. 5. The developed blood glucose sensor to measure the BGL indicator.

$$Acetone_{Concet} = \left(-2.6 \times \log\left(\frac{R}{R_0}\right) + 2.7\right)^{10} \quad (1)$$

Where $Acetone_{Concet}$ is acetone concentration in breath measured in part per million (PPM), R is the converted sensor output from digital pin into resistance, and R_0 is the constant resistance and equal to 10 KΩ. Ultimately, the BGL was quantified based on a linear regression method as shown in Eq. 2 [24].

$$BGL = 91.38 \times Acetone_{Concet} + 6.3743 \quad (2)$$

Where BGL is the blood glucose level in mg/dl.

As for the ST and SH, they were measured through a wearable sensor integrated with a finger strap.

As for the three emotional and cognitive arousal indicators (i.e., EDA, GSR, and SCR), their sensed signals were collected through two electrodes (e.g., IN+ and IN-) attached to two finger straps that were integrated with an AFE biosensor signal acquisition board. The AFE board was paired with the ESP32 microcontroller through an ADC pin.

As for the SpO2, it was measured through an IIC-based low-power plug-and-play biosensor connected to the ESP32 microcontroller by connecting the VCC and GND pins to the 3.3-volts and GND pins of the ESP32 microcontroller. The communication between the SpO2 sensor and the ESP32 microcontroller was based on the IIC serial communication protocol.

As for the PPG signals, they were acquired through a wearable biosensor to detect the changes in the volume of a blood vessel when the heart pumps blood.

As for the BM indicators (e.g., accelerometer and gyroscope data), they were collected for each foot through a 6-DOF inertial measurement unit (IMU) sensor attached to the user's foot (see Fig. 6). It is worth mentioning that the BM indicator which is responsible for tracking body motion includes six sub-indicators as shown in Fig. 6.

As shown in Fig. 6, the BM data include: 1) A 3-axis linear accelerometer that is used to measure linear velocity (i.e., linear velocity in X, Y, and Z directions), and 2) A 3-axis gyroscope accelerometer is used to measure angular velocity and orientation (i.e., angular velocity in X, Y, and Z directions known as pitch, roll, and yaw).

Finally, the BWP data were collected for each foot by developing an insole integrated with 16 pressure sensors and a 16-channel multiplexer

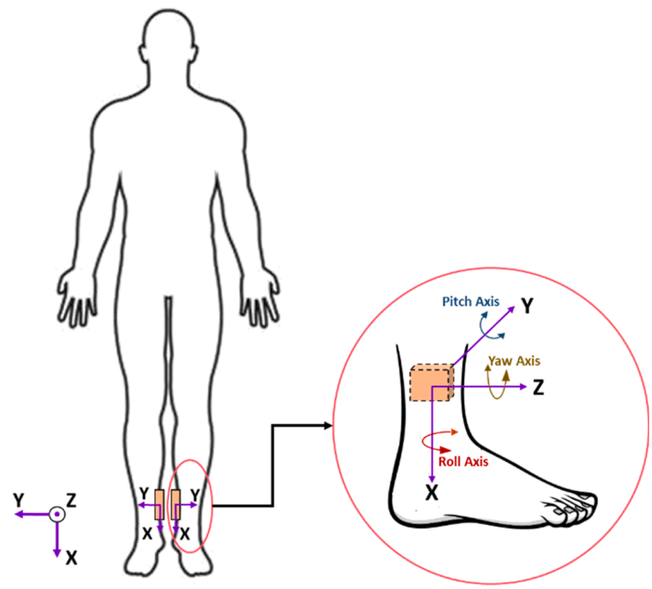

Fig. 6. The position of the BM sensors and corresponding collected accelerometer and gyroscope data.

board to read and transmit all sensors' data to the ESP32 microcontroller in real-time, as shown in Fig. 7.

As depicted in Fig. 7, each insole includes 16 pressure sensors that are connected to the 16-channel multiplexer. The multiplexer collects data from the pressure sensor and sends it to the corresponding ESP32 microcontroller.

A total number of four ESP32 microcontrollers (see Figs. 1 and 2) were considered to collect the 18 health-related indicators from 14 biosensors. Two of these ESP32 microcontrollers were responsible for collecting all health-related data except BM and BWP. Also, each foot was integrated with one ESP32 microcontroller, one IMU sensor to collect BM data, and one developed BWP sensor (see Fig. 2).

All collected data from the ESP32 microcontrollers were transmitted to an edge computing server for further processing and analysis through WSNs communication in real-time. It is noteworthy that a power bank with a capacity of 10,000 mAh was utilized as an external power supply for the ESP32 microcontrollers tasked with collecting all health-related data, except the BM and BWP indicators where a 7.4-volt battery served as an external power supply for each ESP32 microcontrollers responsible for gathering the BM- and BWP-related data. These external power

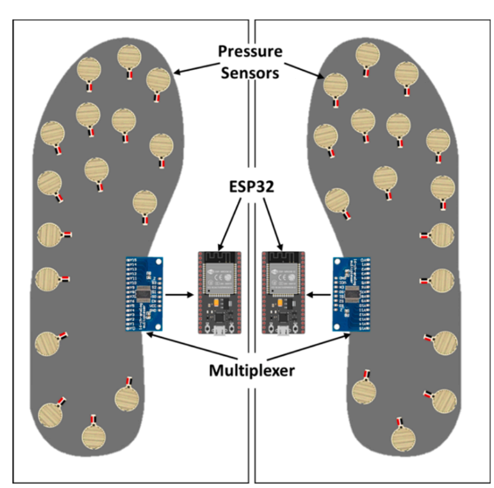

Fig. 7. The developed body weight pressure sensor to measure the BWP indicator.

supplies were instrumental in ensuring sufficient power operation for the AFEs and the developed biosensors. Moreover, they provided a quiet power supply, thereby minimizing power supply noise, a critical factor in maintaining the integrity of the collected data [68].

The power of the proposed device when it is collecting and analyzing the data for the 18 indicators from all the 14 sensors concurrently is around 3.8 watts (i.e., assuming all sensors are active at the same time) divided as follows: around 2.115 watts for the 4 ESP32 microcontrollers, around 0.2 watts for the Analog Front-End boards, around 0.035 watts for the IMU sensors, around 0.15 watts for the BWP sensors, around 1 watts for the BGL sensor, around 0.05 watts for the SpO2 sensor, and around 0.25 watts for all other sensors combined (i.e., ECG, HRV, PPG, etc.).

4.2. Data processing and digital dashboard creation

After collecting health- and physiological- related signals through IoT-enabled WSNs communication, they were sent from the ESP32 microcontrollers to the edge computing server (i.e., Jetson Xavier NX) for further processing as detailed in the next subsections. In addition, the Jetson board was responsible for hosting a user-friendly GUI-based digital dashboard capable of visualizing health-related indicators with varying quantification approaches, sample rates, and time delays as detailed below.

4.2.1. Data processing

To collect the biosensors' health-related physiological signals and indicators synchronously, each ESP32 microcontroller was assigned a developed integrated programming and computational script to collect the corresponding indicators. The integrated code for each ESP32 microcontroller was uploaded using the Arduino Integrated Development Environment (IDE). Afterward, the collected data were transferred to the Jetson board via WSNs communication for further processing. The Jetson board was chosen based on its compact size, powerful CPU (which is a 6-core NVIDIA Carmel ARM v8.2 64-bit), efficient GPU (which includes 384 NVIDIA CUDA cores and 48 Tensor cores), and 16 GB of memory. These features make it suitable for implementing the health monitoring system. Additionally, it comes with a built-in WiFi module, which is essential for enabling IoT capabilities.

The Jetson board was used to: 1) perform signal processing (e.g., Fast Fourier Transform (FFT)) on the EEG, ECG, EOG, EMG, PPG, EDA, GSR, and SCR signals; 2) develop an IoT-based web server user-friendly GUI-based dashboard to visualize all collected physiological signals and indicators in real-time as detailed in following sub-section.

4.2.2. Signal processing techniques

Various signal processing techniques were used in order to process the raw signal obtained from the various integrated sensors and extract meaningful data. More specifically, filtering techniques such as low-pass, high-pass, and band-pass filters have been used to eliminate noise and drift and to retain the signals of interest (i.e., isolating the frequencies of interest). Also, moving average techniques have been implemented to smoothens the signals. In addition, signal amplification methods were used to increase the strength of week signals to ensure that the signals are within the detectable range of the sensors. Furthermore, Fast Fourier Transform (FFT) techniques were conducted to convert time-domain signals into frequency-domain representations to help in determining the frequency components of the signal and in the identification of periodic signals or noise, which is essential in characterizing biosensor responses. As for analyzing non-stationary signals, wavelet transform methods were used to provide both time and frequency information (i.e., allow for time-frequency analysis) that can capture transient features of the biosensor response that might be missed in traditional Fourier analysis. Finally, peak detection methods were employed to identify and analyze signal peaks that can correspond to, or indicate the presence of, specific events.

4.2.3. IoT-based digital dashboard

In order to design a user-friendly GUI-based digital dashboard that dynamically visualizes the collected health-related physiological signals and indicators in real-time from the developed multi-modal sensing system, the collected data from ESP32 microcontrollers were transmitted to the Jetson board through IoT-enabled WSNs communication. On the Jetson side, these data are received through utilizing the Django framework, which is a high-level, free, and open-source Python-based web framework that runs on a web server [44]. Due to Django's advantages such as scalability, simplicity of use, flexible framework, fast processing, numerous available resources, secure framework, and ability to design powerful administrative dashboards, Django was selected as a suitable backend web development choice for handling heterogeneity, multimodality, and complexity of the collected data/information.

In terms of the front-end framework, the React (i.e., React.js) which is a free and open-source front-end JavaScript library was used to design the GUI for the various health-related physiological signals and indicators. React's advantages such as fast rendering, friendly search engine, reliable development tools, the capability of designing mobile applications, effortless maintenance, and stable and streamlined code make it the proper choice for developing comprehensive and user-friendly GUI [41].

To accommodate multi-user scenarios, enhance privacy access to the collected data, and improve the tracking of collected data for users, a fingerprint sensor was integrated with the Jetson board. This integration is noteworthy as it adds an additional layer of security and personalization to the system. Initially, users are prompted to authenticate their identity. Upon successful authentication, users are requested to provide basic information such as age, weight, and height. This information is utilized to calculate the Body Mass Index (BMI), a widely accepted measure of body fat based on height and weight that applies to adult men and women [8]. The BMI is categorized into four distinct groups: (1) "Underweight" for a BMI less than 18.5 kg/m^2; (2) "Normal weight" for a BMI in the range of 18.5–25 kg/m^2; (3) "Overweight" for a BMI in the range of 25–30 kg/m^2; and (4) "Obesity" for a BMI greater than 30 kg/m^2. Subsequently, the developed multimodal sensing health monitoring digital dashboard collects, stores, and visualizes the user's vital signs. This process ensures a personalized and secure health monitoring experience for each user, thereby enhancing the overall utility and effectiveness of the developed system.

5. Results and analysis

This section presents the results of the developed IoT-based multimodal sensing system for collecting and analyzing the health-related signals and indicators and its designed web-based digital dashboard or GUI for visualizing these vital symptoms. In addition, the validation of the collected signals and indicators is presented based on comparing the collected data with consumer-level devices.

5.1. Developed IoT-based multimodal sensing device

As detailed in the "Methodology" section, the multimodal sensing device includes a total number of 18 indicators that are collected through four ESP32 micron rollers. The collected data are transmitted to an edge computing server for further processing and analysis through WSNs communication in real-time. Fig. 8 shows the developed multimodal sensing device for health monitoring of all considered health-related indicators except BM and BWP, which are presented in Fig. 9.

It is worth that 3D modeling and 3D printing was used to design and construct an enclosure (i.e., cover made from 3D printed parts) for the developed health monitoring system in this paper, as shown in Fig. 8.

As shown in Fig. 8 (a) and (b), the developed multimodal sensing device collects various health-related indicators including EEG, EOG, BGL, ECG, EMG, RR, BP, PPG, SpO2, ST, HT, EDA, GSR, and SCR, where the HR and HRV indicators are calculated through on-sensor ECG and

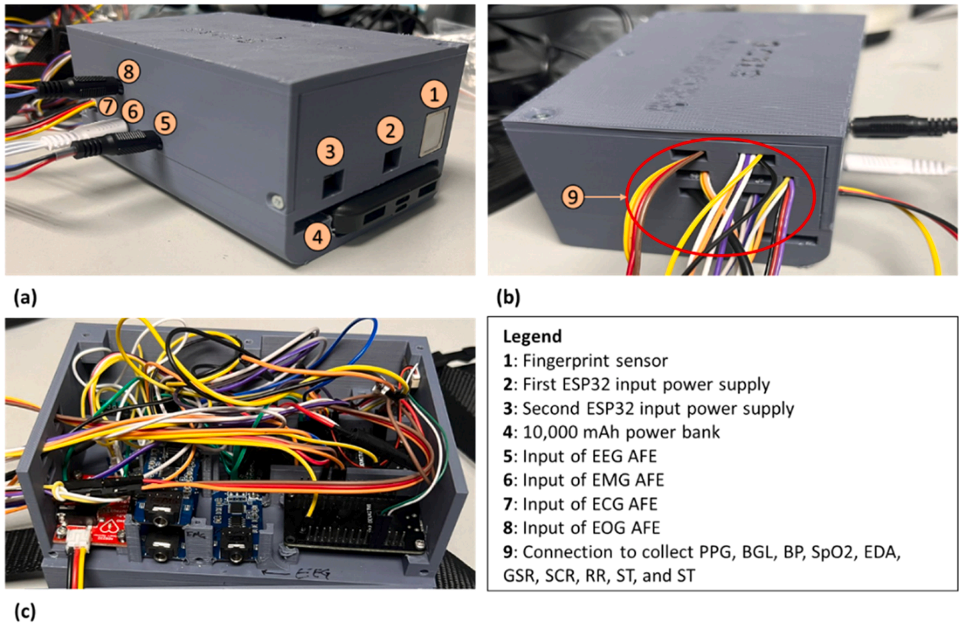

Fig. 8. The developed multimodal sensing device; (a) isometric view of the device and its connections; (b) left side view; (c) inside view.

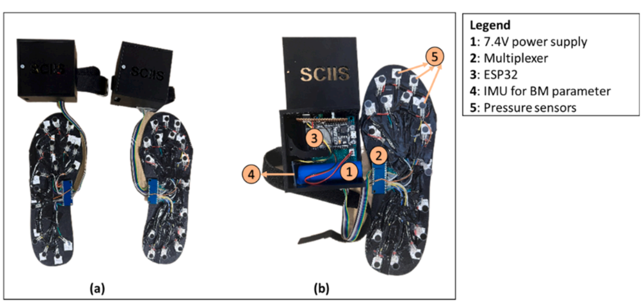

Fig. 9. The developed multimodal sensing device for BM and BWP monitoring.

PPG signal processing by the ESP32 microcontrollers. Thus, a total number of 16 indicators are collected by the device shown in Fig. 8, while the remaining 2 indicators (i.e., BM and BWP) are collected through the system present in Fig. 9. Fig. 8(a) also shows the fingerprint sensor for authorizing users along with the 10,000 mAh power bank for providing sufficient power operation for the AFEs and the various biosensors.

Fig. 9 shows the system used to collect and monitor the remaining 2 indicators (i.e., BM and BWP).

As depicted in Fig. 9(a), the BM and BWP data is collected for each foot. Fig. 9(b) also shows that each unit includes a battery charger module, a 7.4 V battery as the external power supply, an IMU sensor for collecting the 3-axis linear velocity and 3-axis gyroscope accelerometer, an on/off switch, and an ESP32 microcontroller.

To show the developed multimodal sensing device for the comprehensive monitoring of the various health- and physiological-related indicators, it was placed on a subject's body as shown in Fig. 10.

As illustrated in Fig. 10, the developed wearable multimodal sensing device was attached to three parts of the subject's body to collect all 18 health-related physiological indicators (i.e., on the hip, on the right foot, and on the left foot). The collected data are then transmitted to the edge computing server (i.e., Jetson board) through WSNs for further signal processing and analysis in real-time, and, subsequently, the visualization of the results in the developed web-based digital dashboard or GUI, as detailed below.

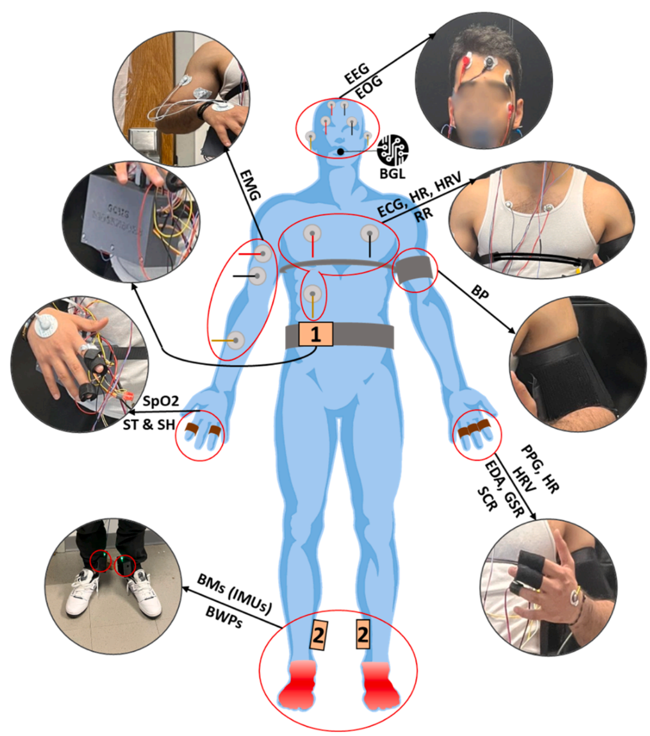

Fig. 10. The developed multimodal sensing device placed on a subject's body.

5.2. Developed web-based GUI and digital dashboard

A comprehensive user-friendly GUI was developed as detailed in the "Methodology" section. Leveraging the capabilities of the Jetson Xavier embedded system's WIFI module, the received data from the various ESP32 microcontrollers through the Django framework were further processed by applying FFT to calculate the frequency domain component (e.g., for calculating the HRV indicator). Additionally, the React JavaScript library was used as the front-end framework to design the web-based GUI or digital dashboard to create a graphical representation for each health-related indicator. The developed GUI was comprised of two main sections. The first section is the "Home" page and includes graphical representations and plots of 16 (out of the 18) indicators, as shown in Fig. 11. It is worth mentioning that user's access to the developed web-based GUI is only available after the authorization step (i.e., using the fingerprint sensor).

As depicted in Fig. 11, the authorized user has access to the homepage (i.e., main page) of the web-based GUI or digital dashboard to visualize the collected data. In addition, the age, height, and weight of the authorized user along with his/her BMI calculated are also shown (see top left corner in Fig. 11). Fig. 11 also shows the user accessibility of the various health-related indicators in real-time.

In addition to the "Home" page, the developed digital dashboard also includes another page/section which provides the graphical representation of the developed sensor for tracking the weight distribution on the feet (i.e., the BWP indicator) along with the 3-axis linear velocity and 3-axis gyroscope accelerometer data collected for each foot from the IMU sensor (i.e., the BM indicator). The visualization of the BM and BWP indicators shown in the developed digital dashboard is illustrated in Fig. 12.

As shown in Fig. 12, for the feet position shown in Fig. 12 (a), the weight distribution on the user's feet was visualized in the developed digital dashboard (i.e., Fig. 12 (b)). Additionally, the 3-axis linear velocity and 3-axis gyroscope accelerometer data collected from IMUs for each foot were also displayed in Fig. 12 (b).

5.3. Validation of the collected data from the developed multi-modal sensing device

The validation process is crucial in establishing the reliability and accuracy of the data collected from the developed IoT-enabled multimodal sensing system. To validate the data collected on the 18 health-related physiological indicators by the proposed multimodal sensing system, a comparative and benchmark analysis was conducted against available commercial consumer-grade devices. These devices, while widely used, often collect a limited range of health- and physiological-related indicators and they are not cost-effective. In contrast, the proposed multimodal sensing device offers a more comprehensive monitoring solution, collecting a broader range of indicators. Table 3 presents the results of the accuracy of the proposed health monitoring system compared and benchmarked with similar available commercial devices.

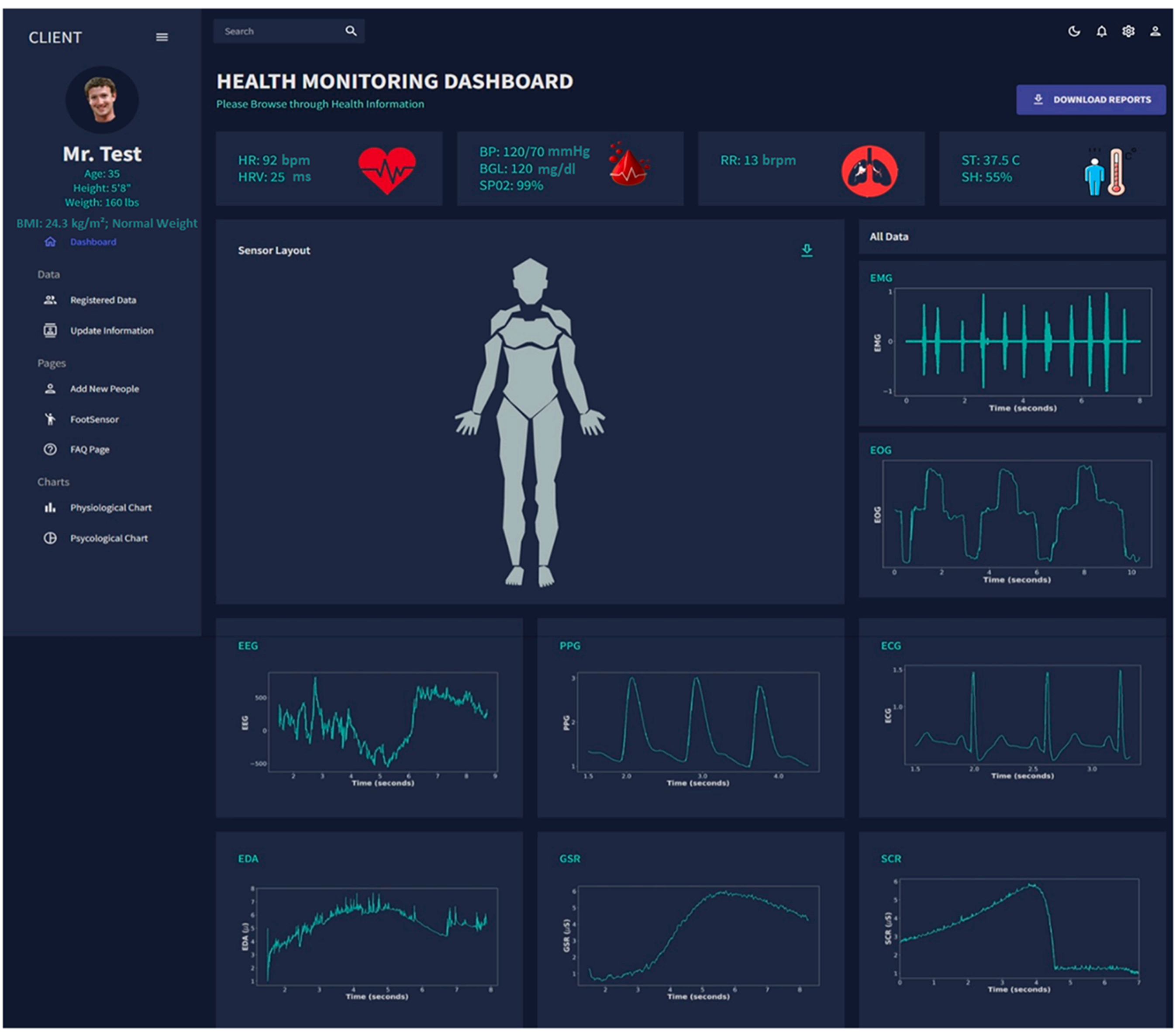

Fig. 11. A snapshot of the home page of the developed digital dahsboard and web-based GUI.

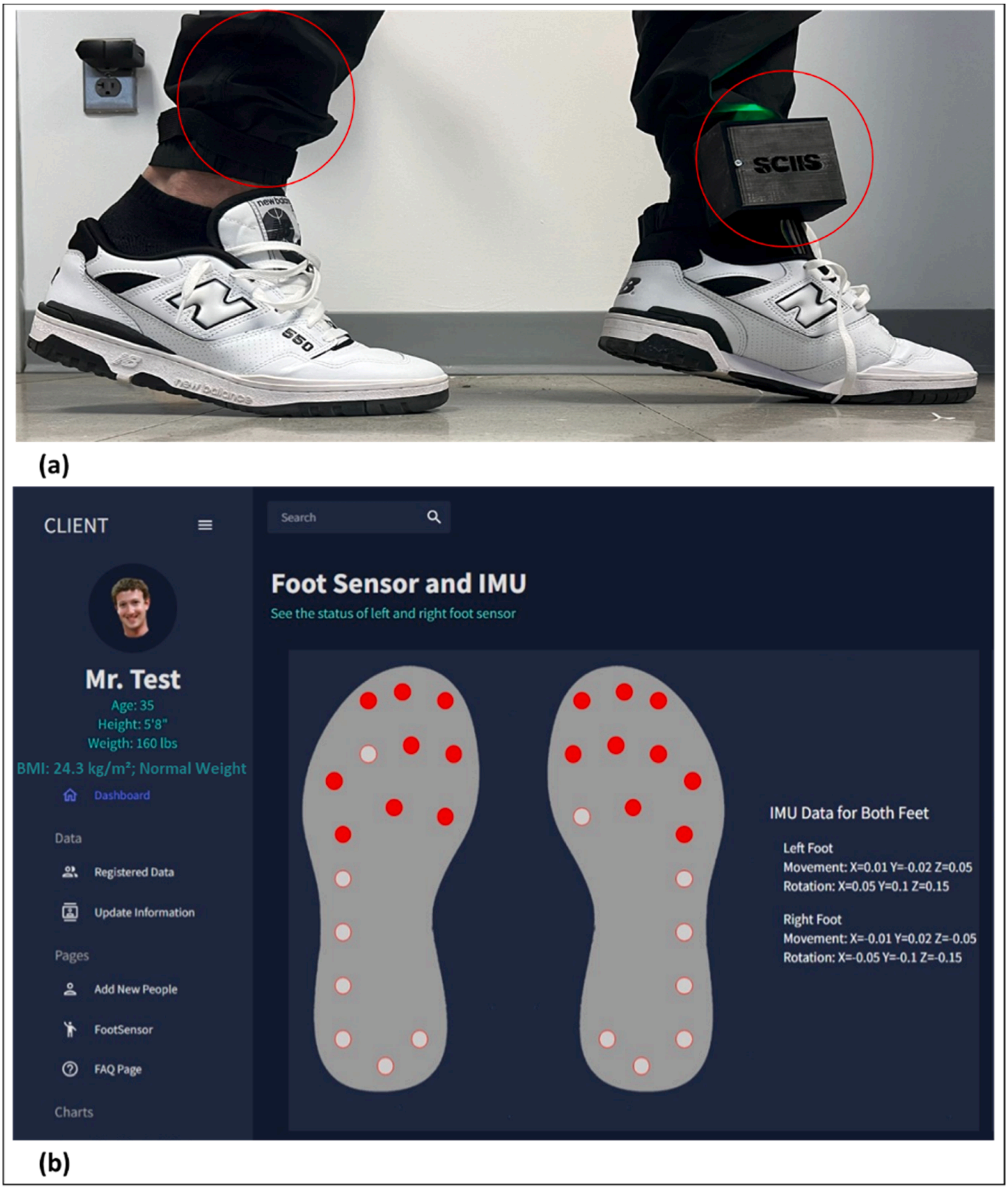

Fig. 12. The snapshot of the plot representations of the BM and BWP indicators.

This comparison not only validates the accuracy of the collected data but also highlights the enhanced capabilities of the proposed device.

As delineated in Table 3, the proposed multimodal sensing device demonstrates a high degree of accuracy across all 18 health-related physiological indicators, when compared with available commercial devices. Specifically, indicators such as EEG, EOG, PPG, HRV, RR, ST, SH, BGL, SpO2, BWP, SCR, and GSR exhibit an accuracy of 90 % or more, relative to their corresponding consumer-grade commercial devices. In addition, indicators such as ECG, EMG, and EDA display an accuracy within the range of 85–89.9 % when compared with their respective commercial devices. The HR indicator, with an error margin of ± 1 bpm (calculated through PPG signals) and ± 2 bpm (calculated through ECG signals), also demonstrates a high degree of accuracy. Lastly, the BM indicator, which measures body motion, records a high accuracy with an error of ± 0.35 m/s in linear velocity and $\pm 3.1^{\circ}$/sec in the gyroscope accelerometer.

These validation results underscore the potential of the proposed multimodal sensing device as a robust and comprehensive solution for health monitoring.

As for the indicators that achieved an accuracy less than 90 % such as ECG, EMG, and EDA, while the obtained accuracies in Table 3 are considered to be acceptable for non-medical applications, different

Table 3
The results of the accuracy of the proposed multimodal device vs available commercial devices.

Indicator	Accuracy of the developed sensing system in this paper against benchmark commercially available devices	Commercial device used for benchmark
ECG	89.9 % in the detection of heart peaks	PC−80B easy ECG monitor
EEG	99.67 % in detection blinking or focusing on context	EEG-Z3-T7680
EOG	96 % upward eye movements and 87.67 % left-right eye movements	Biosignalsplux EOG sensor
EMG	86.86 % in recognition of elbow muscle activity	Qubit EMG sensor
PPG	96.5 % in the detection of heart peaks	DigiDop PPG vascular
HR	1 bpm for the PPG signals 2 bpm for the ECG signals	Meet Fitbit Inspire 3
HRV	95.90 % for the PPG signals 93.16 % for the ECG signals	Frontier
RR	92 %	CONTEC CA10S
ST	+/- 1.0 °C or 99.2 %	Thermometer- ETB−018
SH	+/- 3 % or 97 %	Bio-Therapeutic bt-analyze
BGL	99.5 %	Medline EvenCare G2
BP	96.26 %	ZIQING BP monitor
SpO2	99.62 %	Santamedical fingertip pulse oximeter
BWP	94 % in recognizing pressure distribution	Foot film pressure sensor
BM	0.35 m/s linear velocity accuracy 3.1°/sec gyroscope accuracy	Amazfit band 7
EDA	85 % in emotion recognition	PLUX Biosignals, EDA
SCR	90 % emotion recognition	monitor
GSR	90 % in recognition of immediate memory recall	NeuLog, GSR monitor

measures could be implemented to further enhance the accuracies of these indicators. More specifically, to increase the accuracy of ECG, additional measures include the following: 1) properly placing the electrodes and maintaining skin preparation by cleaning the skin to reduce impedance; 2) using a higher-quality electrodes that can reduce noise; 3) minimizing motion artifacts by securing electrodes properly and instructing participants to remain still; 4) regularly calibrating the ECG sensing system; 5) using additional digital signal filtering techniques to remove noise and/or software improvements (such as baseline correction, QRS detection, and morphological analysis); 6) and controlling participant factors by ensuring proper hydration and minimizing stress before the ECG recording as these can influence heart rate and rhythm. As for increasing the accuracy of the EMG data, the following measures could be implemented: 1) ensuring electrodes are placed correctly on the muscle and avoiding tendons and bony areas; 2) removing oils and dirt using alcohol swabs or abrasive pads to enhance electrode contact; 3) relying on electrodes with better conductivity and durability; 4) instructing participants to stay still and avoid muscle contractions unrelated to the task; 5) reducing electrical noise from surrounding equipment; 6) using high-quality amplifiers to boost EMG signals while minimizing noise; 7) and applying further data processing methods (such as rectification, smoothing, and envelope detection) to enhance the signal for analysis. As for the EDA data, measures for increasing the accuracy include: 1) placing electrodes on areas with high sweat gland density (such as the fingers or palms) to capture clearer signals; 2) using conductive gel or adhesive to improve electrode contact with the skin; 3) minimizing hair interference by shaving the needed area if necessary to reduce impedance; 4) maintaining consistent environmental conditions as temperature and humidity can affect EDA readings; and 5) using other data processing methods to account for individual baseline variations and improve the accuracy of arousal detection or extracting relevant features such as the skin conductance level (SCL) and phasic responses (SCRs) for more precise analysis.

6. Contributions

The paper offers significant and various contributions. This research is the first of its kind in integrating this high number of 14 biosensors capable of collecting 18 health-related vital signs; and thus, it represents a substantial leap forward in sensor fusion technology. This comprehensive approach allows for the simultaneous collection of diverse health-related physiological indicators, providing a more holistic view of an individual's health status. In fact, the various integrated biosensors provide rich information on various vital signs into a single monitoring system, including: health (e.g., ECG, HR, HRV, PPG, SpO2, BGL, BP); emotional and arousal status (e.g., EDA, SH); mental and cognitive status (e.g., EEG, GSR, SCR); behavioral, physical, and attention status (e.g., EOG, EMG, BWP, BM); and physiological status (e.g., ST, RR); thus, reflecting the wide window of applications for which the developed system could be used.

By fusing multiple sensors into a single device, the system simplifies data collection processes and reduces the need for multiple, disparate devices, thereby streamlining the monitoring process for both researchers and users. Also, by relying on open-source sensing devices (i.e., the ES32 microcontroller and the associated used biosensors in this paper) fosters multi-disciplinary collaboration and innovation within the research community working on biosensing and health monitoring. Researchers and developers have the flexibility to adapt and customize the developed system to meet the specific needs of their applications, enabling rapid prototyping and experimentation. The use of open-source hardware promotes transparency and reproducibility in research; ultimately, facilitating the sharing of knowledge and accelerating progress in the field of health monitoring systems. In addition, the obtained promising validation results reflect the efficacy and reliability of the proposed multimodal sensing system and its ability to accurately capture and analyze physiological data in real-time, paving the way for its potential integration into clinical settings and real-world applications. These validation results provide confidence in the device's performance and underscore its potential as a robust solution for health monitoring. Furthermore, the integration of a user-friendly GUI and digital dashboard enhances the accessibility and usability of the proposed system for both researchers and end-users. A visually appealing and intuitive interface not only simplifies data visualization but also promotes user engagement and adoption. By leveraging familiar technologies such as Django (i.e., Django framework as the back end for receiving data from ESP32s through WSNs) and React JavaScript (i.e., React JavaScript as the front-end framework for designing web-based GUI), the GUI facilitates seamless interaction with the system, empowering users to explore and interpret collected data effectively and in real-time.

The paper also offers various advancements. The developed system's ability to track a wide range of heart-related indicators, including ECG, PPG, HR, HRV, RR, BGL, BP, and SpO2, holds immense significance. Early detection of abnormalities in these indicators can aid in the timely diagnosis and management of cardiovascular diseases, potentially saving lives and improving patient outcomes [25,48]. Furthermore, insights gained from continuous monitoring of heart behavior can inform personalized interventions and preventive strategies, leading to better overall cardiac health. Furthermore, the system's capabilities in monitoring EEG, EOG, EMG, EDA, GSR, and SCR signals provide valuable insights into brain function and cognitive states. These insights have far-reaching implications across various domains, including neuroscience, psychology, and clinical medicine [23]. The ability to non-invasively assess brain activity opens up new possibilities for diagnosing neurological disorders, understanding cognitive processes, and developing targeted interventions for conditions such as autism, depression, and anxiety. The sensing capabilities of the developed system also offer early musculoskeletal disorder detection, enabling timely intervention for musculoskeletal disorders which can significantly improve patient outcomes and quality of life [40]. More specifically, by monitoring foot movement (i.e., through the 3-axis linear velocity and

3-axis gyroscope accelerometer of each foot) and pressure distribution (i.e., through the 16 pressure sensors used for each foot), the proposed system enables early identification of abnormalities that may contribute to musculoskeletal issues. This proactive approach to monitoring can prevent the progression of conditions such as foot deformities and postural abnormalities, reducing the need for invasive treatments and improving long-term musculoskeletal health.

Overall, the proposed system in this paper is a powerful technology that can play a significant role in various fields, including personalized medicine, fitness monitoring, diagnosis, and personal health management. More specifically, it could be useful for personalized medicine through real-time monitoring of biomarkers in real-time, thus allowing for personalized treatment adjustment based on each individual's response to therapy. It could also be used for fitness monitoring as a wearable system that monitors various bio-markers such as heart rate, oxygen levels, and even sweat to assess hydration and electrolyte balance during workouts and, or a system that analyzes data on individuals' physical performance to help in refining training regimens and improving outcomes, or as a tool that can provide feedback on physical activity levels to motivate individuals to reach their fitness goals. The proposed work could also be used for diagnosis and monitoring as the various integrated biosensors can detect diseases at an early stage by identifying specific biomarkers, thus improving timely diagnosis and treatment. Other use cases include for personal health management and tracking where the proposed system can be used by individuals to monitor vital signs (e.g., heart rate, temperature) and other health indicators at home including stress and mental health as the integrated biosensors can track physiological responses to stress, providing insights for mental health management. Although the proposed system possesses many of the features of a medical-grade patient monitoring system, it does not have any certifications for medical use (it is not officially approved for medical or diagnostic use), but rather it is considered a consumer and research grade device that could either be used for research and experimentation purposes or for personal use, making it accessible to individual users. Also, while the proposed system demonstrates promising validation results and accuracy, its effectiveness in diverse real-world scenarios and populations is recommended to be further validated by future studies.

The importance of this paper and its proposed application in health monitoring cannot be overstated. The broad applicability of the proposed system across various industry sectors significantly enhances its value. For instance, in sectors such as construction, underground mining, chemical, and logistics, tracking the health and performance of workers are of paramount importance. The proposed IoT-enabled multimodal wearable bio-sensing health monitoring system can play a crucial role in these sectors. By providing real-time, comprehensive tracking of physiological symptoms, the system can help ensure the safety and well-being of workers. It can alert supervisors to potential health issues before they become serious, enabling timely intervention. Moreover, this paper not only addresses significant knowledge gaps in the field of wearable bio-sensing health monitoring and assessment systems but also proposes a solution with far-reaching implications. The proposed system has the potential to revolutionize health monitoring across various industries, contributing to safer work environments and more efficient operations. This underscores the significance of this study and the potential impact of its findings.

Moreover, the developed user-friendly GUI makes the proposed health monitoring system a suitable choice for individuals to track their health status and early identify and diagnose health abnormalities. With an intuitive interface and seamless interaction, users can easily interpret the collected data, empowering them to take proactive measures to improve their health and well-being.

The effect of this real-time health monitoring on individual well-being and society as a whole is profound. By providing timely insights into physiological indicators, the proposed system enables individuals to make informed decisions about their health and lifestyle choices. Early detection of health issues allows for prompt intervention and treatment, potentially reducing healthcare costs and improving patient outcomes. Furthermore, at the societal level, the widespread adoption of wearable health monitoring systems can lead to a healthier population, reduced burden on healthcare systems, and improved overall quality of life. As researchers and developers continue to refine and expand upon these innovations, the impact on public health and well-being is poised to grow exponentially, ushering in a new era of preventive healthcare and personalized medicine.

7. Conclusion and limitations

To enhance health monitoring and assessment practices, this paper introduced a comprehensive wearable sensor fusion multimodal sensing device and health monitoring system. Through the integration of 14 different sensors capable of acquiring the entire data for the 18 different health- and physiological-related indicators, coupled with an open-source IoT-enabled hardware architecture based on four ESP32 microcontrollers, this research represents a significant advancement in the field. The validation results underscore the reliability and efficacy of the proposed system, demonstrating its potential for real-world implementations in various sectors and industries and for various applications. The user-friendly GUI or digital dashboard developed in this study enhances accessibility and usability of the developed system, making health monitoring more intuitive and engaging for both researchers and end-users. Furthermore, the ability to track a wide range of indicators, including EEG, EOG, EMG, ECG, PPG, HR, HRV, SpO2, BP, BGL, RR, ST, SH, EDA, GSR, SCR, BM, and BWP, holds promise for early disease detection and personalized interventions.

To the best of the authors' knowledge, the proposed multimodal sensing device in this paper is the first inaugural development of a health monitoring system exhibiting such a remarkable level of comprehensiveness. By collecting 18 health-related indicators, leveraging sensor fusion and IoT capabilities for seamless data transmission through WSNs, harnessing Django for efficient data reception, utilizing React for intuitive GUI design, and ensuring secure access to collected data via fingerprint sensor authentication, this innovative system sets a new standard in health monitoring technology. This pioneering approach not only advances the boundaries of wearable sensor technology but also revolutionizes data visualization techniques, representing a significant milestone in the realm of health monitoring practices.

Similar to any research study, this paper has some limitations. Although the proposed system possesses many of the features of a medical-grade patient monitoring system, it does not have any certifications for medical use (it is not officially approved for medical or diagnostic use), but rather it is considered a consumer and research grade device that could either be used for research and experimentation purposes or for personal use, making it accessible to individual users. Also, while the proposed system demonstrates promising validation results and accuracy, its effectiveness in diverse real-world scenarios and populations is recommended to be further validated by future studies. Additionally, challenges related to data privacy, security, and interoperability could be further improved to ensure the widespread adoption and ethical use of wearable health monitoring technologies. Despite these limitations, this research lays a solid foundation for future advancements in health monitoring systems. Looking ahead, future research can explore the integration of additional sensors to further expand the capabilities of the multimodal sensing device. Moreover, the development of advanced data analytics techniques (such as machine learning models or other data processing capabilities) can enhance the system's ability to derive actionable insights from collected data. Additionally, conducting longitudinal studies to assess the long-term efficacy and user acceptance of the proposed system would provide valuable insights for its refinement and optimization.

The findings of this research have broader implications for future research and clinical practice. More specifically, the findings obtained from the developed multi-modal biosensing system provides the needed foundations and seed for continued research in this area by driving further technological advancements that can leading to the development of more sophisticated multimodal biosensing devices (both hardware and software) with improved accuracy and functionality. In fact, integrating multiple biosensing modalities allows researchers to understand the interplay between different health, physiological, emotional, and cognitive processes, leading to more nuanced insights. Also, due to the multidisciplinary nature of the proposed system, the research findings could improve the collaboration among disciplines (e.g., engineering, psychology, medicine), thus fostering innovative research approaches. The research outcomes will ultimately enhance clinal practice by making multi-modal biosensing systems more commonly used in practice, thus allowing the simultaneous capture of data from various physiological signals to provide a more comprehensive view of an individual's health status. Also, the proposed system could be used in clinical practice to combine data from multiple biosensors in order to: identify subtle changes across different signals, enabling earlier detection of potential health issues; enhance the accuracy of diagnosing complex conditions, such as mental health disorders, cardiovascular diseases, and chronic illnesses; and enable clinicians to better tailor interventions and treatments based on an individual's specific physiological responses; and provide real-time feedback, allowing for adjustments to treatment plans as needed. Thus, the proposed multi-modal biosensing system can be integrated into clinical workflows, improving efficiency in patient monitoring and data collection through improved data analytics that can better support clinical decision-making by providing clinicians with actionable insights based on comprehensive patient data.

CRediT authorship contribution statement

Rayan Assaad: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Mohsen Mohammadi:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Oscar Poudel:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data generated or analyzed during the study are included in the published paper.

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Rayan H. Assaad, Ph.D.: Dr. Rayan H. Assaad is an Assistant Professor at the Civil and Environmental Engineering Department at NJIT, and he is the founding director of the Smart Construction and Intelligent Infrastructure Systems (SCIIS) lab at NJIT. Dr. Assaad obtained his Ph.D. degree in Civil Engineering in 2021. Dr. Assaad's research interests span over different multi-disciplinary areas, including multi-modal sensing systems (both hardware and software); construction automation and robotics; computational methods and applied machine learning; modeling, simulation, and optimization; infrastructure asset management; and sustainability, resilience, and environmental impacts in the built environment.

Mohsen Mohammadi, Ph.D.: Dr. Mohsen Mohammadi is currently a Senior Engineer at Schnabel Engineering. He obtained his Ph.D. degree in Civil Engineering in 2024 from the Civil and Environmental Engineering Department at NJIT under the supervision of Dr. Rayan H. Assaad.

Oscar Poudel: Oscar is currently a Ph.D. student at the Civil and Environmental Engineering Department at NJIT, working under the supervision of Dr. Rayan H. Assaad.