Connected Health in Action: An IoT-Driven Web Dashboard for Real-Time HRV and Stress Monitoring in a Private Cloud

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ABSTRACT

Stress is one of the main factors associated with the worsening of cardiovascular diseases and psychological disorders, with Heart Rate Variability (HRV) being one of the most widely used physiological indicators for its detection and monitoring. This work proposes the development of a continuous stress monitoring architecture based on the Internet of Things (IoT), using the Polar H9 heart rate sensor connected via Bluetooth Low Energy (BLE) to an embedded processing unit based on the Raspberry Pi 4. The system performs real-time acquisition and transmission of heart signals through Python-based scripts. Communication with the private cloud is handled via the RabbitMQ, and data visualization is implemented through a web dashboard accessible via WebSocket, enabling continuous and multiplatform monitoring. The architecture was designed to extract classical HRV metrics, such as RMSSD, SDNN, and pNN50, which are collected from the R-R intervals transmitted by the system. The results obtained demonstrate that the architecture is capable of capturing, processing, and transmitting these metrics with high stability, providing a solid foundation for applications in HRV analysis and stress indicators. Future work will focus on integrating machine learning models for automatic stress classification and conducting clinical validation with multiple participants to enhance the system's reliability and applicability.

KEYWORDS

Heart Rate Variability, Stress, IoT, Raspberry Pi, Python, RabbitMQ, Web Dashboard, Private Cloud, Connected Health

1 INTRODUCTION

Mental health and emotional well-being have become key priorities in public policies and global health initiatives, especially in response to the substantial increase in stress-related disorders in the 21st century [4, 21]. Chronic stress, when left untreated, may result in serious consequences, such as cardiovascular diseases, anxiety, depression, and diminished quality of life [17, 28]. In today's fast-paced society, continuous stress monitoring has emerged as a critical requirement not only in clinical contexts but also across workplace, educational, and domestic environments [8, 15, 30].

Within this context, the concept of Connected Health emerges as a key paradigm [24], referring to the integration of digital technologies, physiological sensors, and interactive platforms aimed at delivering more accessible, personalized, and continuous healthcare. Through the remote collection and real-time analysis of health data, Connected Health enables proactive monitoring of an individual's physiological state, facilitating preventive interventions and adaptive strategies in response to psychological disorders such as chronic stress and anxiety. This approach enhances both clinical and personal decision making, fostering a more dynamic, contextualized, and user-centered health management process [2].

The architecture of Connected Health is grounded in the integration of IoT devices, interactive dashboards, and private cloud, which together form the technological backbone enabling continuous monitoring, remote analysis, and real-time personalization of care [3]. The use of IoT devices, such as physiological sensors and embedded units (e.g., Raspberry Pi 4), enables automated, continuous, and contextualized collection of vital signs outside clinical settings, including homes, workplaces, and gyms. These data are transmitted in real time to a private cloud, where they are securely stored and processed to extract relevant metrics, such as HRV. The processed information is then made available through interactive web dashboards, accessible to both users and healthcare professionals, allowing remote monitoring of physiological conditions, early detection of anomalies, and informed decision-making. This technological ecosystem supports a preventive, proactive, and user-centered approach, fostering timely, evidence-based interventions.

HRV has emerged as one of the most prominent noninvasive biomarkers for assessing the autonomic nervous system [32]. It refers to the analysis of the intervals between consecutive heartbeats (R-R intervals), where higher variability is associated with better autonomic function and greater adaptive capacity. In comparison, lower variability indicates autonomic dysfunction and increased susceptibility to stress [26, 33].

In this context, the growing demand for continuous HRV monitoring solutions outside laboratory environments has driven the adoption of emerging technologies such as the IoT and edge computing. These advancements have enabled the development of accessible and efficient systems for real-time acquisition and analysis of physiological signals [19]. The use of reliable commercial sensors, such as the Polar H9, combined with embedded platforms like the Raspberry Pi, facilitates the construction of distributed systems capable of collecting, transmitting, processing, and interpreting physiological data beyond controlled laboratory settings. This approach significantly expands access to continuous health monitoring across clinical, athletic, and occupational contexts, effectively realizing the principles of Connected Health in practice [6].

Despite these technological advances, critical gaps remain that hinder the applicability, scalability, and reliability of such solutions

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in real-world scenarios. Among these, the need for rigorous clinical validation both of the inference algorithms and the integrity of the acquired data stands out, as discussed in [31]. These challenges highlight the importance of studies that demonstrate the technical feasibility and accuracy of such architectures under practical usage conditions.

In this work, we propose an IoT-based architecture for continuous HRV monitoring and stress level inference, employing the Polar H9 heart rate sensor, an electrocardiogram (ECG) based device connected via BLE to a Raspberry Pi 4. The Raspberry Pi operates as the acquisition and processing unit, forwarding the data to a private cloud using the RabbitMQ broker. Python scripts running on the device extract HRV metrics such as Root Mean Square of Successive Differences (RMSSD), Standard Deviation of NN intervals (SDNN), and Percentage of NN50 (pNN50), and the cleaned and processed data are made available through a WebSocket interface for real-time visualization via an interactive dashboard."

The Polar H9 was selected due to its high accuracy in detecting R-R intervals, which are essential for HRV analysis, even during movement or in uncontrolled environments. Data are transmitted in real time to the Raspberry Pi, where they are processed using Python and specialized libraries for HRV analysis. Metrics such as RMSSD and SDNN, widely recognized as sensitive indicators of physiological stress levels, are computed locally [1].

The main objective of this study is to demonstrate the feasibility of a portable, low-cost, and high-accuracy system based entirely on reliable commercial hardware for real-time, continuous HRV monitoring. The Polar H9 enables robust signal acquisition, while the Raspberry Pi provides sufficient computational resources for local processing and seamless integration with private cloud services. The proposed architecture targets applications in Conected Health, sports, telemonitoring, and workplace environments, offering a modular, open-source, and adaptable solution for diverse contexts and user profiles.

1.1 State of the Art

Health and well-being are fundamental aspects of human life and must not, under any circumstances, be overlooked. Emerging technologies, such as the IoT, have been gaining increasing prominence in the healthcare domain, driving significant advancements in environments that were previously inaccessible or unsuitable for clinical intervention and continuous monitoring. The authors in [9] present a comprehensive review of the state of the art in smart fitness, with an emphasis on the integration of wearable sensors, motion analysis, fitness-oriented applications, and artificial intelligence algorithms. They further highlight how both wearable and non-wearable sensors are employed to track physiological and biomechanical parameters such as heart rate, oxygen consumption, posture, movement, and calories burned. Several initiatives have been exploring the potential of IoT in this context [7, 11, 12, 16].

The study conducted in [27] demonstrates that the contact pressure (CP) between the photoplethysmography (PPG) sensor and the skin has a direct impact on signal quality, being more influential than the intensity of physical activity. Tests with 17 volunteers showed that a CP value of 54 mmHg yielded the highest correlation with an ECG chest strap (r = 0.81 to 0.95), with a mean percentage error below 4%. These findings indicate that proper adjustment of contact pressure can significantly improve the accuracy of heart rate measurements in wearable devices based on PPG.

Another study described in [23] conducted an experiment with 50 healthy athletes running on a treadmill at six different speeds. Four commercial smartwatches were compared against a chest strap sensor (Polar H7) and a reference ECG. The results indicated that the Polar H7 showed the highest agreement with the ECG (rc = 0.98), followed by the Apple Watch Series 3 (rc = 0.96). Other devices, such as the Fitbit Ionic, Garmin Vivosmart HR, and TomTom Spark 3, demonstrated lower performance (rc = 0.89). The study concluded that chest strap sensors or smartwatches with more robust hardware, such as the Apple Watch, are more suitable for endurance athletes in high physiological demand scenarios.

The study presented in [19] describes an intelligent IoT-based system for real-time detection and monitoring of symptoms related to heart attacks. Using wearable sensors, the system collects physiological data such as heart rate, which is processed via the Arduino IDE and transmitted to an IoT server. Signal analysis is performed using machine learning algorithms, including Support Vector Regression (SVR) and Artificial Neural Networks (ANN), which are capable of identifying abnormal patterns associated with acute cardiac events.

Another study presented in [25] proposes the development of a wireless sensor node prototype embedded in firefighters' gloves, aiming at real-time stress level detection. The system integrates Galvanic Skin Response (GSR) and heart rate sensors, a microcontroller for local processing, a ZigBee communication module, and a rechargeable power supply. Data transmission is performed using the MQTT protocol, with the Adafruit IO platform employed for data storage, analysis, and visualization. Based on the analyzed data, alerts are generated and displayed on the fire truck's user interface (UI).

Several studies have explored IoT, fog, and cloud architectures for physiological parameter monitoring. Islam et al. [10] provide a comprehensive overview of IoT applications in healthcare; however, they do not evaluate latency or security in distributed architectures, which are critical for real-time applications. Shaffer and Ginsberg [29], as well as Laborde et al. [13], offer methodological guidelines for HRV analysis, but focus primarily on metric standardization without addressing integration with web-based visualization platforms. Farrokhi et al. [9] review the use of AI and IoT in fitness contexts, yet do not provide details regarding private cloud deployment or multi-user scalability. Mahmud et al. [14] propose a fog–edge architecture for the Internet of Medical Things (IoMT) with a focus on threat resilience; however, their system lacks an interactive web front-end to support remote monitoring by healthcare professionals. Younas et al. [34] analyze quality of service in edge devices, but do not address the presentation layer or user experience. Daraghmi et al. [5] present an Edge–Fog–Cloud hierarchy for NB-IoT, yet without incorporating user experience (UX) metrics or dashboard usability. These gaps highlight the need for a comprehensive system that combines: (i) distributed HRV data acquisition and processing using IoT devices, (ii) real-time delivery of metrics and AI-based inferences, and (iii) a secure, scalable web platform hosted in a private cloud.

Given recent advancements, there is growing interest in the application of wearable and embedded technologies for real-time physiological monitoring, with particular emphasis on heart rate and stress levels. The reviewed studies indicate that, although PPG sensors have gained popularity due to their low cost and portability, their accuracy can be significantly affected by factors such as contact pressure and exercise intensity. In contrast, ECG-based sensors, such as chest straps, have proven to be more robust and reliable, especially in high-demand physical contexts. Furthermore, various system architectures have explored the use of IoT to continuously transmit and analyze this data, integrating efficient protocols such as MQTT and AI algorithms for decision-making. However, there remains a need for technically feasible, low-cost, and clinically reliable solutions capable of operating outside controlled laboratory environments. In this context, the present work proposes an architecture based on the Polar H9 sensor and Raspberry Pi, aimed at real-time HRV analysis and stress detection, with a focus on accuracy, portability, and accessibility. This approach seeks to address existing gaps by highlighting:

- a BLE → RabbitMQ pipeline containerized via Docker on an Ubuntu 24.04 virtual machine, protected by a firewall, responsible for the continuous acquisition and forwarding of R-R intervals;
- edge processing (Raspberry Pi 4) of classical HRV metrics (RMSSD, SDNN, and pNN50), made available in real time;
- a cross-platform Web dashboard (Next.js/React) with an interactive interface for continuous visualization of stress indicators;
- continuous HRV and stress monitoring, integrating data acquisition, processing, and visualization into a unified IoT–Web solution.

1.2 Comparative Analysis of Related Works

Table 1: Comparison of IoT–Fog–Cloud Architectures for Health Monitoring

Work	Year	Architecture	Web UI	Limitation
Islam et al.[10]	2015	IoT–Cloud	No	Lacks integrated Web platform
Shaffer and Ginsberg[29]	2017	N/A	No	Focused only on metrics, no IoT architecture
Laborde et al.[13]	2017	N/A	No	HRV methodology without IoT practical application
Farrokhi et al.[9]	2021	IoT	Partial	No detailed deployment in private cloud
Mahmud et al.[14]	2025	Edge–Fog	No	No Web dashboard or real-time HRV measurement
Younas et al.[34]	2023	Edge	No	No user-facing data visualization
Daraghmi et al. [5]	2022	Edge–Fog–Cloud	No	No demonstration of continuous monitoring
This work	2025	IoT–Fog–Cloud	Yes	Real-time HRV, continuous monitoring, and Web dashboard

2 MATERIALS AND METHODS

The system architecture was designed to provide a continuous, portable, low-cost, and high-precision physiological monitoring solution. To achieve this, widely available commercial IoT components from the maker and academic ecosystems were employed, integrated through efficient communication protocols and open-source libraries.

2.1 System Architecture

The proposed architecture adopts a distributed and modular approach, consisting of four main layers: (i) physiological sensing, (ii) edge unit (Raspberry Pi 4), (iii) private cloud, and (iv) web interface. Detailed descriptions of these layers are presented in Sections 2.2, 2.3, and 2.5, while the web interface layer is discussed in Section 3. The Figure 1 illustrates the hierarchical organization of the proposed architecture, emphasizing the functional segmentation of the system into logically independent yet interconnected layers, which promotes modularity, scalability, and a clear separation of responsibilities within the solution.

Each layer was designed to perform specific and complementary functions within the physiological monitoring ecosystem. The adoption of this multi-layered architecture provides greater flexibility for component updates and maintenance, as modifications in one layer do not necessarily affect the others. Furthermore, this model facilitates interoperability among heterogeneous devices, the integration of new services, and the customization of the platform according to different usage contexts (clinical, athletic, or home-based). The functional isolation between layers also contributes to enhanced security, robustness, and system resilience against failures or localized infrastructure disruptions.

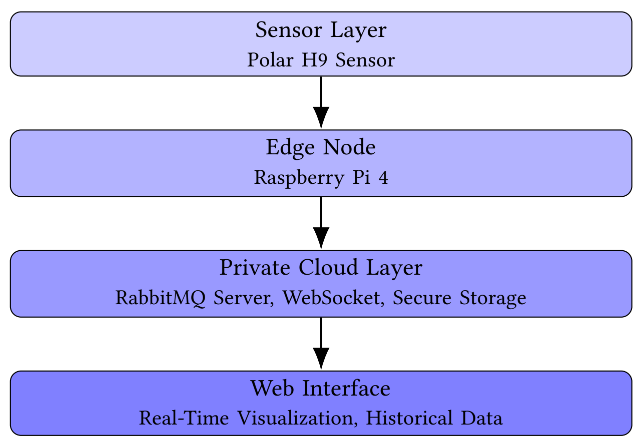

Figure 1: Layered architecture of the proposed system

Figure 2 provides a detailed view of the system's prototyped implementation, highlighting the main physical and logical components of the embedded solution. It illustrates the integration between the Polar H9 heart rate sensor and the Raspberry Pi 4 via Bluetooth, as well as communication with the private cloud using RabbitMQ broker and WebSocket. This structure brings the conceptual architecture shown in Figure 1 into a practical context, demonstrating the distribution of functionalities across hardware, software, and network services, and reinforcing the practical feasibility of the solution in real-world physiological monitoring scenarios during various activities.

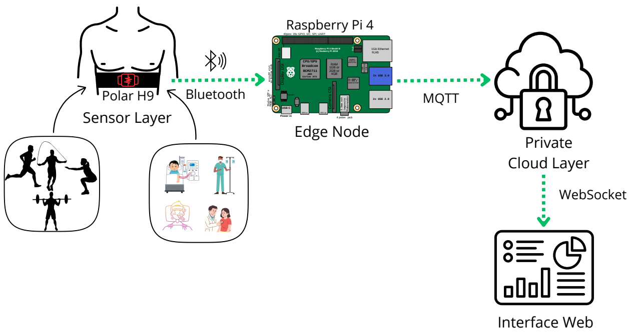

Figure 2: Prototyped system architecture.

The Table 2 summarizes the main components of the developed architecture. These elements make the architecture suitable for Connected Health applications, particularly in contexts that require local processing, portability, and low power consumption.

Table 2: Components used in the system architecture

Component	Description
Polar H9	ECG-based heart rate sensor with high R-R interval accuracy and BLE compatibility.
Raspberry Pi 4	Edge unit with quad-core processor, up to 4 GB RAM, BLE/Wi-Fi support, enabling local processing and data transmission to the private cloud.
RabbitMQ	Lightweight message broker for data forwarding between the Raspberry Pi and the private cloud.
Next.js	Framework used to build a responsive web dashboard with real-time integration.

2.2 Sensor Layer

The Polar H9 sensor performs continuous acquisition of ECG-based R-R intervals and transmits the data via BLE to the edge node. The strap is positioned as specified by the manufacturer, ensuring efficient contact and minimizing artifacts.

2.2.1 Acquisition of Physiological Signals. Physiological data collection was performed using the Polar H9 sensor, positioned in the lower thoracic region, according to the manufacturer's recommendations [22] and shown in Figure 3. The sensor measures the heart's electrical signals and calculates the intervals between consecutive beats (R-R intervals), which are transmitted via BLE to the Raspberry Pi.

All procedures involving data collection, storage, and processing were conducted in accordance with the protocol approved by the Research Ethics Committee (Approval Nº. 82489124.0.0000.5659/CAEE), ensuring compliance with applicable ethical standards.

(a) Initial placement of the chest strap

(b) Final adjustment with firm contact.

Figure 3: Process of putting on the Polar H9 heart rate sensor chest strap on the participant.

2.3 Edge Node: Raspberry Pi 4

The Raspberry Pi 4 acts as the acquisition and preprocessing unit. Data is published via RabbitMQ broker to a secure private cloud instance presented in the subsection (2.5). The Table 3 presents the device's main technical specifications, highlighting its connectivity and processing capabilities.

Table 3: Embedded Device Specifications (Raspberry Pi 4)

Component	Description
Processor	Broadcom BCM2711, quad-core Cortex-A72 (64-bit), 1.5 GHz
RAM	4 GB LPDDR4
Network connectivity	Gigabit Ethernet, Wi-Fi 802.11ac, Bluetooth 5.0
Operating system	Linux (Raspberry Pi OS)
GPIO	40-pin General Purpose Input/Output (GPIO) interfaces
Video outputs	2 micro-HDMI ports, supporting up to 4K
USB ports	4 ports (2 × USB 3.0, 2 × USB 2.0)
Dedicated connectors	CSI interface for camera and DSI for display

The Raspberry Pi 4 was configured to operate as an edge node, continuously acquiring signals and relaying them to the private cloud using RabbitMQ. The data was temporarily stored and processed locally on the device itself, ensuring robustness even in situations with limited connectivity. Figure 4 represents a prototype of a Raspberry Pi 4 Model B.

Furthermore, the Raspberry Pi 4 offers ideal characteristics for serving as an edge unit in distributed architectures and has sufficient processing power to perform real-time physiological signal preprocessing tasks. This flexibility allows integration with commercial biomedical sensors and the local execution of filtering algorithms, artifact detection, and HRV metric extraction, such as RMSSD and SDNN. Local operation reduces latency and network data traffic. It ensures greater resilience in contexts with intermittent connectivity, making the system more reliable for continuous physiological monitoring applications outside the laboratory environment.

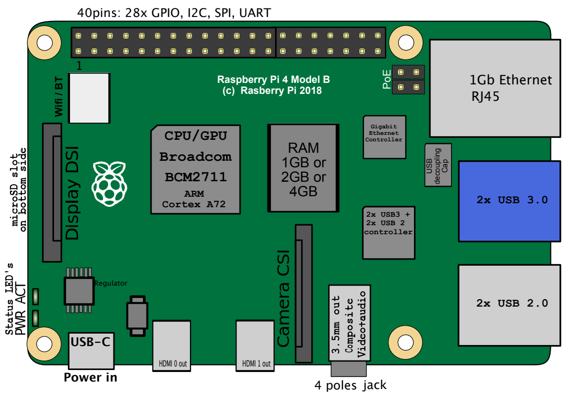

Figure 4: Raspberry Pi 4 Model B, single board computer used.

2.4 HRV Analysis

The R-R signal analysis was performed in real time using Python scripts running locally on the Raspberry Pi. Two classic HRV metrics, widely recognized as sensitive indicators of physiological stress levels, were extracted:

- **RMSSD**: represents the beat-to-beat variation and is strongly related to the parasympathetic activity of the nervous system [13, 29].

$$\text{RMSSD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(NN_{i+1} - NN_i)^2}$$

- **SDNN**: reflects the global variability of the cardiac signal and is influenced by sympathetic and parasympathetic autonomic mechanisms [20].

$$\text{SDNN} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(NN_i - \overline{NN})^2}$$

- **pNN50**: is the percentage of pairs of successive normal-to-normal (NN) intervals that differ by more than 50 ms [29].

$$\text{pNN50} = \frac{100}{N-1}\sum_{i=1}^{N-1}\mathbf{1}\{|NN_{i+1} - NN_i| > 50\}$$

2.5 Private Cloud Layer

The private cloud was implemented on a self-managed virtual machine (VM) hosted in a dedicated private infrastructure. This VM runs Ubuntu Server 24.04 LTS and is configured to provide high availability through containerized deployment. The environment includes 32 GB of DDR4 RAM and 100 GB of SSD storage, ensuring sufficient computational resources for real-time data processing, database management, and web hosting, with scalability and fault tolerance. Web and backend services are deployed in Docker containers, protected by UFW and IPTables firewall rules controlling access to RabbitMQ, WebSocket. Additionally, network security is reinforced with TLS certificates, user/password authentication.

3 DASHBOARD VISUALIZATION AND USABILITY WEB PLATFORM

Real-time physiological data visualization is an essential component of the proposed architecture, allowing users to monitor their stress levels and heart rate variability in an intuitive and accessible way. To achieve this, we developed a responsive web platform using the Next.js framework, which offers high page load performance and excellent integration with React for building dynamic interfaces.

The *Dashboard* acts as the system's presentation layer, connecting to the remote database that stores the physiological data transmitted via RabbitMQ/WebSocket. The system architecture enables data to be sent from the Raspberry Pi to the private cloud after processing, and then made available via WebSocket for direct consumption by the interface.

3.1 Usability and User Experience

The developed platform incorporates a set of features aimed at providing clear, accessible, and real-time visualization of physiological data. Key features include the continuous display of heart rate in beats per minute, essential for assessing the user's autonomic balance. This data is presented through intuitive graphs and color-coded visual indicators, facilitating immediate identification of stress levels categorized as low, moderate, or high. This type of visual representation allows for quick understanding by non-specialized users. It expands the tool's potential application in clinical and sports settings, as shown in Figure 5.

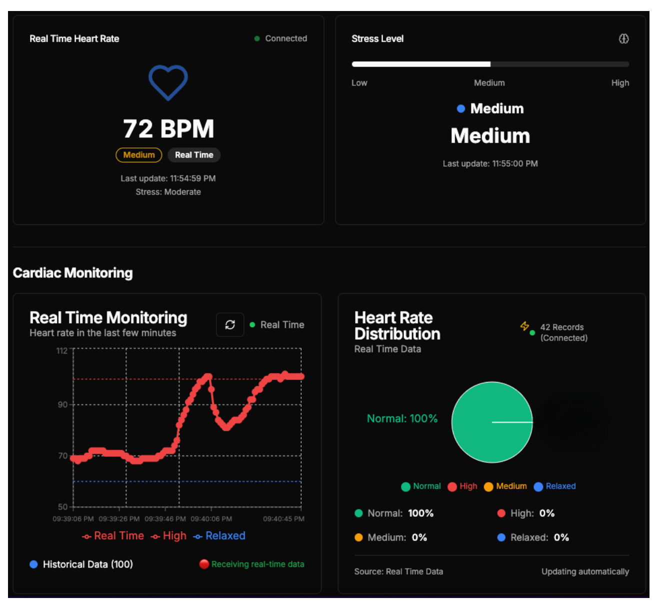

Figure 5: System Dashboard

Furthermore, the platform offers historical graphs with customizable filters by period (last hour, day, week), enabling detailed temporal analysis and longitudinal monitoring of physiological status. The interface is fully responsive, compatible with mobile devices and desktops, ensuring accessibility and practicality in various usage contexts. An integrated status dashboard provides real-time information on the quality of the connection to the sensor via BLE and the stability of communication with the server via RabbitMQ/WebSocket, contributing to the system's operational reliability and facilitating the diagnosis of potential technical failures during field use.

The interface was designed with simplicity and objectivity in mind, catering to users with varying levels of technology familiarity. Navigation is straightforward, with reduced menus and a focus on key metrics, using icons and colors that facilitate quick interpretation of the user's current physiological status.

Preliminary usability tests were conducted with a small group of volunteers, indicating good acceptance of the interface, ease of navigation, and comprehension of the displayed metrics. The interface's responsiveness also enables its use on cell phones, tablets, and larger monitors without compromising functionality or readability.

For demonstration purposes, the platform[1] can be accessed using the credentials username: *user@cardio.com* and password: **40302010**. These credentials provide read-only access, allowing users to explore the dashboard features and visualizations without altering or deleting any data.

4 RESULTS AND DISCUSSIONS

Tests performed with the developed prototype demonstrated the technical feasibility of the proposed architecture for monitoring HRV and inferring stress levels.

During the testing phase, the Polar H9 sensor operated stably, capturing R-R intervals with high fidelity under different conditions of rest and light physical activity. The data acquisition rate was approximately 1 Hz, compatible with HRV analysis standards. Transmission via BLE to the Raspberry Pi occurred without significant loss, even during prolonged sessions. All data were collected over a 12-hour period, which proved sufficient to obtain relevant and representative information about the physiological variability of the monitored individual. The metric results can be seen in Table 4.

Table 4: HRV Metrics Summary

Metric	Value
RMSSD	521.57 ms
SDNN	331.69 ms
pNN50	75%
HR Mean	81.12 bpm
HR Std	38.75 bpm

Heart rate consistently remained within the normal range throughout the experiment, demonstrating significant hemodynamic stability during the acquisition period. Values remained narrowly concentrated around 81 bpm with a 38.75 standard deviation, suggesting a physiological resting state without significant autonomic disturbances. Such stability is an essential indicator of cardiovascular homeostasis, especially in continuous monitoring contexts, where abrupt variations can signal responses to stress, postural changes, or physical exertion.

As illustrated in Figure 6, the heart rate curve reveals a regular pattern with low dispersion, reinforcing the reliability of the sensor and the transmission architecture used. This consistency in readings also supports the accuracy of the HRV metric extraction algorithms, since minimized fluctuations reduce noise in the calculations derived from the R-R intervals. These data, therefore, confirm not only the technical efficiency of the proposed system but also its applicability in prolonged monitoring scenarios with low levels of interference.

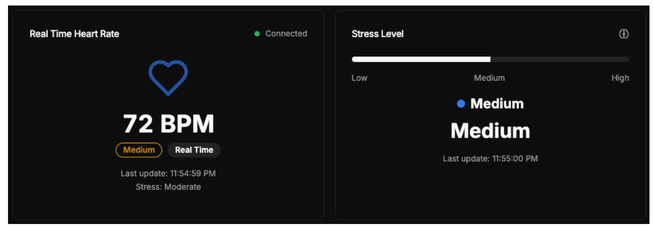

Figure 6: Heartbeat state represented as 72 bpm and as a relaxed stress level.

During heart rate data analysis, a predominance of the "normal" state was observed, corresponding to 66% of the monitoring time. This pattern indicates that, for most of the acquisition period, the user maintained balanced autonomic activity, with a stable heart rate within the reference range. The high prevalence of the normal state may be associated with the absence of intense stressors and the good adaptation of the cardiovascular system to rest or light activity, as shown in Figure 7.

Additionally, states classified as "relaxed" represented 17% of the total time, reflecting moments of likely parasympathetic predominance, with a slowing of the heart rate. The "medium" (10%) and "high" (7%) states occurred to a lesser extent and may be associated with transient variations, such as brief physical movements, emotional changes, or changes in posture. These fluctuations are expected in continuous recordings and help provide a more comprehensive understanding of the user's autonomic dynamics.

The distribution presented in the pie chart offers a direct and intuitive visualization of cardiovascular behavior over time. This type of analysis is beneficial for self-awareness and therapeutic monitoring, allowing the user and healthcare professional to assess the frequency and intensity of different physiological states. The heart rate dashboard, by consolidating these proportions graphically and segmenting them, facilitates decision-making, whether for immediate interventions or adjustments to rehabilitation, training, or stress management programs.

Figure 8 presents a visualization of the real-time heart rate monitoring module, demonstrating the stability of the heart rate over the last few minutes. The blue line indicates the evolution of the BPM (beats per minute) value, which fluctuates slightly between 65 and 67 bpm during the recorded period. The regularity of the data reflects a stable hemodynamic pattern, without acceleration peaks or abrupt drops, which is indicative of a controlled physiological state, possibly at rest or light activity.

[1]Access link: http://andromeda.lasdpc.icmc.usp.br:5063 or https://andromeda.lasdpc.icmc.usp.br:5063

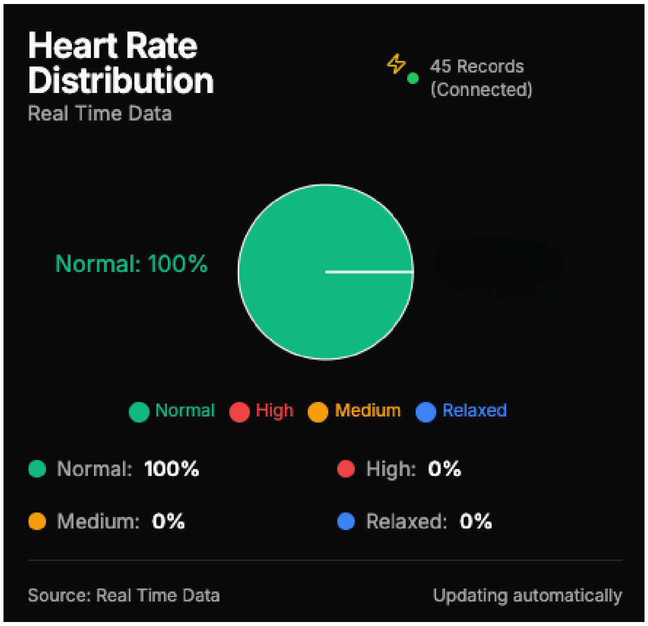

Figure 7: Distribution of beats in percentage (Normal, High, Medium, and Relaxed).

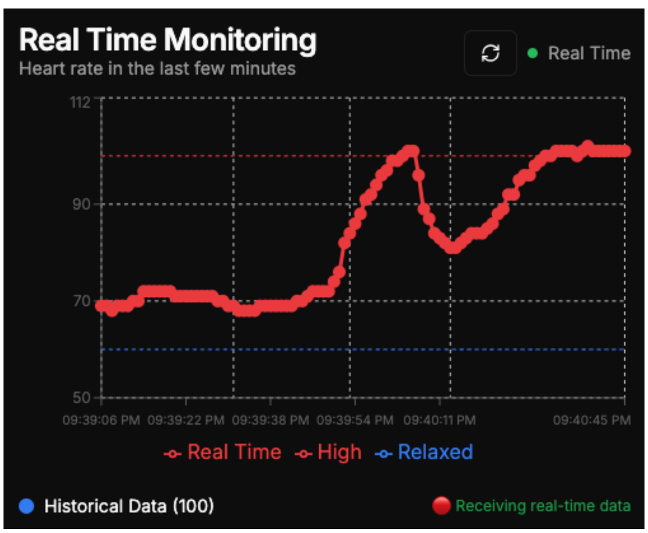

Figure 8: Real-time heart rate monitoring interface. The blue line represents the evolution of beats per minute (BPM) over the last few seconds, varying between 65 and 67 bpm.

The graph also includes visual references with boundary lines for "High" (red) and "Relaxed" (light blue) zones, facilitating immediate interpretation of the user's current state. The green "Connected" marker in the upper right corner confirms that the system is operational and communicating actively with the WebSocket server. This graphical interface is crucial for practical applications, as it allows continuous and responsive heart rate monitoring, offering support to both the user and professionals monitoring remotely.

Figure 9 presents the Stress History module, which displays the temporal evolution of stress levels (%) and heart rate variability (HRV in milliseconds). The red line represents the user's stress percentage, while the blue line shows the corresponding HRV values. It can be seen that, initially, the stress level remains high, with a slight downward trend over time. At the same time, HRV shows a progressive increase, indicating greater cardiac variability—a physiological signal associated with lower stress and increased parasympathetic activity.

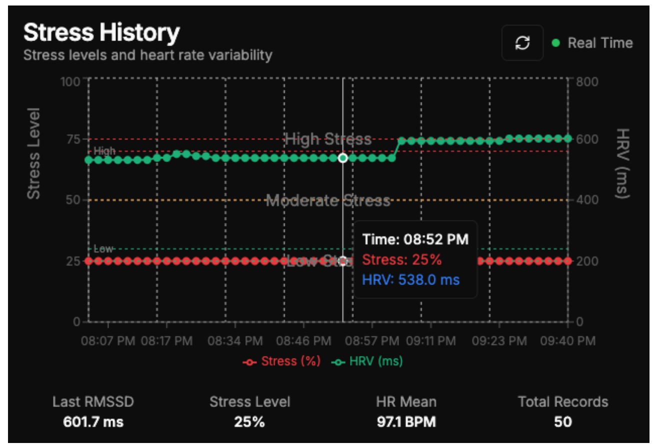

Figure 9: Graph shows the drop in stress (red) and the increase in HRV (blue) with the sensor connected at all times.

At the bottom of the graph, a clear inflection is noted: while the stress curve shows a sharp decline, HRV reaches its maximum peak. This pattern reinforces the inversely proportional relationship between heart rate variability and perceived stress, highlighting the functioning of the autonomic nervous system. The "Connected" status indicator confirms that the sensor was operational throughout the analyzed period. This integrated visualization allows a dynamic understanding of autonomic fluctuations and offers valuable support for interventions based on biofeedback, stress management, or real-time clinical monitoring.

The observed pattern is consistent with the findings of [25], which used GSR and heart rate sensors in firefighters and also identified greater retention in zones of physiological normality in low-stress contexts.

Compared to the solutions analyzed by [6] and [18], which use more complex wearable devices and proprietary infrastructure, the proposal presented here stands out for its architectural simplicity, portability, and adherence to the open-source ecosystem. The adoption of the Raspberry Pi as an edge unit reduces costs and expands the system's adaptability, making it accessible to diverse contexts such as clinics, homes, and sports centers.

Furthermore, by aligning with the trends discussed by [9], this architecture fits into the *smart fitness* paradigm, but with a particular emphasis on mental health and emotional well-being—topics that, according to [2], are critical today and require preventive and continuous approaches.

4.1 Benefits for end users

The developed architecture provides an effective solution for continuous cardiovascular health monitoring with a focus on the end-user experience. By integrating a heart rate sensor, Raspberry Pi, and a private cloud, physiological variations can be monitored in real time without invasive procedures or frequent travel. This mobility offers users greater freedom, allowing them to carry out their daily activities while remaining under passive yet constant surveillance.

Additionally, real-time data visualization through the dashboard enables healthcare professionals and caregivers to monitor the patient's physiological status remotely. Significant changes in HRV metrics can be detected quickly, allowing for immediate interventions in risky situations, such as episodes of acute stress or early signs of autonomic dysfunction. This real-time responsiveness marks a significant advancement in preventing clinical events and aiding medical decision-making.

Another key aspect is empowering users to manage their own health. The system's user-friendly and accessible interface allows for intuitive understanding of their physiological data, promoting self-awareness and encouraging healthier behaviors. In contexts such as cardiac rehabilitation, active aging, or chronic stress management, the solution is especially promising by expanding access to personalized and continuous care outside hospital settings.

In sports environments, the platform also proves beneficial by enabling continuous monitoring of autonomic responses during training sessions or competitions. Real-time analysis of HRV metrics enables coaches and health professionals to quickly identify signs of fatigue, overload, or incomplete recovery, thereby optimizing exercise plans based on the athlete's individual physiological condition. This data-driven approach helps reduce the risk of injuries from overtraining and supports athletic longevity.

Additionally, the system's portability allows it to be used across different sports, both indoors—such as gyms and rehab centers—and outdoors—such as fields, tracks, or trail training. Athletes can wear the sensor during physical activity without hindering mobility, while the Raspberry Pi performs local data processing and transmits information to the private cloud. This provides coaches and trainers with immediate access to physiological performance data, enabling targeted interventions and real-time strategy adjustments.

5 CONCLUSIONS

From a social and technological perspective, this solution aligns with the principles of Connected Health, expanding access to preventive and personalized care. By enabling real-time visualization of physiological data, individuals can adopt proactive strategies such as adjusting exercise intensity, improving lifestyle habits, or receiving remote professional guidance upon detection of abnormal physiological patterns reducing the need for frequent hospital visits and promoting a patient-centered model of care.

However, certain limitations must be acknowledged. The current version has not yet undergone clinical validation with multiple participants, and it does not integrate machine learning models for automatic stress classification. These aspects will be addressed in future developments.

Future work will therefore focus on: (i) Integrating machine learning algorithms for automatic detection and classification of stress levels using HRV metrics; and (ii) Conducting large-scale clinical validation to assess performance, reliability, and applicability across diverse populations, including scalable load testing in hybrid cloud environments.

In conclusion, the proposed architecture represents a significant contribution to the field of Connected Health, offering a reliable, scalable, and secure foundation for the continuous and personalized monitoring of stress and cardiac variability.

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