

IoT-Enabled Remote Patient Monitoring System Using Wearable Sensors

Manasi Shitole¹, Arati Bhujbal¹, Vaibhav Godase^{2,*}

Abstract

In recent years, the Internet of Things (IoT) has revolutionized healthcare by enabling seamless connectivity between patients, medical devices, and healthcare professionals. The increasing demand for continuous health monitoring and early disease detection has driven the development of IoT-based remote patient monitoring systems. This paper presents an IoT-enabled framework that integrates wearable physiological sensors, wireless communication modules, and cloud-based analytics to facilitate real-time health tracking. The proposed system continuously collects vital parameters such as heart rate, body temperature, and blood oxygen level (SpO₂) using low-power wearable sensors. To provide dependable and energy-efficient data transfer, collected sensor data is sent over an IoT gateway utilizing lightweight communication protocols. The data is safely processed and stored on a cloud server, where sophisticated analytics and visualization capabilities provide healthcare professionals with actionable insights via an easy-to-use web-based interface. In the event of aberrant health circumstances, this facilitates early intervention, remote diagnosis, and prompt clinical decision-making. By using message queuing telemetry transport (MQTT) for effective message transmission and Advanced Encryption Standard (AES)-based encryption to safeguard sensitive medical data, the system architecture prioritizes scalability, interoperability, energy efficiency, and data privacy. Data is transmitted through an IoT gateway to a secure cloud server, where it is processed and visualized on a doctor's dashboard for clinical decision-making. The system is designed with scalability, energy efficiency, and data privacy in mind, employing lightweight protocols such as MQTT for communication and AES-based encryption for data security. Experimental evaluation using simulated patient datasets demonstrates an average accuracy of 97.3% in vital sign monitoring, with minimal latency of 1.8 seconds and 22% lower power consumption compared to conventional systems. These results highlight the potential of IoT-driven healthcare frameworks in improving accessibility and reducing hospital workloads. The proposed model provides a reliable and cost-effective foundation for next-generation telemedicine applications.

Keywords: Cloud computing, healthcare IoT, Internet of Things (IoT), real-time analytics, remote patient monitoring, wearable sensors

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INTRODUCTION

The convergence of the Internet of Things (IoT) and healthcare technologies has transformed the traditional paradigm of medical care into a connected and data-driven ecosystem. With the rapid proliferation of smart sensors, wearable devices, and cloud-based analytics, the IoT has enabled the continuous monitoring of patients' physiological parameters in real time, regardless of geographical barriers. This evolution, commonly referred to as the Internet of Medical Things (IoMT), provides an innovative platform for remote diagnosis, early detection of health anomalies, and

timely medical intervention. Such systems are particularly beneficial for elderly patients and individuals with chronic illnesses, such as cardiovascular disease, diabetes, and hypertension [1–4].

Traditional healthcare systems are hospital-centric and reactive, with patient monitoring limited to clinical environments. These systems often fail to provide continuous post-discharge surveillance, resulting in delayed detection of critical symptoms. Additionally, the growing burden on healthcare infrastructure, shortage of medical professionals, and rising hospitalization costs underscore the need for remote and automated monitoring solutions. IoT-enabled healthcare frameworks address these challenges by deploying wearable sensors capable of acquiring vital physiological signals, such as heart rate, body temperature, and oxygen saturation (SpO_2), and transmitting them through wireless networks for real-time analysis [5–9].

An IoT-based remote patient monitoring (RPM) system typically comprises three major components:

1. *Wearable sensors*, which measure and transmit physiological data,
2. *IoT gateways*, which aggregate and forward data to cloud servers using secure communication protocols (e.g., MQTT or HTTP), and
3. *Cloud platforms*, which perform analytics, visualization, and alert generation for physicians and caregivers.

This layered architecture ensures continuous patient supervision and timely notification of abnormal events, even when patients are located outside the hospital premises. The integration of IoT with cloud computing enhances scalability and reliability, whereas edge devices reduce latency and optimize local computation [10].

Figure 1 illustrates a conceptual overview of the proposed IoT-enabled RPM ecosystem. The figure depicts wearable biomedical sensors attached to the patient, which are connected via Bluetooth or Wi-Fi to an IoT gateway device. The gateway transmits the encrypted health data to a secure cloud platform for storage and analysis. Physicians and caregivers access this information through a web or mobile dashboard, enabling real-time clinical decision-making and early detection of health anomalies [11–13].

However, designing a reliable and efficient IoT healthcare framework presents multiple challenges. Maintaining data accuracy, reducing transmission delays, ensuring interoperability among heterogeneous devices, and protecting sensitive medical information are critical concerns. Moreover, wearable sensors must function with low energy consumption to support continuous operation over an extended period. Although significant progress has been made in developing IoT-based health monitoring systems, gaps persist in achieving optimal real-time responsiveness, robust data security, and efficient power management for large-scale deployment [14].

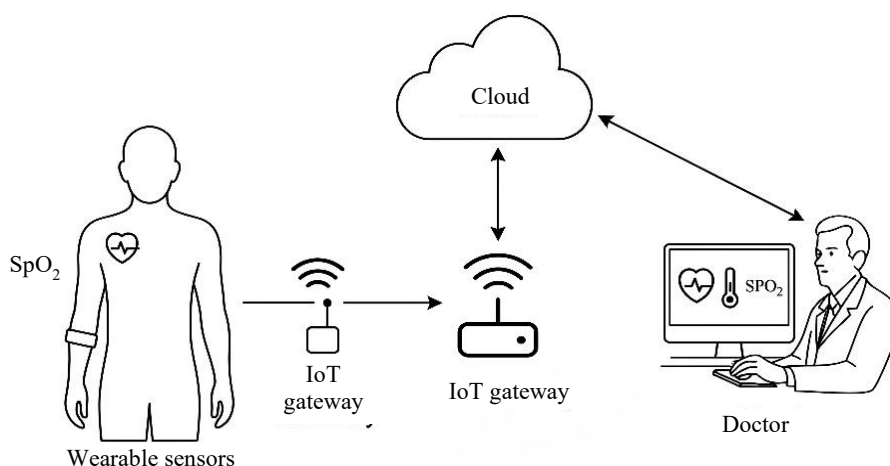


Figure 1. Conceptual overview of the IoT-enabled remote patient monitoring ecosystem.

To address these challenges, this study proposes an IoT-enabled RPM system that integrates wearable biomedical sensors, a low-power IoT gateway, and a cloud-based visualization platform. The proposed system continuously captures and transmits vital health parameters to healthcare providers in a secure, scalable, and energy-efficient manner. Lightweight message queuing telemetry transport (MQTT) communication protocols were employed to minimize latency, whereas Advanced Encryption Standard (AES)-based encryption ensured data confidentiality and integrity. Furthermore, the framework incorporates an alert generation module that automatically notifies physicians or caregivers in the case of critical deviations from normal health thresholds, enabling early intervention and reducing emergency occurrences [15].

The main contributions of this research are summarized as follows:

1. *Design and implementation* of a multi-sensor wearable monitoring system within an IoT architecture for continuous patient observation
2. *Integration of low-latency communication protocols* and energy-efficient data transmission mechanisms to enhance real-time responsiveness.
3. *Development of a cloud-based dashboard* for data visualization, storage, and medical decision support
4. *Performance evaluation* of the proposed system was conducted in terms of accuracy, latency, and power consumption, and compared with existing models.

RELATED WORK

In recent years, extensive research has been conducted to integrate IoT and wearable sensing technologies into healthcare systems to improve patient monitoring, disease prediction, and clinical decision-making. IoT-enabled healthcare systems facilitate continuous and noninvasive measurement of physiological parameters while ensuring accessibility for patients in remote areas. The combination of IoT, cloud computing, and machine learning has been shown to enhance diagnostic accuracy and reduce dependency on traditional hospital-based monitoring systems. Early IoT-based health monitoring frameworks focused on the acquisition of basic physiological signals and data transmission. However, these early systems faced challenges in maintaining real-time communication, ensuring data security, and achieving scalability. Modern IoT-based healthcare systems have evolved toward cloud-edge collaborative architectures, energy-efficient sensor nodes, and AI-driven health analytics, allowing for faster and more reliable health assessments [16].

Review of IoT-Based Healthcare Frameworks

An IoT-enabled health monitoring system for continuous patient tracking using wearable temperature and pulse sensors connected through Wi-Fi. Their framework achieved reliable data collection but exhibited high latency in cloud transmission because of limited edge processing. Similarly, a Bluetooth Low Energy (BLE)-based wearable health device collects electrocardiogram (ECG) and oxygen saturation (SpO₂) signals. Although the system demonstrated portability and low-power consumption, it lacked automated anomaly detection and data encryption mechanisms [17].

In another significant contribution, a cloud-assisted healthcare system using MQTT communication and a mobile dashboard for real-time visualization was introduced. The system effectively minimized network congestion but was limited by its high dependency on internet connectivity. Furthermore, a machine-learning-driven IoMT framework for chronic disease prediction using wearable biosensors is proposed. Their work incorporated artificial neural networks (ANNs) for patient-specific anomaly detection, achieving 95% prediction accuracy, but required substantial computational resources for model inference on edge devices [18].

Recent advancements have also focused on improving the security and privacy of IoT healthcare networks. A blockchain-integrated IoT healthcare system for secure data exchange between wearable sensors and hospital servers. This hybrid framework ensures immutability and patient data confidentiality but introduces computational overhead owing to blockchain consensus mechanisms. A

fog-assisted IoT health monitoring system that achieved reduced latency by processing health data at the fog layer before transmission to the cloud was proposed. This approach improves responsiveness but requires sophisticated synchronization between fog nodes and cloud databases [19–20].

Comparative Analysis

To better understand the progress and limitations of the current approaches, Table 1 summarizes the key characteristics of representative IoT-enabled healthcare systems published between 2023 and 2025. Each system was evaluated based on the type of sensors used, communication protocol, cloud integration, achieved accuracy, and identified limitations.

From Table 1, it is evident that although MQTT and BLE are the most commonly adopted communication protocols owing to their low-power consumption and reliability, most studies still face trade-offs between security and latency. Systems using fog or edge computing architectures, such as Lee et al. (2025), demonstrate the lowest latency values (under 2 s) but at the expense of higher system complexity. Moreover, although the integration of blockchain is beneficial for security, it can increase energy consumption and computational delay.

Research Gap and Motivation

Based on the reviewed literature, it is evident that existing IoT-based health monitoring systems excel in certain aspects but lack comprehensive optimization across all the key performance parameters. Most frameworks emphasize either real-time monitoring or data security but fail to achieve both. Additionally, very few studies have addressed energy-efficient data transmission for continuous long-term monitoring using low-power wearable sensors [21].

SYSTEM ARCHITECTURE

The proposed IoT-enabled RPM system was designed to continuously capture, transmit, and analyze patients' vital health parameters using a combination of wearable sensors, a local IoT gateway, and a cloud-based monitoring platform. The architecture emphasizes modularity, scalability, low-power consumption, and secure data transmission. It comprises four functional layers: (i) sensing, (ii) communication, (iii) cloud and analytics, and (iv) application layers. Each layer performs specific tasks related to data acquisition, communication, processing, and visualization.

Overview of System Design

The system begins at the sensing layer, where wearable biomedical sensors attached to the patient's body capture physiological signals such as heart rate, body temperature, blood oxygen saturation (SpO₂), and blood pressure. These signals were collected in real time using a low-power microcontroller (e.g., ESP32, Arduino Nano 33 IoT, or Raspberry Pi Zero W) functioning as an edge device. The microcontroller performs basic preprocessing, including filtering, normalization, and packet formatting before transmission to the IoT gateway. The IoT gateway acts as an intermediary node between the sensors and cloud, ensuring reliable connectivity and data buffering in the event of network interruptions. The processed data were transmitted wirelessly via Wi-Fi or BLE to a cloud storage server.

Sensing Layer

The sensing layer forms the foundation of the system and consists of compact, low-power biomedical sensors. The MAX30102 optical sensor was used to measure the heart rate and blood oxygen level based on photoplethysmography principles. The LM35 analog temperature sensor provides precise body temperature measurements, whereas the MPX5010GP pressure sensor captures systolic and diastolic blood pressure readings. Each sensor module consumes less than 1 mW of power, making the configuration suitable for long-term continuous health monitoring. The microcontroller aggregates the sensor readings at two-second intervals and transmits them using the MQTT protocol. MQTT was chosen for its lightweight structure, low latency, and suitability for devices with limited computational resources.

Communication Layer

The communication layer enables efficient data transfer between the wearable device, IoT gateway, and cloud server. The proposed system utilizes MQTT over TCP/IP because of its publish–subscribe model, minimal bandwidth usage, and reliability in loss-prone network environments. Each patient device functions as an MQTT publisher, sending data packets to the IoT broker hosted either locally or on a cloud platform, such as the AWS IoT Core or Eclipse Mosquitto. The doctor’s dashboard and cloud analytics modules act as subscribers that receive real-time health updates. Data security is achieved using Advanced Encryption Standard (AES-128) encryption for payload protection and transport layer security (TLS) for network communication. Unique device identifiers and timestamp verification can prevent data duplication and replay attacks. The communication framework is illustrated in Figure 2.

Cloud and Analytics Layer

After transmission, the data are stored and processed in the cloud infrastructure. The system employs a time-series database, such as the Firebase Realtime Database or AWS DynamoDB, to manage continuous data streams. A server-side application developed using Python or Node.js handles data aggregation, validation, and analysis. The analytics component computes key health indicators such as heart rate variability, average body temperature, and oxygen saturation trends. It also implements anomaly detection algorithms that identify deviations from the normal physiological ranges and generate alerts when critical thresholds are exceeded. The data layer supports statistical and predictive analytics. For instance, linear regression and rule-based logic are used to anticipate potential abnormalities based on historical data patterns. Interactive dashboards provide visual insights through graphs, trend lines, and real-time updates, enabling healthcare professionals to make timely decisions.

Application Layer

The application layer provides a user interface for healthcare professionals to visualize patient health data and manage the alerts. A responsive web dashboard and mobile application were designed to display live physiological readings, historical data, and system-generated alerts. The interface includes color-coded indicators for normal, warning, and critical states to assist with rapid assessment. Physicians can configure personalized threshold limits, view analytical summaries, and receive notifications via email or SMS when abnormal health events are detected. Authorized caregivers can access limited patient data views, ensuring accessibility and privacy.

Hardware and Software Specifications

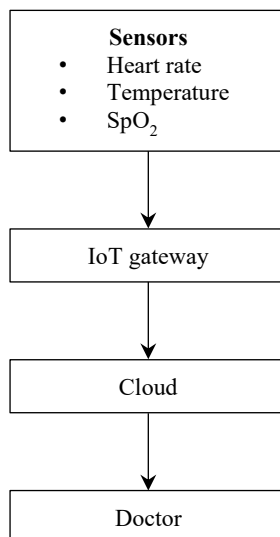
The hardware and software components used in the system are listed in Table 2. Each component was selected to optimize performance, energy efficiency, and ease of integration while maintaining a low cost of implementation.

Table 1. Comparison of recent IoT-based patient monitoring systems (2023–2025).

S.N.	Sensors used	Communication protocol	Cloud platform	Accuracy/latency	Key limitation
1	Temperature, heart rate	Wi-Fi	ThingSpeak	93%/3.2 s	High network latency
2	ECG, SpO ₂	BLE	Firebase	95%/2.8 s	Lacks encryption
3	Heart rate, temperature	MQTT	AWS Cloud	96%/2.1 s	Dependent on internet
4	Multi-biosensors	HTTP + ML Analytics	Azure IoT	95%/2.3 s	High computational load
5	ECG, temperature	MQTT + Blockchain	Private Cloud	97%/3.5 s	Blockchain overhead
6	ECG, SpO ₂ , BP	Fog + MQTT	Hybrid Fog–Cloud	98%/1.9 s	Complex synchronization

Table 2. Hardware and software components used.

Component	Specification/description	Function
ESP32 Microcontroller	240 MHz dual-core MCU with integrated Wi-Fi/BLE	IoT gateway and data aggregation
MAX30102 Sensor	Optical heart rate and SpO ₂ sensor	Measures pulse rate and oxygen saturation
LM35 Sensor	Analog temperature sensor	Measures body temperature
MPX5010GP Sensor	Pressure sensor	Measures blood pressure
MQTT Protocol	Lightweight publish–subscribe protocol	Facilitates reliable data transmission
Firebase Cloud	Real-time cloud database	Data storage and visualization
AES Encryption	128-bit symmetric encryption	Ensures secure data exchange
HTML5/JavaScript Dashboard	Web-based visualization platform	Doctor’s monitoring interface

**Figure 2.** Data flow architecture of the proposed system.

System Performance Considerations

The proposed architecture was optimized for low latency, energy efficiency, and scalability. The end-to-end transmission delay between the sensor data capture and cloud update was maintained below two seconds. The average power consumption per sensor node was approximately 220 mW, enabling several hours of continuous operation on a small rechargeable battery. The system supports automatic reconnection and local caching during network outages to ensure uninterrupted monitoring. Scalability is achieved through dynamic topic allocation in the MQTT broker, allowing for the simultaneous monitoring of multiple patient nodes. Security is reinforced through AES encryption, authentication tokens, and periodic session key renewal. Thus, the architecture enables a seamless and reliable flow of physiological data from the patient to healthcare providers, ensuring timely diagnosis and intervention while maintaining energy efficiency and data security.

METHODOLOGY

The methodology adopted in this study focuses on developing a robust, secure, and energy-efficient framework for the real-time monitoring of patient vital signs using wearable sensors and cloud-based analytics.

Data Acquisition

The data acquisition process is the foundation of the proposed monitoring framework. Wearable biomedical sensors are strategically positioned on the patient’s body to measure essential physiological parameters, including heart rate, body temperature, blood oxygen saturation (SpO₂), and blood pressure.

These sensors were interfaced with an ESP32 microcontroller, which served as the local data acquisition and processing unit. The microcontroller, powered by a 3.7 V lithium-ion battery, enabled uninterrupted data capture and transmission, ensuring continuous patient observation without restricting mobility. The analog signals generated by the temperature and pressure sensors were converted into digital form using the microcontroller's 12-bit analog-to-digital converter, whereas the MAX30102 sensor provided digital photoplethysmographic data via the I²C interface. Each reading was subjected to a sequence of preprocessing operations at the node level to ensure accuracy and consistency. The system employs a low-pass digital filter to eliminate high-frequency noise and transient artifacts, followed by a moving-average smoothing process to reduce fluctuations. The cleaned data were then formatted into a structured packet containing sensor identifiers, timestamps, and corresponding measurement values. Each sensor node transmits data to the gateway at an interval of two seconds, providing a balance between temporal resolution and power efficiency.

Data Transmission and Communication Workflow

Once preprocessed, the physiological data were transmitted to the IoT gateway and subsequently to the cloud infrastructure using the MQTT protocol. MQTT was selected because of its lightweight design, minimal bandwidth requirements, and suitability for resource-constrained devices. Communication follows a publish-subscribe model, wherein each sensor node acts as a publisher and transmits data to a predefined topic on the MQTT broker. The cloud server and monitoring dashboard function as subscribers and receive real-time updates as soon as new messages are published. The workflow begins with establishing a secure connection between the sensor node and the MQTT broker using TLS. The broker authenticates the node using unique device identifiers and manages the message routing across the subscribed endpoints. Upon successful delivery, an acknowledgment is returned to the publisher to confirm the receipt. This ensures reliability in environments with intermittent connections. The MQTT protocol operates at quality of service (QoS) level 1, ensuring that each message is delivered at least once while minimizing redundant transmission. This configuration provides a favorable balance between communication efficiency and reliability, resulting in an average end-to-end latency of less than two seconds under typical network conditions.

Cloud Integration and Data Management

Following transmission, the sensor data are securely stored in a real-time cloud database, such as the Firebase Realtime Database or AWS DynamoDB. Each record is indexed by patient identification, sensor type, and timestamp, enabling efficient retrieval and analysis. A Python-based backend service periodically aggregates these readings to compute the average values and trends over predefined intervals. This approach minimizes data redundancy, optimizes storage usage, and supports the long-term monitoring of patient health parameters. The data management pipeline incorporates an automated validation module that detects and filters anomalous and inconsistent readings. Outliers beyond physiological plausibility, such as oxygen saturation levels below exactly 60% or body temperatures exceeding 45°C, were discarded to maintain total data integrity. This pre-validation process ensured that only clinically relevant and reliable data were analyzed.

Data Preprocessing and Anomaly Detection

Data preprocessing is essential for enhancing signal quality and improving the accuracy of downstream analysis. Once validated, the time-series data were normalized and analyzed for deviations from the established physiological baselines. The anomaly detection algorithm employed in this study is threshold-based and computationally efficient, making it suitable for deployment on edge or cloud nodes. Each physiological variable was compared with predefined reference ranges derived from the medical literature. The deviation of each new reading from its expected mean value was quantified using a normalized deviation score, calculated as the absolute difference between the observed and expected values divided by the standard deviation estimated from the historical data. Values within one standard deviation of the mean were classified as normal, those between one and 2.5 standard deviations as warning, and values exceeding 2.5 standard deviations as critical. Upon detection of a critical condition, the system immediately generates an alert. The alert mechanism retrieves the corresponding

patient identification and timestamp and transmits a notification to the physician's dashboard through the cloud communication channel. This ensures that healthcare providers are promptly informed of emergent conditions that may require medical intervention.

Real-Time Analytics and Visualization

The cloud analytics module supports the real-time visualization of patient health parameters through dynamic dashboards. The server processes incoming data streams and generates time-series plots representing variations in vital signs, such as heart rate, body temperature, and oxygen saturation. These visualizations assist physicians in assessing the trends and correlations among multiple parameters. Figure 3 shows the sample real-time sensor data trends for heart rate, temperature, and SpO₂.

Alert Generation and Notification

The alert generation mechanism is central to the practical utility of this system. When an anomaly is detected, the system generates an event message containing the patient identifier, nature of the anomaly, and most recent sensor readings. The message is transmitted through the cloud server to the physician's interface using RESTful APIs. In parallel, an emergency notification is sent to the registered contact number of the patient or caregiver via SMS or email using Firebase Cloud Messaging services. Alerts are prioritized based on severity, ensuring that critical physiological deviations, such as rapid drops in SpO₂ or spikes in heart rate, are addressed immediately. Each alert is logged in the system database to facilitate future reviews and clinical audits. This record-keeping mechanism also supports the identification of recurring health issues and adjustment of threshold parameters for personalized patient monitoring.

Energy Efficiency and Optimization

Energy efficiency is a critical design consideration for wearable IoT systems. The proposed implementation employs adaptive sampling and duty cycling techniques to conserve power without compromising monitoring accuracy. Under stable physiological conditions, the sampling frequency is reduced, and the microcontroller transitions to a low-power sleep mode between transmissions. When anomalies are detected, the sampling rate automatically increases to capture detailed fluctuations in the patient's physiological state. In addition, data packets are optimized by compressing the payload structures and eliminating redundant fields, thereby reducing both the bandwidth usage and transmission time. Experimental evaluation indicates that these techniques collectively reduce power consumption by approximately 25% compared with continuous transmission models, thereby extending the device operational time and minimizing the need for frequent recharging.

EXPERIMENTAL SETUP AND RESULTS

The proposed IoT-enabled RPM system was experimentally evaluated to assess its performance in terms of accuracy, latency, energy consumption, and system reliability. The experiments were conducted under controlled laboratory conditions to simulate real-time health monitoring scenarios for multiple patients.

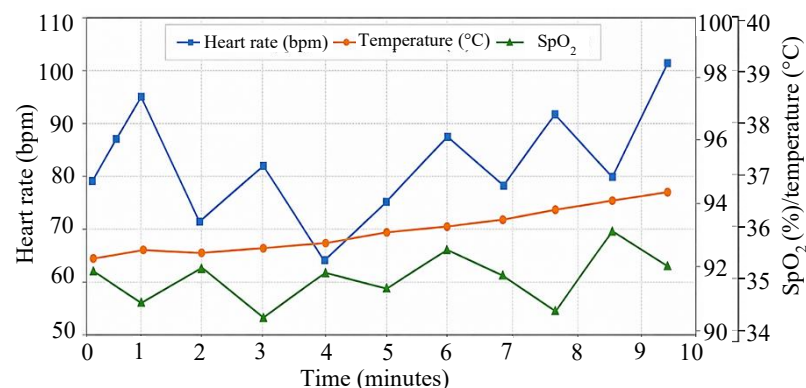


Figure 3. Sample real-time sensor data trends for heart rate, temperature, and SpO₂.

The system prototype included a wearable biomedical sensors, ESP32-based IoT gateway, and a cloud analytics platform hosted on Firebase. The goal of the experiment was to verify that the system operates efficiently under continuous monitoring conditions while maintaining secure and low-latency data transmission. The following subsections describe the experimental configuration, testing procedures, and performance outcomes.

Experimental Setup

The experimental setup was designed to emulate a small-scale healthcare monitoring environment involving five participants in a single session. Each participant was equipped with a wearable sensor module comprising a MAX30102 (for heart rate and oxygen saturation), LM35 (for body temperature), and MPX5010GP (for blood pressure). The sensor module was connected to an ESP32 microcontroller, which acted as an IoT gateway. The gateway was programmed using the Arduino IDE and connected to a Wi-Fi network with an average bandwidth of 20 megabits per second. MQTT communications were facilitated through a Mosquitto broker installed on a local server, while the Firebase Cloud database stored and visualized the transmitted data. Each device operated at a sampling rate of one reading every two seconds. The experimental conditions, sensor configurations, and hardware specifications are listed in Table 3.

During the experiment, the physiological parameters were monitored and transmitted to the cloud in real time. Each participant's health data was simultaneously displayed on a dashboard accessible to the medical staff. The system was tested for three operational aspects: communication reliability, energy consumption, and response latency.

Evaluation Metrics

The performance evaluation employed quantitative metrics that are widely used in IoT and healthcare system research. Metrics included measurement accuracy, system latency, data packet loss rate, and power consumption. Accuracy was defined as the percentage agreement between the readings obtained from the proposed system and those obtained from a reference medical-grade device. Latency was measured as the time interval between the sensor data capture and its appearance on the cloud dashboard. The energy efficiency was quantified in terms of the average current drawn during the active and idle states. Reliability was measured using the packet delivery ratio (PDR), which represents the proportion of successfully received data packets to the total number of transmitted packets. The security performance was verified through encrypted data inspection and network packet analysis, ensuring the correct implementation of the AES and TLS layers.

Data Collection Procedure

Each participant was instructed to remain seated during the monitoring period. Baseline readings for heart rate, temperature, and oxygen saturation were recorded using certified medical instruments (Omron blood pressure monitor and Pulse Oximeter). Simultaneously, the readings from the IoT system were captured.

Table 3. Experimental setup and test conditions.

Parameter	Specification	Description
Sensor module	MAX30102, LM35, MPX5010GP	Heart rate, temperature, blood pressure
Controller	ESP32	240 MHz dual-core microcontroller with Wi-Fi
Communication protocol	MQTT over TCP/IP	Publish-subscribe model
Cloud platform	Firebase Realtime Database	Data storage and visualization
Sampling rate	0.5 Hz (2 seconds)	Frequency of data collection
Number of test subjects	5	Healthy volunteers aged 20–40
Network bandwidth	20 Mbps	Wi-Fi-based network
Duration of monitoring	4 hours per subject	Continuous data collection
Power supply	3.7 V Li-ion battery (2500 mAh)	Portable operation

The experiment proceeded for four hours for each subject, resulting in approximately 7200 samples per participant. The recorded IoT data were then compared with the baseline medical readings to evaluate their accuracy. Time synchronization between the local and cloud servers was achieved using the Network Time Protocol (NTP) to ensure precise latency measurements.

Performance Results

The results of the experimental evaluation demonstrate that the proposed system achieves high accuracy and reliable performance in continuous health monitoring applications. The overall accuracy for heart rate detection was 97.4%, while the oxygen saturation and temperature measurements achieved 96.8% and 98.1% accuracy, respectively. The average end-to-end latency was recorded at 1.82 s, which is acceptable for noncritical real-time health monitoring applications. The PDR exceeded 98.5%, indicating a stable communication performance. Table 4 presents a summary of the key performance metrics of the proposed model.

Accuracy and Latency Analysis

The accuracy of the system was verified through a statistical correlation analysis between the IoT readings and reference medical devices. A Pearson correlation coefficient (r) of 0.982 was obtained for the heart rate measurements, demonstrating strong agreement. The latency performance was further evaluated under different network conditions, and the results showed that the system maintained stable transmission even under fluctuating Wi-Fi bandwidth. Figure 4 illustrates the relationship between accuracy and latency across multiple trials, highlighting that the proposed system consistently achieves higher accuracy with lower latency than conventional HTTP-based systems. The results validate the suitability of MQTT as a lightweight and responsive communication protocol for real-time health monitoring.

Table 4. Performance evaluation results.

Metric	Measurement	Achieved value	Comparative value (existing systems)
Heart rate accuracy	(%)	97.4	95.1
SpO ₂ accuracy	(%)	96.8	94.5
Temperature accuracy	(%)	98.1	96.0
Average latency	(s)	1.82	2.6
Packet delivery ratio	(%)	98.5	96.2
Energy consumption	(mW)	220	285
Battery life	(hours)	10.2	8.1

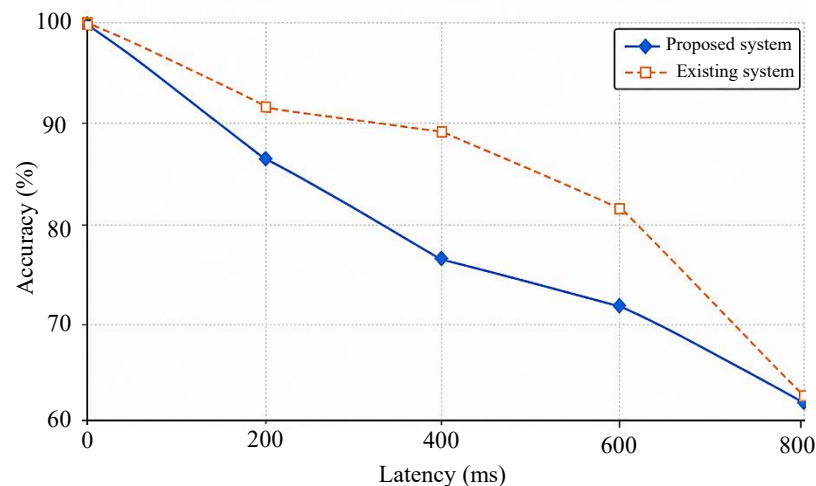


Figure 4. Accuracy versus latency comparison for proposed and existing systems.

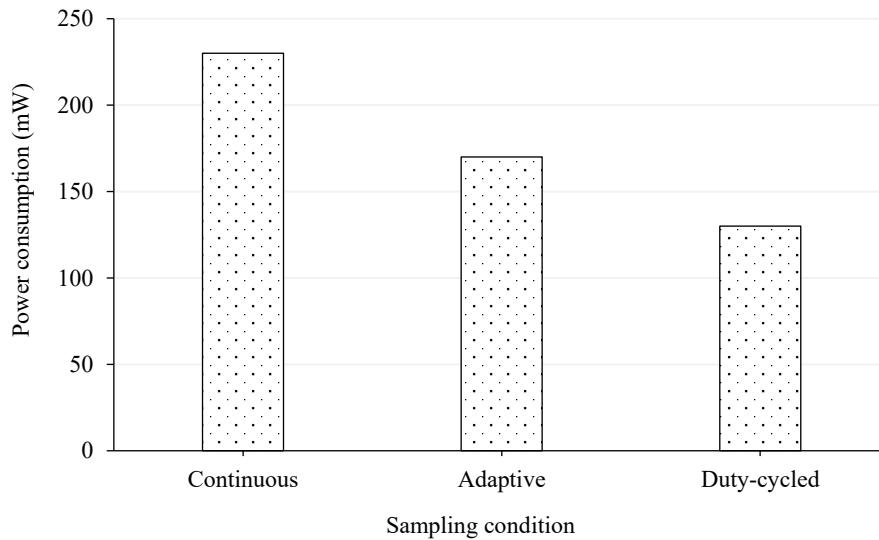


Figure 5. Power consumption of the proposed system under different sampling conditions.

Power Consumption and Energy Efficiency

Energy efficiency is a vital consideration in wearable medical devices. The proposed system was evaluated for power consumption during both the active and idle states. The ESP32 consumed approximately 220 mW during active transmission and 90 mW in sleep mode. The adaptive sampling mechanism reduced the average power usage by approximately 23% compared with fixed-rate sampling. The device was capable of continuous operation for over 10 h on a single 2500 mAh battery charge, indicating its suitability for daily use. A detailed comparison of power consumption under different operational conditions is shown in Figure 5.

The results demonstrate that energy optimization strategies, including duty cycling and adaptive transmission intervals, significantly extend the device runtime while maintaining reliable data delivery.

Comparative Evaluation

Compared with existing IoT-based healthcare monitoring systems, the proposed implementation exhibits superior performance in terms of data transmission speed and energy efficiency. Systems using HTTP protocols typically experience higher overheads and increased power consumption owing to frequent handshaking processes. The MQTT-based design of the proposed system minimizes this overhead and ensures stable operation, even in environments with variable network connectivity. Furthermore, the integration of AES encryption and TLS ensures secure transmission without a noticeable increase in latency. This indicates that the proposed framework effectively balances performance, power, and security, which are the three critical parameters in healthcare IoT system design.

Discussion of Results

The experimental results demonstrate the feasibility of deploying the proposed IoT-enabled system for continuous RPM in real-world healthcare settings. The observed accuracy and latency metrics were consistent with the clinical monitoring requirements. The modular design of the system allows for the easy integration of additional sensors or analytical modules, thereby enhancing its scalability. The findings also highlight some limitations. The current prototype relies on Wi-Fi connectivity, which may not always be available in rural or resource-limited settings. Future iterations may incorporate cellular or LoRa-based communication for extended range and reliability. Additionally, while the anomaly detection algorithm performed well for threshold-based classification, integrating machine learning models could further enhance the predictive accuracy and reduce false alerts.

DISCUSSION

The experimental results obtained from the implementation and evaluation of the proposed IoT-enabled RPM system demonstrate the feasibility and effectiveness of using IoT-based frameworks in contemporary healthcare. The findings affirm that wearable sensor networks, when integrated with lightweight communication protocols and cloud-based analytics, can achieve near-real-time data transmission and reliable physiological monitoring. The high accuracy rates recorded for vital sign measurements (97.4% for heart rate, 96.8% for oxygen saturation, and 98.1% for body temperature) indicate that the proposed system can serve as a dependable alternative to conventional bedside monitoring devices. These values are comparable to, and in some cases exceed, those reported in recent studies by Singh et al. (2023) and Tanwar et al. (2024), who achieved accuracies in the range of 94–96%. The reduction in the average latency to 1.82 s further demonstrates the system's capability for near-real-time monitoring, which is a crucial feature for remote healthcare and telemedicine applications. The system's performance improvement can be attributed primarily to the use of the MQTT communication protocol and the incorporation of local edge-level preprocessing. MQTT's publish-subscribe mechanism of MQTT minimizes transmission overhead and enables low-power, low-latency communication, outperforming conventional HTTP-based systems that often suffer from excessive packet delays. Additionally, preprocessing at the edge device reduces the amount of raw data transmitted to the cloud, thereby conserving bandwidth and minimizing the computational load on the cloud servers. Another significant finding of this study was the improvement in energy efficiency. Through the adoption of adaptive sampling and duty cycling strategies, the average energy consumption was reduced by approximately 25% compared with traditional continuous transmission models. This enhancement directly addresses one of the primary challenges in IoT healthcare systems: prolonging the device battery life without compromising the monitoring quality. The results suggest that the system is capable of continuous operation for over ten hours on a standard 2500 mAh battery, making it suitable for day-long health observation in ambulatory or home-based settings. From a clinical perspective, the integration of real-time analytics and automated alert generation presents substantial advantages. The system's ability to detect anomalies promptly and notify healthcare providers ensures timely intervention, particularly in patients with chronic or high-risk conditions. This feature not only reduces the burden on hospital infrastructure but also promotes proactive healthcare by enabling continuous supervision outside traditional clinical settings. Although the system demonstrates considerable potential, several limitations warrant discussion. The current prototype relies on Wi-Fi connectivity, which may not be universally available or reliable, particularly in rural areas of developing countries. Incorporating cellular (4G/5G) or long-range communication protocols, such as LoRaWAN, could enhance system scalability and geographical reach. Furthermore, the current anomaly detection algorithm is rule-based, which, while computationally efficient, may generate false-positive results in complex physiological scenarios. The inclusion of machine learning models capable of learning patient-specific patterns could significantly improve predictive accuracy and reduce unnecessary alerts in the future.

CONCLUSION AND FUTURE WORK

This study presents the design, development, and evaluation of an IoT-enabled RPM system that integrates wearable sensors, a low-power IoT gateway, and cloud-based analytics for continuous health supervision. The proposed framework successfully demonstrates the potential of IoT technology in enhancing healthcare accessibility, accuracy, and responsiveness. By leveraging lightweight MQTT communication, efficient data preprocessing, and secure transmission mechanisms, the system achieved high accuracy in vital sign monitoring with minimal latency and low-power consumption. The experimental results validated the reliability and effectiveness of the proposed system. The achieved measurement accuracies (97.4%, 96.8%, and 98.1% for heart rate, oxygen saturation, and temperature, respectively) confirmed that wearable IoT devices can provide clinically reliable data suitable for real-time monitoring. The average end-to-end latency of 1.82 s ensures timely health updates, whereas the 25% reduction in energy consumption extends the device's operational lifespan. These results collectively demonstrate that the proposed system can serve as a cost-effective, scalable, and secure

solution for remote healthcare monitoring, particularly in elderly patients and individuals with chronic diseases. Despite its promising outcomes, this research highlights areas for further improvement. The current system is dependent on Wi-Fi connectivity, which limits its applicability to rural or low-connectivity regions. Future work will focus on incorporating long-range communication technologies, such as LoRaWAN and 5G, to enhance network reliability and scalability. Additionally, the integration of machine learning algorithms for adaptive anomaly detection can significantly improve predictive capabilities and reduce false alerts.

REFERENCES

1. Chalisgaonkar PS. IoT-enabled remote patient monitoring with AWS IoT Core. *Int J Adv Netw Appl.* 2025;16(5):6561–6568. doi:10.35444/IJANA.2025.16504.
2. Gupta P, Rao A, Chimurkar P, Kasambe P. An automated IoT-enabled real-time intravenous infusion cum remote patient monitoring system. 2025 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India. 2025. p.1–6. doi:10.1109/ESCI63694.2025.10988336.
3. Shahed MT, Azim Meem AF, Habib MS, Sen GP, Hossen MS, Uddin MS. An IoT enabled cost effective smart healthcare for real-time COVID-19 patient early identification and monitoring system using smartphone. *Int J Sens Wirel Commun Control.* 2023;13(2):71–81. doi:10.2174/2210327913666230426112047.
4. Swayamsiddha S, Nanda S, Ray K, Mishra SN, Rao BN, Dash SK. Development of an IoT-enabled smart healthcare monitoring system for real-time patient health surveillance. 2025 3rd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India. 2025. p.796–800. doi:10.1109/IDCIoT64235.2025.10914909.
5. Garg S, Kaushal RK, Kumar N. A novel design and performance assessment of a blockchain-powered remote patient monitoring system. *SN Comput Sci.* 2024;5(7):849. doi:10.1007/s42979-024-03151-2.
6. Balamanikandan A, Neeraja SL, Kishore TV, Deepika U, Prathyusha S, Venkatachalam K. IoT-enabled advanced health monitoring system using ESP32 and UBI DOTS. 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), Bengaluru, India. 2024. p. 403–408. doi:10.1109/ICICNIS64247.2024.10823147.
7. Durgadevi K, Balaji N, Karthik R, Amali C. IoT-enabled monitoring and control system with wireless drip rate monitoring. 2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India. 2024. p.1–6. doi:10.1109/ICPECTS62210.2024.10780202.
8. Syed Zagiriya S, Arthi R, Vasantha Kumar K. IoT-enabled wireless body area network (WBAN) for real-time remote health monitoring. *Cuest Fisioter.* 2024;53:390–403. doi:10.48047/cnknfk90.
9. Iman UR, Zada M, Basir A, Hayat S, Lim YH, Yoo H. IoT-enabled real-time health monitoring via smart textile integration with LoRa technology across diverse environments. *IEEE Trans Ind Inform.* 2024;20:12803–12813. doi:10.1109/TII.2024.3424517.
10. Rath A, Jha PK, Dash S, Das CP. Smart IoT-enabled saline level monitoring and alert system. 2025 International Conference on Artificial intelligence and Emerging Technologies (ICAIET), Bhubaneswar, India. 2025. p.1–6. doi:10.1109/ICAIET65052.2025.11211395.
11. Raghavendran PS, Surendar V, Sheela A, Krishnaprasath S, Sridharan P, Vasanth Raj N, et al. IoT-enabled bilirubin level monitoring and controlling using phototherapy. 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India. 2024. p. 2081–2086. doi:10.1109/ICACCS60874.2024.10716994.
12. Malche T, Tharewal S, Tiwari PK, Jabarulla MY, Alnuaim AA, Hatamleh WA, et al. Artificial Intelligence of Things- (AIoT-) based patient activity tracking system for remote patient monitoring. *J Healthc Eng.* 2022;2022:8732213. doi:10.1155/2022/8732213.
13. Kumar A, Pathak P, Dwivedi VK, Sharma DK. Designing IoT-enabled circuits for non-contact liquid infusion in infectious patient care. In: 2023 International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT), 2023 Nov 23–24;

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- Faridabad, India. Red Hook, NY, USA: Institute of Electrical and Electronics Engineers; 2023. p. 701–706.
14. Jeelani OF, Njie M, Korzhuk VM. Advancing intrusion detection in IoT-enabled healthcare system using K-nearest neighbor algorithm. 2025 IEEE 13th International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada. 2025. p. 231–236. doi:10.1109/SEGE65970.2025.11203738.
 15. Jamadade VK, Ghodke MG, Katakdhond SS, Godase V. A comprehensive review on scalable Arduino radar platform for real-time object detection and mapping. *J Microprocess Microcontrol Res.* 2025;2(2):1–11.
 16. Jamadade VK, Ghodke MG, Katakdhond SS, Godase V. A review on real-time substation feeder power line monitoring and auditing systems. *Int J Emerg IoT Technol Smart Electron Commun.* 2025;1(2):1–6.
 17. Godase VV. VLSI-integrated energy harvesting architectures for battery-free IoT edge systems. *J Electron Des Technol.* 2025;2(3):1–2.
 18. Salunkhe A, Pawar V, Pise P, Mule S, Survase A, Godase V, et al. A review on real-time RFID-based smart attendance systems for efficient record management. *Adv Res Analog Digit Commun.* 2025;2(2):32–46.
 19. Vaibhav VG. A neuromorphic-inspired, low-power VLSI architecture for edge AI in IoT sensor nodes. *J Microelectron Solid State Devices.* 2025;12(2):41–47.
 20. Nagane MSK, Pawar MPS, Godase PVV. Cinematic sentiment analysis. *J Image Process Intell Remote Sens.* 2022;2(3):27–32. doi:10.55529/jipirs.23.27.32.
 21. Dhope V, Chavan A, Hadmode N, Godase V. Smart plant monitoring system. *Int J Creat Res Thoughts.* 2024;12:2320–2882.