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Self-Management of Long-Term Conditions by Integrating Artificial Intelligence With Wearable Devices and Internet-of-Thing Technology: A Review

The aim of this study was to investigate the impact on the delivery, adoption, and effectiveness of Generative Artificial Intelligence integrated wearable devices and internet-of-thing (IoT) for long-term condition monitoring. We adopted preferred reporting items for systematic reviews and meta-analyses review methodology and screened a total of 226 articles. After considering the eligibility and selection criteria, we selected 13 articles published between 2020 and 2024. The selection criteria were based on the inclusion of studies that report on the adoption and effectiveness of Generative Artificial Intelligence integrated wearable devices and IoT for long-term condition monitoring. We found wearable health monitoring and personalized patient care plans leveraged Generative Artificial Intelligence (Gen AI) to predict health events by analyzing continuous data from wearables devices and IoT devices like smartwatches, glucose monitors, and various health and well-being sensors. Gen AI models provided tailored advice on physical activity, diet, and sleep, leading to improved health outcomes and user satisfaction. Comparative analysis from reviewed studies demonstrates substantial performance improvements: accuracy enhanced from 85.6% to 97.7%, precision improved from 85.1% to 96.8% and computational latency reduced significantly from 320 ms to 120 ms. Moving AI processing closer to the data source (e.g., on the wearable device itself) can reduce latency and improve real-time decision-making. This is particularly useful for critical health and safety applications. Moreover, robust integration with electronic health records and healthcare providers can enhance the usefulness of data collected by wearables, allowing for more comprehensive and coordinated care. Continued advancements in AI algorithms will improve the predictive capabilities of these systems, enabling even more pro-active and personalized interventions.
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Keywords: wearable health applications, adoption of IoT apps, long-term conditions, adoption of wearable health applications, effectiveness of Generative Artificial Intelligence health monitoring, clinical decision support applications, long-term condition monitoring, IoT health apps

1 Introduction

Wearable technology combined with Generative Artificial Intelligence (Gen AI) has significant potential to improve the monitoring and management of long-term health conditions. This synergy can lead to more personalized, efficient, and pro-active healthcare. One of the most impacted areas is the continuous monitoring and data collection using internet-of-things (IoT) and wearable heath monitoring systems (WHMSs). Wearable devices and IoT applications, such as smartwatches, fitness trackers, and medical-grade sensors, can continuously monitor various health parameters, including heart rate, blood pressure, glucose levels, physical activity, and sleep patterns. Gen AI can process this vast amount of data to detect anomalies and identify unusual patterns or deviations from baseline health metrics that may indicate exacerbations or complications. Moreover, Gen AI-based models can

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easily be designed and developed to predict health trends to generate predictions about the patient's health trajectory, allowing for early intervention and better management of long-term conditions [1–4].

Integrating Generative AI with wearable devices and IoT can significantly enhance personalized health insights, patient care plans, and long-term condition management. Recent studies highlight the significant increase in the personalized patient care plan designed for tailored exercise, diet, and medication plans based on the unique needs and conditions of the patient. Also, generate real-time suggestions and reminders to encourage healthy behaviors, such as taking medications on time, staying active, managing stress or many use-cases of activity of daily life [5–7].

The integration of Gen AI with WHMS and IoT applications is driving a new era of innovation and intelligence across various industries. This convergence harnesses the strengths of both technologies to create systems that are more responsive, adaptive, and efficient. Early adoption can be seen in (1) remote patient monitoring by tracking health metrics continuously, while Gen AI analyzes this data to detect anomalies, predict potential health issues, and generate personalized treatment plans, (2) virtual health assistants in providing real-time health advice, reminders for medication, and lifestyle recommendations based on data from wearables and (3) self-management of long-term condition monitoring by early detection and prediction of abnormal health trends, reminders and notifications based on individual's health plans, medication adherence, education and other recourses tailored for better health and well-being [8–12].

2 A Practical Framework for Integrating Generative Artificial Intelligence With Wearable and Internet-of-Thing Applications

Creating a practical framework for integrating Gen AI with wearable and IoT applications involves a multifaceted approach that addresses data collection, processing, analysis, and user interaction while ensuring security, privacy, and interoperability [11,13–15]. Figure 1 shows key components for a practical framework for integrating Generative AI with wearable and IoT applications. Figure 2 shows a general framework for Gen AI decision making in wearables. It begins with the user wearing the wearable device, which collects sensor data such as heart rate, movement, and other biometrics. The data undergoes processing and feature extraction to filter noise and extract relevant insights. This data are processed using on or a combination of various AI approaches, including traditional machine learning (ML) models for pattern recognition, transformer-based models for context-aware AI, federated learning for decentralized model training, and edge computing for low-latency AI processing. These AI approaches contribute to generating personalized insights, health monitoring, and activity tracking, which are fed back to the user for improved experience. Additionally, data security measures ensure privacy, while cloud-based processing enhances computational efficiency when needed. This structured process enables wearables to deliver intelligent, real-time insights while maintaining data security and efficiency. Integrating Gen AI with wearable and IoT applications requires a comprehensive framework that addresses data collection, infrastructure, AI model development, user interaction, security, privacy, and compliance. By focusing on these areas, developers can create effective, secure, and user-friendly systems that leverage the power of Gen AI to enhance wearable health, IoT applications, health and well-being applications [16–20].

3 Methodology

3.1 Article Search and Selection Criteria. In order to review the literature that deals with adoption and effectiveness of Generative Artificial Intelligence integrated wearable devices and IoT for long-term condition monitoring, related keywords were used to cross-search for thousands of related papers in significant databases of scientific publications including IEEE Xplore, Springer Link, Scopus, and PubMed Library. We chose the preferred reporting items for systematic reviews and meta-analyses as the

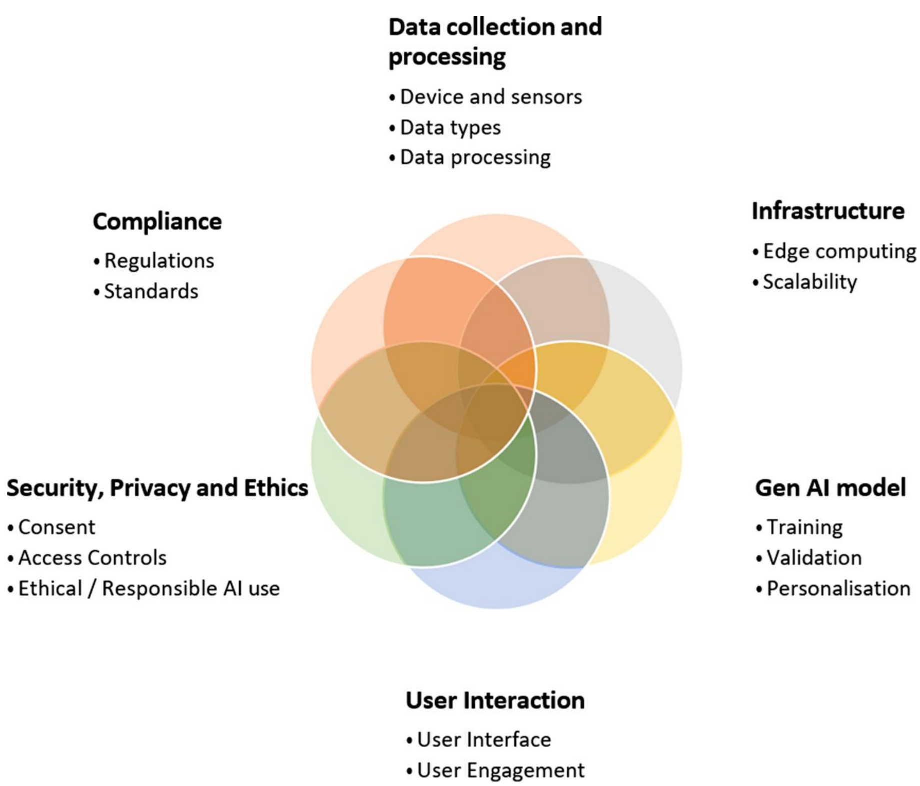

Fig. 1 Key components for a practical framework for integrating Generative AI with wearable and IoT applications

systematic review methodology [21]. The key terms queries were "Generative AI," "wearable technology," "IoT," "health monitoring," and "long-term monitoring." One of the authors conducted an initial screening of the retrieved records. Duplicated articles were eliminated, and additional records were excluded after reviewing individual titles and abstracts. A second author then reviewed the included studies and evaluated the full-text articles or eligibility. The eligibility criteria for inclusion in the review are:

1. Original articles mainly published as journal articles.
2. Paper published or reported between 2020 and 2024 (inclusive).
3. Wearable health applications for long-term conditions management using Generative Artificial Intelligence were the primary subject of this study.
4. It is targeted toward wearable and IoT studies using Generative Artificial Intelligence
5. Written and published in English.

We excluded articles that were not considered original research, such as letters to editors, comments or reviews. Because this review paper focused on rapid response applications to deteriorating patients, we also excluded studies that solely focus on patient monitoring, remote monitoring, IoT-connected device monitoring, and other general tracking and monitoring applications.

3.2 Article Search Results. Initially, 226 studies were identified through database searching. A total of 174 records did not meet our inclusion criteria based on the initial screening, and therefore, 52 studies were included for checking against the eligibility. Full-text records were retrieved and reviewed by two authors. After excluding unrelated studies, duplicate records, a total of 13 articles ($n = 13$) were selected for the final review. Categorization of the articles selected for this review and their area of application are given in Table 1.

4 Review of Wearable Monitoring and Internet-of-Things Based Applications Using Generative Artificial Intelligence

4.1 Key Analysis of Review and Survey Articles in This Space. A review by Mukhopadhyay et al. [15] discuss the key role of sensors, smart data processing, communication protocol, and artificial intelligence which will enable the deployment of AI-based sensors for next-generation IoT applications and found that to

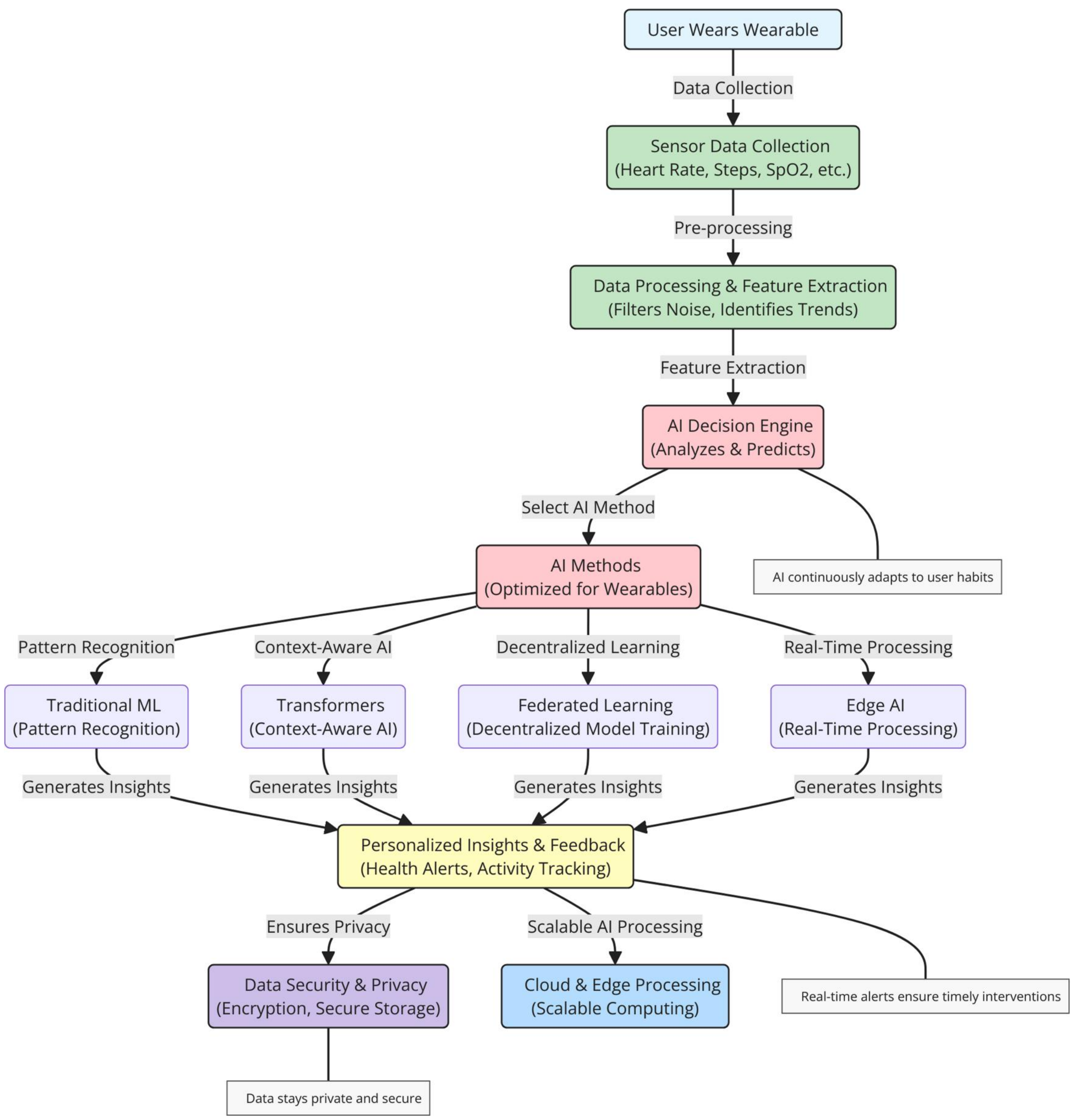

Fig. 2 A template framework showing incorporation of different Gen AI methods used in AI decision making through wearables

Table 1 Categorization of the selected articles

Year of publication	References	Area of application	Total (%) $N=13$
2024	Ref. [8]	AI-based medical sensors [8]	1 (8%)
2023	Refs. [11,12], and [22–24]	Review and survey [22], heart disease detection [12], track vital indicators [23], AI-based wearable sensors [11]	5 (38%)
2022	Refs. [25–28]	Prediction of LTC [25], survey [26], posture recognition [27], IoT-based wearable apps [28], IoT and AI overview [24]	4 (31%)
2021	Refs. [14] and [15]	Review [15] and opportunities and challenges review [14]	2 (15%)
2020	Ref. [29]	IoT based disease prediction [29]	1 (8%)

achieve the high level of automation required in today's smart IoT applications, sensors incorporated into nodes must be efficient, intelligent, context-aware, reliable, accurate, and connected. Such sensors must also be robust, safety-, and privacy-aware for users interacting with them [15]. A review of domain-specific applications was carried out by the Nahavandi et al. [14] to analyze applications of supervised and unsupervised learning for medical diagnosis and combining the internet of things, wearables, and reinforcement learning. The outcome of the review is very aligned with our findings as well—wearable technology is an essential building block in future information and communication technology systems. However, wearable technology has not reached an acceptable level of maturity yet. Multiple challenges are still unaddressed with regard to data collection, data processing, communications, security, confidence, and user engagement [14].

Al-Turjman and Baali [26] discussed wearable systems, and how ML can be used to enhance the performance of this data centric networks and found various applications of ML were categorized into system optimization and collected data preprocessing [26]. Similarly, Seng et al. [22] did a classification of smart wearables and research prototypes using machine learning and AI technologies and found that there are significant technical challenges for AI smart wearables in networking and communication aspects such as issues for routing and communication overheads, information processing, and computational aspects such as issues for computational complexity and storage, and algorithmic and application-dependent aspects such as training and inference [22]. Among other similar reviews [8,10,13,30], Rahmani et al. [28] explored IoT-based wearable apps, an overview of new trends and technologies such as IoT and AI were explored by Fabbrizio et al. [24] and Shajari et al. [11] reviewed the use of AI technology in combination with wearable technology for big data processing, self-learning, power-efficiency, real-time data acquisition and processing, and personalized health for an intelligent sensing platform. Table 2 summarizes the review articles focusing on using AI and IoT systems in medical technologies.

4.2 Adoption of Wearable Heath Monitoring System and Internet-of-Thing-Based Applications for Long-Term Conditions Management. Ramasamy et al. [25] proposes an AI-enabled IoT-cyber-physical systems (CPS) which doctors can utilize to discover diseases in patients based on AI. AI was created to find a few disorders such as diabetes, heart disease,

Table 2 Summary of the review articles

Authors and references	Title, year of publication	Type of study	Focus areas	Key topics covered	Key findings
Mukhopadhyay et al. [15]	Artificial intelligence-based sensors for next generation IoT applications: a review, 2021	Review	Framework for communication technologies that support AI-IoT	IoT architecture, review of the types of sensor data and review of the types of sensor data and the integration of AI and IoT in embedded smart sensing systems in industry	The complexity of embedding AI techniques can be best achieved through a better understanding of the role of embedded smart sensing systems in industry 4.0, IoT architecture and technologies
Nahavandi et al. [14]	Application of artificial intelligence in wearable devices: opportunities and challenges	Review: opportunities and challenges	Reviews the recent applications of wearables that have leveraged AI to achieve their objectives	Comprehensive treatment of domain-specific applications of wearable devices such as health and well-being wearable technologies challenges such as data collection, data transmission, etc., are pointed out	Applications of supervised and unsupervised learning for medical diagnosis and combining the internet of things, wearables, and reinforcement learning are reviewed
Al-Turjman and Baali [26]	Machine learning for wearable IoT-based applications: A survey, 2022	Survey	Review discussed wireless body area network (WBAN), and how ML can be used to enhance the performance of this data centric networks	Paper summarized the categories of ML used in WBAN, and the design factors, i.e., power, accuracy, reliability, and scalability	Various applications of ML in WBAN were categorized into system optimization and collected data preprocessing
Seng et al. [22]	Machine learning and AI technologies for smart wearables, 2023	Review and comprehensive survey	Classification of smart wearables and research prototypes using machine learning and AI technologies	Smart wearables empowered by machine learning and AI; data collection of architectures; and applications for AI smart wearables	Significant technical challenges for AI smart wearables in networking and communication aspects

and gait disturbances. Dataset is retrieved from the Kaggle repository to execute AI-enabled IoT-CPS technology. For classification, AI-enabled IoT-CPS Algorithm is used to discover diseases. The experimental results demonstrate that compared with existing algorithms, the proposed AI-enabled IoT-CPS algorithm detects patient diseases and fall events in elderly more efficiently in terms of accuracy, precision, recall, and F-measure [25,31]. Hong et al. [27] introduced an AI-IoT-based solution (namely, wearable monitoring for human poster recognition (WMHPR)) that embeds with advanced AI-assisted approach. The WMHPR system includes multiposture recognition and an offline algorithm on wearable hardware to identify posture based on multidimensions data.

Muthu et al. [29] designed and developed a generalize approximate reasoning base intelligence control with regression rules to gather the information about the patient from the IoT and they used deep learning mechanism Boltzmann belief network. Subsequently Regularization _ Genome wide association study is used to predict diseases. The results achieved are significantly accurate and effective, the predicting rate is 96% and accuracy is 96.33% [29]. Advancement toward heart disease detection was conducted by Shafiq et al. [12], a smart e-health system for heart disease detection using artificial intelligence and the internet of things. The study used biosensor enabled stethoscope collects the heart sound of a patient and the heart sound signal is separated from other noises using the blind source separation algorithm. The PASCAL (The PASCAL visual object classes dataset is a well-known object detection, segmentation, and classification dataset) dataset is used to train and test the deep convolutional neural network. The study achieved the accuracy of deep convolution neural network is 98.4% and the precision of deep convolutional neural network (CNN) is 99% [12]. A study by Palanisamy et al. [23] aimed to track multiple COVID-19-related vital indicators using a wearable monitoring device with an IoT focus. The proposed system is built with three tiers of functionalities: a cloud layer using an application peripheral interface for mobile devices, a layer of wearable IoT sensors, and a layer of Android web for mobile devices. The efficiency of the model was successfully evaluated on the Kaggle dataset, is significantly higher than that of other cutting-edge deep neural models and it surpassed existing products in local and public datasets, achieving accuracy of 97.7%, precision of 96.8%, and an F-measure of 97.75% [23].

Wang et al. [9] designs wearable devices through the IoT and virtual reality technology, four daily physical parameters of the elderly, such as exercise heart rate, blood pressure, plantar health, and sleep function, are measured. The experimental results showed that the accuracy of the measurement method based on the reflective photoplethysmography signal was high. In the blood pressure measurements, the correlation coefficient between the *Prs* estimate and the reference value was 0.81. The estimation accuracy of the device used in the article was high, with the highest correlation coefficient of 0.96±0.02 for subjects' heart rate at rest, and its estimation error rate was 0.02±0.01 [9].

Table 3 summarizes different studies targeting adoption of AI and IoT based platforms in wearable systems, highlighting the main aim/area of each research, tools/techniques used and study outcomes.

Table 3 Summary of the studies and applications targeting adoption of AI and IoT in WHMS

References	Aim and area of study	Tools/techniques	Outcomes
Ramasamy et al. [25]	An AI-enabled IoT-CPS which doctors can utilize to discover diseases in patients based on AI. AI was created to find a few disorders such as diabetes, heart disease, and gait disturbances.	Study used four existing disease prediction algorithms, namely, Naïve Bayes, SVM, KNN, and ANN and compared with the proposed AI-enabled IoT-CPS algorithm in terms of accuracy, precision, recall, F-measure, and execution time	The experimental results showed the proposed AI-enabled IoT-CPS algorithm is more effective for diagnosing the patient's disease than existing algorithms in terms of accuracy, precision, recall, F-measure, and execution time
Hong et al. [27]	An AI-IoT-based solution that embeds with advanced AI-assisted approach	The WMHPR system includes multiposture recognition and an offline algorithm on wearable hardware to identify posture based on multidimensional data	Results show that the solution is significantly outstanding in terms of accuracy and reliability while comparing with other typical algorithms
Muthu et al. [29]	Generalize approximate reasoning based intelligence control with regression rules to gather information about the patient from the IoT	Train the data to the AI with the use of deep learning mechanism Boltzmann belief network. Subsequently Regularization _ Genome wide association study is used to predict the diseases.	The study achieved the predicting rate is 96% and accuracy is 96.33%. IoT (internet of things) in data mining-big data analytics is connected to service providers or hospitals.
Shafiq et al. [12]	A smart e-health system for heart disease detection using artificial intelligence and the internet of things	The study used biosensor enabled stethoscope collects the heart sound of a patient and used the PASCAL data set to train and test the deep convolutional neural network	The accuracy of deep convolution neural network is 98.4% and the precision of deep CNN is 99%
Palanisamy et al. [23]	The study aimed to track multiple COVID-19-related vital indicators using a wearable monitoring device with an IoT focus	The proposed system is built with three tiers of functionalities: a cloud layer using an application peripheral interface for mobile devices, a layer of wearable IoT sensors, and a layer of android web for mobile devices	The efficiency of this model, which was successfully evaluated on the Kaggle dataset, achieved accuracy of 97.7%, precision of 96.8%, and an F-measure of 97.75%
Wang et al. [9]	Study designs wearable devices through the internet of things technology and virtual reality technology	Four daily physical parameters of the elderly, such as exercise heart rate, blood pressure, plantar health, and sleep function, are measured	The estimation accuracy of the device used in the article was high, with the highest correlation coefficient of 0.96±0.02 for subjects' heart rate at rest

5 Discussion and Conclusions

5.1 Challenges and Barriers Related to the Wearable Heath Monitoring System and Internet-of-Thing Application. Integrating Gen AI into wearable health and IoT applications holds great promise but also comes with a range of challenges and barriers. These issues need to be addressed to ensure the technology is effective, secure, and widely accepted. Table 4 lists the key challenges and barriers, approach and action plan and key pointers toward addressing the challenges.

Integrating Gen AI with wearable health and IoT applications offers immense potential but requires careful consideration of various challenges and barriers. Addressing these issues through robust security measures, standardization, user education, and ethical practices will be crucial to unlocking the full benefits of these advanced technologies [8,9,17,30,36–39].

5.2 Key Finding. Wearable Health Monitoring and Personalized Patient Care Plans: Studies demonstrated that Gen AI could

Table 4 Summary of challenges, action items, and pointers for addressing the challenges toward better adoption of the WHMS and IoT applications integrated with Gen AI

Improvements/challenges	Challenge	Approach/action points	Addressing the challenges	Studies in this area
Data privacy and security	Wearable health devices and IoT applications collect a vast amount of sensitive personal data, including health metrics, location, and daily activities. Ensuring this data are protected from breaches and unauthorized access is critical.	Adhering to regulations such as GDPR, HIPAA, and other data protection laws can be complex and vary by region. Companies must navigate these legal requirements to ensure compliance.	Implementing strong encryption methods to protect data both in transit and at rest. Strict access controls and regular audits to prevent unauthorized data access. Federated learning approaches through decentralized training models can enhance privacy.	Ref. [32]
Interoperability and standardization	Wearable devices and IoT systems come from various manufacturers with different standards and protocols. Ensuring seamless interoperability between devices and platforms is challenging.	Integrating data from multiple sources (e.g., wearables, home IoT devices, medical records) into a cohesive system that Gen AI can effectively analyze is complex	Promoting the use of open standards (IEEE) and protocols to facilitate interoperability. Encouraging collaboration between device manufacturers, software developers, and healthcare providers.	Refs. [33] and [34]
Data quality and accuracy	The effectiveness of Gen AI depends on the accuracy of the data collected by wearable sensors and IoT devices. Inaccurate or inconsistent data can lead to incorrect insights and recommendations.	Variability in data due to differences in device calibration, user behavior, and environmental conditions can affect the performance of AI algorithms	Regular calibration and validation of sensors to ensure data accuracy. Implementing robust data cleaning and preprocessing techniques.	Refs. [5] and [35]
Algorithmic bias	AI algorithms can inherit biases present in the training data, leading to unfair or inaccurate predictions and recommendations. Ensuring fairness and mitigating bias is crucial, especially in health applications.	AI models must be trained on diverse datasets to ensure they are applicable to different populations and do not favor one group over another	Training AI models on diverse datasets to minimize bias. Regularly auditing AI models for bias and implementing corrective measures.	Refs. [11] and [13]
Transparency and confidence	Users need to understand how their data are being used and how AI-driven insights and recommendations are generated. Lack of transparency can lead to distrust.	Encouraging consistent use of wearable devices and adherence to AI-generated recommendations can be challenging. Users need to see clear benefits and value in using these technologies.	Providing clear information and education about the benefits and functioning of AI-driven systems. Implementing feedback mechanisms to continuously improve user experience.	Refs. [14] and [15]
Technology	Gen AI models require significant computational power, especially for real-time analysis. Ensuring sufficient infrastructure to support these demands is essential.	For applications requiring real-time decision-making (e.g., WHMS and IoT), minimizing latency in data processing and AI response is critical	Utilizing edge computing to process data closer to the source, reducing latency. Investing in scalable infrastructure to handle computational demands.	Refs. [16] and [17]
Ethics	Ensuring that users are fully informed about what data are being collected and how it will be used is crucial. This includes obtaining explicit consent.	Determining who is accountable for decisions made by AI systems, especially in critical health applications, is a complex issue	Developing clear policies and guidelines for ethical and responsible AI use. Ensuring transparency in AI decision-making processes.	Refs. [36–38]
Accessibility	Costs associated with advanced wearable devices and AI systems can be a barrier for widespread adoption, particularly in low-resource settings	Ensuring equitable access to these technologies across different socioeconomic groups is a significant challenge	Developing cost-effective solutions to make wearable and IoT technologies more accessible. Designing inclusive technologies that consider the needs of diverse user groups.	Refs. [17] and [39]

predict health events by analyzing continuous data from wearables devices and IoT devices like smartwatches, glucose monitors, and various health and well-being sensors. Gen AI models provided tailored advice on physical activity, diet, and sleep, leading to improved health outcomes and user satisfaction. Several studies reported wearables and IoT devices were used for elderly care, with AI detecting falls and unusual patterns, thereby alerting caregivers in real-time. Moreover, studies also investigated the concept of gamification and real-time feedback through Gen AI to increase user engagement and adherence to personalized programs [16–20,40–42].

There are several challenges need to be addressed for wider adoption and integrating of Gen AI with wearable and IoT applications, data privacy and security were significant concerns, especially regarding health data, including consent, audit, sharing of data and responsible use of AI [8,14,17,29,30].

5.3 Future Directions. Moving AI processing closer to the data source (e.g., on the wearable device itself) can reduce latency and improve real-time decision-making. This is particularly useful for critical health and safety applications. Moreover, robust integration with electronic health records and healthcare providers can enhance the usefulness of data collected by wearables, allowing for more comprehensive and coordinated care.

Continued advancements in AI algorithms will improve the predictive capabilities of these systems, enabling even more proactive and personalized interventions [11,13–15].

The integration of Gen AI with wearable and IoT applications holds significant promise across various domains, particularly in health monitoring, personalized wellness, and supporting activities of daily life. While there are considerable benefits, addressing challenges such as data privacy, interoperability, and user trust is crucial for broader adoption. Future research and scientific investigations should focus on improving data quality, developing ethical AI frameworks, interoperability, standardization, and fostering regulatory harmonization to realize the full potential of these technologies [16,43–45].

Data Availability Statement

No data, models, or code were generated or used for this paper.

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