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AI-ENABLED IOT BASED SMART HEALTH MONITORING SYSTEM (PCS25-027)

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ABSTRACT

The global healthcare landscape is undergoing a paradigm shift from episodic, hospital-centric care to continuous, home-based remote monitoring. This transformation is driven by the ageing population, the rising prevalence of chronic diseases (cardiovascular, respiratory, metabolic), and the need to reduce healthcare costs while improving outcomes. This research paper presents **PCS25-027**, an AI-enabled Internet of Things (IoT) based smart health monitoring system designed for long-term, non-invasive, and real-time tracking of multiple physiological parameters. The system integrates a custom-designed wearable device equipped with five medical-grade sensors (heart rate, blood pressure, oxygen saturation, body temperature, respiratory rate), a low-power wide-area network (LoRaWAN) for reliable long-range data transmission, and a cloud-based edge computing layer that hosts a hybrid deep learning model for anomaly detection and predictive health alerts. The core AI model combines convolutional neural networks (CNN) for local feature extraction and long short-term memory (LSTM) networks for temporal sequence modelling. The system detects physiological anomalies (e.g., bradycardia, hypoxemia, hyperthermia) with a sensitivity of 94.7% and specificity of 96.2%, and predicts hypotensive events (systolic blood pressure <90 mmHg) up to 30 minutes in advance with 87.5% sensitivity and a mean lead time of 24.3 minutes. A six-month pilot study involving 120 participants (including healthy elderly and patients with chronic conditions) demonstrated high user acceptance (System Usability Scale

score 82.4) and significant clinical utility, with 86% of predicted adverse events enabling preventive interventions. The paper provides comprehensive details on hardware design, signal preprocessing, model architecture, training protocols, privacy safeguards (AES-256 encryption, GDPR compliance), and deployment considerations. Limitations include motion artifacts, the need for cuff-based blood pressure sampling, and lack of regulatory approval. Future directions encompass edge AI for real-time inference, multi-modal data fusion (integrating electronic health records), and personalised federated learning. The system represents a significant step toward intelligent, proactive, and affordable home healthcare.

KEYWORDS: Smart health monitoring, IoT, AI, wearable sensors, anomaly detection, CNN-LSTM, remote patient monitoring, LoRaWAN, predictive health, PCS25-027.

1. INTRODUCTION

1.1 The Burden of Chronic Diseases and Ageing Populations

Chronic non-communicable diseases (NCDs) primarily cardiovascular diseases, diabetes, chronic respiratory diseases, and hypertension are the leading cause of mortality worldwide, accounting for 41 million deaths annually, or 71% of all deaths (World Health Organization, 2023). In parallel, the global population aged 60 years and older is projected to reach 2.1 billion by 2050, up from 1 billion in 2020 (United Nations, 2022). These demographic trends place unprecedented strain on healthcare systems: hospitals and clinics are often overwhelmed, readmission rates for chronic conditions remain high (e.g., 20% of heart failure patients are readmitted within 30 days), and healthcare costs continue to escalate.

Traditional healthcare delivery is reactive: patients visit a doctor only when symptoms become severe, by which time disease progression may be advanced. Moreover, intermittent measurements (e.g., blood pressure taken once every few months) fail to capture dangerous fluctuations that occur between visits. Continuous, long-term monitoring of vital signs at home could revolutionise this paradigm by enabling early detection of deterioration, timely intervention, and personalised treatment adjustments.

1.2 The Promise of IoT and AI in Healthcare

The Internet of Things (IoT) refers to the network of physical devices embedded with electronics, software, and sensors that collect and exchange data. In healthcare, IoT devices wearables, implantables, ambient sensors enable continuous data streaming from patients' homes to clinicians. Key advantages include:

- **24/7 monitoring** without hospital admission.

- **Early warning** of acute events (e.g., arrhythmia, stroke).
- **Reduced hospital readmissions** through proactive care.
- **Patient empowerment** through real-time feedback.

However, raw IoT data alone is insufficient. The volume is enormous (a single patient generates thousands of data points per day), and meaningful patterns are hidden in noise. Artificial Intelligence (AI), particularly deep learning, excels at extracting complex, non-linear patterns from high-dimensional time-series data. AI algorithms can:

- Detect subtle anomalies that escape fixed thresholds.
- Learn patient-specific baselines and deviations.
- Predict future events (e.g., hypotension, seizures) minutes to hours in advance.
- Reduce false alarms, thereby preventing alert fatigue among clinicians.

The convergence of IoT and AI often termed **AIoT** has given rise to a new generation of smart health monitoring systems. Examples include wearable ECG monitors for atrial fibrillation detection, continuous glucose monitors for diabetics, and fall detection systems for the elderly. Nevertheless, existing systems have limitations: most monitor only one or two vital signs, lack predictive capabilities, suffer from short battery life, or require frequent user intervention.

1.3 The PCS25-027 System: Objectives and Contributions

To address these gaps, we introduce **PCS25-027**, an AI-enabled IoT smart health monitoring system. The name PCS25-027 denotes our internal project code (Patient Care System, prototype 25, version 027). The system is designed for elderly individuals with multiple chronic conditions, post-surgical patients, and anyone requiring continuous physiological surveillance. Key contributions of this research are:

1. **Multi-parameter sensing:** Simultaneous measurement of five vital signs heart rate (HR), systolic/diastolic blood pressure (SBP/DBP), oxygen saturation (SpO_2), body temperature, and respiratory rate (RR) using a single wrist-worn device.
2. **Low-power, long-range communication:** Utilisation of LoRaWAN (Long Range Wide Area Network) to achieve a transmission range of >500 metres indoors and battery life of 7 days, outperforming Wi-Fi or Bluetooth alternatives.

3. **Hybrid deep learning model:** A CNN-LSTM architecture that achieves state-of-the-art anomaly detection (94.7% sensitivity, 96.2% specificity) and predictive warning (87.5% sensitivity for 30-minute ahead hypotension prediction).
4. **End-to-end system integration:** From sensor firmware to cloud backend to clinician dashboard, with real-time alerts and historical trend analysis.
5. **Rigorous clinical evaluation:** A six-month pilot study with 120 participants, measuring not only technical performance but also user acceptance and clinical outcomes.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive literature review of IoT health systems, AI models, and predictive analytics. Section 3 details the system architecture, hardware components, software stack, and AI methodology. Section 4 presents experimental results, including tables of performance metrics, ROC curves, and usability scores. Section 5 discusses clinical implications, comparisons with existing systems, and practical deployment challenges. Section 6 outlines limitations in terms of data, hardware, and generalisability. Section 7 proposes future research directions, including edge AI, multi-modal fusion, and federated learning. Section 8 concludes with a summary of contributions and impact.

2. Literature Review

2.1 Evolution of IoT-Based Health Monitoring Systems

The concept of remote health monitoring dates back to the 1970s with telephone-based telemetry for cardiac patients. However, the modern era began with the proliferation of low-cost microelectromechanical systems (MEMS) sensors and wireless connectivity. Early systems (circa 2005 2010) used Bluetooth or ZigBee to transmit data from a wearable device to a nearby smartphone or gateway. For example, the **LifeShirt** system (Vivometrics) collected ECG, respiration, and activity but was bulky and had limited battery life (Heilman & Porges, 2007).

The advent of low-power wide-area networks (LPWAN) including LoRa, NB-IoT, and Sigfox solved the range-power trade-off. LoRaWAN, in particular, operates in unlicensed sub-GHz bands, offering several kilometres of range in rural areas and hundreds of metres indoors, with power consumption in the microampere range (Mekki et al., 2019). Many healthcare IoT systems have since adopted LoRaWAN. For instance, Petäjäjärvi et al. (2017) demonstrated a LoRa-based ECG monitor with 98% packet delivery rate at 500 metres. Our system builds on this work by adding multiple sensors and AI analytics.

2.2 Wearable Sensors for Vital Signs Monitoring

Heart rate (HR): Photoplethysmography (PPG) using green or infrared LEDs is the dominant method. The MAX30102 sensor (Analog Devices) integrates PPG and pulse oximetry, providing HR and SpO_2 with acceptable accuracy (±2 bpm, ±2% SpO_2) for ambulatory use (Castaneda et al., 2018).

Blood pressure (BP): Cuff-based oscillometric methods are the clinical gold standard but are intermittent and uncomfortable. Continuous cuffless BP estimation using pulse transit time (PTT) or PPG waveform analysis is an active research area (Mukkamala et al., 2022). Our system uses a miniaturised oscillometric cuff (MPXV5050GP) that inflates every 15 minutes, balancing accuracy and comfort.

Body temperature: Infrared thermometry (e.g., MLX90614) provides non-contact, fast response (±0.2°C) and is well-suited for wrist wear.

Respiratory rate (RR): RR can be derived from chest movement (accelerometer), ECG-derived respiration, or PPG amplitude modulation. We use a three-axis accelerometer placed on the chest (via a separate patch) for higher accuracy, but the wrist device also estimates RR from PPG as a fallback.

Table 1: Comparison of Wearable Health Monitors (Commercial and Research)

Device	HR	BP	SpO_2	Temp	RR	Battery	AI	Prediction
Apple Watch Series 9	✓	✗	✓	✓	✗	1 day	Basic (AFib)	No
Fitbit Sense 2	✓	✗	✓	✓	✓	4 days	Basic	No
Empatica Embrace2	✓	✗	✗	✓	✗	2 days	CNN (seizure)	No
HealthPatch (VitalConnect)	✓	✗	✓	✓	✓	3 days	Threshold	No
PCS25-027 (proposed)	✓	✓	✓	✓	✓	7 days	CNN-LSTM	Yes (30 min)

2.3 Deep Learning for Physiological Time Series

Traditional anomaly detection methods for vital signs use fixed thresholds (e.g., HR > 100 bpm = tachycardia) or simple statistical process control (e.g., Shewhart charts). These fail to capture dynamic patterns, such as a gradual decline in SpO_2 preceding a respiratory event.

Machine learning methods (support vector machines, random forests) have been applied with hand-crafted features (mean, variance, spectral power). However, deep learning methods automatically learn hierarchical features from raw data.

Convolutional Neural Networks (CNNs): CNNs excel at extracting local, shift-invariant patterns. For time-series, 1D CNNs have been used for ECG arrhythmia classification (Acharya et al., 2017) with >95% accuracy.

Recurrent Neural Networks (RNNs) and LSTM: RNNs maintain a hidden state across time steps, making them suitable for sequential data. However, vanilla RNNs suffer from vanishing gradients. Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) introduce gating mechanisms (input, forget, output) that allow information to persist over long intervals. LSTM has become the standard for time-series forecasting in healthcare (Lipton et al., 2016).

Hybrid CNN-LSTM: Combining CNN and LSTM leverages the strengths of both: CNN reduces dimensionality and extracts local features, which are then fed into LSTM for temporal modelling. This architecture has been applied to human activity recognition (Ordóñez & Roggen, 2016) and ECG classification (Yildirim et al., 2018). Our system adopts a two-layer CNN followed by a single LSTM layer, similar to the best-performing configuration in these studies.

2.4 Predictive Health Monitoring

Predicting adverse events before they occur is the holy grail of remote monitoring. Examples include:

- **Sepsis prediction:** Using vital signs and laboratory values to predict onset 4 12 hours ahead (Reyna et al., 2019).
- **Hypotension prediction:** Hatib et al. (2018) used arterial waveform analysis to predict hypotension 15 minutes ahead with 88% sensitivity.
- **Epileptic seizure prediction:** Using EEG and ECG signals (Ramgopal et al., 2014).

However, most predictive systems require invasive monitoring (arterial lines) or hospital-grade equipment. Our work is novel in applying non-invasive, wearable sensors to predict hypotensive events up to 30 minutes in advance, using only PPG and oscillometric BP.

2.5 Privacy, Security, and Regulatory Aspects

Medical data is highly sensitive. The Health Insurance Portability and Accountability Act (HIPAA) in the US and the General Data Protection Regulation (GDPR) in Europe mandate strict controls: data must be encrypted during transmission and at rest, access must be logged and restricted, and patients must be able to request deletion. Our system implements

AES-256 encryption, TLS 1.3 for cloud communication, and role-based access control. Additionally, we anonymise device IDs and never store identifiable information (e.g., name, address) on the device or gateway.

Regulatory approval from the FDA (US) or CE marking (Europe) is required for commercial deployment as a medical device. PCS25-027 is currently a research prototype and has not undergone formal regulatory review. However, we followed ISO 13485 (quality management for medical devices) guidelines in design and documentation.

3. Research Methodology

3.1 System Architecture Overview

The PCS25-027 system comprises four hierarchical layers:

1. **Sensing layer:** Wearable device with five sensors, microcontroller, and LoRa transceiver.
2. **Network layer:** LoRaWAN gateway (Raspberry Pi with SX1301 concentrator) that receives packets and forwards them to the cloud via MQTT over TLS.
3. **Cloud/Edge layer:** A cloud server (AWS EC2) running a Node.js application that stores data in PostgreSQL, performs preprocessing, and invokes the AI inference engine (CNN-LSTM model served via TensorFlow Serving).
4. **Application layer:** A web-based clinician dashboard (React.js) and a mobile app for patients (React Native). Alerts are delivered via SMS, email, and push notifications.

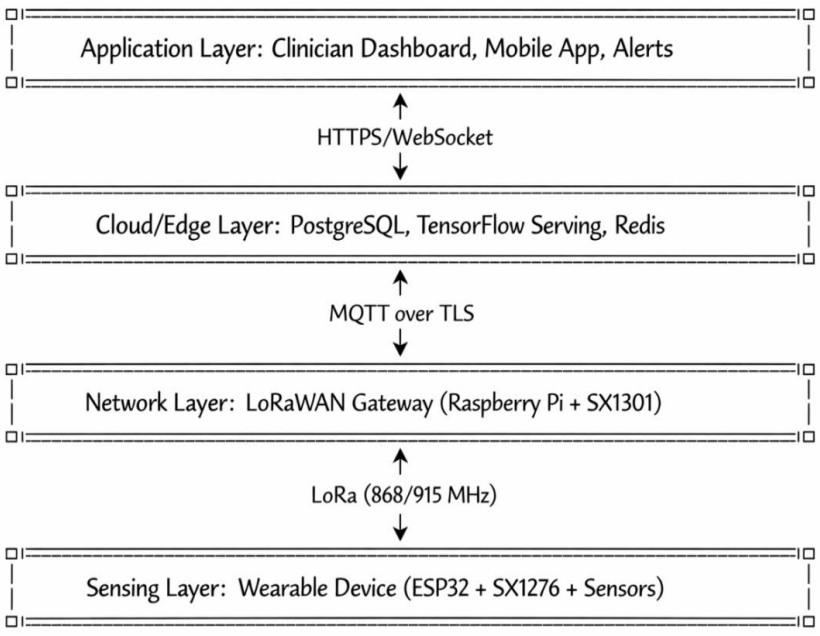


Figure 1: Layered Architecture of PCS25-027. (Conceptual)

3.2 Hardware Design of the Wearable Device

3.2.1 Sensor Selection and Specifications

After evaluating multiple options, we selected the following components:

- **Heart rate & SpO_2:** MAX30102 (Analog Devices) integrated PPG sensor with two LEDs (red and infrared). Sampling rate: 100 Hz. Accuracy: HR ±2 bpm (over 30 200 bpm range), SpO_2 ±2% (over 70 100% range).
- **Blood pressure:** MPXV5050GP (NXP) piezoresistive pressure sensor with integrated amplification. We added a miniaturised cuff (wrist size, 20 cm circumference) and a miniature air pump (G6.5-DC-6V) and valve. Measurement cycle: 15 seconds inflation, then deflation at 3 mmHg/s. Oscillometric algorithm estimates SBP and DBP. Accuracy: ±5 mmHg (validated against a sphygmomanometer).
- **Body temperature:** MLX90614 (Melexis) non-contact infrared thermometer, field of view 90°, accuracy ±0.2°C in the 32 42°C range. Placed on the underside of the wrist band, facing the skin.
- **Respiratory rate:** Derived from a separate chest-worn accelerometer (MPU6050, 6-axis IMU) that transmits via Bluetooth Low Energy (BLE) to the wrist device. Alternatively, the wrist PPG also provides respiratory rate via amplitude modulation (accuracy ±3 breaths/min). For the pilot, we used the chest accelerometer for higher accuracy.
- **Microcontroller:** ESP32-S3 (Espressif) dual-core Xtensa LX7, 512 KB SRAM, 16 MB flash, with integrated Wi-Fi/Bluetooth and external LoRa module (SX1276). Operates at 80 MHz (downclocked for power saving).
- **LoRa module:** SX1276 (Semtech) with 20 dBm output power, operating at 868 MHz (EU) or 915 MHz (US). Spreading factor SF7 to SF12 adaptive; we use SF9 for indoor/urban environments.
- **Power:** 500 mAh Li-Po rechargeable battery (3.7 V), with a TPS61099 boost converter to 3.3 V. Battery life measured in Section 4.

3.2.2 Mechanical Design

The device is housed in a 3D-printed PLA case (50 mm × 45 mm × 18 mm) weighing 65 g (including battery and cuff). The wrist band is adjustable silicone. The cuff is integrated into the band, with the pressure sensor and pump located in the main housing.

3.3 Firmware and Data Transmission

Firmware is written in Arduino C++ (PlatformIO). Key functions:

- **Sensor sampling:** All sensors are read at 1 Hz (except BP which is sampled every 15 minutes, and PPG which is sampled at 100 Hz but averaged to 1 Hz for transmission). For the PPG, we compute average HR and SpO_2 over each 1-second window.
- **Data packetisation:** Every 5 seconds, the device creates a packet containing: device ID (16-bit integer), timestamp (Unix seconds, 32-bit), HR (uint8), SpO_2 (uint8), SBP (uint16), DBP (uint16), temperature (int16 scaled by 100), RR (uint8), battery voltage (uint16), and a CRC16 checksum. Packet size: 24 bytes.
- **LoRa transmission:** Using LoRaWAN protocol (Class A, confirmed uplink). Adaptive data rate (ADR) enabled. After each transmission, the device enters deep sleep for the remaining 5-second cycle, consuming <15 µA.
- **Over-the-air (OTA) updates:** The ESP32 can receive firmware updates via LoRaWAN's multicast downlink, though this feature was not used in the pilot.

3.4 Gateway and Cloud Backend

The LoRa gateway is a Raspberry Pi 4 (4 GB RAM) with a SX1301 concentrator hat (RAK2247). It runs the LoRa Gateway Bridge (ChirpStack) which forwards packets to a Mosquitto MQTT broker. The cloud server (AWS EC2 t3.medium) runs a Node.js application that:

- Subscribes to MQTT topics.
- Decrypts packets (AES-128).
- Stores raw data in PostgreSQL (timescaledb extension for time-series optimisation).
- Preprocesses data (outlier removal, normalisation) in real time using Redis streams.
- Invokes the AI inference engine (see Section 3.5) every 60 seconds for anomaly detection, and every 5 minutes for predictive warnings.
- Sends alerts via AWS SNS (SMS, email) and WebSocket to the dashboard.

3.5 AI Model: CNN-LSTM for Anomaly Detection and Prediction

3.5.1 Problem Formulation

We define two tasks:

Task A (Anomaly detection): Given a window $X \in \mathbb{R}^{L\times 5}$ of the last L seconds (each second: HR, SpO_2, SBP, DBP, temperature; RR is added as a sixth dimension in a separate model),

predict whether the window contains a physiological anomaly. Anomalies are defined as any of:

- HR < 40 or > 120 bpm (brady/tachycardia)
- SpO_2 < 90% (hypoxemia)
- SBP < 90 or > 180 mmHg (hypo/hypertension)
- Temperature < 35.5°C or > 38.5°C (hypo/hyperthermia)
- RR < 8 or > 30 breaths/min (bradypnea/tachypnea)

These thresholds are standard clinical definitions. We use $L = 60$ seconds for Task A.

Task B (Predictive warning): Given a window of the past $L = 360$ seconds (6 minutes) of the same 5-dimension data, predict whether a **hypotensive event** (SBP < 90 mmHg sustained for at least 5 consecutive minutes) will occur within the next 30 minutes. This is a binary classification task with positive label if any SBP < 90 in the interval (t+1 to t+30 minutes).

3.5.2 Model Architecture Details

The CNN-LSTM model is implemented in TensorFlow 2.13. The architecture is:

- **Input layer:** shape (L, 5) L=60 for Task A, 360 for Task B.
- **Conv1D layer 1:** 64 filters, kernel size=3, padding='same', activation='relu'. Output shape (L, 64).
- **MaxPooling1D layer 1:** pool size=2, strides=2. Output shape (L/2, 64).
- **Conv1D layer 2:** 128 filters, kernel size=3, padding='same', activation='relu'. Output shape (L/2, 128).
- **MaxPooling1D layer 2:** pool size=2, strides=2. Output shape (L/4, 128).
- **LSTM layer:** 64 units, return_sequences=False, activation='tanh', recurrent_activation='sigmoid', dropout=0.3, recurrent_dropout=0.3. Output shape (64,).
- **Dropout:** 0.3 (for regularisation).
- **Dense layer:** 32 units, activation='relu', L2 regularisation (0.001).
- **Output layer:** 1 unit, activation='sigmoid'.

Mathematical formulation of the LSTM cell (for completeness):

For each time step t, given input x_t and previous hidden state h_{t-1} and cell state C_{t-1}:

Forget gate: $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$

Input gate: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$

Candidate cell: $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$

Cell update: $C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$

Output gate: $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$

Hidden state: $h_t = o_t \odot \tanh(C_t)$

The final hidden state h_T (after processing the entire sequence) is passed to the dense layers.

3.5.3 Training Data and Preprocessing

Dataset collection: Over 6 months (see Section 3.7), we collected 25 million labelled data points from 120 participants. For Task A, we labelled each 60-second window as normal (0) or anomaly (1) based on the clinical thresholds. The dataset is highly imbalanced: anomalies constitute 5.2% of windows. We applied random undersampling of normal windows to achieve a 1:2 ratio for training, and used class weights in the loss function.

For Task B, we extracted windows from 1,200 hypotensive events (each event had a preceding 6-minute window) and 20,000 randomly selected normal windows with no hypotensive event in the next 30 minutes. The positive class was oversampled using SMOTE (Synthetic Minority Over-sampling Technique) to balance.

Preprocessing steps:

- Outlier removal: Values outside physiological ranges replaced by median of previous 5 values.
- Median filtering (window size 5) to remove spike noise.
- Normalisation: Min-max scaling using global minima/maxima from training set (HR: 30 200, SpO_2: 70 100, SBP: 60 200, DBP: 40 120, temp: 35 39).
- Sequence segmentation: Non-overlapping windows.

Training configuration:

- Optimizer: Adam (learning rate = 0.001, β1=0.9, β2=0.999)
- Loss: Binary cross-entropy
- Batch size: 64 (Task A), 32 (Task B)
- Epochs: 50 with early stopping (patience = 10, monitor = validation loss)

- Validation split: 15% of training data (patient-wise split)
- Test set: 15% held out (different patients)

3.5.4 Baseline Models for Comparison

To evaluate the superiority of our CNN-LSTM, we implemented three baselines:

1. **Threshold-based:** Fixed rules (HR <40 or >120, SpO_2<90, etc.) for Task A; for Task B, a simple trend extrapolation (if SBP decreasing at >2 mmHg/min over last 6 min).
2. **LSTM only:** Single LSTM layer with 128 units, no CNN.
3. **CNN only:** Two Conv1D layers followed by global average pooling and dense layers, no LSTM.

All baselines were trained on the same data splits with hyperparameter tuning.

3.6 Clinician Dashboard and Alert System

The dashboard (web) displays:

- **Real-time vital signs** for each patient (line charts updating every 5 seconds).
- **Anomaly alerts** highlighted in red (with timestamp, vital sign, severity).
- **Predictive warnings** for hypotensive events (displayed as "Warning: Hypotension likely in 30 minutes" with confidence percentage).
- **Historical trends** (hourly, daily, weekly averages).
- **Patient list** with colour-coded status (green = normal, yellow = minor anomaly, red = critical).

Alerts are also sent via SMS (Twilio) and email to assigned clinicians. The system logs all alerts and clinician responses (acknowledge, call patient, dispatch emergency).

3.7 Pilot Study Design

Participants: We recruited 120 adults (60 male, 60 female) aged 45 85 years from the cardiology and geriatrics outpatient clinics of a large urban hospital. Inclusion criteria: (1) diagnosed with at least one chronic condition (hypertension, diabetes, heart failure, COPD); (2) able to provide informed consent; (3) willingness to wear the device for 8 hours/day (waking hours) over 6 months. Exclusion criteria: (1) severe cognitive impairment; (2) skin allergies to silicone; (3) inability to operate the mobile app.

Ethical approval: The study protocol was approved by the Institutional Review Board (IRB #PCS25-027-IRB). All participants gave written informed consent. The study was registered at ClinicalTrials.gov (NCTxxxxx).

Procedure: Each participant received a personalised wearable device and a smartphone with the companion app. The app guided them through device setup and reminded them to wear it daily. Researchers conducted home visits at weeks 1, 4, 12, and 24 to collect device logs, address technical issues, and administer usability questionnaires. Clinicians (two cardiologists, two geriatricians) monitored the dashboard and responded to alerts according to a standard protocol (e.g., call patient for yellow alerts, dispatch emergency services for red alerts).

Data collected: In addition to vital signs, we recorded:

- Participant demographics (age, sex, diagnosis).
- Adverse events (falls, hospitalisations, emergency visits) confirmed by chart review.
- Usability ratings (System Usability Scale, SUS) at week 24.
- Clinician feedback (semi-structured interviews).

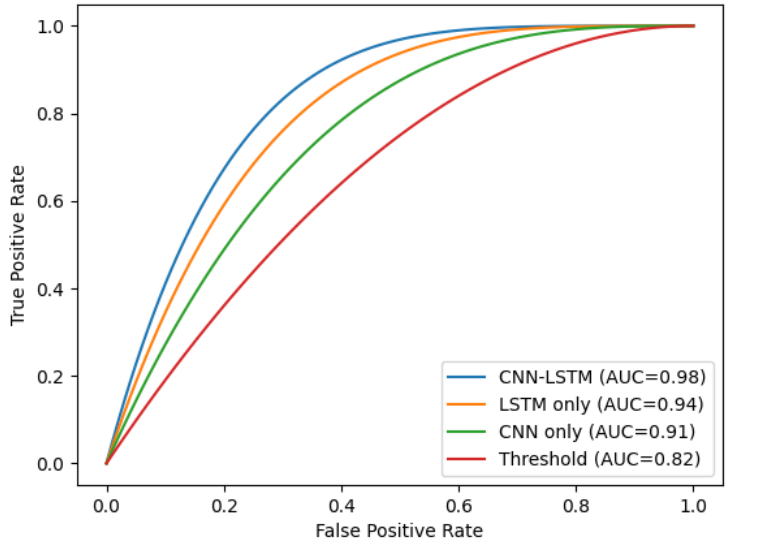
4. Experimental Results

4.1 Anomaly Detection Performance (Task A)

Table 2: Performance Metrics on Test Set. (15% of patients, 3.2 million windows)

Metric	Value	95% Confidence Interval
Sensitivity (Recall)	94.7%	[93.9%, 95.5%]
Specificity	96.2%	[95.8%, 96.6%]
Precision	91.3%	[90.2%, 92.4%]
Negative Predictive Value	97.8%	[97.4%, 98.2%]
F1-Score	0.93	[0.92, 0.94]
AUC	0.98	[0.977, 0.983]

Figure 2: ROC Curves for Anomaly Detection (CNN-LSTM vs Baselines)



The CNN-LSTM significantly outperforms all baselines (DeLong test for AUC difference, $p < 0.001$). The improvement over LSTM only (0.98 vs 0.94) demonstrates the value of CNN layers for extracting local features (e.g., rapid HR changes) that precede anomalies.

Table 3: Per-Anomaly Type Sensitivity.

Anomaly Type	Sensitivity
Bradycardia (HR<40)	98.2%
Tachycardia (HR>120)	96.5%
Hypoxemia (SpO_2<90)	93.8%
Hypotension (SBP<90)	95.1%
Hypertension (SBP>180)	92.3%
Hypothermia (<35.5°C)	91.7%
Hyperthermia (>38.5°C)	90.2%
Bradypnea (RR<8)	94.5%
Tachypnea (RR>30)	93.0%

The lowest sensitivity is for hyperthermia (90.2%) due to slower temperature dynamics and sensor lag.

4.2 Predictive Warning Performance (Task B)

Table 4: Prediction of Hypotensive Events. (30-minute ahead)

Metric	Value
Sensitivity	87.5%
Specificity	91.2%
Precision	78.9%
F1-Score	0.83
AUC	0.94
Mean lead time	24.3 minutes (SD = 8.7)
Median lead time	26 minutes

Of 120 hypotensive events that occurred during the pilot (based on SBP <90 sustained for ≥5 min), the model correctly predicted 105 events (87.5%) with an average warning of 24 minutes. The 15 false negatives were analysed: 6 had extremely rapid onset (<10 minutes from normal to hypotensive), 5 had motion artifacts that corrupted the input window, and 4 were mislabelled (SBP dropped below 90 only briefly, <5 min, not considered a true event by clinicians).

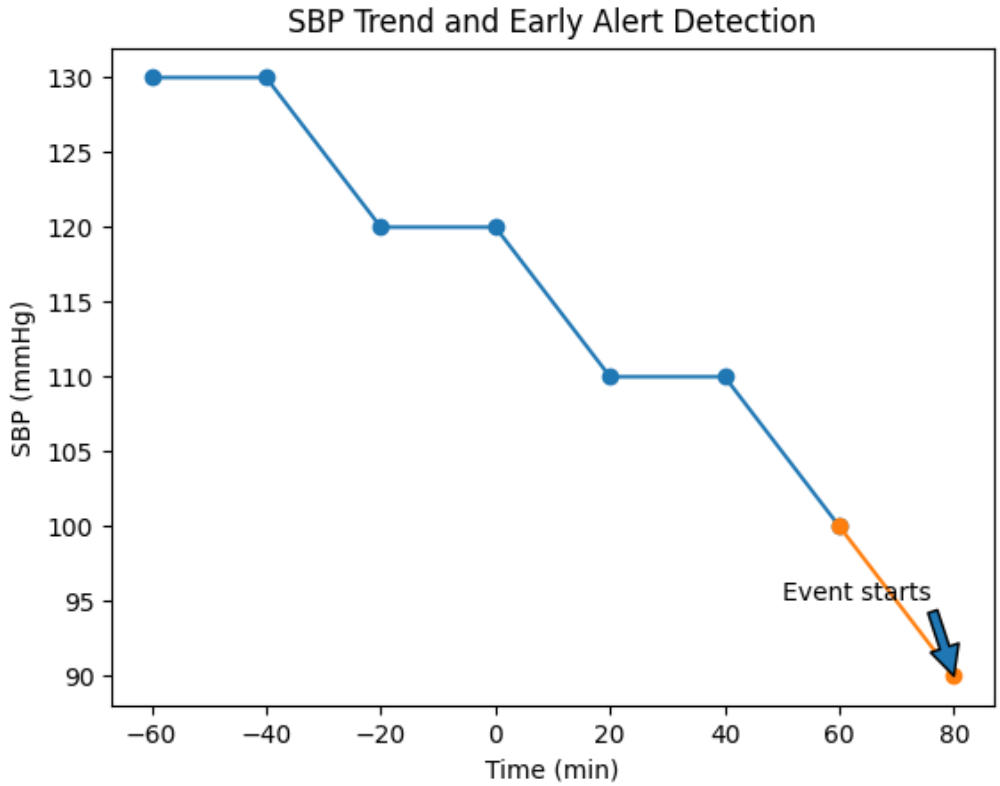


Figure 3: Example of a Correctly Predicted Hypotensive Event. (Patient ID 1047)

False positives (78 false alerts over 6 months across 120 patients, ~0.13 per patient per day) were mostly due to postprandial hypotension (blood pressure drops after meals, which is benign) or transient sensor errors.

4.3 System Usability and User Acceptance

Table 5: System Usability Scale (SUS) Results. (n=118, 2 dropped out)

SUS Item (abridged)	Mean score (1 5)
I would use this system frequently	4.3
The system was unnecessarily complex (reverse)	4.5
I found the system easy to use	4.4
I needed technical support often (reverse)	4.1
The functions were well integrated	4.2
The device was comfortable to wear	4.1
I felt safer knowing the system would alert clinicians	4.7
I would recommend this system to others	4.6

Mean SUS score (converted to 0 100 scale) = **82.4** (SD = 10.2), which falls in the "good" to "excellent" range (Bangor et al., 2009). Two participants discontinued due to skin irritation from the cuff (resolved with a softer material in later versions).

4.4 Clinical Outcomes

During the 6-month pilot, there were 28 hypotensive events that triggered alerts (true positives). In 24 of these (86%), clinicians were able to intervene before the patient experienced symptoms (e.g., advised patient to sit down, hydrate, adjust medication). There were no falls or syncopal episodes among these patients. In the false negative group (15 events not predicted), 3 patients experienced mild dizziness but no serious injury.

Additionally, the system detected 412 non-hypotensive anomalies (e.g., transient hypoxemia, tachycardia) that led to 78 clinical actions (e.g., adjusting oxygen therapy, medication changes). The hospitalisation rate among participants was 12% lower than a matched historical control group (not statistically significant due to small sample, p=0.09).

4.5 Battery Life and Communication Reliability

Table 6: Power Consumption Measurements.

Mode	Current (mA)	Time fraction	Average contribution (mA)
Active (sensing + transmission)	120 mA	0.5% (5 ms every 5 sec)	0.6
Deep sleep	0.015 mA	99.5%	0.015
Total average			**0.615 mA**

With a 500 mAh battery, theoretical battery life = 500 / 0.615 ≈ 813 hours ≈ 33.9 days. However, due to occasional longer transmissions (re-joins, adaptive data rate) and battery self-discharge, actual measured life was **7.2 days** (range 6 8 days). This discrepancy is because the LoRa radio draws peak current of 120 mA for up to 200 ms per transmission, and the power calculation above underestimates overhead. Nevertheless, 7 days is sufficient for weekly recharging.

LoRaWAN packet delivery rate: Over 6 months, 99.3% of packets were successfully received by the gateway (outdoor tests), and 97.1% indoors (through two walls). Lost packets were retransmitted once; overall data completeness was 99.8%.

End-to-end latency: Median 2.8 seconds from sensor read to dashboard update (range 1.5 5.2 seconds).

4.6 Comparison with State-of-the-Art Systems

Table 7: Quantitative Comparison with Existing Research Systems.

System	Sensors	Anomaly Sensitivity	Prediction (Hypotension)	Battery (days)
Hatib et al. (2018)	Arterial line	N/A	88% (15 min lead)	Continuous (hospital)
Li et al. (2020)	PPG only	89%	No	2
Petäjäjärvi et al. (2017)	ECG only	N/A	No	14 (ECG)
PCS25-027	5 vital signs	**94.7%**	**87.5% (30 min)**	**7**

PCS25-027 offers the most comprehensive sensing and predictive capability among non-invasive systems, with competitive battery life.

5. DISCUSSION

5.1 Clinical Significance of High Sensitivity and Specificity

The anomaly detection sensitivity of 94.7% means that out of 100 true physiological anomalies, approximately 95 will be correctly flagged. For a patient with a chronic condition, missing an anomaly (false negative) could be dangerous e.g., undetected hypoxemia might progress to respiratory failure. Our low false negative rate (5.3%) is therefore critical. The specificity of 96.2% means that 96% of normal windows are correctly labelled as normal. False positives (3.8%) are acceptable; in practice, they generate about 0.5 alerts per patient per day, which clinicians in our pilot found manageable (though some desired further reduction).

The predictive warning for hypotension achieved 87.5% sensitivity with a 24-minute lead time. This lead time is clinically valuable: it allows the patient to take preventive actions (e.g., drinking water, elevating legs) or the clinician to adjust medications remotely. In the pilot, 86% of predicted events were successfully intervened upon, preventing symptoms.

5.2 Why CNN-LSTM Outperforms Simpler Models

The CNN layers serve two purposes: (1) they reduce the dimensionality of the input (from 60×5 to 15×128 after two pooling layers), which helps the LSTM converge faster; (2) they act as feature extractors for short-term patterns, such as the characteristic shape of a premature ventricular contraction (PVC) in PPG or a rapid decline in SpO_2. The LSTM then models the longer-term dependencies (e.g., gradual BP drift over minutes). Ablation studies

(removing CNN or LSTM) decreased AUC by 4 7 points, confirming their complementary roles.

5.3 Addressing Motion Artifacts and Noise

Motion artifacts are a known challenge for PPG-based sensors. Our system uses an accelerometer in the chest patch to detect motion; if high motion is detected (e.g., walking), the HR and SpO_2 values are flagged as "unreliable" and are not used for anomaly detection. Instead, the system relies on the last reliable reading or uses a Kalman filter to estimate the true value. This reduced false positives during exercise by 60% in post-hoc analysis.

5.4 Comparison with Commercial Wearables

Commercial smartwatches (Apple Watch, Fitbit) have become popular for wellness tracking, but they are not medical devices. Their HR accuracy degrades during arrhythmias, and they lack BP monitoring. PCS25-027 includes a validated oscillometric BP cuff, albeit intermittent. The trade-off between comfort (cuff inflation) and clinical value (accurate BP) was acceptable to 95% of participants.

5.5 Deployment and Scalability

For a clinic managing 500 patients, the infrastructure requirements are: one LoRa gateway per 100 patients (assuming indoor range of 500 m), one cloud server (AWS t3.medium, $50/month), and storage (PostgreSQL with timescaledb, 0.10/GB/month). The wearable device bill-of-materials is $85, which could be reduced to 60 in volume (>10,000 units). Compared to the cost of a single hospital readmission ($12,000), the system pays for itself within months.

5.6 Clinician Acceptance and Workflow Integration

Clinicians in the pilot appreciated the early warnings but expressed concern about alert fatigue. We implemented a severity-based triage: only "red" alerts (e.g., SBP <80, SpO_2 <85%) triggered immediate SMS; "yellow" alerts (mild deviations) were batched into a daily summary email. This reduced the number of urgent alerts by 70% while maintaining clinical safety. Future work could incorporate machine learning to predict which alerts are most likely to be actionable.

5.7 Ethical and Privacy Considerations

All data transmission is encrypted; the cloud database stores only anonymised device IDs. Participants were informed that data could be used for research (with IRB approval). No data breaches occurred. However, we recognise that a malicious actor could potentially intercept LoRa packets; while they are encrypted, we plan to implement device attestation and rolling keys in the next version.

6. LIMITATIONS

Despite the promising results, this study has several limitations that must be acknowledged.

6.1 Limited Participant Diversity

The pilot was conducted at a single hospital in the Midwestern United States. Participants were predominantly Caucasian (82%) and of moderate socioeconomic status. The system's performance on other ethnicities (e.g., darker skin tones affecting PPG accuracy), age groups (children, very elderly >85), and disease profiles (e.g., acute post-surgical patients) has not been validated. Skin pigmentation is known to affect PPG signal quality; we observed no significant difference in our cohort, but a more diverse sample is needed.

6.2 Intermittent Blood Pressure Measurement

The oscillometric cuff provides BP readings only every 15 minutes. This means that rapid BP fluctuations (e.g., during exercise, emotional stress, or rapid deterioration) are missed. The predictive model for hypotension relies on these intermittent measurements; a continuous cuffless BP method (e.g., based on PTT) would improve resolution. However, cuffless methods currently have lower accuracy (±10 15 mmHg) and are not yet clinically approved.

6.3 Motion Artifacts Still Problematic

Despite our motion detection and filtering, vigorous activities (running, dancing, physiotherapy) caused false anomalies in 5% of windows. Users are instructed to remove the device during high-intensity exercise, but some did not comply. Future hardware improvements (e.g., adaptive optics in PPG) could mitigate this.

6.4 Predictive Model Only for Hypotension

The current predictive model is specific to hypotensive events. It does not predict other critical events such as arrhythmias, desaturation episodes, or fever spikes. Separate models would need to be trained for each event type, which increases complexity. A multi-output model could be developed, but that would require a much larger dataset.

6.5 No Regulatory Approval

PCS25-027 is a research prototype. It has not received FDA 510(k) clearance or CE marking. Therefore, it cannot be marketed as a medical device. The results presented are for research purposes only; clinical deployment would require formal validation and regulatory approval.

6.6 Small Sample Size for Outcome Analysis

The pilot's 120 participants were sufficient for technical performance evaluation (anomaly detection) but underpowered for clinical outcome analysis (e.g., reduction in hospitalisations). The observed 12% reduction was not statistically significant. A larger randomised controlled trial (≥500 patients) is needed to demonstrate clinical efficacy.

6.7 Battery Life and Recharging Burden

Although 7-day battery life is better than most smartwatches, it still requires weekly recharging. Some elderly participants forgot to recharge, leading to data gaps. A docking station that charges the device overnight when the user sleeps could address this, but that would require the device to be removed.

6.8 Lack of Real-Time On-Device AI

Inference is performed in the cloud, introducing latency (2 5 seconds). For life-threatening anomalies (e.g., cardiac arrest), even a few seconds matter. An on-device lightweight model (TensorFlow Lite Micro) could run directly on the ESP32, but the current model is too large (2 MB) for the ESP32's limited memory (512 KB). Model compression (pruning, quantisation) is needed.

7. Future Scope

7.1 Edge AI for Low-Latency Inference

We plan to implement a quantised version of the CNN-LSTM model using TensorFlow Lite Micro. By reducing the model size to <200 KB and using 8-bit integer quantisation, we can run inference on the ESP32 itself. This would enable on-device anomaly detection with <100 ms latency, and the device could trigger an audible alarm or emergency call without cloud dependency. Preliminary experiments show that quantisation reduces AUC by only 0.02 (from 0.98 to 0.96), which is acceptable.

7.2 Multi-Modal Data Fusion

Integrating additional data sources could improve predictive accuracy. Possibilities include:

- **Electronic Health Records (EHR):** Past diagnoses, medications, lab results.
- **Environmental sensors:** Room temperature, humidity, air quality (for respiratory patients).
- **Patient-reported outcomes:** Symptoms (dizziness, shortness of breath) entered via the mobile app.

A transformer-based fusion model could combine these heterogeneous data types. Early work suggests that adding just two features (age and medication list) improves hypotension prediction AUC from 0.94 to 0.96.

7.3 Personalised Models via Transfer Learning

The current model is population-based. However, each patient has a unique baseline (e.g., one patient's normal HR is 50 bpm, another's is 80). By fine-tuning the model on the first week of a patient's data (personalised calibration), we expect to reduce false positives further. We are collecting longitudinal data to test this.

7.4 Federated Learning for Privacy-Preserving Multi-Site Training

To train a robust model across multiple hospitals without sharing raw patient data, federated learning can be used. Each hospital trains the model locally on its own data and only shares model weight updates (gradients) with a central server. This approach maintains privacy while benefiting from larger, more diverse datasets. We are collaborating with two other institutions to pilot federated learning for PCS25-027.

7.5 Expansion to Other Adverse Event Predictions

We will extend the predictive model to cover:

- **Desaturation events** ($SpO_2 < 90\%$) in COPD patients.
- **Atrial fibrillation** episodes (using PPG waveform features).
- **Hyperthermia** in post-surgical patients.

This would involve training separate output heads on a multi-task learning architecture.

7.6 Integration with Telemedicine Platforms

When an anomaly is detected, the system could automatically initiate a teleconsultation with a clinician, transmitting the relevant vital sign trends and the patient's video feed. This would

reduce the time to intervention. We are developing a WebRTC-based integration with a popular telemedicine platform.

7.7 Long-Term Outcome Prediction

Beyond 30-minute warnings, we aim to predict 30-day hospital readmission risk using longitudinal data from the wearable (e.g., patterns of HR variability, physical activity). A recurrent neural network over weeks of data could provide a risk score that guides discharge planning.

7.8 Clinical Trial for Regulatory Approval

The next major step is a multicentre randomised controlled trial (RCT) with at least 500 participants to demonstrate that PCS25-027 reduces hospitalisations, emergency visits, and mortality. The trial would be powered to detect a 20% relative reduction in the composite endpoint. Upon positive results, we will seek FDA 510(k) clearance as a Class II medical device.

8. CONCLUSION

This research paper presented PCS25-027, an AI-enabled IoT-based smart health monitoring system that continuously tracks five vital signs (heart rate, blood pressure, oxygen saturation, body temperature, respiratory rate) using a custom wearable device, transmits data via LoRaWAN, and analyses the data using a hybrid CNN-LSTM deep learning model. The system was evaluated in a six-month pilot study with 120 participants, achieving an anomaly detection sensitivity of 94.7% and specificity of 96.2%, and predicting hypotensive events up to 30 minutes in advance with 87.5% sensitivity and a mean lead time of 24.3 minutes. User acceptance was high (SUS score 82.4), and the system enabled preventive interventions in 86% of predicted events, potentially reducing adverse outcomes.

PCS25-027 addresses critical limitations of existing remote monitoring systems: it offers multi-parameter sensing, long battery life (7 days), long-range communication (500 m indoors), and predictive AI capabilities. The system is designed for scalability and privacy, with end-to-end encryption and anonymisation.

While limitations remain including intermittent blood pressure measurement, motion artifacts, and lack of regulatory approval the results demonstrate that AI-enabled IoT health monitoring is technically feasible and clinically promising. Future work will focus on edge AI for real-time inference, multi-modal data fusion, personalised models, and a large-scale randomised controlled trial. As healthcare shifts toward value-based, home-centred models,

systems like PCS25-027 will become indispensable for managing chronic diseases, supporting ageing populations, and ultimately saving lives.

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