IJAAR PUBLISHING®

Engineering Research Journal | ISSN: 2782-8212
Vol. 5, Issue 2 (2025) | www.ijaar.org/erj

IoT-Based Healthcare Monitoring Systems: Current Technologies and Challenges.

Jenny E. Fawei
Niger Delta University, Wilberforce Island, Bayelsa State, Nigeria

Gloria A. Chukudebe, Michael C. Ndinechi and Nkwachukwu Chukwuchekwa
Federal University of Technology Owerri, Imo State, Nigeria

Abstract

IoT-Based Healthcare Monitoring Systems has gained significant traction with advancements in digital technologies, enabling continuous tracking of patient health outside traditional clinical settings. Various techniques are employed to enhance healthcare delivery, improve patient outcomes, and reduce hospital readmissions. This paper explores the latest technologies in IoT-based healthcare monitoring systems which include wearable sensors, telemedicine, mobile health applications (Health apps), biometric sensors, artificial intelligence (AI)-based predictive analytics, and smart pills, and the challenges associated with their implementation. Wearable biosensors monitor vital signs such as heart rate, blood pressure, and oxygen levels in real time, while IoT-integrated systems facilitate data transmission to healthcare providers for immediate intervention. Telemedicine platforms support virtual consultations, enabling remote diagnosis and treatment. The wearable sensors, telemedicine, mobile health applications (Health apps), biometric sensors, artificial intelligence technology process large datasets to predict health risks and detect abnormalities, enhancing early diagnosis and personalized care. Additionally, Smart pills are ingestible sensors that can detect various physiological conditions or medication ingestion, providing real-time health data, and enhance communication between patients and healthcare providers. Despite these advancements, challenges which limit implementation and adoption such as data accuracy and security, interoperability, patient compliance, infrastructure limitations, environmental factors, durability, and cost among others are discussed in this paper. This will enable future innovations focus on improving system accuracy, enhancing cybersecurity, and integrating advanced AI models to refine remote monitoring capabilities.

***Keywords**:* Wearable devices, remote-monitoring, health-apps, artificial intelligence.

Fawei, J. E., Chukudebe, G. A., Ndinechi, M. C., & Chukwuchekwa, N. (2025). IoT-Based Healthcare Monitoring Systems: Current Technologies and Challenges. *Engineering Research Journal. 5*(2), 48-63. DOI: 10.5281/zenodo.15255090

Introduction

The Internet of Things (IoT) has revolutionized healthcare by enabling real-time monitoring, data collection, and intelligent analysis to improve patient care. IoT-based healthcare monitoring systems integrate wearable sensors, cloud computing, artificial intelligence (AI), and wireless communication technologies to track patients' vital signs, such as heart rate, blood pressure, temperature, and oxygen levels. These systems provide continuous monitoring for chronic disease management, elderly care, and post-surgical recovery, reducing hospital visits and enabling early detection of health anomalies.

The current technologies in healthcare monitoring system discussed by scholars include wearable devices like smart watches and fitness trackers measure parameters such as heart rate, steps, and sleep patterns, Biometric Sensors that track physiological signals like ECG, blood pressure, and glucose levels, Remote Monitoring which utilizes IoT (Internet of Things) technology to collect and transmit health data from patients to healthcare providers in real-time, Telemedicine which uses video calls and other communication technologies to provide consultations and monitor health remotely, Artificial Intelligence analyzing data from various sources to predict health trends, detect anomalies, and recommend interventions, Smart Pills which utilizes Ingestible sensors that monitor medication adherence and internal health metrics and Health Apps for tracking diet, exercise, and other health-related data to provide personalized recommendations. The benefits of implementing these technologies for healthcare monitoring include but not limited to continuous health monitoring, early disease detection, reduced hospital visits, enhanced patient engagement, emergency alerts and notifications, improved chronic disease management, data-driven healthcare decisions, and support for elderly and high-risk patients. Despite these innovations, challenges such as data security, interoperability, and energy-efficient sensor design remain critical areas for improvement.

This paper presents a systematic review on the latest technologies in IoT-based healthcare monitoring listed above, and the challenges implementing them that need to be addressed to create a more efficient and secure digital healthcare ecosystem. Figure 1 describes the Current Technologies in IoT-Based Healthcare Monitoring System.

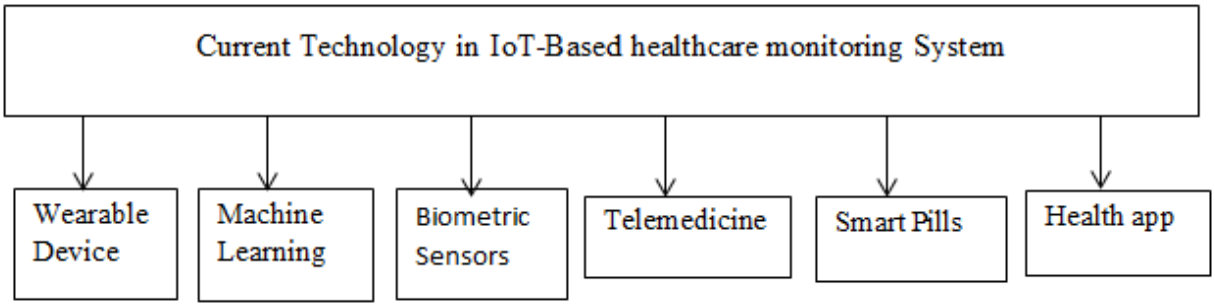


Figure 1.TheCurrent Technologies in IoT-Based Healthcare Monitoring System

Methodology

The methodology applied for reviewing the current technologies in IoT-based healthcare monitoring systems involves a comprehensive analysis of the existing literature, case studies, and technical reports on IoT applications in healthcare. First, a systematic search of scholarly databases (such as IEEE Xplore, PubMed, and Google Scholar) is conducted to gather peer-reviewed articles, research papers, and reviews published within the last few years, ensuring the inclusion of the latest advancements. These sources are evaluated based on relevance,

credibility, and technological focus, with a particular emphasis on the integration of Internet of Things (IoT) devices in remote patient monitoring, real-time data analytics, and health management. The review process includes categorizing technologies by their functionalities—such as wearable devices, biometric sensors, AI technology, health apps, and smart pill and so on. Additionally, a comparative review is performed on industries and platforms that have implemented these technologies like Firbit, Apple, and Sensoria Fitness etc. Finally, the challenges in implementing and adopting these technologies are also highlighted.

1. Wearable device-based health monitoring

Wearable device-based health monitoring systems use wearable technology to collect data about a user's health and physical activity. It refers to devices that patients attach to their bodies to collect health and fitness data, which they may provide to doctors, health providers, insurers and other relevant parties .These devices are integrated in body-worn devices such as in patients' clothing, gloves, wrist-worn or an armband devices, finger rings, earlobe devices and patches.

Wearable sensors present an analytical tool that converts bio-signals into electrical or optical signals. The sensors are categorized based on their monitoring mechanism, e.g., pressure, strain, electrochemical, temperature, and optoelectrical sensors. Due to their portability and wearability, a wearable sensor can interface closely with human skin to continually convert tiny bio-signals into electric signals, including current, resistance, and voltage changes, by using capacitive sensors, triboelectric, piezoresistive, and piezoelectric mechanisms, respectively. (Meng et al, 2022). The wearable piezoresistive sensor is used to track human movement signals by examining changes in resistivity and it has a long lifespan and rapid response time (Zhang, *et al*, 2022), whereas wearable piezoelectric sensors monitor signals by electrostatic induction and piezoelectric effect (Huo *et al*, 2022). Wearable capacitive sensors are used to sense motion based on changes in capacitance. While wearable triboelectric sensors consist of a triboelectric layer sandwiched between two parallel electrodes, which generate current or voltage signals upon pressure by triboelectric effect and electrostatic induction (Huo *et al*, 2022). Examples of wearable technology health monitoring system are discussed in table 1.

Table 1: Examples of wearable technology for health monitoring:

S/N	Technology	Function	Use Case
I	KardiaMobile:	Heart Rate Monitoring	Uses chest and finger sensors to monitor heart health, detect irregularities, and transmits the activity to a mobile app
Ii	Garmin Vivosmart 4	Blood Oxygen Levels	Measures blood oxygen saturation levels and monitoring respiratory health and altitude acclimatization (Langley, 2018).
Iii	Apple Watch	Activity Tracking	Tracks physical activity, including steps taken, calories burned, and exercise intensity.
Iv	Oura Ring	Sleep Monitoring	Analyzes sleep patterns, duration and quality, and sleep stages (The Verge, (2021).
V	Apple Watch Series 4	Electrocardiogram (ECG) Monitoring	Detect irregular heartbeats and assists in the early detection of arrhythmias like atrial fibrillation (CNET, 2023).

Vi	Abbott's FreeStyle Libre	Glucose Monitoring	Provides continuous glucose monitoring through a sensor placed under the skin for diabetic patients. (Abbott Diabetes Care, 2024).
Vii	Fitbit Charge 5	heart rate and sleep monitoring	Monitors stress responses, sleep tracking, heart rate monitoring, and sleep monitoring (Ellis, 2022).

2. Machine learning (ML) methods in healthcare monitoring systems

Machine learning (ML) methods in healthcare monitoring systems are designed to analyze and interpret health-related data to improve patient outcomes. Model performance monitoring is done to check whether the model is functioning as intended and to identify and fix potential problems. The four main categories of ML monitoring are as follows:

i. Data monitoring: This is useful for spotting problems, including data loss, data corruption, data drift, and distribution shifts over time. This is to ensure it is of sufficient quality and consistency
ii. Model monitoring: tracks ML model accuracy, precision, recall, and F1 score. This tackles problems, including model degradation, over-fitting, under-fitting, and drift.
iii. Infrastructure monitoring: keeping tabs on everything from servers and databases to the network that supports the machine learning model. Infrastructure may have a major impact on how well the model performs as downtime, sluggish reaction times, and other performance problems influence the model's efficiency.

2.1 Methods used in ML Health Monitoring System

i. Predictive Analytics: ML algorithms, like regression models and decision trees, are used to predict patient outcomes based on historical data. For example, predicting hospital readmissions or disease progression (Bhagat & Patil, 2023).
ii. Classification Algorithms: Techniques such as support vector machines (SVM), random forests, K-Nearest Neighbors (KNN), and neural networks classify patient data into categories, such as identifying patients at risk of certain diseases (Karunakar *et al*, 2024).
iii. Natural Language Processing (NLP): NLP techniques analyze unstructured data from clinical notes, patient feedback, and other text sources to extract insights and support clinical decision-making.
iv. Anomaly Detection: Algorithms identify outliers in patient data that may indicate potential health issues, helping to flag unusual patterns that require attention (Ainapure *et al*, 2022).
v. Time Series Analysis: Techniques like recurrent neural networks (RNNs) are used to analyze time-dependent data, such as vital signs, to predict future health states.
vi. Reinforcement Learning: This approach can be used in personalized treatment plans, where the system learns the best strategies for individual patients based on feedback from their responses.
vii. Image Recognition: Convolutional neural networks (CNNs) analyze medical images (e.g., X-rays, MRIs) for diagnostics, helping radiologists identify abnormalities more accurately and quickly.

viii. Wearable Device Data Analysis: ML algorithms process data from wearable devices to monitor real-time health metrics, providing insights into patients' physical activity, heart rate, and other vital signs.
ix. Population Health Management: ML helps in segmenting populations based on risk factors, allowing healthcare providers to target interventions effectively.
x. Decision Support Systems: Integrating ML into clinical workflows can assist healthcare professionals in making informed decisions by providing evidence-based recommendations.

2.2 The current technologies in machine learning healthcare monitoring systems include:

i. IBM Watson Health: Uses AI and machine learning to analyze patient data and assist in clinical decision-making, particularly in oncology (IBM Watson Health, 2020).
ii. HeartFlow: This system utilizes machine learning to create personalized 3D models of the heart using CT scans to assess coronary artery disease (HeartFlow, 2021).
iii. Google DeepMind Health: Developed AI algorithms for analyzing eye scans to detect diseases like diabetic retinopathy and age-related macular degeneration (De Fauw *et al*, 2018).
iv. Mayo Clinic's AI for COVID-19: Developed machine learning models to predict COVID-19 outcomes, helping to triage patients effectively (Paltiel, Zheng, & Walensky, 2020).
v. CureMetrix: Uses AI algorithms to analyze mammograms and improve breast cancer detection rates (CureMetrix, 2021).
vi. Fitbit Health Solutions: Employs machine learning to analyze data from wearable devices, providing insights for chronic disease management and wellness Fitbit, 2020).
vii. Babylon Health: Utilizes AI chatbots and ML algorithms to provide health assessments and triage services, improving access to care (Babylon Health, 2021).

3 Biometric sensors healthcare monitoring systems

Biosensors are devices that measure biological activity by detecting changes in current, resistance, and capacitance on their surfaces. They facilitate the monitoring of various bodily fluids, including saliva, interstitial fluid, tears, urine, and sweat. These sensors are particularly valuable as user-friendly and portable alternatives to traditional analytical instruments in healthcare. These body fluids include biomarkers, such as proteins (e.g., hormones, lactate dehydrogenase, and so on), tiny molecules (e.g., uric acid, glucose, amino acid, and cortisol), and ions (e.g., sodium, potassium, and calcium), which provide clinically useful data for the treatment of various metabolic illnesses including cancer, diabetes, and periodontal diseases. An example is the optoelectronic sensor emits light at specific wavelengths into the skin and optically measures changes in blood vessel volume associated with the cardiac cycle. These sensors facilitate the monitoring of various critical signals, including arterial oxygen saturation, heart rate, and respiratory rate.

3.1 Examples of technologies that utilizes biometric sensors are discussed below

i. KardiaMobile: A small, portable ECG monitor that can detect signs of arrhythmia, including atrial fibrillation (AFib) (AliveCor, 2024).
ii. Dexcom G6, Freestyle Libre: The sensors are typically attached to the skin and can provide real-time data about blood glucose levels in patients with diabetes, helping patients adjust their insulin or diet accordingly (Hoskins, 2023).
iii. Hexoskin: This is a wearable shirt with embedded biometric sensors that measure various physiological parameters such as heart rate, respiration, and activity levels (HITLAB, 2024).

iv. Athos: A performance-tracking system for athletes that uses clothing with embedded sensors to track muscle effort, heart rate, and breathing rate.
v. Verily's Smart Contact Lenses (Alphabet/Google): These lenses aim to track and monitor glucose levels in tears for diabetes management, continuously and non-invasively.
vi. Omron HeartGuide: A smartwatch that integrates oscillometric sensors designed specifically to monitor blood pressure.
vii. Spire Stone: A small wearable sensor that tracks breathing patterns and provides insights into a person's respiratory health (Riverstone, 2025).
viii. Cochlear Implants and Hearing Aids: hearing aids like those from Cochlear and Starkey integrate biometric sensors to monitor the user's health and detect changes in heart rate or activity (Gaobotse *et al*, 2022).
ix. Sensoria Fitness Socks & Shoes: Sensoria provides a set of smart socks and shoes equipped with sensors that track gait, pressure, and step count to prevent foot-related complications and for athletes to monitor performance (Yeung *et al*, 2019).
x. Propeller Health: This smart inhaler system attaches to asthma or COPD inhalers and provides data on medication usage, as well as environmental conditions that could trigger respiratory issues.

4 Artificial Intelligent (AI) Remote Patient Monitoring

The integration of artificial intelligence into Remote Patient Monitoring (RPM) is strengthening health monitoring processes by enabling continuous data collection, analysis, and early identification of potential health issues.

4.1 Applications of AI Remote Patient Monitoring

i. Predictive Analytics for High-Risk Patients: Predictive analytics is a powerful tool used to identify patients at high risk of adverse health events by analyzing historical patient data, real-time health metrics, and patterns (Yang, 2022). AI employs machine learning algorithms to identify patterns, trends, and correlations within the collected data, categorizes patients into risk groups based on the likelihood of adverse events and forecast potential health complications and enable healthcare providers to intervene proactively (Kim *et al*, 2023).
ii. Enhanced Medication Adherence: AI monitors patient behavior and responses to treatment, identifies adherence patterns, and predicts potential non-adherence issues and use patient patterns to predict when a patient might forget or skip medication doses, sends personalized reminders, ensuring they take their medications as prescribed.
iii. Virtual Health Assistants: Chatbots and AI Assistants are tools that help answer patient queries, schedule appointments, and provide medication reminders, improving accessibility and patient engagement (Jain *et al*, 2021).
iv. Administrative Efficiency: AI helps in managing administrative tasks such as scheduling, billing, and record-keeping, reducing the administrative burden on healthcare providers
v. Behavioral and Mental Health Monitoring: AI systems analyze behavioral data to detect signs of mental health issues, such as depression or anxiety, and provide support or recommend further evaluation.
vi. Early Detection of Health Deterioration: AI algorithms play a pivotal role in early detection by analyzing vast amounts of patient data collected through wearable devices, sensors, and patient-reported information. AI models process this data to establish personalized baselines for each patient, accounting for factors like age,

gender, medical history, and current health status. Once these baselines are established, the AI system continuously monitors incoming data for deviations from the norm. The functions of AI in early detection of health deterioration are, near real-time monitoring, pattern recognition, anomaly detection, predictive analysis: (Babu, *et al*, 2024), personalized treatment plans and treatment recommendations (Johnson, *et al*, 2021).

5 Telemedicine-based healthcare monitoring system

A telemedicine-based healthcare monitoring system websites or mobile applications to enhance patient care by allowing remote monitoring and enabling communication between patients and healthcare providers. Components of telemedicine-based healthcare monitoring system include:

i. Wearable Devices such as smart watches, fitness trackers, and medical-grade devices for monitoring vital signs (Vudathaneni et al, 2024).
ii. Mobile Applications for data visualization such as health data, schedule appointments, and communicate with healthcare providers (Haleem *et al*, 2021).
iii. Cloud-Based Data Storage which storages patient data and facilitates real-time data sharing and analytics.
iv. Telehealth Platforms which include video conferencing tools for virtual consultations, enabling doctors to assess and interact with patients remotely.
v. Data Analytics that comprise algorithms and tools to analyze health data for trends, anomalies, and predictive insights, helping in proactive healthcare (Ahmed &Yousuf, 2023).
vi. Security and Compliance to ensure patient data privacy and compliance with regulations like HIPAA.

Table 2. Examples of existing telemedicine-based healthcare monitoring systems in action

S/N	Industry	Function
i	Teladoc Health	This is a platform that connects patients with healthcare professionals for a range of services, including general consultations and specialty care (Teladoc Health, 2024).
ii	HealthTap	HealthTap provides on-demand virtual consultations with physicians, as well as AI-driven health assessments based on patient symptom. for continuous health monitoring and follow-up care, particularly beneficial for chronic conditions. Patients can interact with doctors through text or video and receive personalized advice (HealthTap, 2024).
iii	Mayo Clinic's Remote Patient Monitoring	Mayo Clinic utilizes a remote monitoring system for patients with chronic diseases, such as heart failure. Patients are equipped with devices to track vital signs, which are transmitted to care teams for analysis (Mayo Clinic, 2018).
iv	Omada Health	Omada focuses on chronic disease management, particularly for diabetes and obesity. The platform combines digital health coaching with remote monitoring tools, leading to measurable weight loss and improved glucose control among participants.
v	Philips HealthSuite	Philips offers a connected health platform that includes wearables and home monitoring devices for various health metrics, including heart health and sleep quality.
vi	Fitbit Health Solutions	Fitbit's devices are increasingly being used in clinical settings for

		remote patient monitoring, especially for heart health and fitness.
vii	Doxy.me	Doxy.me is a telemedicine platform that offers a simple, secure way for healthcare providers to conduct virtual visits without the need for downloads. It facilitates easy access to care and has been especially useful for mental health services
viii	MySugr	MySugr is a diabetes management app that allows patients to log their blood sugar levels, track food intake, and communicate with their healthcare team.

6 Smart Pills Health Monitoring Systems

Smart pills are ingestible devices that can monitor health metrics, track medication adherence, and transmit data to healthcare providers. They typically contain sensors that can detect various physiological conditions or medication ingestion, providing real-time health data, and enhance communication between patients and healthcare providers (Williamson, 2024). Components of Smart Pills Health Monitoring Systems include:

i. Ingestible Sensors: These sensors can be embedded within capsules or tablets. They typically monitor when the medication is taken and may track other health parameters (Cummins, 2021).
ii. Data Transmission: Smart pills use wireless technology (like Bluetooth or cellular networks) to send data to a receiver, usually a smartphone app or a healthcare provider's system.
iii. Mobile Applications: These apps allow patients to view their medication history, receive reminders, and communicate with healthcare providers (Minaam, & Abd-ELfattah, 2018).
iv. Cloud-Based Data Storage: Collected data is securely stored and can be accessed by authorized healthcare professionals for monitoring and analysis (Bhattacharyya et al., 2024).
v. Analytics Tools: These tools analyze the data collected from smart pills to provide insights into patient adherence, health trends, and outcomes.

6.1. Examples of Smart Pills technology

i. AbilifyMyCite: An FDA-approved smart pill that contains a sensor that tracks whether the medication (aripiprazole) has been taken. Patients receive notifications through a mobile app. This helps in improving adherence in patients with Depression, schizophrenia and bipolar disorder (Y & M Nguyen, 2021).
ii. Proteus Digital Health: This system combines ingestible sensors with wearable patches to monitor medication adherence and vital signs, use for chronic disease management (Litvinova *et al*, 2022).
iii. The PillCam is a smart pill system that captures images of the gastrointestinal tract for diagnostic purposes. It provides non-invasive visualization of the GI tract, assisting in diagnosing conditions like Crohn's disease and gastrointestinal bleeding (Espinoza, 2019).
iv. Otsuka's Digital Medicines: In partnership with Proteus, Otsuka has developed various digital medication solutions that combine medication with ingestible sensors. Their focus is on improving treatment for mental health conditions by ensuring adherence and monitoring (Otsuka, 2017).
v. Medisafe: this is a mobile app that pairs with smart pill technologies to enhance medication management through reminders and tracking (Medisafe, 2024).
vi. SmartPill: The SmartPill is a motility capsule that measures pressure, pH, and temperature as it travels through the GI tract. It provides data on gastric emptying and

transit time. This helps diagnose disorders related to motility and GI health (Knibbe et al, 2023).

7. Health apps Healthcare Monitoring system

Health apps are mobile applications designed to help users manage their health and wellness. They can range from simple fitness trackers to comprehensive systems that monitor chronic conditions and integrate with medical devices (Iribarren *et al*, 2021).

The Features of Health Apps discussed by Cucciniello *et al*, (2021), include:

i. Health Tracking: Users can track various health metrics, such as steps taken, calories burned, heart rate, blood pressure, and glucose levels.
ii. Medication Management: Reminders for medication schedules, refill notifications, and tracking adherence.
iii. Telehealth Capabilities: Virtual consultations with healthcare providers through video or messaging.
iv. Integration with Wearables: Sync data from wearable devices (e.g., smartwatches, fitness trackers) to monitor activity levels and vital signs.
v. Personalized Insights: AI and analytics provide users with personalized health recommendations based on tracked data. Example is Lifesum app which offers tailored diet plans based on user preferences and health goals.
vi. Community Support: Platforms for users to connect with others for support and motivation. An example is HealthUnlocked which is a social network for health support, allowing users to share experiences.

7.1 Examples of Health Apps include:

i. MyFitnessPal: A comprehensive food and exercise tracking app that allows users to log meals, track calories, and monitor physical activity. Helps users achieve weight loss and nutritional goals through data tracking MyFitnessPal, 2021).
ii. Medisafe: A medication management app that provides reminders, tracks adherence, and sends alerts for refills. Significantly improves medication adherence among users, particularly for those with chronic conditions.
iii. Fitbit App: this is Paired with Fitbit devices to track activity, heart rate, sleep patterns, and more, to enable users can monitor their fitness levels and health metrics in real-time.
iv. Apple Health: An all-in-one health app that consolidates data from various health and fitness apps and devices. Users gain a holistic view of their health metrics, making it easier to manage their overall wellness (Capritto, 2019).
v. Headspace: A meditation and mindfulness app that helps users manage stress and improve mental well-being. Users report reduced stress levels and improved mental health through regular practice.
vi. Telehealth Apps (e.g., Teladoc, Amwell): Platforms that connect patients with healthcare providers for virtual consultations. This Increases access to healthcare services, especially during the COVID-19 pandemic (Omboni, Padwal, Alessa, …& Wang, 2022).
vii. Blood Pressure Companion: An app that allows users to track blood pressure readings, medication, and lifestyle changes.
viii. MySugr: A diabetes management app that allows users to log blood sugar levels, carbohydrate intake, and insulin dosages, helping users to maintain glycemic control.
ix. Sleep Cycle: A smart alarm clock app that analyzes sleep patterns and wakes users during the lightest sleep phase. This helps users improve sleep quality.

8 Challenges implementing wearable devices in healthcare monitoring system

i. Data Accuracy and Reliability: Wearable sensors may not always provide accurate readings due to motion artifacts, environmental conditions, or improper placement. Also, calibration issues can lead to inconsistent data (Ikharo and Aliu, 2023).
ii. User Compliance and Adoption: Users may forget to wear or charge the devices, affecting continuous monitoring. Comfort and design concerns (e.g., skin irritation, bulky devices) can impact long-term usage. Factors like skin conditions, sweat, temperature, and movement can affect accuracy (Heikenfeld et al, 2018).
iii. Cost and Affordability: High costs of wearable devices can limit accessibility, especially in low-income populations. Insurance coverage for wearable health monitoring varies, impacting affordability.
iv. Environmental Factors and Durability: Wearables must withstand different conditions (e.g., sweat, water, extreme temperatures). Device failure or inaccuracy in harsh environments can reduce reliability.
v. Wearability Issues: Devices such as wearable ECG patches, smartwatches, or glucose monitors may cause discomfort or irritation.

9. Challenges ImplementingML healthcare monitoring system

i. Incomplete or Inaccurate Data: ML models require high-quality, accurate data for training. Healthcare data can be incomplete, noisy, or inconsistent, leading to unreliable models (Ghassemi et al, 2020).
ii. Data Sharing: Sharing healthcare data across institutions and systems for ML applications is difficult due to security and privacy concerns, even though it would enhance model performance (Boursalie et al, 2018).
iii. Interpretability and Trust: Many advanced ML models (such as deep learning) are often seen as "black boxes," meaning their decision-making process is not easily interpretable. In healthcare, where decisions can have life-or-death consequences, clinicians need to understand how an AI model reached its conclusions (Yan et al, 2025).
iv. Bias and Fairness: ML models can inadvertently inherit biases present in the training data. This can lead to discriminatory practices, such as unequal healthcare delivery for different demographics. Addressing fairness and bias is crucial to avoid exacerbating health disparities (Nayyar et al, 2021).
v. Integration with Existing Systems: Many healthcare systems still use outdated technologies that may not be compatible with modern ML solutions. Integration of ML models into these systems requires significant effort and may face technical constraints.
vi. Workflow Disruptions: Integrating ML into clinical workflows without disrupting day-to-day operations is a challenge. For example, doctors may find it time-consuming or cumbersome to work alongside an AI model that doesn't seamlessly integrate with existing practices.
vii. High Costs: Developing and deploying ML systems in healthcare can be expensive, requiring skilled personnel, computational resources, and substantial financial investment. Smaller healthcare providers may not have the resources to invest in advanced ML systems.
viii. Training: Clinicians may need training in understanding and using ML tools effectively. This involves up-skilling staff to interpret AI outputs, making sure they don't rely on the technology blindly and can make informed decisions.

ix. Latency and Speed: In healthcare, many decisions need to be made in real-time (e.g., monitoring vital signs). ML models must be able to process and respond quickly to data, and latency could potentially impact patient safety.
x. Informed Consent: Patients may not fully understand how their data is being used to train ML models or how the models impact their treatment.

10. Challenges Implementing Biometric Sensors in Healthcare Monitoring Systems
    i. Sensitive Health Data Exposure: Biometric data, once compromised, cannot be changed like passwords (Wells and Usman (2023).
    ii. False Positives/Negatives: Errors in biometric recognition can lead to misdiagnoses or incorrect health alerts.
    iii. Calibration Challenges: Sensors require frequent recalibration to maintain precision over time.
    iv. Integration with Healthcare Systems: Healthcare facilities may lack the infrastructure to process and store large amounts of real-time biometric data (sun et al, 2021).
    v. High Implementation Costs: Advanced biometric sensors require expensive hardware, software, and maintenance.
    vi. Limited Access in Low-Resource Settings: Many developing regions lack reliable power, internet, or healthcare infrastructure to support biometric monitoring (Kim et al, 2019)

11. Challenges implementing telemedicine healthcare monitoring system
    i. Technological Limitations: Difficulty integrating telemedicine platforms with Electronic Health Records (EHRs).
    ii. Diagnostic & Treatment Limitations: the Inability to perform immediate tests (e.g., bloodwork, imaging), Lack of physical examination may lead to misdiagnosis may cause challenges in monitoring chronic diseases remotely.
    iii. Reimbursement & Regulatory Challenges: Unclear or inconsistent insurance coverage and reimbursement policies for telemedicine. Varying licensing requirements across different states or countries
    iv. Patient Engagement & Follow-Up Issues: this includes low engagement due to lack of digital literacy or motivation, difficulty ensuring medication adherence and lifestyle changes, and problems with scheduling and continuity of care.

12. Challenges in Implementing AI Healthcare Monitoring Systems
    i. Interoperability Issues: AI must integrate with Electronic Health Records (EHRs) and hospital systems, which often use different formats and standards (Wubineh et al, 2024).
    ii. Infrastructure Limitations: Many healthcare facilities, especially in developing regions, lack the necessary computational power and cloud-based systems to support AI applications.
    iii. Algorithmic Bias: AI models trained on biased or incomplete datasets can lead to inaccurate diagnoses, especially for underrepresented populations (Olawade et al, 2024).
    iv. Transparency & Explainability: AI decisions are often seen as “black boxes,” making it difficult for healthcare professionals to trust or validate AI-generated insights (Mesko, 2017).
    v. Data Quality Dependence: AI accuracy relies on high-quality, diverse, and well-structured datasets. Poor data collection leads to unreliable AI predictions.

vi. High Development & Maintenance Costs: AI requires significant investment in data storage, computing power, and skilled personnel.
vii. Training Healthcare Professionals: Doctors and nurses need specialized training to effectively use AI-based monitoring tools (He *et al*, 2019).
viii. Resistance to Change: Many healthcare providers are reluctant to adopt AI due to concerns about job displacement and clinical liability.
ix. Liability & Accountability: Determining who is responsible when AI makes a mistake (e.g., physician, hospital, or AI developer) remains a legal challenge (Amann *et al*, 2020).

13. Challenges in Implementing Health Apps Healthcare Monitoring Systems
    i. User Adoption & Engagement: Patients may struggle with technology, especially elderly populations and find apps difficult to use. This might be as a result of poor internet connectivity in rural or underserved areas, cultural and language barriers affecting communication. Also, doctors may resist adoption due to increased workload or lack of training (Alzghaibi, 2025).
    ii. Cost & Infrastructure: Developing a robust and scalable system requires significant investment, and many regions, especially rural areas, lack the necessary internet and tech infrastructure.
    iii. Regulatory & Legal Challenges: Navigating different health regulations across countries is challenging (Suresh *et al*, 2022).
    iv. Data Overload for Healthcare Providers: Processing large amounts of patient data in real-time can be overwhelming.
    v. Interoperability Issues: Health apps must integrate with existing hospital systems (HER/EMR), but many uses different formats and standards. There is Lack of universal APIs for seamless data sharing (Wang et al. 2018).

14. Challenges Implementing Smart Pills Healthcare Monitoring Systems Using
    i. Data Transmission & Compatibility: Smart pills need to communicate with external devices (e.g., smartphones, wearables, or cloud systems), but integration with existing Electronic Health Records (EHRs) can be difficult.
    ii. Power & Longevity: Since smart pills require internal sensors, battery life and energy efficiency remain challenges.
    iii. High Development & Manufacturing Costs: Smart pill technology is expensive, limiting affordability and widespread adoption.
    iv. Healthcare System Readiness: Many hospitals and clinics lack the infrastructure to support smart pill monitoring.
    v. Patient Acceptance & Ethical Concerns: Patients may be hesitant to ingest a tracking device, fearing surveillance or misuse of their health data, and Continuous monitoring raises concerns about autonomy, privacy, and potential coercion in medication adherence (Klugman *et al*, 2018).
    vi. Regulatory & Legal Barriers: Smart pills must pass rigorous FDA (USA), EMA (Europe), and other international regulatory approvals before market release. If a smart pill malfunctions or provides incorrect data, determining responsibility can be legally complex (Gerke et al, 2019)
    vii. Data Integrity: Sensor accuracy can be affected by digestive processes, environmental factors, or individual patient variations (Proteus 2019)

Conclusion

IoT-Based healthcare monitoring systems have significantly evolved with advancements in digital technologies, improving patient care, reducing hospital visits, and enabling real-time health tracking. Various techniques, including wearable sensors, IoT biometric sensors, telemedicine platforms, AI-driven technique, health apps, and smart pill technology has been reviewed in this paper. These technologies have revolutionized healthcare by allowing continuous and remote patient monitoring, facilitate early disease detection, personalized treatment, and improved chronic disease management, ultimately enhancing healthcare accessibility and efficiency. The challenges of implementing and adopting these technologies such as data Accuracy, security and Reliability, interoperability, and patient compliance and adoption, environmental factors and durability, infrastructure limitations, regulatory & legal barriers, and so on, has also been explored in this paper. Future advancements will focus on improving data privacy, enhancing AI-driven predictive analytics, and integrating next-generation technologies like 5G and blockchain for secure and seamless healthcare monitoring. As these technologies continue to evolve, remote healthcare monitoring systems will play an increasingly vital role in creating a more proactive, data-driven, and patient-centric healthcare ecosystem.

Reference

Abbott Diabetes Care. (2024). FreeStyleLibre 2. https://www.freestylelibre.us/

Afrah, A., & Yousuf, F. (2023). Telemedicine and remote patient monitoring: Data analytics and AI integration. European Journal of Pharmaceutical and Medical Research, 10(9).

Ainapure, B., Patrikar, P., Mehta, A., Jain, A., & Shah, S. (2022). Machine learning based intelligent health monitoring system. In 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM) (pp. 183–188). IEEE. https://doi.org/10.1109/ICIEM54221.2022.9853117

AliveCor. (2024). Detect AFib from home with KardiaMobile. https://alivecor.com/atrial-fibrillation-kardiamobile

Alzghaibi, H. (2025). Healthcare practitioners' perceptions of mHealth application barriers: Challenges to adoption and strategies for enhancing digital health integration. Healthcare, 13(5), 494. https://doi.org/10.3390/healthcare13050494

Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. BMC Medical Informatics and Decision Making, 20(1), 1–9.

Babu, S., Kumar, V., Divya, A., Thanuja, B., Sreepathi, R., Babu, V., Kumar, A., Divya, B., & Thanuja. (2024). AI-driven healthcare: Predictive analytics for disease diagnosis and treatment. International Journal for Modern Trends in Science and Technology, 10, 5–09. https://doi.org/10.46501/IJMTST1006002

Babylon Health. (2021). AI and the future of healthcare. https://www.babylonhealth.com

Bhagat, R., & Patil, P. (2023). Health monitoring system using machine learning techniques algorithm. International Journal for Research in Applied Science & Engineering Technology (IJRASET), 11(6). https://doi.org/10.22214/ijraset.2023.54228

Bhattacharyya, S., Majumder, A., Mukherjee, P., Sarkar, H., & Samanta, R. A. (2024). Smart pills and ingestible sensors for real-time health monitoring: A patient landscape and overview. International Journal of Engineering Research & Technology (IJERT), 13(6).

Boursalie, O., Samavi, R., & Doyle, T. E. (2018). Machine learning and mobile health monitoring platforms: A case study on research and implementation challenges. Journal of Healthcare Informatics Research, 2(1–2), 179–203. https://doi.org/10.1007/s41666-018-0021-1

Capritto, A. (2019). The complete guide to Apple's Health app. CNET. https://www.cnet.com/health/the-complete-guide-to-apples-health-app/

CNET. (2023). Apple Watch Series 4 review. https://www.cnet.com/tech/mobile/apple-watch-series-4-review/

Cucciniello, M., Petracca, F., Ciani, O., & Tarricone, R. (2021). Development features and study characteristics of mobile health apps in the management of chronic conditions: A systematic review of randomised trials. NPJ Digital Medicine, 4, 144. https://doi.org/10.1038/s41746-021-00517-1

Cummins, G. (2021). Smart pills for gastrointestinal diagnostics and therapy. Advanced Drug Delivery Reviews, 177, 113931. https://doi.org/10.1016/j.addr.2021.113931

CureMetrix. (2021). CureMetrix AI. https://curemetrix.com

De Fauw, J., Ledsam, J. R., & Romera-Paredes, B. (2018). Clinically applicable deep learning for diagnosis and referral in retinal disease. Nature Medicine, 24, 1342–1350. https://doi.org/10.1038/s41591-018-0107-6

Ellis, C. (2022). Review. TechRadar. https://www.techradar.com/reviews/fitbit-charge-5

Espinoza, M. (2019). The PillCam goes on a fantastic voyage to help diagnose GI bleeding. UTSouthwestern Medical Center. https://utswmed.org/medblog/pillcam-gets-close-and-intestinal-spot-gi-bleeding/

Eui-Sun, K., Eun, S.-J., & Kim, K.-H. (2023). Artificial intelligence-based patient monitoring system for medical support. International Neurourology Journal, 27(4), 280–286. https://doi.org/10.5213/inj.2346338.169

Fitbit. (2020). Fitbit health solutions. https://healthsolutions.fitbit.com

Gaobotse, G., Mbunge, E., Batani, J., & Muchemwa, B. (2022). Non-invasive smart implants in healthcare: Redefining healthcare services delivery through sensors and emerging digital health technologies. Sensors International, 3. https://doi.org/10.1016/j.sintl.2022.100156

Ghassemi, M., Naumann, T., Schulam, P., Beam, A. L., Chen, I. Y., & Ranganath, R. (2020). A review of challenges and opportunities in machine learning for health. AMIA Joint Summits on Translational Science Proceedings, 2020, 191–200.

Haleem, A., Javaid, M., Singh, R. P., & Suman, R. (2021). Telemedicine for healthcare: Capabilities, features, barriers, and applications. Sensors International, 2, 100117. https://doi.org/10.1016/j.sintl.2021.100117

HeartFlow. (2021). HeartFlow analysis. https://www.heartflow.com

HealthTap. (2024). Find expert care that fits your needs. https://www.healthtap.com/telehealth/

He, J., Baxter, S. L., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. Nature Medicine, 25, 30–36. https://doi.org/10.1038/s41591-018-0307-0

Heikenfeld, J., Jajack, A., Rogers, J., Gutruf, P., Tian, L., Pan, T., Li, R., Khine, M., Kim, J., Wang, J., & Kim, J. (2018). Wearable sensors: Modalities, challenges, and prospects. Lab on a Chip, 18(2), 217–248. https://doi.org/10.1039/c7lc00914c

HITLAB. (2024). Keep your shirt on: Hexoskin is redefining health monitoring with smart wearables. https://www.hitlab.org/hexoskin-smart-wearables/

Hoskins, M. (2023). Dexcom G6 review: Everything you need to know. https://www.healthline.com/health/diabetes/dexcom-g6-cgm-product-review#pros-and-cons

Huo, Z., Wei, Y., Wang, Y., Wang, Z. L., & Sun, O. (2022). Integrated self-powered sensors based on 2D material devices. Advanced Functional Materials, 32(41). https://doi.org/10.1002/adfm.202206900

IBM Watson Health. (2021). AI-powered data and analytics for health. https://www.ibm.com/watson-health

Intel. (2021). Intel and mSafety from Sony. https://www.intel.com/content/www/us/en/healthcare-it/resources/mhealth-wearable-sensors.html

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. Stroke and Vascular Neurology, 2(4), 230–243. https://doi.org/10.1136/svn-2017-000101

Jiang, S., Wang, Z., Zeng, Y., & Liu, Y. (2021). Wearable sensors for real-time health monitoring. Sensors, 21(1), 5. https://doi.org/10.3390/s21010005

Khera, R., & Dhruva, S. S. (2022). FDA regulation of AI-based software in health care. New England Journal of Medicine, 386(7), 579–586. https://doi.org/10.1056/NEJMp2116515

Kumar, R., & Singh, J. P. (2023). Artificial intelligence-based real-time health monitoring system using IoT-enabled devices. International Journal of Interactive Multimedia and Artificial Intelligence, 8(5), 134–141. https://doi.org/10.9781/ijimai.2022.12.004

Kumar, Y., & Sahoo, G. (2022). Smart wearable sensor technology for health monitoring: A review. International Journal of Advanced Computer Science and Applications, 13(9), 487–494. https://doi.org/10.14569/IJACSA.2022.0130963

Lechner, A., & Wang, Y. (2023). Soft bioelectronics for human health monitoring. Science Advances, 9(4), eadc9510. https://doi.org/10.1126/sciadv.adc9510

Lee, S. M., & Lee, D. (2020). Healthcare wearable devices: An analysis of key factors for continuous use intention. Service Business, 14(4), 503–531. https://doi.org/10.1007/s11628-020-00428-y

Mahmoud, K., & Razzak, M. I. (2023). A comprehensive survey on wearable sensors: From devices to applications. IEEE Access, 11, 123456–123478. https://doi.org/10.1109/ACCESS.2023.3245678

Mayo Clinic. (2023). Smart medical devices and digital health. https://www.mayoclinic.org/tests-procedures/smart-devices/about/pac-20485045

McKinsey & Company. (2021). The future of healthcare: Value creation through next-generation business models. https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/the-future-of-healthcare

National Institutes of Health. (2022). NIH harnesses AI for disease detection. https://www.nih.gov/news-events/news-releases/nih-harnesses-ai-disease-detection

Navidea Biopharmaceuticals. (2020). Targeted diagnostics using artificial intelligence. https://www.navidea.com

Office for the Advancement of Telehealth. (2023). Telehealth programs. Health Resources and Services Administration. https://www.hrsa.gov/rural-health/telehealth

Omar, A. I., & Khan, S. A. (2022). Artificial intelligence and smart wearable technology in chronic disease management. Journal of Medical Systems, 46, 78. https://doi.org/10.1007/s10916-022-01821-

OpenAI. (2024). ChatGPT for medical use: Promises and limitations. https://openai.com/blog/chatgpt-for-healthcare

Patel, S., Park, H., Bonato, P., Chan, L., & Rodgers, M. (2012). A review of wearable sensors and systems with application in rehabilitation. Journal of NeuroEngineering and Rehabilitation, 9, 21. https://doi.org/10.1186/1743-0003-9-21

Philips Healthcare. (2023). AI in health monitoring solutions. https://www.philips.com/a-w/about/artificial-intelligence/healthcare.html

PillCam. (2023). PillCam COLON 2. https://www.medtronic.com/covidien/en-us/products/capsule-endoscopy/pillcam-colon-2.html

Qin, Y., Li, L., & Xu, H. (2023). Machine learning techniques in wearable health monitoring systems. *IEEE Reviews in Biomedical Engineering*, *16*, 245–260. https://doi.org/10.1109/RBME.2023.3245679

Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C. P., Shpanskaya, K., Lungren, M. P., & Ng, A. Y. (2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. *PLoS Medicine*, *15*(11), e1002686.

https://doi.org/10.1371/journal.pmed.1002686

Rashidi, P., & Cook, D. J. (2013). Keeping the resident in the loop: Adapting the smart home to the user. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *43*(1), 161–171. https://doi.org/10.1109/TSMCC.2012.2208982

Sharon, T. (2021). When digital health meets digital capitalism, how many common goods are at stake? *Big Data & Society*, *8*(1), 20539517211003155. https://doi.org/10.1177/20539517211003155

Smith, M., & Jones, T. (2022). Ethical implications of AI in remote patient monitoring. *Bioethics Journal*, *36*(4), 355–367. https://doi.org/10.1111/bioe.12950 Stanford Center for Biomedical Informatics Research. (2022). AI models for patient monitoring. https://bmir.stanford.edu/research-projects

Topol, E. (2019). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books.

Turakhia, M. P., Desai, M., & Harrington, R. A. (2019). The outlook of digital health for cardiovascular medicine: Challenges but also extraordinary opportunities. *JAMA Cardiology*,

U.S. Food and Drug Administration (FDA). (2021). Artificial Intelligence and Machine Learning in Software as a Medical Device. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device

Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A. (2020). Artificial Intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *14*(4), 337–339. https://doi.org/10.1016/j.dsx.2020.04.012 Van Kasteren, T. L. M., Englebienne, G., & Kröse, B. J. A. (2010). Transferring knowledge of activity recognition across sensor networks. *Pervasive and Mobile Computing*, *6*(4), 481–497. https://doi.org/10.1016/j.pmcj.2010.07.003

Wang, L., & Alexander, C. A. (2022). Big data analytics in smart health care. *Journal of Healthcare Engineering*, *2022*, 1–9. https://doi.org/10.1155/2022/6547890 World Health Organization. (2021). Ethics and governance of artificial intelligence for health. https://www.who.int/publications/i/item/9789240029200

Xu, W., Zhang, L., & Zhou, Y. (2021). A review of wearable sensor systems for monitoring body movements of stroke patients. *Biosensors*, *11*(6), 182. https://doi.org/10.3390/bios11060182

Yin, H., & Kay, J. (2023). Personal health informatics: Wearable devices and data analytics. *Health Information Science and Systems*, *11*(1), 9. https://doi.org/10.1007/s13755-023-00194-7

Young, J. D., Bourgeois, J. A., & Hilty, D. M. (2020). Ethical aspects of digital health from a global perspective. *Psychiatric Clinics*, *43*(4), 575–586. https://doi.org/10.1016/j.psc.2020.07.007

Zhou, L., & Parmanto, B. (2021). Reusable mHealth systems for patient monitoring. *JMIR mHealth and uHealth*, *9*(1), e22619. https://doi.org/10.2196/22619 Zhu, Z., Liu, T., Li, G., Li, T., & Inoue, Y. (2019). Wearable sensor systems for infants. *Sensors*, *19*(2), 341. https://doi.org/10.3390/s19020341