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International Journal of Artificial Intelligence and Machine Learning

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Research Paper Open Access

An Intelligent IoT and AI Framework for Real-Time Remote Patient Monitoring and Healthcare Management

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Abstract
This study proposes an integrated Artificial Intelligence (AI)-driven Internet of Things (IoT) framework for real-time remote patient monitoring and intelligent healthcare management. The proposed framework brings together physiological data acquisition, preprocessing, intelligent analysis, and healthcare decision support within a unified monitoring architecture. To establish the data foundation for the proposed framework, the study analyzes 53 patient recordings from the BIDMC PPG and Respiration Dataset. The recordings contain complementary cardiovascular, respiratory, oxygenation, and demographic information, including heart rate, pulse rate, respiratory measurements, oxygen saturation, age, and gender. Descriptive analysis was conducted to examine the availability and characteristics of the physiological measurements and to identify differences in the completeness of individual variables. The analysis demonstrates that combining multiple physiological parameters can provide a broader basis for continuous remote monitoring than relying on a single measurement. Variations in data availability also emphasize the need for appropriate preprocessing and data-quality management before intelligent analysis is applied. Based on these findings, the proposed framework establishes a structured pathway from physiological sensing and data communication to preprocessing, AI-oriented analysis, and healthcare decision support. The framework is intended to support future development of automated monitoring and timely identification of potential physiological abnormalities. However, the study does not report empirical AI model training, clinical validation, or physical IoT deployment. Future research should therefore focus on developing and validating AI models, implementing real-time IoT connectivity, incorporating explainable AI and secure communication mechanisms, and evaluating the framework using larger and clinically diverse datasets.

Keywords: Artificial intelligence, Healthcare management, Internet of Things, Remote patient monitoring, Wearable healthcare

1. Introduction

The rapid development of digital technologies has created new possibilities for delivering healthcare beyond conventional hospital and clinic settings. Traditional patient monitoring often depends on scheduled consultations and intermittent measurements, which may provide only a limited view of changes in a patient's physiological condition (Bhambri and Khang, 2024). Remote patient monitoring (RPM) addresses this limitation by enabling physiological information to be collected from patients outside conventional healthcare facilities. The integration of the Internet of Things (IoT) and artificial intelligence (AI) can further strengthen RPM by combining continuous sensing, wireless communication, automated data analysis, and intelligent decision support (Jeddi and Bohr, 2020). Previous studies have demonstrated the growing importance of IoT and AI for remote healthcare monitoring and the potential of these technologies to support more responsive and personalized healthcare services (Alshamrani, 2022).

RPM has become an increasingly important component of digital healthcare; connected sensors and wearable devices can collect physiological information without requiring patients to remain continuously in healthcare facilities (Shaik *et al.*, 2023). IoT-enabled monitoring systems can acquire parameters such as heart rate, respiratory rate, oxygen saturation, and other patient-related measurements and transmit them to computational platforms for analysis (Kolawole, 2024). Studies have investigated IoT-based RPM for chronic disease management, patient activity monitoring, and continuous healthcare delivery (Kantipudi *et al.*, 2021). Wearable technologies also generate substantial physiological datasets that can be analysed using AI and big-data techniques to support remote patient care (Kanakaprabha *et al.*, 2024). Similarly, IoT sensor integration with artificial intelligence has been explored for patient activity recognition and health-status monitoring (Palanisamy *et al.*, 2023). These developments indicate that RPM can move healthcare monitoring from episodic observation toward more continuous and data-driven assessment.

IoT provides the sensing, connectivity, and communication infrastructure through which patient data can be acquired and transmitted, whereas AI provides computational methods for identifying patterns and generating analytical information from those data (Malathi *et al*., 2024). Their integration therefore creates an opportunity to develop intelligent healthcare systems capable of transforming raw physiological measurements into actionable information. AIoMT-based architectures have been proposed to combine medical sensing technologies with AI algorithms for intelligent patient monitoring (Dahan *et al*., 2023). A study has also examined AI-integrated RPM frameworks for virtual care management, demonstrating the potential of intelligent technologies to support next-generation healthcare delivery (AL-Shihhi and AL-Breiki, 2025). Edge-AI architectures can additionally process information closer to the point of data generation, which may be valuable when rapid responses are required (Rathi *et al*., 2021). More recent work has considered fog computing, AI models, and intelligent data-routing mechanisms for real-time healthcare decision-making (Devarajan and Ganesan, 2026). These developments support the concept of an integrated AI-driven IoT framework rather than treating sensing, computation, and healthcare management as independent functions. Despite these technological advances, the development of reliable real-time RPM systems remains challenging. Physiological signals acquired from sensors may contain noise, missing observations, measurement variability, and other forms of data imperfection that can influence subsequent AI analysis. The continuous generation of health information also creates computational and communication requirements that must be addressed when designing scalable monitoring systems. AI-based systems must additionally provide sufficiently reliable predictions or classifications to avoid inappropriate clinical alerts. Recent studies have therefore examined secure and resilient AI-enabled distributed healthcare architectures (Pamulaparthyvenkata *et al*., 2024), while other research has investigated the use of digital twins and secure intelligent systems for real-time healthcare monitoring (Jameil and Al-Raweshidy, 2025). Security and privacy are particularly important since connected healthcare systems process sensitive physiological information and may expose patient data to cybersecurity risks (Awotunde *et al*., 2023). Consequently, effective RPM requires simultaneous consideration of data quality, computational efficiency, security, privacy, and intelligent decision-making. Although previous studies have established the potential of AI and IoT in healthcare, important gaps remain in the integration of these technologies into comprehensive RPM frameworks. Existing investigations have addressed individual aspects, including AI-based monitoring, IoT architectures, wearable devices, edge computing, chronic disease management, and secure healthcare communication. For example, Kumar *et al*. (2020) proposed an AI-IoT collaborative framework for healthcare applications, while Sharma *et al*. (2021) examined an ontology-based IoT framework for RPM. Other studies have focused on real-time healthcare innovations and their implications for healthcare delivery and outcomes (Satyanarayana *et al*., 2024). However, the continued development of AI-enabled RPM requires a structured approach that connects physiological data acquisition, preprocessing, intelligent analysis, risk identification, and healthcare management within a unified framework (Sharma *et al*., 2025). The literature consequently supports further investigation of integrated approaches capable of linking IoT-generated physiological data with AI-oriented monitoring and decision-support mechanisms.

The central problem addressed in this study is the difficulty of transforming continuously collected physiological information into timely and meaningful information for remote healthcare management. Although IoT devices can facilitate continuous physiological data acquisition and AI techniques can support automated analysis, the effectiveness of RPM depends on how these components are integrated. Fragmented approaches may collect large quantities of physiological data without providing an effective analytical pathway for identifying relevant patterns and supporting healthcare decisions. Furthermore, the practical implementation of intelligent RPM must account for data quality, computational requirements, communication reliability, privacy, and security. Therefore, there is a need for a structured AI-driven IoT framework that connects physiological sensing, data preprocessing, intelligent analysis, and remote healthcare decision support in a coherent manner. Such an approach can provide a methodological foundation for developing more responsive and intelligent remote monitoring systems.

The study has objectives to develop a structured AI-driven IoT framework for remote patient monitoring that integrates physiological data acquisition, preprocessing, intelligent analysis, and healthcare decision-support functions, and to establish an analytical foundation for AI-enabled physiological monitoring and intelligent healthcare management, with emphasis on health-status assessment, potential abnormality identification, and decision-support capabilities.

2. Materials and Methods

2.1 Study Design

This study employed a quantitative, secondary-data-based research design to establish an analytical foundation for an AI-driven IoT approach to remote patient monitoring. The methodology was organized into sequential stages involving dataset acquisition, physiological data characterization, data-quality assessment, preprocessing, feature preparation, and statistical analysis. The proposed framework connects physiological sensing with data processing and AI-oriented healthcare decision support. The methodological design was chosen to align with the target journal's focus on artificial intelligence, machine learning, healthcare, and IoT. The study emphasizes transparent analysis of physiological information and development of an implementable conceptual framework rather than claiming completed clinical or hardware deployment.

2.2 Data Source and Dataset Description

The empirical analysis used the BIDMC PPG and Respiration Dataset v1.0.0 obtained from PhysioNet. The dataset contains 53 recordings, with each recording lasting approximately eight minutes. PPG, ECG, and impedance respiratory signals are sampled at 125 Hz, while heart rate, pulse rate, respiratory rate, and oxygen saturation are provided at 1 Hz. The dataset also includes demographic information consisting of age and gender, together with manually annotated breaths from two annotators. The available physiological measurements provide an appropriate secondary-data foundation for examining variables relevant to remote patient monitoring. The dataset was therefore used to characterize physiological observations and establish the analytical basis for the proposed intelligent monitoring framework.

2.3 Proposed AI-Driven IoT Framework

The proposed framework is structured as an integrated pipeline connecting physiological sensing, data communication, preprocessing, intelligent analysis, and healthcare decision support. At the sensing level, connected monitoring devices can acquire physiological signals and measurements, including PPG, ECG, respiratory activity, heart rate, respiratory rate, pulse rate, and SpO_2. The acquired information can subsequently be transmitted to computational resources for preprocessing and analytical processing. The AI layer is intended to identify meaningful physiological patterns and potential deviations, while the decision-support layer can transform analytical outputs into information suitable for remote healthcare management. The framework therefore provides a conceptual pathway from patient-side sensing to intelligent interpretation while maintaining flexibility for future real-time implementation.

2.4 Patient Health Parameters and Data Preprocessing

The principal physiological variables analysed in this study were heart rate (HR), pulse rate (PULSE), respiratory rate (RESP), and oxygen saturation (SpO_2). The numerical records were examined for completeness, missing observations, central tendency, variability, and measurement ranges. Each recording contained observations indexed from 0 to 480 seconds, producing 25,493 time-point records across the 53 recordings before accounting for missing values. Preprocessing focused on identifying incomplete observations, checking variable consistency, and preserving the original measurement units and distributions. No observations were removed solely since they appeared unusual without an explicit analytical justification. This approach reduced unnecessary alteration of the source data and ensured that the descriptive findings remained traceable to the original dataset.

2.5 Feature Engineering and AI-Oriented Analysis

The physiological variables were treated as primary analytical features for the proposed intelligent monitoring framework. HR and PULSE were considered indicators of cardiovascular activity, whereas RESP represented respiratory activity and SpO_2 represented blood-oxygen saturation. Age and gender were retained as contextual demographic variables. The feature structure was designed to support subsequent AI/ML applications such as physiological-state classification, anomaly identification, and risk-oriented analysis. However, the study does not claim empirical training or validation of a machine-learning model. Consequently, model-specific outcomes such as accuracy, precision, recall, F1-score, sensitivity, specificity, or AUROC were not generated. The feature analysis instead establishes a reproducible foundation for future AI-based modelling using the characterized physiological measurements.

2.6 Statistical Analysis

Descriptive statistical analysis was conducted to summarize the characteristics of the physiological measurements and demographic information. For HR, PULSE, RESP, and SpO_2, the number of valid observations, mean, median, standard deviation, minimum, and maximum values were calculated. Missing observations were also identified to assess data completeness. Demographic characteristics were summarized using the available age and gender information. These statistics were used to establish the empirical baseline for the proposed AI-driven IoT framework. The current study does not report a completed AI model or physical IoT implementation; model-performance measures and system-level indicators such as classification accuracy, inference latency, packet loss, and edge-processing time were not calculated.

3. Results

3.1 Overview of the Study Data

The study provides several physiological and demographic components relevant to remote healthcare monitoring. It contains 53 patient recordings, each approximately eight minutes long, as shown in Table 1. The waveform data include photoplethysmographic, electrocardiographic, and impedance-based respiratory signals sampled at 125 Hz. In addition, heart rate, pulse rate, respiratory rate, and oxygen saturation are recorded at 1 Hz. Manual breath annotations and demographic information, including age and gender, are also provided. This combination of synchronized physiological signals and clinical measurements provides an appropriate data foundation for investigating AI-based approaches to continuous patient monitoring.

Table 1. Characteristics of the BIDMC PPG and Respiration Dataset

Characteristic	**Value**
Number of recordings	53
Recording duration	8 min per recording
Physiological signal sampling frequency	125 Hz
Physiological parameter sampling frequency	1 Hz
PPG	Photoplethysmographic signal
ECG	Electrocardiographic signal
RESP	Impedance respiratory signal
Physiological parameters	HR, PULSE, RESP, SpO_2
Manual breath annotations	2 independent annotators
Demographic variables	Age and gender

Source: *BIDMC PPG and Respiration Dataset v1.0.0, PhysioNet, DOI: 10.13026/C2208R.*

3.2 Participant Demographic Profile

The demographic information provides an overview of the patient population represented in the dataset. Age information is available for most of the recordings, while one recording does not contain a corresponding age value, as shown in Table 2. The recorded participants include both male and female patients, with females representing a larger proportion of the available gender records. The dataset covers a relatively broad adult age range, from 19 years to records identified as 90+. This demographic variation is useful when examining physiological measurements, as patient characteristics can influence observed vital-sign patterns.

Table 2. Demographic Characteristics of the BIDMC Dataset

Demographic characteristic	**Value**
Total recordings	53
Age data available	52 (98.1%)
Age data missing	1 (1.9%)
Median age (years)	67
Minimum recorded age (years)	19
Maximum recorded age	90+
Male	20 (37.7%)
Female	32 (60.4%)

Gender unknown	1 (1.9%)

Source: *Author's calculations based on the BIDMC PPG and Respiration Dataset v1.0.0, PhysioNet, DOI: 10.13026/C2208R.*

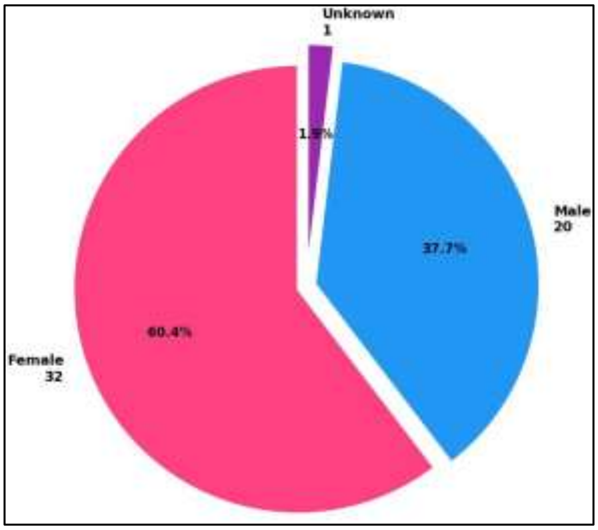

Figure 1. Gender Distribution of the Study Population

The gender distribution of the study population is presented in Figure 1**.** Among the 53 recordings included in the dataset, 32 were female (60.4%)**,** representing the largest proportion of the study population. Male participants accounted for 20 recordings (37.7%)**,** while one recording (1.9%) had an unknown gender. The distribution therefore indicates a higher representation of female participants than male participants within the available dataset. Although the gender composition provides useful demographic context for interpreting the physiological measurements, it should not be interpreted as evidence of gender-specific physiological differences; the analysis does not perform comparative statistical testing by gender.

3.3Distribution of Physiological Measurements

The physiological measurements demonstrate variation across the observations contained in the dataset. Heart rate and pulse rate show broadly comparable central values, while respiratory rate and oxygen saturation provide additional indicators of respiratory and cardiovascular status as shown in Table 3. The reported standard deviations indicate variability around the respective mean measurements. Respiratory-rate observations range from 0 to 34 breaths per minute, whereas oxygen saturation ranges from 83% to 100%. These measurements provide the principal physiological variables for the proposed monitoring framework and can serve as inputs for subsequent preprocessing, feature analysis, and AI-based modelling.

Table 3. Descriptive Statistics of Physiological Parameters in the BIDMC Dataset

Physiological parameter	**Valid observations (n)**	**Mean**	**Median**	**SD**	**Minimum**	**Maximum**
Heart rate (beats/min)	25,489	89.18	89.00	13.33	44	139
Pulse rate (beats/min)	25,365	88.51	88.00	13.81	37	129
Respiratory rate (breaths/min)	25,340	17.50	18.00	3.44	0	34
SpO_2 (%)	25,365	96.72	98.00	3.30	83	100

Source: *Author's calculations based on the BIDMC PPG and Respiration Dataset v1.0.0, PhysioNet, DOI: 10.13026/C2208R.*

4. Discussion

The findings provide a clear empirical description of the physiological information available for an AI-driven IoT approach to remote patient monitoring. The dataset comprised 53 recordings, each lasting approximately eight minutes, with physiological waveforms sampled at 125 Hz and numerical health parameters recorded at 1 Hz. The analysis identified 25,489 valid HR observations, 25,365 PULSE observations, 25,340 RESP observations, and 25,365 SpO_2 observations. HR showed a mean of 89.18 beats/min, while PULSE had a mean of 88.51 beats/min. The mean RESP was 17.50 breaths/min, and the mean SpO_2 was 96.72%. These results demonstrate that the dataset contains sufficiently structured cardiovascular, respiratory, and oxygenation information to support systematic physiological monitoring. The relatively close HR and PULSE values also indicate consistency between these two measurements. At the same time, the observed variability demonstrates why automated processing may be useful when large numbers of physiological observations must be examined continuously. The findings therefore establish a practical data foundation for the proposed framework rather than claiming clinical prediction performance. The findings are broadly consistent with previous research emphasizing the integration of AI, IoT, and connected healthcare technologies for continuous monitoring. Shumba *et al*. (2022) highlighted the potential of combining IoT-aware technologies with AI techniques for real-time critical healthcare applications, supporting the integrated sensing-and-analysis perspective adopted in this study. Similarly, Snigdha *et al*. (2023) described AI-powered healthcare tracking as a means of supporting real-time patient monitoring and predictive analytics. The proposed framework is also consistent with the AI-enabled medical Internet of Things approach discussed by Srivastava *et al*. (2023), in which connected medical technologies can contribute to remote healthcare delivery. Villegas-Ch *et al*. (2024) emphasized AI applications for real-time IoT analysis and prediction, while Zeshan *et al*. (2023) demonstrated the relevance of ontology-based intelligent IoT frameworks for remote patient monitoring. Compared with these studies, the work differs in its empirical emphasis: rather than reporting a completed predictive or hardware-based implementation, it uses physiological secondary data to establish the analytical foundation for an integrated AI-driven IoT monitoring framework. The descriptive physiological results therefore complement existing architectural and intelligent-monitoring research by demonstrating the characteristics of the data that such a framework can process.

The findings have several implications for AI-enabled remote healthcare management. First, the availability of multiple physiological parameters within a single dataset supports a multidimensional monitoring strategy in which cardiovascular, respiratory, and oxygenation information can be considered together rather than independently. Second, the presence of thousands of time-indexed observations demonstrates the volume of information that an intelligent monitoring system may need to process. This supports the proposed use of automated preprocessing and AI-oriented analytical components. Third, the framework provides a pathway through which physiological observations could eventually be connected to anomaly identification and decision-support mechanisms. From a healthcare-management perspective, such integration could help organize continuously generated information and potentially relevant changes to healthcare personnel. However, these implications should be interpreted as methodological and technological rather than as evidence of improved clinical outcomes, as the study did not conduct prospective patient monitoring or clinical intervention.

Several limitations should be acknowledged. First, the study relies on a secondary dataset containing only 53 recordings, which limits the generalizability of the findings to broader patient populations. Second, the recordings are relatively short, with each lasting approximately eight minutes, and therefore do not represent long-term home-based monitoring. Third, the dataset was not collected specifically to evaluate the proposed IoT framework, and no physical IoT devices or communication infrastructure were experimentally deployed. Fourth, the current analysis is descriptive and does not include the training and validation of an AI/ML prediction model. Consequently, claims concerning classification accuracy, anomaly-detection performance, sensitivity, specificity, F1-score, or real-time inference cannot be made from the results. Finally, the presence of missing observations and zero-valued respiratory measurements indicates that physiological datasets require careful quality assessment before being used for automated modelling. These limitations define the boundaries within which the findings should be interpreted.

Future research should extend the analytical foundation toward full experimental validation of the proposed AI-driven IoT framework. A larger and more diverse collection of physiological recordings should first be incorporated to improve representativeness and robustness. Subsequent work can develop and compare machine-learning and deep-learning models for physiological-state classification, anomaly detection, and health-risk prediction. The manually annotated respiratory information available in the dataset may also support development of respiratory-rate estimation models. Future implementation should additionally investigate wearable or IoT sensing devices, edge-based processing, cloud integration, secure communication, and automated alert generation. Model explainability should be incorporated so that healthcare professionals can understand the factors contributing to algorithmic decisions. Finally, prospective validation using real-time patient data would be necessary to determine whether the proposed framework can provide reliable and clinically meaningful decision support in practical healthcare environments.

5. Conclusion

This study developed a structured AI-driven IoT framework for real-time remote patient monitoring and intelligent healthcare management. The proposed approach integrates physiological data acquisition, data preprocessing, feature preparation, intelligent analysis, and healthcare decision support within a unified monitoring architecture. The study demonstrates the importance of combining IoT-enabled sensing with AI-oriented analytical processes to support continuous interpretation of patient physiological information. The framework provides a systematic pathway for transforming health-monitoring data into meaningful information that can contribute to timely monitoring and informed healthcare management. It also establishes a foundation for incorporating intelligent anomaly identification and decision-support mechanisms into future remote healthcare applications. Further research should focus on developing and validating machine-learning and deep-learning models, implementing the framework with real-time IoT devices, incorporating explainable AI, strengthening secure data communication, and evaluating the approach across larger and more diverse patient populations. Clinical validation will also be important for determining the reliability, usability, and practical value of the proposed system in real healthcare environments. The study contributes a coherent framework for advancing AI and IoT integration in remote patient monitoring and supports the development of more intelligent, responsive, and technology-enabled healthcare management systems.

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