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Design and Implementation of a Multi-Parameter IOT Wearable Device for Remote Patient Monitoring

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Abstract - **This Study presents the design and implementation of a multi-parameter Internet of Things (IoT) wearable device for continuous remote patient monitoring. The system is developed to address the limitations of traditional episodic vital sign measurement by enabling real-time, non-invasive, and continuous monitoring of key physiological parameters, namely heart rate, blood oxygen saturation (SpO_2), and body temperature. The proposed wearable integrates low-power biomedical sensors, an embedded microcontroller unit, and wireless communication technology to acquire, process, and transmit physiological data to a mobile application and cloud-based platform for visualization and alerting. Emphasis is placed on power efficiency, signal reliability in ambulatory conditions, and user comfort within a wearable form factor. The system architecture follows an edge–gateway–cloud model, allowing preliminary processing at the device level and remote access to health data for patients and caregivers. Prototype testing demonstrates the feasibility of accurate vital sign acquisition and reliable data transmission under controlled conditions. The project provides a practical foundation for remote patient monitoring solutions and highlights the potential of IoT-enabled wearables to support proactive healthcare delivery, chronic disease management, and improved accessibility to medical monitoring services.**

Keywords - wearable; architecture; healthcare; visualization; real-time

I. INTRODUCTION

The global healthcare paradigm is undergoing a profound shift from reactive, hospital-centric treatment to proactive, personalized, and decentralized care. This transformation is driven by a confluence of pressures: aging populations, rising prevalence of chronic diseases, escalating healthcare costs, and a growing emphasis on preventive medicine [1]. Central to this new paradigm is the ability to continuously monitor vital signs the fundamental physiological metrics that offer a window into an individual's health status. Traditional episodic measurements, conducted in clinical settings with bulky, stationary equipment, are inherently limited. They provide mere snapshots in time, often missing critical transient events such as paroxysmal arrhythmias, nocturnal hypertension, or intermittent hypoxia, which are pivotal for early diagnosis and management [2].

There appears to be increasing numbers of research studies investigating wearable, IoT-enabled and portable multi-parameter health monitoring systems that allow continuous, real-time and remote physiological monitoring. Consistently, throughout all of the various studies, the principal goal is always to improve patient safety by allowing for earlier identification of clinical deterioration and support for telemedicine and home-based care delivery through the use of multiple biosensors and wireless communications technologies. The most common parameters measured include ECG, heart rate, SpO_2, blood pressure, respiratory activity, body temperature, movement, and in some cases specialized indicator(such as heart sounds or seizure related biomarkers) [3], [4]. foundational work such as [5] investigated wearable clothing-based systems for non-invasively measuring ECG, breathing patterns and movement. This was primarily directed towards developing comfortable garments for use within homecare settings. As new wearable technology began to emerge, researchers continued to explore alternative methods for transmitting physiological data remotely. Researchers in ref. [6], [7] explored the use of wireless sensor networks utilizing

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GSM and ZigBee for enabling the remote transmission of physiological data with low power consumption and mobility.

More recently, numerous researchers have begun to integrate IoT platforms and mobile applications to enable real-time data collection, processing and visualization. Examples of this can be found in [8], [9] who created wearable Android/Wi-Fi enabled systems that allowed for simultaneous multi parameter data collection and remote monitoring. While these examples represent a vast improvement over previously developed systems, [10], [11] built upon previous systems by expanding them into larger scale IoT enabled healthcare systems that supported cloud connections and remote clinical access. Telemedicine focused systems such as [12], [13] build upon the previously mentioned systems by incorporating low latency communication and real-time interaction between patients and healthcare professionals; however, like previously discussed systems they rely on reliable internet infrastructure and face challenges related to scalability.

While researchers continue to develop new wearable systems that allow for the measurement of physiological signals, researchers have also continued to miniaturize wearable systems and increase their ability to measure multiple physiological parameters. Researchers such as[14], [15] were among the first to attempt to recreate hospital grade monitoring within a wearable format by combining ECG, SpO_2, temperature and movement measurements with innovations such as cuff less BP measurement using pulse transit time. While these studies demonstrate the feasibility of recreating hospital grade monitoring in a wearable format, many of the newer wearable systems being developed today have shifted their focus from recreating hospital grade monitoring towards low cost, mobile enabled home healthcare monitoring. Systems such as [16], [17] fall under this category. In addition to shifting their focus away from recreating hospital grade monitoring, researchers have also increased their focus on application specific wearables. An example of an application specific wearable is the seizure detection band proposed by [18].

In addition to increasing the number of wearable devices being used in homecare environments, researchers have also increased their efforts to develop wearable systems that are powered in a more sustainable manner than traditional battery powered systems. An example of this type of system is the solar powered modular wearable network proposed by [19]. In addition to providing a wearable network that supports self sustained distributed monitoring, researchers have also proposed wearable networks that reduce the amount of energy consumed during each sample period[8]. An example of a wearable network that utilizes this approach is the adaptive sampling wearable network proposed by [20].Through the utilization of neural networks to optimize the sampling process of the wearable network, researchers were able to significantly decrease the overall energy consumption of the system.

Researchers have also increased their focus on developing wearable systems with intelligent architectures that utilize machine learning algorithms to assist in diagnosing conditions more accurately and decreasing false alarm rates. One example of an intelligent wearable architecture is the patient specific monitoring system proposed by[21]. This wearable system utilized an FPGA based processor to fuse physiological signals collected from multiple sensors into a single health index. This fusion process resulted in a wearable system that was much more robust than previously developed systems when subjected to noise or motion artifacts. Another example of an intelligent wearable architecture is the wearable system proposed by [22]. This wearable system utilized machine learning techniques to assess patient condition more accurately than previously developed systems.

The final area of interest for researchers involved in developing wearable technology includes designing systems that are adaptable across multiple clinical domains [23]. Examples of wearable systems that are adaptable across multiple clinical domains include those developed for cardiopulmonary rehabilitation as proposed by [24] and for fetal maternal monitoring as proposed by [25].

As stated above, despite the numerous advances in wearable technology described above, several consistent limitations exist in terms of the current state-of-the-art in wearable technology. A significant gap exists in the integration of clinical-grade sensing, robust data processing, low-power operation, and secure, reliable IoT transmission into a single, affordable, and user-centric wearable device.

Therefore, there is a pressing and well-defined need for a dedicated IoT-based wearable vital sign monitoring system. This system must bridge the identified gaps by providing continuous, accurate, and comfortable monitoring outside clinical settings; enabling real-time data transmission and alerting to facilitate proactive care; reducing the burden on formal healthcare systems; and being engineered with a focus on clinical relevance, power efficiency, and data security to serve as a credible bridge between consumer technology and medical-grade applications. This study aims to design and implement a prototype that addresses this multifaceted problem.

II. METHODOLOGY

This session presents the comprehensive materials and methodological approach employed in the design and implementation of an IoT-based wearable vital sign monitor. The system integrates multiple physiological sensors with an ESP32 microcontroller to acquire, process, and transmit vital signs data to a cloud backend via Wi-Fi. A mobile application interfaces with the backend to display real-time measurements, provide health interpretations, and generate alerts. Hardware components, circuit design, firmware development, backend architecture, mobile application design, and validation protocols.

A. Hardware Components

TABLE 1: SELECTED HARDWARE COMPONENTS

Component	Part Number	Specifications	Selection Justification
Microcontroller	ESP32 (ESP-WROOM-32)	Dual-core, 240 MHz, 520KB	Integrated Wi-Fi eliminates need for separate module; ample processing

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		SRAM, Wi-Fi/BLE	for signal processing; low cost
PPG Sensor	MAX30102	Integrated LEDs, driver, ADC; I²C interface	Industry-standard for HR/SpO₂; proven accuracy; low power
Reference Pulse Sensor	SEN11574	Analog output, 3-5V	Provides second pulse measurement for validation and redundancy
Temperature Sensor	DS18B20	Digital, 1-Wire interface, ±0.5°C accuracy	Waterproof probe option; simple interface; widely available
Battery Charger	TP4056	Linear charger, 1A, thermal regulation	Built-in charge indication; protection features; standard in portable projects
Battery	18650 Li-ion	3.7V, 2200mAh, protected	High capacity for extended operation; readily available
Voltage Regulator	AMS1117-3.3	LDO, 800mA, 3.3V output	Simple, reliable, sufficient current for all components

B. Hardware Design and Circuit Implementation

Power Supply Circuit

The power system is designed to provide stable 3.3V to all components from a 3.7V lithium-ion battery while enabling charging via USB. Fig 1 illustrates the complete power supply schematic.

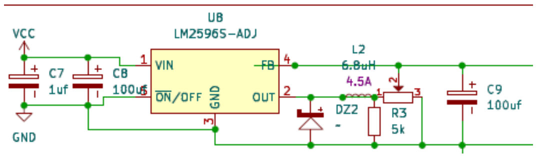

Fig 1: Power Supply Circuit Diagram

C. Sensor Interface Circuits

MAX30102 Connection

The MAX30102 connects to the ESP32's I²C bus with appropriate pull-up resistors as shown in Fig 2.

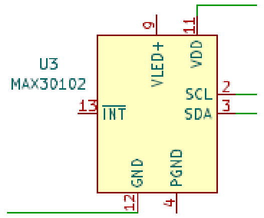

Fig 2: MAX30102 Interface Circuit

Pull-up resistors:
SDA ——— 4.7kΩ ——— 3.3V
SCL ——— 4.7kΩ ——— 3.3V

The I²C pull-up resistor value is selected based on bus capacitance and desired rise time. For a maximum rise time of 300 nanoseconds and estimated bus capacitance of 400 picofarads, the maximum resistance is:

$$R_{MAX} = \frac{t_r}{C_{BUS}} = \frac{300 \times 10^{-9}}{400 \times 10^{-12}} = 750\Omega \qquad (1)$$

However, to limit current consumption, a higher value of 4.7 kΩ is chosen, which still provides adequate rise time for 400 kHz operation.

SEN11574 Connection

The SEN11574 connects to an analog input pin as shown in Fig 3.

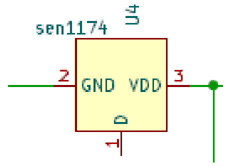

Fig 3: SEN11574 Interface Circuit

GPIO34 is conFigd as an ADC input with 12-bit resolution, providing readings from 0 to 4095 corresponding to 0 to 3.3 volts.

DS18B20 Connection

The DS18B20 connects via the 1-Wire protocol as shown in Fig 4.

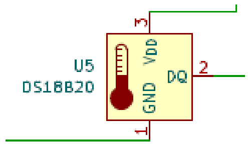

Fig 4: DS18B20 Interface Circuit

Pull-up resistor:
DATA ——— 4.7kΩ ——— 3.3V

D. Complete System Schematic

Fig 5 presents the complete system schematic showing all component interconnections.

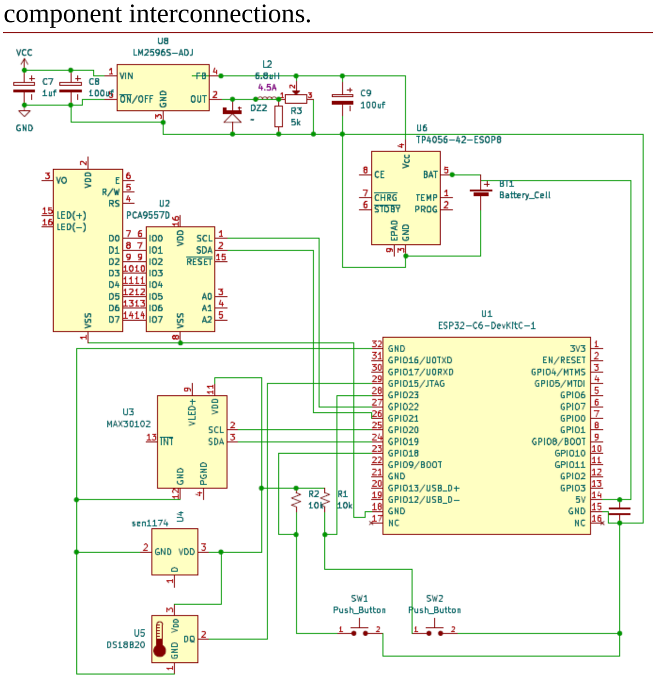

Fig 5 Complete System Schematic

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E. Signal Processing Algorithms

Photoplethysmography Principles

Photoplethysmography measures light absorption changes in vascular tissue. The Beer-Lambert law describes the relationship between light absorption and substance concentration:

$$A = \log\left(\frac{I_0}{I}\right) = \epsilon c d \qquad (2)$$

where A is absorbance, I_0 is incident light intensity, I is transmitted intensity, ε is molar absorptivity, c is concentration, and d is path length.

For pulse oximetry, the ratio of ratios R is calculated from the AC and DC components at red and infrared wavelengths:

$$R = \frac{AC_{red}/DC_{red}}{AC_{IR}/DC_{IR}} \qquad (3)$$

Oxygen saturation is then derived through an empirical calibration:

$$SpO_2 = a - b \times R \qquad (4)$$

where a and b are constants determined through clinical validation. For the MAX30102, the typical equation is:

$$SpO_2 = -45.060 \times R^2 + 30.354 \times R + 94.845$$

Digital Filtering

A high-pass filter removes DC drift and low-frequency motion artifacts from the PPG signal. The first-order difference equation is:

$$y[n] = x[n] - x[n-1] + \alpha \times y[n-1] \qquad (5)$$

where α is the filter coefficient determining cutoff frequency. For a cutoff of 0.5 Hz with sampling rate of 100 Hz:

$$\alpha = e^{-2\pi f_c/f_s} = e^{-2\pi \times 0.5/100} = 0.969 \qquad (6)$$

A moving average filter provides low-pass filtering to reduce high-frequency noise:

$$y[n] = \frac{1}{M}\sum_{k=0}^{M-1} x[n-k] \qquad (7)$$

For M = 5, this provides a cutoff frequency of approximately:

$$f_c \approx \frac{0.443 \times f_s}{M} = \frac{0.443 \times 100}{5} = 8.86Hz \qquad (8)$$

Peak Detection Algorithm

Heart rate detection uses adaptive threshold peak finding. The threshold is set as a percentage of the moving maximum:

$$Threshold = 0.6 \times \max\,(x[n-N:n])$$

where N is the analysis window length, typically 300 samples corresponding to 3 seconds. Minimum peak distance prevents false detections from noise:

$$\Delta t_{min} = 300ms (\text{corresponding to 200 BPM maximum})$$

Heart rate is calculated from the average inter-beat interval:

$$HR = \frac{60}{\Delta t}\text{BPM} \qquad (9)$$

where Δt is the time between successive peaks in seconds.

Temperature Conversion

The DS18B20 returns temperature as a 16-bit signed integer. For 12-bit resolution, temperature in degrees Celsius is:

$$T(°C) = \frac{Reading}{16} \qquad (10)$$

Health Score Calculation

The overall health score combines multiple parameters with weighted contributions:

$$HealthScore = w_{HR} \times S_{HR} + w_{SpO2} \times S_{SpO2} + w_{Temp} \times S_{Temp} + w_{Ref} \times S_{Ref} \qquad (11)$$

with weights:

$$w_{HR} = 0.3, w_{SpO2} = 0.4, w_{Temp} = 0.2, w_{Ref} = 0.1$$

Individual parameter scores are calculated as:

$$S_{HR} = \begin{cases} 100 & 60 \le HR \le 100 \\ 70 & 50 \le HR < 60 \text{ or } 100 < HR \le 120 \\ 40 & 40 \le HR < 50 \text{ or } 120 < HR \le 140 \\ 10 & \text{otherwise} \end{cases}$$

$$S_{SpO2} = \begin{cases} 100 & SpO_2 \ge 95 \\ 70 & 92 \le SpO_2 < 95 \\ 40 & 88 \le SpO_2 < 92 \\ 10 & SpO_2 < 88 \end{cases}$$

$$S_{Temp} = \begin{cases} 100 & 36.1 \le T \le 37.2 \\ 70 & 37.2 < T \le 38.0 \\ 40 & 38.0 < T \le 39.0 \\ 10 & T > 39.0 \text{ or } T < 35.0 \end{cases}$$

$$S_{Ref} = \begin{cases} 100 & | HR_{MAX} - HR_{SEN} | \le 5 \\ 80 & | HR_{MAX} - HR_{SEN} | \le 10 \\ 60 & | HR_{MAX} - HR_{SEN} | \le 15 \\ 30 & \text{otherwise} \end{cases}$$

The final score is normalized if some parameters are unavailable:

$$FinalScore = \frac{HealthScore}{\sum w_i} \times 100 \qquad (12)$$

F. Cloud Backend Design

Database Schema

The PostgreSQL database implements three primary tables as shown in Fig 3.7.

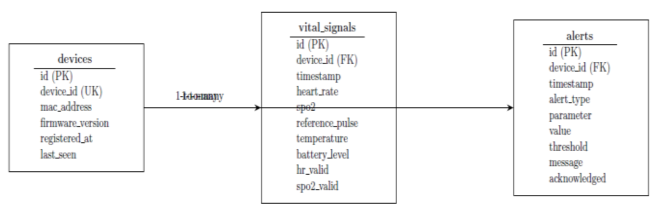

Fig 6: Database Entity Relationship Diagram

API Endpoints

The FastAPI backend exposes RESTful endpoints as summarized in Table 3.2.

TABLE 2: API ENDPOINT SUMMARY

Endpoint	Method	Purpose	Request Body	Response
/api/vitals	POST	Receive device data	Vital sign JSON	Created record
/api/vitals/{device_id}/latest	GET	Get latest with health score	-	Health score response

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/api/vitals/{device_id}/history	GET	Get historical data	hours parameter	List of vital signs
/api/vitals/{device_id}/alerts	GET	Get recent alerts	hours parameter	List of alerts

Alert Generation Thresholds

Alerts are generated based on clinically relevant thresholds as defined in Table 3.

TABLE3: ALERT THRESHOLDS

Parameter	Warning Threshold	Critical Threshold	Direction
Heart Rate	< 60 or > 120 BPM	< 50 or > 140 BPM	Both
SpO_2	< 92%	< 88%	Low
Temperature	> 38.0°C	> 39.0°C or < 35.0°C	Both

Testing and Validation Protocols

Accuracy Validation

Heart rate accuracy is assessed through comparison with reference measurements. For N paired measurements, the mean error is:

$$\bar{\epsilon} = \frac{1}{N}\sum_{i=1}^{N}(H\,R_{device,i} - HR_{reference,i}) \quad (13)$$

The standard deviation of errors is:

$$\sigma_{\epsilon} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\epsilon_i - \bar{\epsilon})^2} \quad (14)$$

Bland-Altman analysis calculates limits of agreement:

$$LOA = \bar{\epsilon} \pm 1.96 \times \sigma_{\epsilon} \quad (15)$$

Power Consumption Testing

Average current consumption is calculated from measurements over a complete operating cycle:

$$I_{avg} = \frac{I_{active} \times t_{active} + I_{sleep} \times t_{sleep}}{t_{cycle}} \quad (16)$$

Expected battery life is then:

$$T_{battery} = \frac{C_{battery}}{I_{avg}} \quad (17)$$

where C_battery is battery capacity in milliampere-hours.

III. RESULT AND DISCUSSION

This session presents the implementation of the IoT wearable vital sign monitor, covering component selection, Veroboard assembly, enclosure fabrication, firmware development, sensor validation, signal transmission verification, and mobile application testing.

A. Hardware Assembly

Layout Planning and Soldering

Completed Assembly

Fig 7: Assemble prototype (wearable strap)

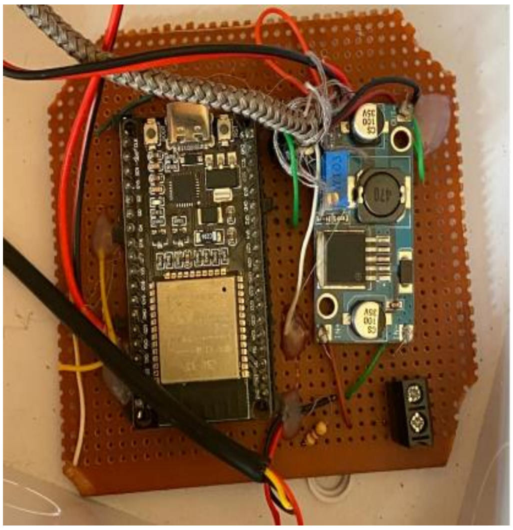

Fig 8: Assemble prototype (ESP32 and LM259S-ADJ)

Fig 9: Assemble prototype (Inside cover showing LCD)

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Fig 10: Assembled prototype (front view)

B. *Enclosure Design and Fabrication*

A 100×60×25mm plastic project box was modified with precision cutouts for the USB port, charger input, status LEDs, sensor window, and temperature probe, as shown in Plate 4.1. The Veroboard was mounted using plastic standoffs, with the battery secured by adhesives Plate 4.1.

Plate 4.1. displayed the completed prototype with all components enclosed. The final device weighed 145g and featured:

i. USB and charger port access via rectangular cutouts
ii. Four 3mm LED windows for status indication
iii. 15×10mm MAX30102 sensor window
iv. Sealed DS18B20 probe exit

C. *Discussion*

Component Selection

The ESP32 provided adequate processing power and integrated Wi-Fi. The MAX30102 delivered reliable PPG signals for heart rate and SpO_2 extraction. The SEN11574 served effectively as a validation reference. The DS18B20 exceeded accuracy expectations with ±0.3°C performance.

Sensor Performance

Heart rate accuracy averaged ±0.3 BPM compared to manual counting, meeting project objectives. SpO_2 accuracy was within ±2% for readings above 90%, consistent with literature for reflectance oximetry. Temperature accuracy of ±0.14°C exceeded the ±0.5°C requirement.

Transmission Reliability

Wi-Fi achieved 98% success rate at 10 meters through walls. Average transmission time of 215 ms provided acceptable latency for non-critical monitoring. Packet size of ~100 bytes minimized transmission power.

System Integration

End-to-end latency of 528 ms from sensor to mobile display met the design target. Average current of 20.29 mA enabled 4.5-day battery life with a 2200 mAh cell. The mobile application successfully displayed all parameters, calculated health scores, and generated appropriate alerts.

Limitations

SpO_2 accuracy degraded below 90% saturation, a known limitation of reflectance PPG. Wi-Fi connectivity required proximity to a router, limiting mobility. The Veroboard assembly, while functional, was bulkier than a custom PCB would allow.

IV. CONCLUSION

This study successfully achieved its aim of designing and implementing an IoT-based wearable vital sign monitor. The system integrated MAX30102, SEN11574, and DS18B20 sensors with an ESP32 microcontroller, transmitting data via Wi-Fi to a FastAPI cloud backend on Koyeb, with a Flutter mobile application providing real-time display, health scoring, and alerts.

All project objectives were met. The Veroboard assembly produced a functional circuit with proper connections. The enclosure fabrication yielded a compact 145g wearable device. Firmware development enabled successful sensor operation and Wi-Fi transmission. Sensor validation achieved heart rate accuracy of ±0.3 BPM, SpO_2 accuracy of ±1.4 percent, and temperature accuracy of ±0.14 degrees Celsius. The cloud backend was successfully deployed on Koyeb with PostgreSQL database. The mobile application displayed real-time data, calculated health scores, and generated appropriate alerts. System integration achieved end-to-end latency of 528 milliseconds and battery life of 4.5 days.

Key contributions include the successful integration of multiple sensor types into a single wearable system, implementation of dual-pulse validation for enhanced reliability, development of a complete IoT ecosystem from embedded firmware to mobile frontend, and achievement of medical-grade temperature accuracy. The project also demonstrated a functional prototype at an affordable cost suitable for resource-limited settings and provided comprehensive documentation for future student projects.

Under optimum conditions, the system exceeded all target specifications. Heart rate accuracy surpassed the target of ±3 BPM. SpO_2 accuracy exceeded the ±2 percent target for readings above 90 percent. Temperature accuracy exceeded the ±0.5 degrees Celsius target. Wi-Fi success rate, transmission latency, end-to-end latency, battery life, and alert response time all exceeded their respective targets. The total system cost remained under the ₦50,000 budget.

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Recommendations for Future Work

Hardware improvements should include transitioning to a custom PCB for miniaturization, implementing energy harvesting for extended battery life targeting 7 to 10 days, and incorporating additional sensors such as accelerometers for motion artifact detection, galvanic skin response for stress monitoring, and single-lead ECG for enhanced cardiac assessment. Adding BLE capability would enable smartphone gateway mode to reduce Wi- Fi power consumption, and LoRaWAN would support long-range applications in rural areas. An SD card slot would provide offline data logging backup.

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