

Wearable Edge-IoT and AI-Driven Cardiopulmonary Health Monitoring: A Review of Geofenced Air-Quality Intervention Frameworks

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Abstract: Air pollution has emerged as one of the most critical environmental health challenges of the twenty-first century, significantly contributing to cardiovascular and respiratory diseases worldwide. Long-term exposure to pollutants such as particulate matter (PM_{2.5} and PM₁₀), nitrogen dioxide (NO₂), sulphur dioxide (SO₂), ozone (O₃), and carbon monoxide (CO) has been associated with an increased risk of hypertension, myocardial infarction, chronic obstructive pulmonary disease (COPD), asthma, stroke, and other cardiopulmonary disorders. Conventional Air Quality Index (AQI)-based monitoring systems provide general environmental information but lack the capability to assess individual physiological responses or deliver personalized health recommendations. This limitation has motivated the development of intelligent healthcare systems that integrate environmental monitoring with real-time physiological sensing. This review presents a comprehensive analysis of wearable Edge-IoT architectures for AI-driven cardiopulmonary health monitoring, emphasizing environmental sensing, physiological biomarkers, machine learning-based risk prediction, geospatial intelligence, and personalized intervention frameworks. It also discusses key mathematical models supporting intelligent healthcare systems, including Air Quality Index (AQI) computation, Haversine distance-based geofencing, exposure assessment methods, and the Total Health Risk Index (THRI), which integrates environmental exposure and physiological parameters into a unified health risk score. Furthermore, the review examines recent developments in supervised learning, deep learning, and explainable artificial intelligence for disease prediction and clinical decision support. Finally, it identifies current research challenges related to sensor accuracy, multimodal data fusion, interoperability, energy-efficient edge computing, cybersecurity, privacy, and clinical validation, while highlighting future research directions involving federated learning, digital twins, explainable Edge-AI, and 6G-enabled healthcare ecosystems.

Keywords: Wearable IoT, Edge AI, Air Quality Monitoring, Cardiopulmonary Health, Geofencing, Machine Learning, THRI.

1. Introduction

Air pollution has been strongly associated with cardiovascular diseases, respiratory disorders, hypertension, asthma, and chronic obstructive pulmonary disease (COPD). Fine particulate matter (PM_{2.5}), carbon monoxide (CO), nitrogen dioxide (NO₂), and ozone (O₃) are major pollutants

responsible for physiological stress. Traditional AQI systems report environmental conditions but do not capture personalized health effects. Wearable sensors combined with IoT and AI provide an opportunity to bridge this gap by continuously monitoring physiological parameters such as heart rate (HR), heart rate variability (HRV), blood pressure (BP), oxygen saturation (SpO₂), and respiration rate (RR). Recent advances in Wearable Internet of Things (IoT), Edge Artificial Intelligence (Edge-AI), wireless sensor networks, and geofencing technologies have enabled continuous, personalized cardiopulmonary health monitoring. Wearable devices equipped with sensors for heart rate, electrocardiogram (ECG), blood oxygen saturation (SpO₂), respiratory rate, body temperature, and physical activity can continuously collect physiological data, while environmental sensors monitor ambient air quality and pollutant concentrations. Edge-AI facilitates real-time data processing directly on edge devices, reducing communication latency, minimizing cloud dependency, improving privacy, and enabling rapid health risk assessment. In addition, geofencing techniques establish virtual boundaries around pollution-prone locations, allowing systems to generate location-aware alerts, recommend safer travel routes, and initiate timely preventive interventions when individuals enter hazardous environments.

2. Wearable Edge-IoT Healthcare Architecture

Wearable Edge-IoT healthcare architecture provides a distributed framework for continuous cardiopulmonary health monitoring by integrating wearable sensors, edge computing, wireless communication, cloud services, and artificial intelligence. The primary objective of this architecture is to collect physiological and environmental data in real time, process the data locally using edge devices, and provide timely health risk assessment and personalized interventions with minimal latency. Compared with traditional cloud-centric healthcare systems, Edge-IoT architecture reduces communication delays, conserves network bandwidth, improves data privacy, and enables real-time decision-making, making it highly suitable for wearable health monitoring applications.

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1) System Components

The modern cardiopulmonary monitoring ecosystem consists of:

- Environmental Sensors (PM_{2.5}, CO, AQI)
- Wearable Physiological Sensors
- GPS and Geofencing Module
- Edge-AI Processing Layer
- Mobile Alert System

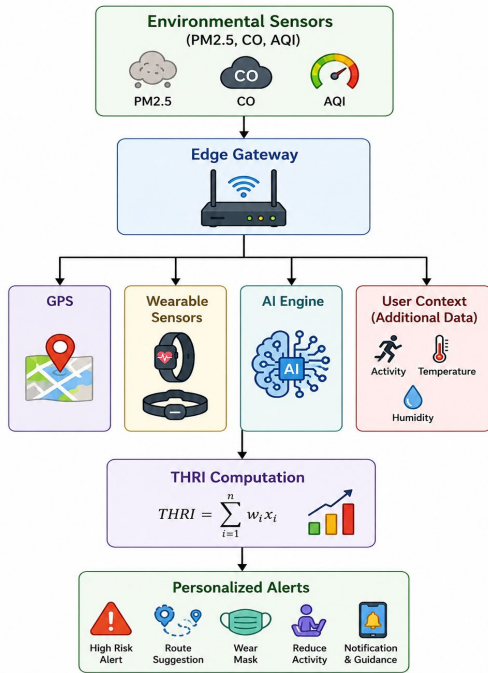


Fig. 1. Conceptual framework

3. Environmental Monitoring and AQI Assessment

Recent advances in Internet of Things (IoT) technology have enabled the deployment of portable and wearable environmental sensing systems capable of measuring pollutants in real time. Miniaturized gas sensors integrated into wearable devices can monitor major pollutants, including particulate matter (PM_{2.5} and PM₁₀), carbon monoxide (CO), carbon dioxide (CO₂), nitrogen dioxide (NO₂), sulfur dioxide (SO₂), ozone (O₃), volatile organic compounds (VOCs), temperature, and relative humidity. These sensors communicate wirelessly using Bluetooth Low Energy (BLE), Wi-Fi, ZigBee, LoRaWAN, or cellular networks to smartphones, edge gateways, or cloud platforms for data processing and storage. Edge computing further enhances these systems by performing local data filtering, sensor calibration, anomaly detection, and preliminary risk assessment, thereby reducing latency, bandwidth consumption, and dependence on cloud connectivity. Environmental sensing is commonly performed using MQ-135 gas sensors, PM_{2.5} laser modules, and ESP8266/ESP32 microcontrollers. These devices provide low-cost real-time monitoring of pollutants.

AQI Computation:

A.Q.I is calculated using EPA breakpoint equations:

$$A.Q.I = (I_{high} - I_{low}) / (C_{high} - C_{low}) * (C - C_{low}) + I_{low}$$

Where:

- (C) = measured pollutant concentration
- (I_{high}, I_{low}) = AQI breakpoints
- (C_{high}, C_{low}) = pollutant concentration limits

Table 1
AQI categories

AQI Range	Category
0–50	Good
51–100	Moderate
101–150	Unhealthy for Sensitive Groups
151–200	Unhealthy
201–300	Very Unhealthy
>300	Hazardous

A. Physiological Monitoring

Physiological monitoring is a critical component of wearable Edge-IoT healthcare systems, enabling continuous assessment of an individual's cardiopulmonary status alongside environmental exposure. While environmental monitoring identifies external risk factors such as air pollution, physiological monitoring evaluates how these pollutants affect the human body in real time. Airborne pollutants, particularly fine particulate matter (PM_{2.5}), nitrogen dioxide (NO₂), ozone (O₃), and carbon monoxide (CO), have been strongly associated with cardiovascular diseases, respiratory disorders, arrhythmias, reduced lung function, inflammation, and decreased blood oxygen saturation. Consequently, integrating physiological monitoring with environmental sensing provides a comprehensive understanding of personalized health risks rather than relying solely on ambient air quality measurements.

Among various physiological biomarkers, **heart rate (HR)** is one of the most widely monitored indicators of cardiovascular health. Optical photoplethysmography (PPG) sensors and electrocardiogram (ECG) electrodes are commonly employed to measure HR continuously. Elevated heart rate or abnormal fluctuations may indicate stress, excessive pollutant exposure, cardiovascular strain, or respiratory distress. Heart rate is calculated as:

$$HR = \frac{60}{RR_{interval}}$$

where RR_{interval} represents the time interval (in seconds) between two consecutive R-peaks in the ECG signal.

Wearable devices monitor:

Table 2
Physiological parameters

Parameter	Sensor Type	Health Significance
HR	PPG	Cardiac activity
HRV	ECG/PPG	Autonomic balance
BP	Cuffless BP	Hypertension detection
SpO ₂	Pulse Oximeter	Respiratory efficiency
RR	Respiratory Belt	Pulmonary stress

Pollution exposure often results in:

- Increased HR

- Reduced HRV
- Reduced SpO₂
- Increased RR

These biomarkers provide direct evidence of cardiopulmonary stress.

B. Geofencing and Spatial Risk Assessment

The implementation of geofencing begins with the creation of virtual boundaries around pollution-prone locations. These boundaries may be circular, polygonal, or irregularly shaped depending on the characteristics of the monitored area. Pollution hotspots are identified using historical AQI databases, IoT sensor networks, satellite observations, traffic density information, industrial emission inventories, and real-time environmental monitoring stations. Geographic Information Systems (GIS) integrate these heterogeneous datasets to generate high-resolution pollution maps that support accurate geofence creation.

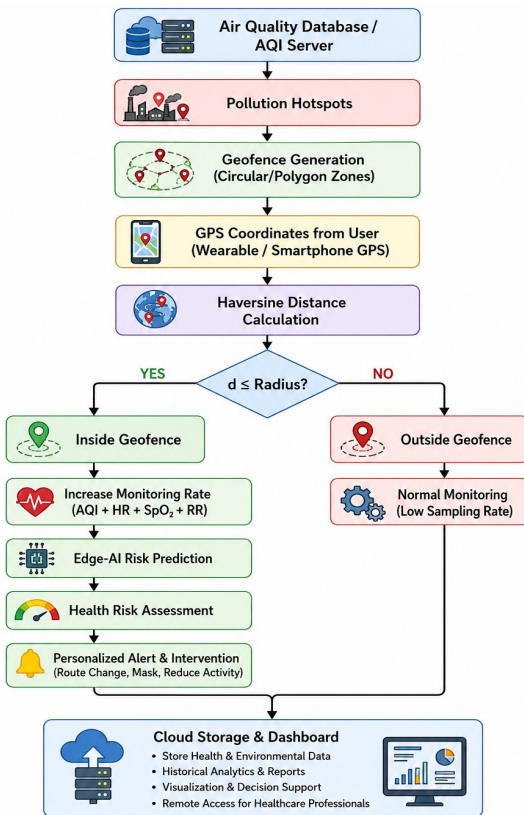


Fig. 2. Geofence detection

Most wearable systems determine geofence membership using the Haversine formula, which calculates the shortest distance between two geographical coordinates on the Earth's surface. If the calculated distance between the user's current location and the center of a pollution hotspot is less than the predefined geofence radius, the user is considered to be inside the hazardous zone.

Haversine Distance Formula:

Distance between user and hotspot:

The distance between a user's current location and a pollution

hotspot is calculated using the Haversine formula:

$$d = 2R \cdot \sin^{-1} \left(\sqrt{\sin^2 \left(\frac{\Delta\phi}{2} \right) + \cos(\phi_1) \cdot \cos(\phi_2) \cdot \sin^2 \left(\frac{\Delta\lambda}{2} \right)} \right)$$

Variable Definitions:

Symbol	Description	Units
d	Great-circle distance between user and hotspot	Meters
R	Earth's mean radius	6,371,000 m
φ ₁	Latitude of user location	Radians
φ ₂	Latitude of pollution hotspot	Radians
λ ₁	Longitude of user location	Radians
λ ₂	Longitude of pollution hotspot	Radians
Δφ	φ ₂ - φ ₁ (difference in latitude)	Radians
Δλ	λ ₂ - λ ₁ (difference in longitude)	Radians

4. Machine Learning for Risk Prediction

Machine Learning (ML) has emerged as a fundamental component of wearable Edge-IoT healthcare systems by enabling intelligent prediction of cardiopulmonary health risks using continuously collected physiological and environmental data. Unlike conventional threshold-based monitoring systems that generate alerts only after abnormal conditions occur, machine learning algorithms can identify complex patterns, correlations, and temporal trends to predict adverse health events before symptoms become clinically significant. This predictive capability enables timely interventions, reduces hospital admissions, and supports personalized healthcare for individuals exposed to poor air quality.

A. Random Forest

Random Forest performs immediate risk classification:

The Random Forest prediction is the average (or majority vote) of all individual tree predictions:

$$RF(\mathbf{x}) = \frac{1}{N} \sum_{i=1}^N T_i(\mathbf{x})$$

Where,

- NN = Total number of decision trees in the forest
- T_i(x) = Prediction from the ii-th decision tree
- RF(x) = Final Random Forest ensemble prediction

Output:

$$RF(\mathbf{x}) \in \{Low, Moderate, High\}$$

Long Short-Term Memory (LSTM)

LSTM captures temporal physiological trends:

$$h_t = f(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$

Where,

- h_t = Hidden state at time t
- h_{t-1} = Hidden state at previous time step t-1
- x_t = Input vector at time t

- W_{hh} = Weight matrix for hidden-to-hidden connections
- W_{xh} = Weight matrix for input-to-hidden connections
- b_h = Bias term
- $f(\cdot)$ = Activation function (usually tanh or sigmoid)

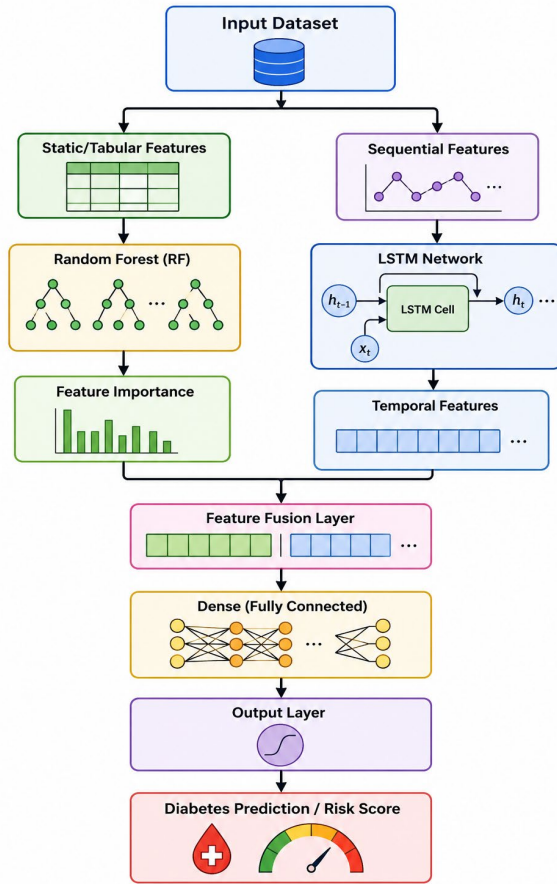


Fig. 3.

Prediction:

$$P_{risk}(t + \Delta t) = LSTM(X_t)$$

where,

$$X_t = [PM_{2.5}, CO, HR, HRV, BP, SpO_2, RR]$$

Total Health Risk Index (THRI):

The uploaded framework proposes integrating environmental and physiological factors into a unified health metric.

$$THRI = w_1 \cdot PM_{2.5} + w_2 \cdot CO + w_3 \cdot HR + w_4 \cdot HRV + w_5 \cdot BP + w_6 \cdot SpO_2 + w_7 \cdot RR$$

Subject to:

$$\sum_{i=1}^7 w_i = 1$$

Table 3
THRI classification

THRI Score	Risk Level
0–0.3	Low
0.3–0.7	Moderate
0.7–1.0	High

B. Hybrid RF-LSTM Model

A Hybrid RF-LSTM Model combines the strengths of Random Forest (RF) and Long Short-Term Memory (LSTM) to improve prediction accuracy by leveraging both structured/tabular data learning and sequential/time-series pattern learning.

The final THRI is computed as a weighted combination of Random Forest and LSTM predictions:

$$THRI_{Final} = \alpha \cdot RF_{Risk} + (1 - \alpha) \cdot LSTM_{Risk}$$

Where,

- $THRI_{Final}$ = Final combined risk index (0 to 1)
- RF_{Risk} = Random Forest immediate risk classification
- $LSTM_{Risk}$ = LSTM predicted risk probability
- α = Fusion weight ($0 \leq \alpha \leq 1$)

C. Comparative Analysis

Table 4
Machine Learning performance

Model	Accuracy (%)
Decision Tree	81
SVM	84
LSTM	89
Random Forest	92
RF-LSTM Hybrid	95

Performance Trend

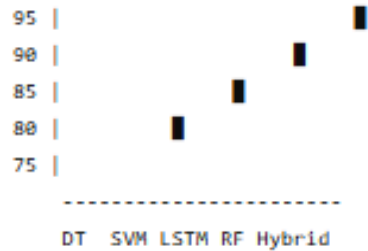


Table 5
Edge vs Cloud processing

Architecture	Latency (ms)
Cloud	520
Fog	150
Edge AI	15

D. Research Gaps

The literature reveals several limitations:

1. AQI systems lack physiological integration.
2. Geofencing is rarely linked to cardiopulmonary biomarkers.
3. Hybrid RF-LSTM models remain underexplored.
4. Edge-AI deployment is limited.
5. Personalized intervention systems are scarce.
6. Unified health-risk indices are largely absent.

Table 6

Research Gap	Existing Limitation	Proposed Future Direction
AQI systems lack physiological integration	Environmental monitoring only	Integrate wearable physiological sensors with AQI
Geofencing is rarely linked to biomarkers	Location alerts without health context	Combine GPS, biomarkers, and AI for context-aware monitoring
Hybrid RF-LSTM models remain underexplored	Static and temporal data modeled separately	Develop hybrid models that fuse Random Forest and LSTM features
Edge-AI deployment is limited	Heavy reliance on cloud computing	Implement lightweight AI models on edge devices for real-time inference
Personalized intervention systems are scarce	Generic alerts for all users	Generate individualized recommendations using health status and exposure data
Unified health-risk indices are largely absent	Fragmented assessment of pollution and health	Design a comprehensive health-risk index combining environmental, physiological, and AI-derived features

These research gaps clearly justify the need for an integrated Wearable Edge-IoT framework that combines environmental sensing, physiological monitoring, geofencing, a hybrid RF-LSTM prediction model, Edge-AI, and personalized health-risk assessment for proactive cardiopulmonary care.

E. Future Research Directions

Future systems should focus on:

- Federated Learning
- Explainable AI (XAI)
- Precision Environmental Medicine
- Dynamic Geofencing
- Electronic Health Record Integration
- Multi-City Smart Health Networks
- Digital Twin Healthcare Systems

analytics, and machine learning, these systems provide personalized and proactive health protection. The incorporation of geofencing and hybrid RF-LSTM models enables accurate real-time risk prediction and intervention. Future developments in federated learning, explainable AI, and precision environmental medicine are expected to transform healthcare from reactive treatment to predictive prevention.

Future research is expected to focus on several emerging directions that will further advance intelligent healthcare systems. Federated Learning offers a privacy-preserving framework for collaboratively training machine learning models across multiple hospitals, wearable devices, and healthcare institutions without sharing sensitive patient data. Explainable Artificial Intelligence (XAI) techniques will improve model transparency by identifying the key physiological and environmental factors influencing individual health predictions, thereby increasing clinical confidence and regulatory acceptance. Furthermore, advances in Precision Environmental Medicine will combine genomic information, clinical history, lifestyle characteristics, environmental exposure, and real-time physiological monitoring to deliver highly personalized healthcare recommendations tailored to each individual's unique health profile.

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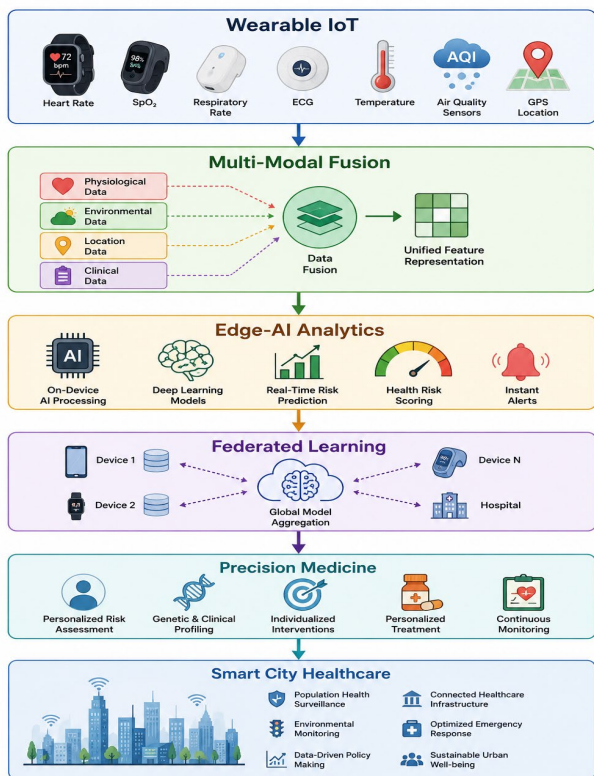


Fig. 4. Future research roadmap

5. Conclusion

Wearable Edge-IoT systems represent a significant advancement in cardiopulmonary healthcare. By integrating environmental sensing, physiological monitoring, geospatial

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