Ghadi *et al. Journal of Cloud Computing* (2025) 14:39
https://doi.org/10.1186/s13677-025-00759-4

Journal of Cloud Computing

REVIEW

Open Access

Integration of wearable technology and artificial intelligence in digital health for remote patient care

Yazeed Yasin Ghadi[1], Syed Faisal Abbas Shah[2], Wajahat Waheed[3], Tehseen Mazhar[4,5*], Wasim Ahmad[6], Mamoon M. Saeed[7*] and Habib Hamam[8,9,10,11]

Abstract

Wearable technology has transformed patient care in the digital health era, offering real-time health monitoring and personalized interventions. However, its full potential is hindered by several challenges, such as data privacy breaches due to insecure transmission of sensitive vitals, poor integration with electronic health records (EHRs), and limited adoption among older populations with low digital literacy. Additionally, the vast volume of real-time health data from wearables leads to data overload and usability issues in clinical settings.

To address these issues, this study identifies and categorizes key barriers to wearable technology adoption and proposes targeted AI-driven solutions. We evaluate methods such as federated learning for privacy, deep learning for noise filtering in EEG data, and real-time anomaly detection to support clinical decision-making. The outcomes show improved data accuracy, reduced workload for healthcare providers, and increased patient engagement and trust.

Moreover, the integration of blockchain with AI is explored to support secure, interoperable, and decentralized healthcare systems. Our work provides a structured, literature-based roadmap that links specific AI methods to clearly defined clinical challenges in remote patient care. This contribution supports developers, clinicians, and policymakers by offering practical insight into scalable and ethically grounded AI-wearable integration. Continued collaboration between technologists, healthcare professionals, and policymakers is essential to ensure scalable, equitable, and secure digital health implementations.

Keywords Digital health, Wearable devices, Patient, Artificial intelligence, Healthcare

*Correspondence:
Tehseen Mazhar
tehseenmazhar719@gmail.com
Mamoon M. Saeed
dr.mamoon@ums-edu.com
[1]Department of Computer Science and Software Engineering, Al Ain University, Abu Dhabi 12555, United Arab Emirates
[2]Département of Computer Science & Information Technology, Virtual University of Pakistan, Lahore 54000, Pakistan
[3]Department of Electrical and Computer Engineering, Purdue University, Indiana 46323, USA
[4]School of Computer Science, National College of Business Administration and Economics, Lahore 54000, Pakistan
[5]Department of Computer Science and Information Technology, School Education Department, Government of Punjab, Layyah 31200, Pakistan
[6]Department of Computing, School of Arts and Creative Technology, University of Greater Manchester, Manchester BL15AB, UK
[7]Department of Communications and Electronics Engineering, Faculty of Engineering, University of Modern Sciences (UMS), Sana'a 00967, Yemen
[8]Faculty of Engineering, Uni de Moncton, Moncton, NB E1A3E9, Canada
[9]School of Electrical Engineering, University of Johannesburg, Johannesburg 2006, South Africa
[10]International Institute of Technology and Management (IITG), Av. Grandes Ecoles, Libreville BP 1989, Gabon
[11]College of Computer Science and Eng.(Invited Prof..), University of Ha'il, Ha'il 55476, Saudi Arabia

Introduction

Context

Artificial Intelligence (AI) refers to the simulation of human intelligence processes by machines and allows computers to accomplish tasks that involve human intelligence, including learning, understanding language, reasoning, problem-solving, and perception [1]. It uses machine learning, natural language processing, and computer vision technologies to process and analyze data. AI systems can learn and become better over time by learning from experience and adapting. AI is frequently used in processing a massive amount of medical data to help with diagnosing diseases, suggesting treatments, as well as continuously monitoring patients through wearable devices [2].

Digital health is the use of digital technologies such as wearable devices, mobile applications, and features and methods of AI to enhance healthcare delivery and the health of patients. Digital wearable devices aim to improve patient outcomes, optimize healthcare services, and encourage individualized care [3]. Remote patient care enables healthcare professionals to deliver care to patients at a distance through technologies such as telemedicine, wearable devices, and mobile health tools. It assists doctors in monitoring, motivating, and treating patients without the need for an in-person visit, enhancing access and comfort, especially in remote areas [4].

Wearable technology refers to any electronic device that is worn on a person's body to collect, send, and display data in real-time. These include devices like fitness trackers, smartwatches, smart glasses, and wearable electroencephalography (EEG) devices. These technologies help keep track of health metrics such as steps, sleep, heart rate, and brain activity. Most wearables connect to mobile applications and online cloud platforms for processing data and insights [5]. These devices are used in healthcare, fitness, and daily life for convenience, improvement, and well-being. Wearable technology combines innovation and functionality to enhance user experience and connectivity.

Wearable EEG devices have gained significant attention in digital health due to their ability to monitor brain activity in real-time. These devices capture electrical signals from the scalp, enabling applications in cognitive assessment, mental health monitoring, neurological disorder detection, and brain-computer interface (BCI) applications. AI plays a crucial role in processing EEG signals by filtering noise, detecting patterns, and providing predictive analytics for medical conditions such as epilepsy, sleep disorders, and mental health conditions like depression and anxiety [6].

Wearable technology and mobile health technology are related in that both seek to improve healthcare through the use of digital tools for monitoring and enhancing health. These devices collect real-time data from users, including factors such as vital signs, cognitive states, or activity levels for analysis and decision-making [7]. These technologies are frequently connected to mobile devices and apps to offer insights and feedback. They promote remote patient care, enabling users to manage their health without needing constant physical visits to healthcare providers. Together, they improve access to personalized and continuous healthcare solutions [8].

Globally, the uptake of wearable health technology has grown rapidly. For instance, the UK's National Health Service (NHS) has launched digital monitoring programs using smartwatches to track atrial fibrillation and heart failure among elderly patients [9]. In the United States, companies like Apple and Fitbit are partnering with hospitals to deliver integrated remote monitoring solutions supported by AI for cardiac and diabetic patients [10]. In Asia, China's Ping An Good Doctor platform and India's Apollo Hospitals have implemented AI-powered wearable solutions for teleconsultation and chronic disease monitoring at national scale [11, 12]. These examples highlight the global relevance and application of AI-integrated wearable devices in enhancing digital health.

Using the Object Storage architecture, this article [13] presents a cloud-based electronic health record (EHR) system storing medical data. Authorized medical professionals can access the system automatically and securely, therefore enabling quicker delivery of health services in emergencies. The suggested approach is assessed to back its justification, and the results are shared. This study [14] was done to find the degrees of relevance and use that healthcare apps have depending on their degree of usability. Medical institutions run nonstop to give patients at any time of the day or night care. A thorough examination and analysis of the features of several different COVID-19 mobile apps were offered for this study. The evaluation was done using both the Google Play Store and the Apple App Store, which are both mobile device compatible. To determine the authenticity and reliability of the apps accessible on these sites, Google conducted several more keyword searches.

The use of wearable technology in remote patient healthcare has a lot of challenges, including data privacy and security issues as sensitive health information is prone to breaches. Accuracy and reliability of data remain concerns, with inconsistencies potentially leading to false alarms or missed warnings [9]. Existing interoperability and standardization gaps make integration with existing healthcare systems challenging [10].

High costs and limited accessibility can exclude low-income or rural populations, while patient compliance and digital literacy hinder widespread adoption [11]. The implementation is also hampered by ethical and legal questions like data ownership and liability. Overcoming these challenges is essential for the full functionality of wearable technology for remote healthcare.

AI improves reliability by filtering noise and finding patterns in data collected using wearables for clinical use. It facilitates predictive analytics to identify potential health problems before they occur, enabling early-stage interventions while also minimizing false alarms [12]. AI-driven algorithms ensure data encryption and privacy, addressing security concerns. AI plays a vital role in reducing the burden on healthcare practitioners by automating processes to make vast amounts of data more manageable and actionable [15]. Moreover, AI engages patients by offering personalized recommendations, enhancing compliance and adoption. Overall, AI bridges gaps in accuracy, security, and efficiency, making wearable technology more effective for remote healthcare [16].

Recent advancements in the Internet of Medical Things (IoMT) have further reinforced the role of wearable technology in digital healthcare. IoMT enables the integration of interconnected medical devices with healthcare networks, allowing real-time acquisition, transformation, and interoperability of patient data. For instance [17], proposed an HL7 FHIR-compliant platform that leverages 5G network slicing to process IoMT data with reduced latency and improved interoperability. Similarly [18], demonstrated the use of edge and cloud computing platforms for deploying e-health applications in IoMT environments, comparing performance in terms of delay and computational efficiency. These developments highlight the relevance of IoMT as a foundational layer supporting the secure, scalable, and responsive deployment of AI-enhanced wearable systems for remote patient monitoring.

Apart from solving these issues, this article [19] offers a data cleansing tool ensuring data accuracy and reliability regardless of its origin. The three distinct components of the system govern the processes for collecting, storing, and cleaning data. Using proven data cleaning techniques, the four stages—"Cleaning," "Verification," "Logging," and "Validation"—ensure a thorough and efficient data cleaning process.

One major challenge blockchain technology could help MEC to overcome is the restricted use of Internet of Things (IoT) medical device applications. This paper [20] provides a comprehensive analysis of healthcare devices using the IoT in order to provide patients answers in real time. The paper looks at the main ways 5G and mobile edge computing (MEC) have enhanced healthcare. The next part of the paper looks at how 5G and MEC networks restrict the IoT medical device sector, especially with respect to the use of distributed computing technologies.

Wearable technology is a game-changer for remote patient care, especially when combined with AI and mHealth. It increases monitoring, enhances patient outcomes, decreases healthcare costs, and solves challenges of accessibility and many other issues [21]. However, tackling challenges such as data privacy, accuracy, and integration will be key to unlocking the true potential of AI. Figure 1 shows the structure of the paper. As these technologies continue to evolve, they will play an increasingly vital role in shaping the future of digital health.

This work offers several key contributions by identifying the technical and practical barriers to adopting AI-integrated wearable systems for remote healthcare. It presents a detailed mapping of AI-driven solutions—including federated learning, deep learning for EEG processing, and blockchain integration—to address specific issues such as data privacy, signal noise, and interoperability. However, this study also recognizes its limitations. While based on extensive literature and recent applications, the analysis is primarily qualitative and lacks a unified experimental framework. Further empirical validation through clinical pilot studies or real-time deployment would be needed to confirm scalability and real-world effectiveness. Despite these limitations, the findings provide actionable insights for researchers and policymakers aiming to improve the adoption and functionality of wearable health technologies.

Rationale for sector and technology selection

This research focuses on wearable technology in remote patient care because this sector represents one of the fastest-growing and most impactful areas within digital health. The growing burden of chronic diseases, aging populations, and healthcare access gaps especially in rural and underserved regions have made continuous, non-invasive, and AI-assisted remote monitoring a global priority. Wearables offer scalable solutions for early diagnosis, real-time health tracking, and personalized interventions. These benefits directly address pressing healthcare delivery challenges and align with current trends in smart healthcare systems worldwide.

The technologies selected in this study namely deep learning, federated learning, blockchain, and wearable EEG were chosen based on their proven potential to address key limitations in remote patient monitoring. Deep learning models offer high accuracy for real-time physiological signal analysis. Federated learning enhances privacy by enabling model training without centralizing patient data. Blockchain ensures secure, tamper-proof data exchange across decentralized healthcare environments. Wearable EEG devices were prioritized due to their ability to capture cognitive and neurological signals non-invasively, supporting use cases in mental health and neurological disorders. These technologies satisfy critical requirements of interoperability, data protection, and

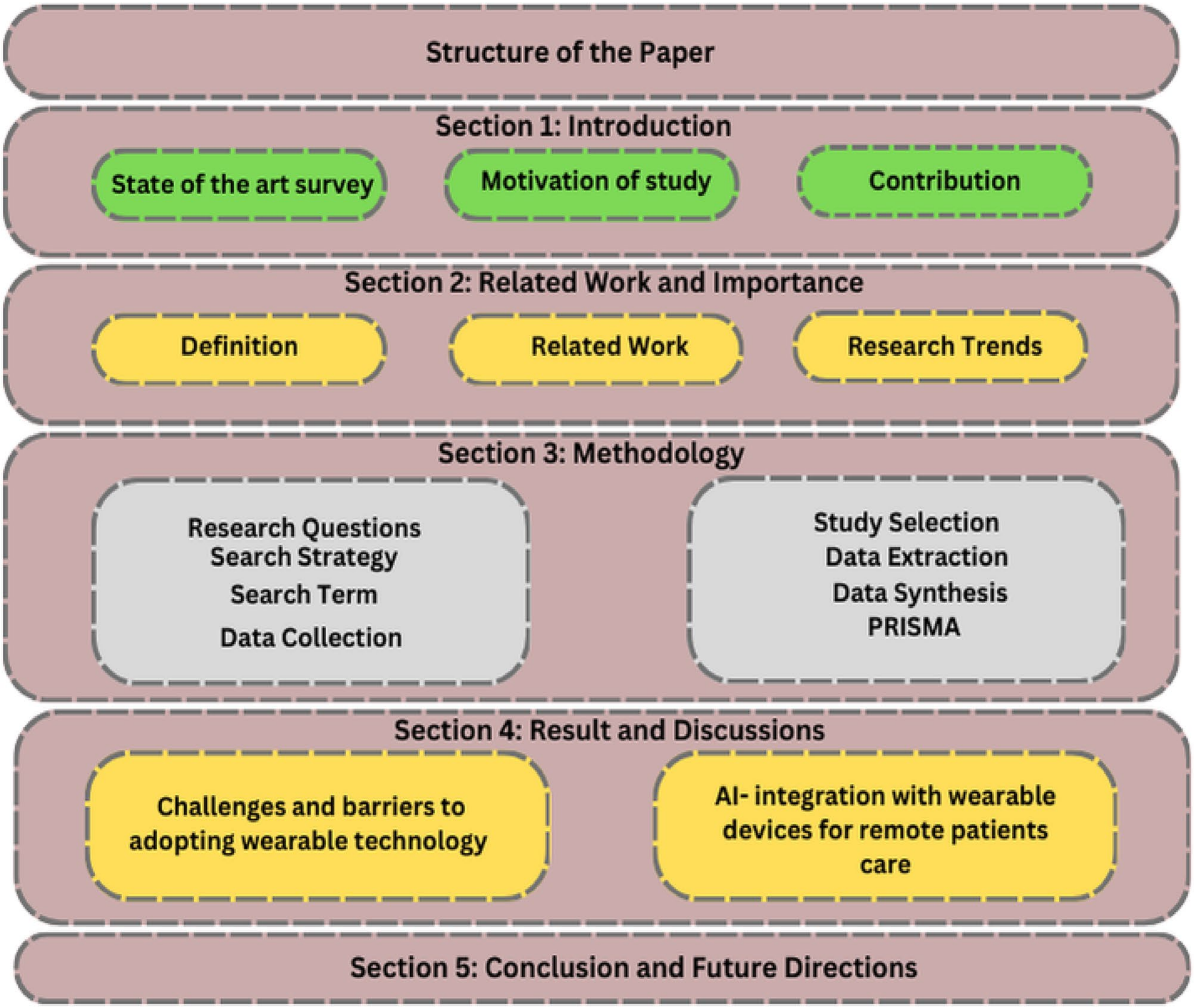

Fig. 1 Structure of the paper

clinical scalability making them highly suitable for real-world deployment in smart healthcare systems.

Scientific contribution

The contribution of this article is outlined in the subsequent sections:

1. This study demonstrates how wearable technology and AI can revolutionize remote patient care by allowing for continuous monitoring, personalized interventions, and improved patient outcomes.
2. This study outlines the key barriers to adoption, from data privacy issues to interoperability challenges to resistance from patients and providers.
3. It suggests actionable AI-powered solutions like federated learning, and interoperable platforms to address challenges including data security and system integration.
4. It describes potential future directions for research, such as solutions that emphasize more inclusive AI algorithms, better regulatory frameworks, and longitudinal studies.
5. The study highlights the need for collaboration among technologists, healthcare professionals, and policymakers to navigate these challenges and foster innovation in digital health for remote patient care.

Composition of the Article

The remainder of the article is summarized as follows. "Related work" section provides an overview of related work. "Methodology" section details the methodology for wearable technology and integration of AI-based techniques and research questions to solve different challenges faced by wearable technology for remote patient care. "Result and discussions" section presents the experimental results for challenges faced by wearable technology and different AI based solutions are provided. Finally, "Conclusion and future directions" section concludes the paper and discusses future direction. And Sect. 6 is the references section.

Related work

Related work on the impact of wearable technology using AI and mHealth in digital health highlights its transformative potential for remote patient care. Research shows that AI-integrated wearables allow continuous monitoring of health factors, leading to better early identification of many diseases. The research emphasizes that mHealth applications enhance the support of patient engagement with tailored feedback and reminders. Yet, different challenges like data privacy, precision, and interoperability persist as enormous barriers. Other aspects of investigation include analyzing AI-centered analytics that has the potential to bring healthcare costs down by reducing unnecessary hospital visits and facilitating early intervention. Wearable technology shows potential in improving access to healthcare in rural and underserved areas of the country. Overall, existing literature focuses on the need for robust frameworks to address ethical, technical, and accessibility concerns in this evolving field [22].

Importance of online healthcare for remote patient care

Wearable devices are transforming online healthcare by supporting real-time monitoring of patients and personalized care in multiple medical disciplines. These technologies enable the wide-scale collection of health data, empowering patients to monitor their health and supporting clinical decision-making [23]. The subsequent section summarizes the key points of wearable devices in inpatient treatment. As mentioned in Fig. 2 wearable devices and digital health for remote patient care remote patient monitoring tools are revolutionizing chronic disease management, providing a means for real-time tracking of health metrics and conditions which helps patients achieve better outcomes and, of course, helps to lower direct and indirect costs through proactive health management [24].

Mostly used wearable devices in remote patient care are smartwatches and fitness trackers. These devices track a variety of vital signs, such as heart rate, physical activity levels, and sleep patterns, and, in newer models, electrocardiogram (ECG) data [25]. By integrating these devices with mobile applications, healthcare providers can remotely monitor patients' daily routines and physiological parameters, thus providing valuable information about their health status and allowing timely interventions when necessary.

Wearable ECG monitors offer continuous, real-time heart data to healthcare providers to help detect arrhythmias, heart disease, and other cardiovascular conditions [26]. These devices are very useful for patients who already have heart conditions and need continuous

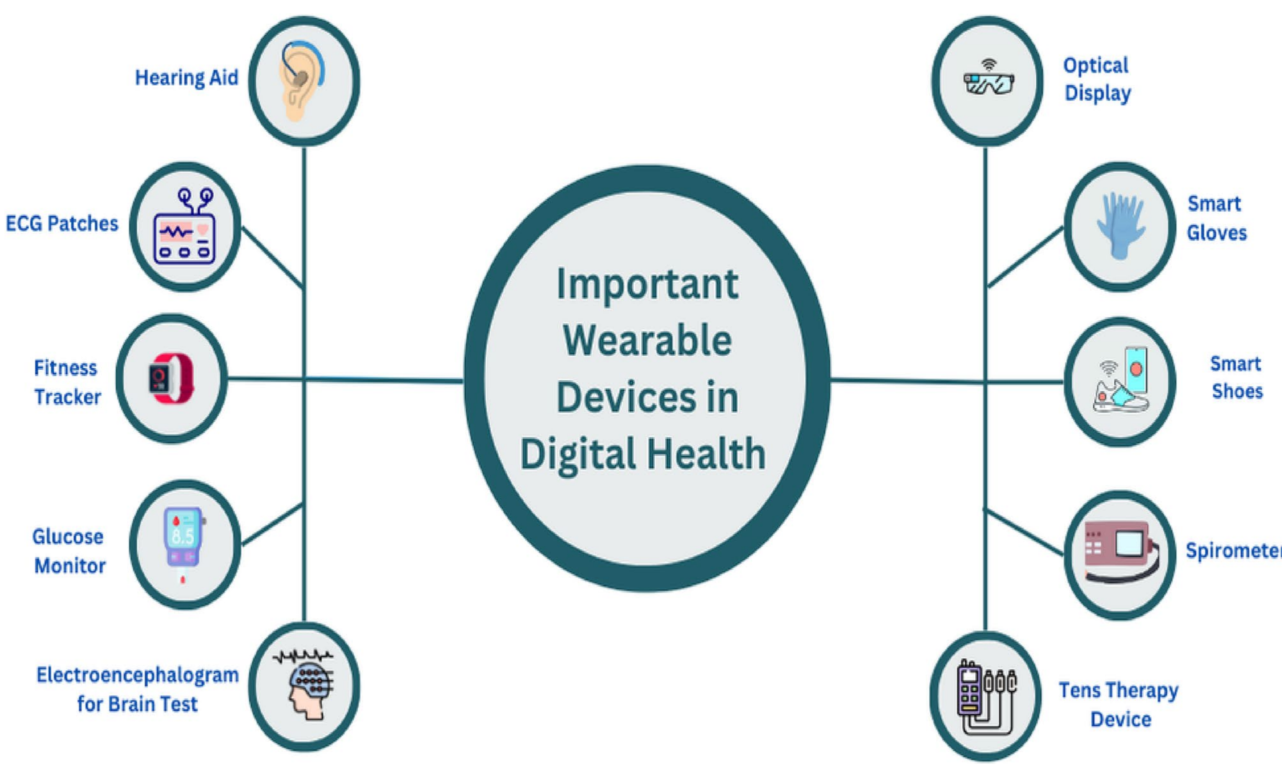

Fig. 2 List of all important wearable devices in digital health for remote patient care

monitoring. Wearable ECG monitors facilitate early identification of abnormal heart activity with direct accessible connection between the patient and healthcare professionals, allowing to avoid unnecessary hospital admissions and distant patients finding it accessible [27].

The importance of Blood pressure monitoring is a critical aspect of managing cardiovascular patient health, particularly for those with hypertension. Traditional blood pressure measurement methods that require patients to go to a healthcare provider for appointments may not accurately represent the fluctuations in blood pressure that occur throughout the day [28]. Wearable blood pressure monitors devices overcome this limitation by enabling patients to monitor blood pressure for longer durations in their everyday environments [29].

Continuous glucose monitoring (CGM) devices are essential for patients with diabetes to manage their blood glucose levels. These devices provide real-time glucose readings and alerts when a patient may be experiencing hyperglycemic events [30]. These devices are usually worn on the skin and provide a constant reading of glucose levels throughout the day, sending information to mobile applications and healthcare providers. For diabetic patients, CGMs enable real-time changes to their insulin regimens, diet, and lifestyle [31].

Wearable respiratory monitors can be particularly useful for patients with chronic respiratory conditions, like chronic obstructive pulmonary disease (COPD), helping them track lung function and manage flare-ups [32]. These devices offer the ability to collect real-time respiratory metrics, which measure breathing patterns, respiratory rate, and oxygen saturation levels. Such wearables in practice will notify patients and healthcare providers when their respiratory problems are getting worse, enabling early correction of the problems and preventing hospitalization [33].

Sleep disorders are common and potentially disruptive to human health. Wearable sleep monitors record the quality of precise metrics for sleep cycles. These devices help patients and their healthcare providers identify potential sleep disorders, such as sleep apnea or restless leg syndrome, by continuously tracking their sleep patterns [34].

Patients with chronic pain conditions such as fibromyalgia, arthritis, or neuropathy could follow fitness advice by using wearable devices. Such devices usually employ transcutaneous electrical nerve stimulation (TENS) technology, delivering gentle electrical pulses to the surface of the skin for targeted pain relief. With the usage of these devices all day or overnight, patients can control pain without using oral medications or making regular clinical visits [35].

To better contextualize the contributions of this study, Table 1 presents a comparison of selected related works that explore the integration of wearable technology, AI, and IoMT in digital health. The comparison highlights the objectives, methodologies, technologies used (e.g., AI models or IoMT frameworks), and identified limitations.

Additionally, Fig. 3 provides a conceptual summary of the functionality of the reviewed methods, outlining their focus on data acquisition, processing, privacy, and clinical application.

Data from several nations supports the recognition of social distancing and self-quarantine as standard procedures during the COVID-19 epidemic. AI's ability to fight COVID-19 is hampered by past restrictions on model accuracy, integration with human knowledge, and other technologies like IoT, as well as the need for continuous updates. Moreover, hospitals and healthcare providers should give patient transfer control top priority, particularly in light of the significant impact of COVID-19 on the supply chain generally [38].

One of the most important qualities of support vector machines (SVM) is their capacity to manage high-dimensional and non-linear data patterns. This feature is accomplished using the kernel trick, which converts the data into a higher-dimensional space where it becomes linearly separable [39]. The ensemble learning method Random Forest is made up of several decision trees. Accurate predictions are produced by training each tree

Table 1 Comparison of selected related works

Ref	Focus Area	Technologies Used	Key Contribution	Limitation
[17]	IoMT Data Interoperability	HL7 FHIR, 5G slicing	Transforms IoMT data into HL7 format via 5G slices	Requires full 5G infrastructure
[18]	Cloud vs. Edge IoMT Deployment	IoMT, Edge, Cloud, SVM, KNN	Shows edge computing reduces latency in IoMT apps	No exploration of integration with EHRs
[6]	Wearable EEG for cognitive states	EEG wearables, signal processing	Assesses mental states with commercial EEG headbands	Limited to experimental studies
[36]	Seizure Prediction	Deep learning (multi-CNN), iEEG	Accurate early seizure detection	Requires specialized EEG hardware
[37]	Privacy in Remote Patient Monitoring	Blockchain, Smart Contracts, AI	Real-time malicious node detection using LSTM	Not evaluated in real clinical settings
Our Work	AI & Wearables for Remote Patient Care	AI (DL, FL), EEG, Blockchain, IoMT	Maps AI methods to healthcare challenges and proposes solutions	No empirical validation (literature-based synthesis)

Fig. 3 Functional architecture of reviewed methods integrating wearable technology, AI, and IoMT for Remote Patient Care

with bootstrap sampling—a method of randomly selecting a portion of the data—and majority voting. Among Random Forest's key advantages in data analysis are its capacity to lower overfitting and its resilience to noisy data [40].

Numerous studies have examined the ways in which patient care, healthcare IT, and innovative solutions can collaborate to enhance accessibility and outcomes. In a seminal study [41], examined the barriers to the Sehaty mobile health app's widespread use, especially among those with chronic illnesses. The results raise issues related to technical performance, privacy, and user interface design. The study's conclusions have significant ramifications for the creation of mobile health platforms that are safer, more reliable, and easier to use. As a result, users will be happier and more involved with the platform.

The effect of digital healthcare platforms on patients' decision-making processes is examined by [42]. Their research focuses primarily on how hospital ratings and reviews affect patients' decisions to seek medical care in various regions. The findings underscore the significance of optimizing these systems to enhance healthcare equity and empower marginalized populations to make more informed choices.

In a study [43], suggested a data-driven strategy for preventing pressure injuries in the elderly by utilizing electronic medical records. Furthermore, it identifies critical components that aid in the detection and prevention of pressure injuries that arise in the community, which greatly improves patient safety and clinical practice.

Artificial intelligence and its impact on healthcare for patient care

AI is used to perform tasks that generally require human intelligence. AI includes different areas such as machine learning (ML), natural language processing (NLP), robotics, and computer vision [44]. In the field of healthcare, AI can improve patient outcomes, drive further efficiency in operational processes, and bring greater personalisation. AI's integration into specialization support is particularly powerful for specialists, which aids in diagnostic accuracy, clinical decision support, treatment management, and patient management [45]. As described in Fig. 4 AI has the most impressive applications in the area of digital health and remote patient management, continuous monitoring, and early-detection opportunities, along with improved, increased access to services. The use of AI in diagnostic tools is one of the most impactful applications of AI in healthcare [46]. Machine learning algorithms, especially Deep learning algorithms, have been trained on massive datasets of medical images, electronic health records (EHRS), and genomic data to promote early disease and condition detection that otherwise could be detected [47].

Through advances in genetics and genomics, personalized medicine seeks to make medicine specifically for each patient according to the interplay of their unique genetic, environmental, and lifestyle factors. AI plays an important role in the development of personalized treatment regimens by analyzing vast amounts of data to predict how patients will respond to different treatments [48]. AI can analyze genetic data to pinpoint specific mutations that may impact the efficacy of particular medicines. AI has been used to develop precision oncology treatments, customized based on the genetic profile of an individual's cancer cells in oncology. This reduces the trial-and-error process traditionally used in cancer treatments, finding patients the most effective therapies sooner [49].

Digital health refers to the use of digital technologies for health care management and public health. AI has been a vital component of remote monitoring of patients, allowing continuous tracking of health, early warning systems, and remote consultations [50]. This is particularly strategically advantageous for patients with chronic illness or those who live in remote or underserved regions where healthcare access may be greatly restricted. Wearable devices like smart watches, fitness trackers, and biosensors are increasingly utilized for remote patient management. This technology allows patients to remotely monitor their vitals like heart rate, blood pressure, and oxygen level, with the result sent, via secure digital platforms, to healthcare professionals [51].

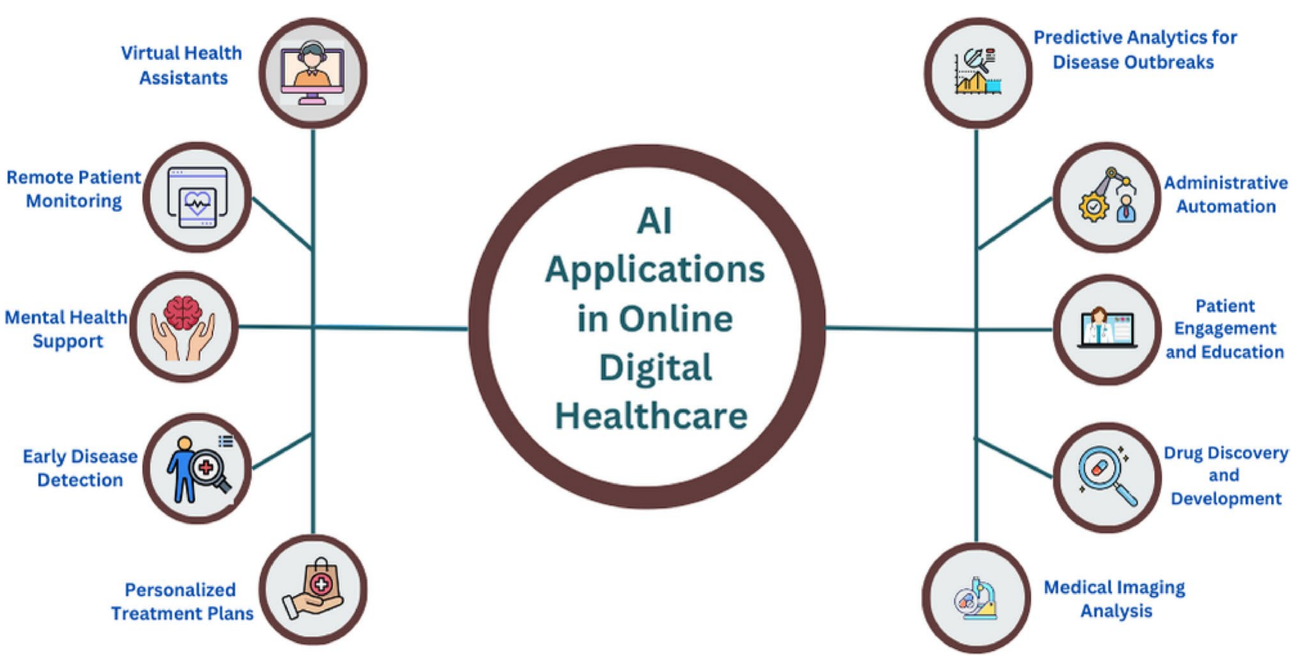

Fig. 4 Applications of AI in healthcare

AI-based Clinical Decision Support Systems (CDSS) help clinicians make evidence-based decisions about diagnosis, treatment, and follow-up [52]. These systems evaluate patients' clinical data and offer evidence-based suggestions based on the current medical knowledge and the individual patient's circumstances. Incorporating AI into clinical workflows can help healthcare providers improve diagnostic accuracy, minimize errors, and enhance patient outcomes [53].

Another remarkable application of technology in the medical industry is robotic surgery, augmented with AI. AI algorithms guide robotic systems while performing surgery with more precision and less chance of human error. The robotic system is particularly helpful in minimally invasive procedures, wherein the surgeon makes small incisions, contributing to faster recovery times, less pain, and fewer complications [54].

Integration of wearable EEG technology and artificial intelligence in digital health for remote patient care

Wearable EEG devices have emerged as a transformative technology in digital health, particularly in remote neurological monitoring and BCI applications. EEG devices measure brainwave activity by capturing electrical signals from the scalp, providing valuable insights into cognitive states, neurological disorders, and mental health conditions. Unlike traditional research-grade EEG systems, wearable EEG devices offer portability, ease of use, and real-time data transmission, making them suitable for continuous patient monitoring outside clinical settings [6].

Applications of wearable EEG in digital health

Brain-Computer Interfaces (BCI) One of the most significant applications of wearable EEG is in BCI, enabling direct communication between the brain and external devices. BCI systems leverage EEG signals to assist individuals with motor disabilities, enabling them to control prosthetic limbs, wheelchairs, and even digital applications through motor imagery (MI) tasks [55, 56]. Recent advances in deep learning models have enhanced the classification of MI tasks, improving the accuracy of BCI systems [55]. CNNs and ANNs have been applied to EEG signal processing, demonstrating promising results in decoding user intentions with increased precision [56].

Seizure detection and epilepsy monitoring Wearable EEG devices play a crucial role in epilepsy monitoring and seizure prediction. By continuously recording brain activity, these devices allow for early detection of seizure onset, providing critical alerts for timely intervention. AI-driven approaches, particularly deep learning models such as multi-CNN architectures, have been developed to improve the accuracy of seizure prediction using intracranial EEG (iEEG) signals [36]. These methods achieve high classification performance, with accuracy levels exceeding 95%, demonstrating the potential of AI-integrated wearable EEG devices for real-time neurological monitoring [36].

Cognitive and mental health assessment

Consumer-grade wearable EEG devices have been increasingly used for mental health monitoring, cognitive performance tracking, and neurofeedback applications. These devices assess brain activity patterns related to stress, anxiety, focus, and sleep quality. Neurofeedback training, powered by AI algorithms, enables users to regulate their cognitive states, contributing to stress reduction and cognitive enhancement [6]. Wearable EEG headbands such as Emotiv, NeuroSky, and Muse have been employed in experimental research, demonstrating their efficacy in detecting affective states and cognitive workload levels [6].

AI-driven signal processing in wearable EEG

One of the primary challenges in wearable EEG technology is the low signal-to-noise ratio (SNR), as these devices often have fewer electrodes than clinical EEG systems. Advanced AI techniques, including wavelet packet decomposition (WPD), common spatial pattern (CSP) feature extraction, and deep learning-based classification, have been developed to improve EEG signal interpretation [55, 56].

For instance, studies have shown that employing CNN architectures with optimized spatial and temporal feature extraction methods can significantly enhance EEG-based classification performance for both BCI and medical applications [52]. Furthermore, AI-based artefact removal techniques, such as Independent Component Analysis (ICA) and adaptive filtering, have improved the reliability of EEG signal processing in mobile environments [57].

Challenges and future directions

Despite the potential of wearable EEG devices in remote neurological monitoring and AI-enhanced diagnostics, several challenges must be addressed:

- Data Quality and Noise: Motion artefacts and environmental interference reduce EEG signal reliability.
- Limited Electrode Coverage: Fewer electrodes in consumer-grade EEG devices limit spatial resolution.
- Regulatory and Privacy Concerns: The transmission of neural data raises significant security and ethical issues.

Future research should focus on enhancing AI-driven noise reduction, integrating multimodal biosensors (e.g., EEG +ECG), and developing secure data-sharing frameworks to expand the clinical applicability of wearable EEG devices [6, 36].

Recapitulation
The integration of wearable EEG technology and AI represents a significant advancement in digital health and remote patient care. AI-driven EEG analysis enhances neurological monitoring, mental health assessment, and BCI applications, making these devices a valuable tool for continuous and personalized healthcare. Incorporating EEG wearables into the broader landscape of wearable health technology will pave the way for more efficient, real-time, and patient-centered medical solutions.

Methodology
The research steps followed in this study were guided by a problem-driven approach grounded in a review of current literature and implementation gaps in AI-assisted wearable healthcare. We began by identifying major recurring challenges such as data noise, privacy risks, and integration issues based on recent studies in digital health. These insights shaped our selection of technologies and techniques, including wearable EEG for brain signal monitoring, deep learning for real-time pattern recognition, federated learning for privacy preservation, and blockchain for secure data handling. Each step of the methodology reflects a direct response to a documented clinical or technical limitation, aiming to construct a cohesive and adaptable solution framework for remote patient monitoring.

This paper utilizes a systematic literature review approach to analyze the integration of AI with wearable technology to provide online healthcare services for remote patient care. According to the base of numerous available academic publications, industry reports, and case studies, they review predictive maintenance, resource recovery, and process optimization research, ultimately identifying major trends, technology advances and industry application. We applied a strict selection process to choose high-quality peer-reviewed papers that cover the importance of wearable technology the different challenges associated with wearable technology and how the integration of AI can handle these challenges and provide solutions. We evaluated how data-driven approaches of AI provide solutions to different challenges in wearable technologies. The review lists the applications of online healthcare systems and also identifies the importance and research gaps which need to be addressed to justify full-scale deployment including interoperability, and the need for a discrete standardized framework. AI-based methods and techniques can enhance the efficiency and sustainability of wearable devices to provide timely results to patients. Figure 5 presents a systematic review process and Table 2 represent research questions. This process starts by defining the research question, it is then followed by a search strategy for relevant studies. Then, the eligibility of selection criteria for articles included in the study with quality criteria being part of it to make sure they are reliable. Following study selection, data extraction and finally, data synthesis which includes analyzing and summarizing the findings.

Research question
Select data sources
Different libraries and repositories that serve as the source are for the findings of different search results is called the actual source. We have selected the top digital libraries to obtain the required results and the libraries are Springer Digital Library, ACM Digital Library, IEEE Explore and Science Direct. To gain the correct results from the previous studies the access of full text literature is necessary and important. There are many means of investigation in looking for the required information in any digital library. The aim is to find the accurate information and it is very important to change the research

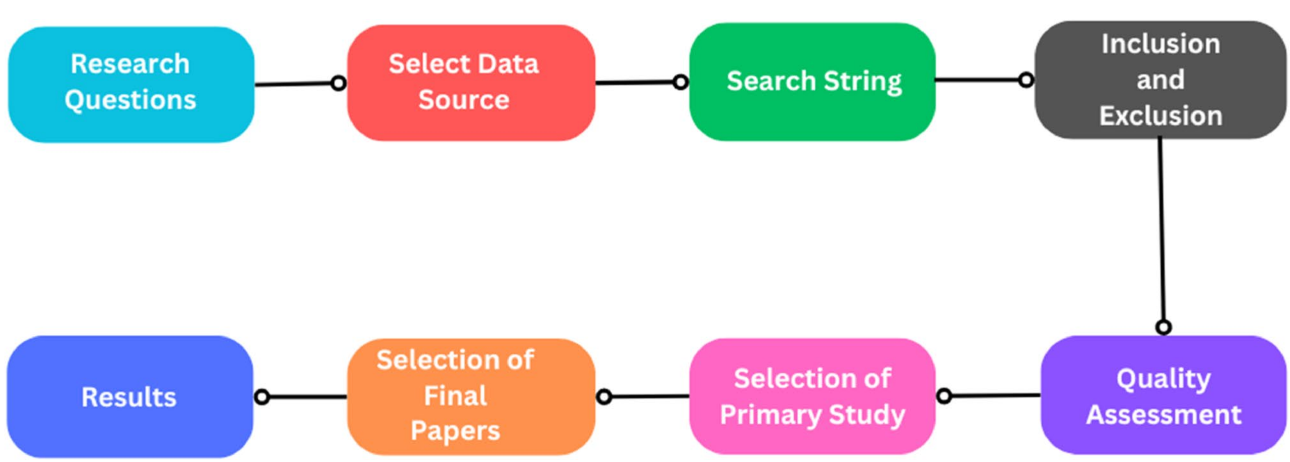

Fig. 5 Systematic review protocol

Table 2 Research questions

Research Question	Motivations
What are the key challenges and barriers to adopting wearable technology and mobile health solutions for remote patient care?	The purpose of this question is to highlight the different challenges in wearable technology that are necessary to overcome to facilitate the patients for remote patient care.
How does wearable technology integrated with artificial intelligence improve the accuracy and efficiency of remote patient monitoring in digital health?	This question aims to find the best techniques of AI that can be integrated with wearable technology to overcome different challenges in remote patient care.
What is the impact of AI-powered wearable devices on patient outcomes, engagement, and healthcare provider decision-making in remote care settings?	The purpose of this question is to highlight the impact of AI-powered wearable devices on patient outcomes, engagement, and healthcare provider decision-making in remote care settings.

Table 3 Query results from data sources

Library	Initial	Title and Keyword	Abstract	Introduction and Conclusion	Full Text
ACM	120	80	55	45	24
IEEE	150	70	45	40	36
Science Direct	130	65	40	30	25
Springer	140	50	30	25	21
Wiley	120	60	40	30	22
Results	660	325	210	170	128

methods to meet the desired outcome of the resource. Being in the table and the figure, Table 3 and the and Fig. 6 depict various data sources and the number of studies, respectively, derived from the search queries.

Search string formulation

Several specific search terms were used across multiple academic databases to ensure an exhaustive review of the literature. These terms were cautiously used after considering all these aspects regarding wearable technology and online patient care, importance, challenges and AI-based solutions to these challenges. Principal keywords used as search queries, such as "wearable technology", "importance", "challenges", "impact", "AI solutions", "integration", "remote patient care", and "digital health" are used. Boolean operators (AND or OR) were used to refine the search results and broaden the range of the relevant studies. Furthermore, also searched for variations and synonyms of these terms so that all the research findings were captured and the result was a comprehensive and concise dataset. The search terms were iteratively improved to ensure maximum literature relevance using preliminary results and database specific recommendations. The systematic literature search of the databases is depicted in the Fig. 7, where predefined research strings are used to search the databases, while studies are selected through established criteria, and revised iteratively to improve search terms if required.

Define inclusion and exclusion criteria

A systematic filtering of literature produced high-quality and relevant publications of wearable technology and AI integration for remote patient care. Relevant papers were found and then distilled using predefined inclusion and exclusion criteria through a comprehensive search across numerous academic databases. To allow the most

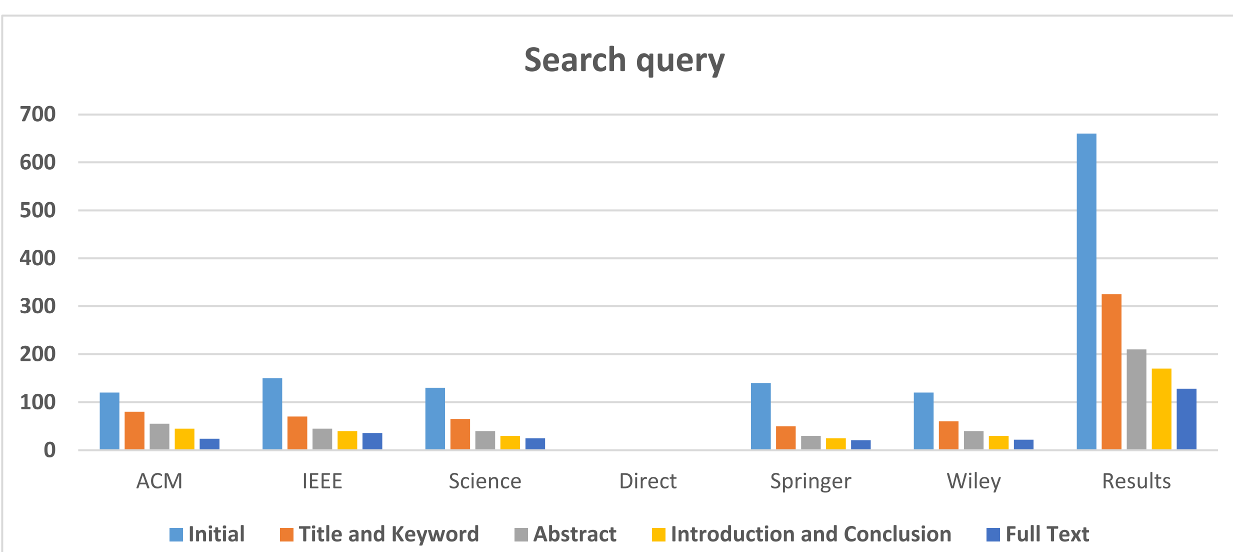

Fig. 6 Search queries representation

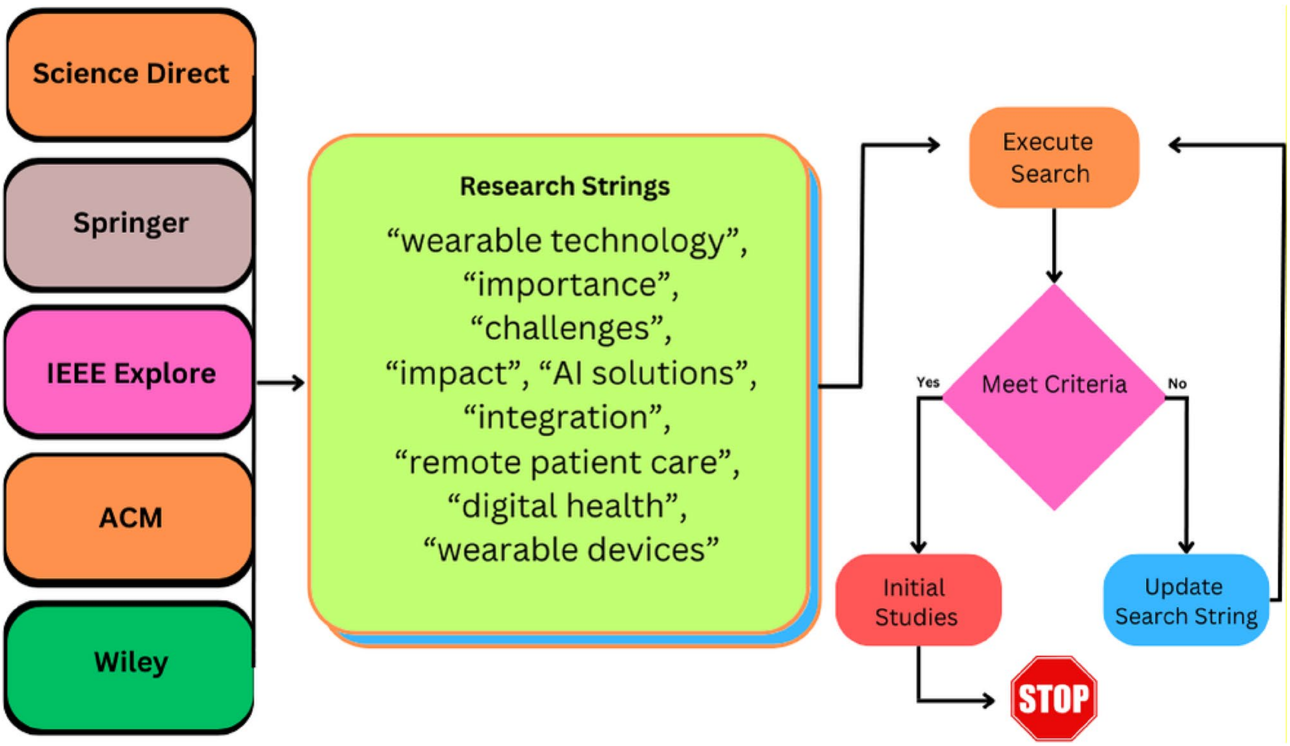

Fig. 7 The process of formulating the search string

Table 4 Inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Publication Type	Peer-reviewed journal articles, conference papers, technical reports, and industry studies	Non-peer-reviewed sources, opinion articles, blog posts, and non-scientific reports
Time Frame	Studies published within the last 06 years (to ensure relevance)	Studies older than 06 years unless foundational or highly cited
Topic Relevance	Research focused on wearable technology, challenges, AI integration, Techniques, remote patient care, digital health and importance.	Studies unrelated to wearable technology, challenges, AI integration, Techniques, remote patient care, digital health and importance.
Methodology	Empirical studies, case studies, systematic reviews, and comparative analyses with clear methodology	Studies lacking empirical evidence, case studies without clear methodology, or anecdotal findings
Application Domain	Studies related to data and security, patient care, interoperability, regulatory, patient engagement and adherence, accessibility and data management.	Studies focused on unrelated fields such as agriculture or unrelated industries.
Language	English-language publications (to ensure accessibility and comprehension)	Non-English publications without official translations

relevant and up-to-date findings, we limited our inclusion to peer-reviewed journal articles that hav been published since 2020. The included studies are data and security, patient care, interoperability, regulatory, patient engagement and adherence, accessibility and data management. Articles about wearable technology and AI integration to solve different challenges for remote patient care without empirical data were excluded. The research articles and review papers from highly impacted publications were selected and preferred. The stringent selection approach ensured that the study was grounded by a broad diversity of quality of the literature available to meet research objectives. Exclusion and Inclusion criteria of the proposed study are shown in Table 4.

Define quality assessment criteria

In systematic literature reviews SLRs and in meta-analyses, qualitative methods are a specified set of techniques for judging the worthiness, credibility and quality of research attempts Qualitative methods are accepted platforms or techniques for determining the validity equivalency and the structure of the quality asserts. By introducing quality control methods and proofs of results, we can ensure that the primary studies which we have selected are able to provide sufficient information to answer our research questions. In this step, each research topic is compared with the standard. The quality assessment is listed in Table 5 and is included starting from QCS.

Table 5 Quality assessment criteria

Sr. No	QA questions
QCS1	Does the following study provide enough information on key factors related to wearable technology?
QCS2	Does the wearable technology integrated with artificial intelligence improve the accuracy and efficiency of remote patient monitoring in digital health?
QCS3	Does the impact of AI-powered wearable devices on patient outcomes, engagement, and healthcare provider decision-making in remote care settings?

Table 6 Final paper selection

Year	Final selection
2020	18
2021	12
2022	20
2023	19
2024	46
2025	13

Primary study selection

The primary study' phrase seeks to specify targeted sections and subsections in a book for specific research question. In order to conduct this review in an effective manner, relevant articles were specifically selected. In this manner, a total of 128 original studies strictly identified based on pre-determined quality criteria. Table 6 shows the final selected papers and Fig. 8 shows the diagram with the years of final selected papers used in this study; Fig. 9 also provides a PRISMA diagram to illustrative the respective selection procedures.

Fig. 8 Final papers selection

Fig. 9 PRISMA for proposed study

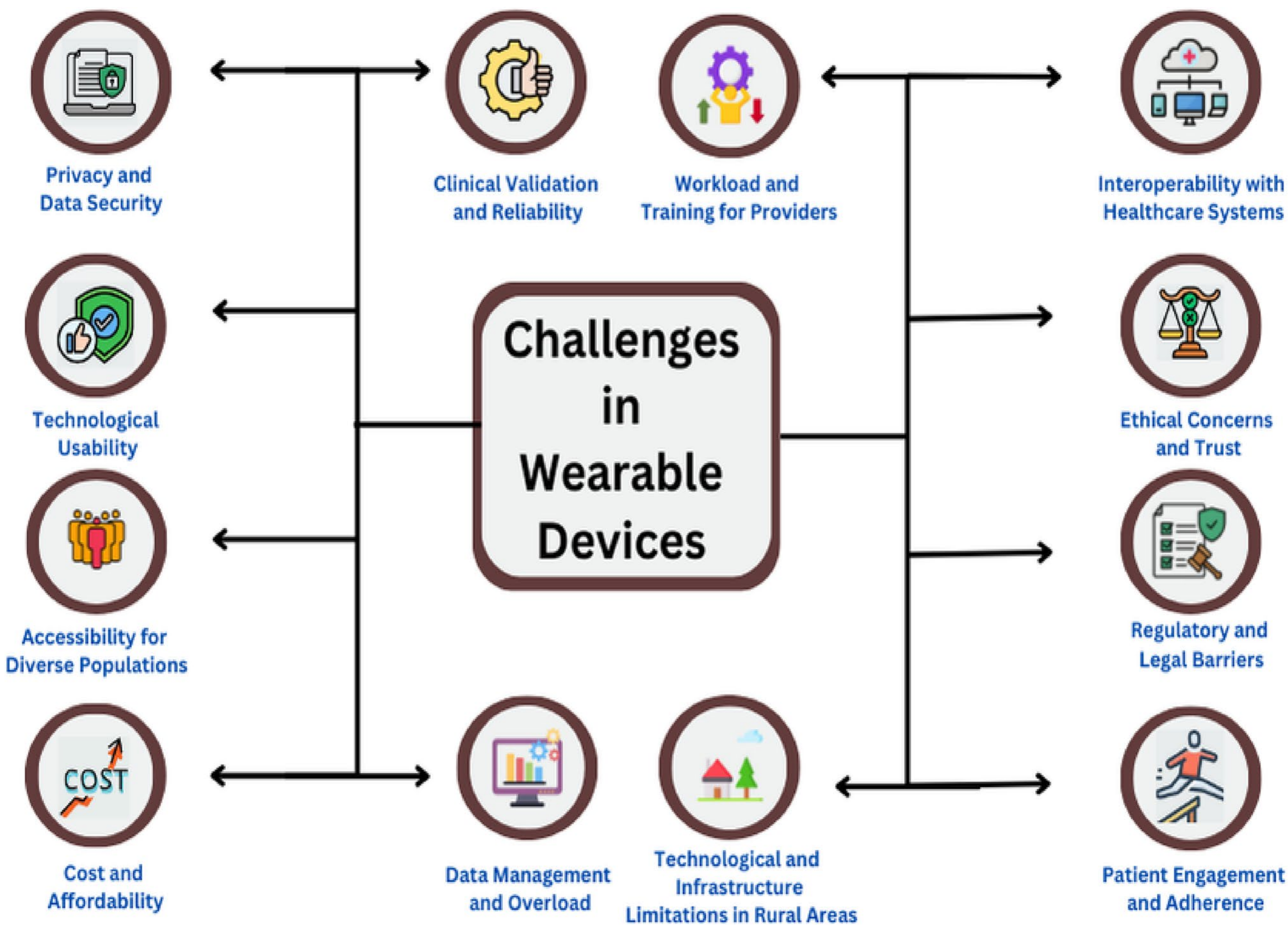

Fig. 10 Challenges in wearable devices

Result and discussions

What are the key challenges and barriers to adopting wearable technology and mobile health solutions for remote patient care?

There are many challenges that come with the adoption of remote patient care via wearable technology and mobile health solutions, including privacy and security of the collected data, which can undermine the trust of the patients and the providers [58]. Figure 10 shows the different challenges in wearable technology and Table 7 describes the details of each challenge with description, advantage and future work. Limited interoperability with existing healthcare systems, which makes integration extremely challenging. Regulatory hurdles and unclear guidelines complicate device approval and clinical use [59]. High cost and not insurance put a lot of effect on the coverage for widespread in the rural areas and low-income areas. Digital literacy is also a big barrier among providers and patients that can limit effective use of wearable devices. Data overload and difficulties in interpreting vast amounts of health data can overwhelm healthcare providers [60]. Data Lack of clinical validation and limited evidence of efficacy delay also hinder broader acceptance. There are no standardized protocols, which undermines care consistency. The cultural and socioeconomic reasons for adoption can influence adoption, as some communities can resist to adopt new technology [61]. Lastly, in rural areas there is infrastructure limitations like access of poor internet, which affects the functionality of remote wearable device to not work properly.

There are concerns about the privacy of sensitive health data generated and transmitted by wearables. Access to patient data without proper authorization may result in breaches in confidentiality, making patients and healthcare providers reluctant to use these technologies. The complexity of wearable devices and the lack of user-friendly interfaces contribute to the challenge, especially for older adults or those with limited technological literacy. Usability issues impede effective use, particularly for patient self-management [72].

Wearable devices and mobile health solutions are often not perfect fit with existing healthcare due to lack of compatibility and lack of infrastructures like electronic health record (EHR). This limits the ability to seamlessly integrate patient generated health data with clinical workflows [73]. The lack of universal and clear regulatory

Table 7 Barriers in wearable devices for remote patient care

Sr. No	Barriers	Description of the barrier	Disadvantages	Future Direction	Ref
1	Privacy and Data Security	Patient data could be at risk and no one should see any patient health data without explicit permission.	Breaches in medical records create trust problems and reduce technology adoption.	Development of improved data encryption and compliance processes.	[62]
2	Technological Usability	Lack of complexity in user interfaces and professional design for the users.	Increased patient non-compliance and efficient utilization.	Designing for accessibility with the user in mind.	[60]
3	Interoperability with Healthcare Systems	Challenge in synchronizing wearables with EHR and clinical systems.	Restricts effortless data transfer between patient, device and health professional.	Establishing standardized communication protocols and integration platforms.	[63]
4	Regulatory and Legal Barriers	Absence of standardized rules for devices and data utilization.	The adoption is hindered by uncertainty in compliance and legal issues.	It includes the need for global standards for device certification and the protection of data.	[64]
5	Cost and Affordability	Vast capital costs and lack of reimbursement coverage for patients.	The financial burden prevents larger-scale utilization, especially among low-income groups.	Development of budget alternatives and increased reimbursement option.	[65]
6	Patient Engagement and Adherence	Challenges to increasing patient engagement in remote monitoring.	Decreases the effectiveness of the technology in long-term care.	Improved patient education and personalized treatment pathways.	[66]
7	Clinical Validation and Reliability	Inadequate clinical trials and validation studies.	Clinical adoption is limited by uncertainty about the accuracy of the devices.	Invest more in large-scale clinical trials to prove the effectiveness of wearable tech.	[67]
8	Accessibility for Diverse Populations	Difficulty adapting devices for elderly and disabled people.	It restricts adoption in key demographics that require the technology the most.	Inclusive, accessible technology development for diverse populations.	[67]
9	Workload and Training for Providers	Healthcare needs to receives training on using and manage for data.	Adds pressure to healthcare providers, making scalability of adoption challenging.	Introduction of user-friendly tools and ongoing professional development.	[68]
10	Data Management and Overload	Wearables generate large volumes of patient data that are hard to manage.	May lead to data burden, which makes timely actions by healthcare providers difficult.	AI-driven data analytics and real-time decision support systems integration.	[69]
11	Technological and Infrastructure Limitations in Rural Areas	Shortage of essential infrastructure in rural locations such as good internet connectivity.	Low risk and low capacity to deliver remote monitoring systems to those communities who need it most.	Investment in infrastructure and alternative communication networks, such as 5G.	[70]
12	Ethical Concerns and Trust	Concerns over data abuse and patient consent.	This reduced trust in the technology can then act as a barrier to patient adoption.	Development Establishment of solid ethical guidelines and patient-oriented consent systems.	[71]

standards for wearables and mHealth solutions inhibits their adoption. Legal uncertainties, including the management of patient data and device compliance, continue to present challenges.

High cost of wearable technologies and mobile health solutions are still a major barrier when it comes to underprivileged populations. The high price has prevented wide-scale adoption, and significantly limits the impact these technologies [74]. Implementation of wearable devices and mobile health solutions rely on continued patient engagement and compliance with monitoring routines. Wearable devices and mobile health solutions depend on sustained patient engagement and adherence to monitoring protocols. However, the effectiveness of these devices may still be compromised by an unwillingness in patients to use them consistently [75].

Most wearable devices aren't adequately clinically validated, creates challenges in the healthcare community regarding the reliability and accuracy of health data. These devices are less likely to be recommended for use without robust evidence of clinical effectiveness [76]. Wearable devices might not be suitable for all patient demography, especially those with physical disabilities or elderly individuals who face challenges in using complex technology. This limits the inclusivity of such healthcare solutions.

The use of wearable technologies in clinical practice necessitates further training of healthcare providers. The challenges are further compounded by increased workloads related to downloading the data from wearable devices and the absence of standard protocols [77]. The massive amount of data produced by wearables can burden healthcare providers, which further adds to data management and interpretation challenges. This data has still significant challenges, including the effective analysis of the data and also how to respond to it. Digital health

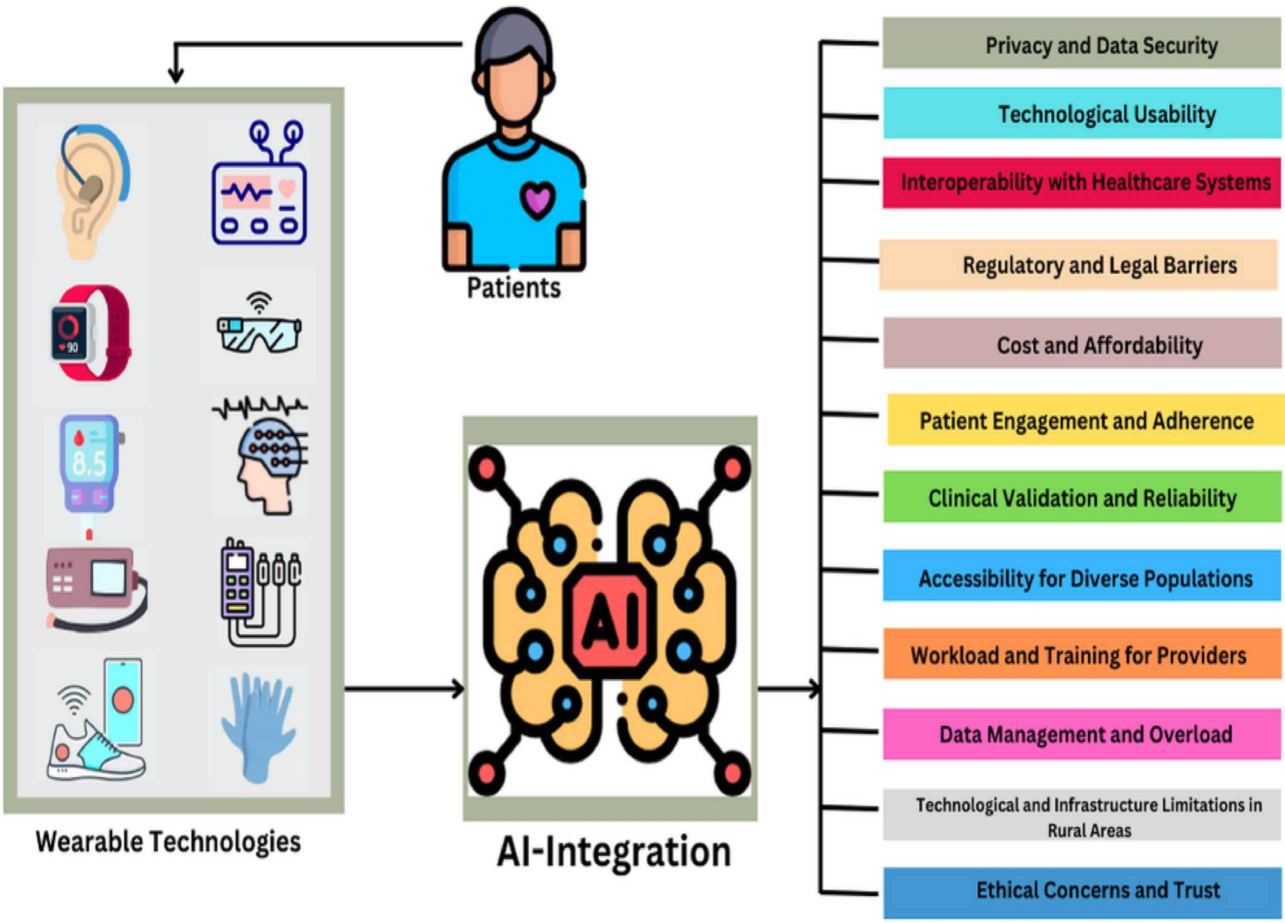

Fig. 11 Integration of AI-based solutions with wearable technology for remote patient care

technologies present a significant challenge in rural areas, where access to healthcare is already poor, due to a lack of supportive infrastructure such as broadband and electricity availability [78].

Ethical issues often arise due to ethical concerns regarding the collection, storage and use of personal health data collected from wearable devices. Mobile health solutions will not be adopted, due in part to patients' fears of data misuse or exploitation [79].

It is worth noting that several related research efforts have also addressed these challenges in meaningful ways. For example, prior studies have emphasized the complexity of ensuring interoperability across heterogeneous systems and the difficulty of achieving patient engagement over extended periods. Other research attempts have explored the use of AI for privacy protection and usability improvements, though many face limitations in terms of real-world deployment or lack of clinical validation. Despite these constraints, such efforts have contributed significantly to advancing the field by highlighting the technical, ethical, and infrastructural barriers that must be overcome. This study builds upon these insights by offering a structured synthesis of AI-driven approaches tailored to overcome these persistent obstacles in remote patient care.

How does wearable technology integrated with artificial intelligence improve the accuracy and efficiency of remote patient monitoring in digital health?

Wearable technology integrated with AI improves efficacy and precision of the remote patient monitoring (RPM) in digital health through several key mechanisms. Figure 11 shows the integration of AI with wearable technology for remote patient care. Wearable tech combined with AI makes remote patient monitoring faster, more accurate and more personalized, ultimately leading to better results and a more efficient health care system. Wearables allow for continuous monitoring of vital health metrics such as heart rate, glucose levels, and steps walked transmitting this data to health care practitioners [80]. AI-based wearables can be integrated with Electronic Health Records (EHR) and other health management systems. The fusion of collected data from wearable sensors, analyzed through AI, enables more correct diagnostics. For patients in rural and under-served regions, the use of wearable devices means that health care providers can monitor patients frequent in-person visits, reducing costs and increasing access to care [81].

AI-based solutions for privacy and data security in wearable technology for remote patient care

The combination of AI and wearable technology to also transform remote patient monitoring (RPM) into a far more secure method of monitoring continuous vitals and conditions. By applying advanced techniques of AI like federated learning, differential privacy, homomorphic encryption, and secure multi-party computation, which protect sensitive health data while allowing for meaningful analysis and insights and ensures that sensitive health data is protected while enabling meaningful analysis and insights [82]. A healthcare framework, for remote patient monitoring, based on AI-induced smart contracts in a public blockchain is proposed in [37] with a positive effect on privacy and data security guarantees. It also aims to address security loopholes and privacy concerns through decentralized healthcare and the management of authenticated IoT devices. In this paper the authors presented a real-time identification of malicious IoT nodes is achieved by incorporating adaptive temporal long-short-term-memory (AT-LSTM), providing a robust system. This revolutionary hyper-parameter system dramatically optimizes data fetching period while limiting energy consumption, enabling the management of patient data in a secure and reliable way. Another study of [83] proposes a DL-driven detection model which deploys machine learning and deep learning techniques to enhance privacy and data security in remote patient care using wearable technology. It focuses on the integrity and confidentiality of patient data from incoming network attacks using a multi-label classification infrastructure. This proposed method focuses on the need for strong security measures so that patient data can continue to be secure in an increasingly information-heavy environment while addressing the concern of data vulnerability in healthcare systems.

AI-based solutions for technological usability in wearable technology for remote patient care

AI-based solutions help make wearable technology usage in remote patient care more viable by facilitating real-time monitoring, customized care, predictive analytics as well as enhanced diagnostics as all of this is in place. The study of [84] presents the potential applications of AI in processing raw data from various sensors, helps in sensor fusion, and trust on AI to provide healthcare analytics (multivariate) from the data travelling from wearable devices. This helps in improving patient outcomes as well as healthcare efficiency through continuous monitoring, real-time analysis and rapid diagnostics, which are all facilitated due to the usability added to remote patient care through these techniques. Another study of [85] proposes a new AI-based method which employs an unsupervised LSTM to denoise ECG signals, followed by a recursive Ensemble Neural Network (ENN) that enhances classification of cardiovascular illnesses, ultimately improving the detail of wellness checks in remote patient care for wearable technology. The study of [86] reviews the machine learning algorithms used in wearable devices such as random forest models, convolutional neural networks, and transformers, which allows for an expansion of technological usability in remote patient care through improvements of diagnosis, management, and monitoring of cardiovascular disease.

AI-based solutions for interoperability with healthcare systems in wearable technology for remote patient care

AI-based interoperability technology in wearable for remote patient care involves a range of methods and techniques focused on ensuring data accessibility, security, and accessing various patient data points in a remote patient care context. The research of the [87] discusses AI and ML approaches to interoperability in healthcare as demonstrated through the use of decentralized architectures to avoid the errors of centralized architectures, using of blockchain mechanisms to provide data integrity, and edge computing to provide a cloud system able to respond to low-latency, low-complexity tasks such as remote patient care all enhanced by wearable technologies. In another study the [88] the authors presented a model of combination of wearable sensor data with AI, that models include Random Forest, LSTM, Support Vector Machines (SVM) for modeling disease progression, predicting exacerbations as well as real-time detection of anomalies in the management of chronic respiratory disease. The paper of [89] presents the Health Translator model, utilizing data enrichment techniques, periodicity management for vital sign readings, and Health level 7 Fast Healthcare Interoperability Resources (HL7 FHIR) standardization to ensure interoperability between wearable devices and healthcare systems, facilitating remote patient care and pre-diagnosis insights.

In addition [90], explores how blockchain and generative AI together enhance interoperability, security, and scalability of digital health systems, offering concrete solutions to persistent challenges in electronic health record integration and data trustworthiness.

AI-based solutions for regulatory and legal barriers in wearable technology for remote patient care

The solutions powered by AI can play a vital role to overcome regulatory and legal hurdles in the use of wearables for remote patient management. These barriers include compliance with healthcare regulations, data privacy concerns, liability issues, and the need for standardization. The research of the [91] presents different AI solutions, such as federated machine learning and privacy-preserving ML techniques intending to target regulatory and legal barriers towards the deployment of wearable technology for remote patient care, along with strategies and regulatory elements to achieve compliance and improve healthcare delivery. The study of [92] presents that regulation standards are required to address data sharing and usage laws in AI healthcare solutions. This highlights the need for AI model validation in order to address regulatory hurdles and to confirm the reliability and efficacy of wearable technology in the provision of remote patient care.

AI-based solutions for cost and affordability in wearable technology for remote patient care

AI-based solutions are significantly enhancing cost-effectiveness and affordability in wearable technology for remote patient care. Combining the capabilities of AI with the wearable devices allow healthcare providers to provide real-time monitoring and personalized care, which leads to lower healthcare costs and better patient outcomes. The study of [93] presents AI-based remote monitoring solutions, like the Vigo platform, improve healthcare services through efficient data collection and cost-effectiveness, reducing errors, and enabling low cost through wearable technology for remote patient care. The study of [94] shows AI can process data related to patients collected from smart wearable devices for creating personalized treatment plans and pattern recognition of high-risk patients for medical imaging diagnosis. This predictive healthcare analytics paradigm makes remote patient care each affordable by lowering the overall care cost and addressing patient and outcome optimization.

AI-based solutions for patient engagement and adherence in wearable technology for remote patient care

The use of wearable technology and patient engagement solutions supported by AI are revolutionizing remote patient care to a new level of monitoring, personalized treatment, and medication adherence. Such innovations take advantage of analysis of real-time data and algorithms in machine learning, resulting in customized health insights and ultimately improved patient outcomes. The author of the research [95] proposed Personalized Medication Engagement System (PMES) is an AI methods-based approach using Reinforcement Learning and Deep Learning to improve patient engagement and adherence at a distance, make the main patient treatment process more effective while at the same time avoiding medication errors by using this type of approach on a cloud-based system. The survey presented by [96] highlights AI-based methodologies in wearable technology that enhance patient engagement and adherence through real-time monitoring, personalized feedback, and predictive analytics, ultimately improving remote patient care and fostering better health outcomes by facilitating tailored medical solutions. The study of [97] presented AI-powered systems and their application in cardiac monitoring specifically in personalizing patient care by adjusting treatment plans through dynamic feedback from real-time data. This facilitates ongoing communication and timely intervention, ultimately leading to improved adherence and engagement, and better outcomes for remote patient care.

AI-based solutions for clinical validation and reliability in wearable technology for remote patient care

The integration of AI into wearable medical devices is pivotal for enhancing clinical validation and ensuring the reliability of remote patient care. AI-driven methodologies address critical challenges such as data accuracy, real-time monitoring, and clinical decision support.

For instance, the study by [98] introduces machine learning (ML) algorithms designed to estimate the reliability metrics of ECG data, thereby bolstering the trustworthiness of AI-based cardiac monitors in remote settings. Similarly, research by [99] demonstrates that a deep neural network (DNN)-based AI algorithm achieved high clinical validation in detecting atrial fibrillation from ECG signals using smart devices. The findings indicate that this DNN algorithm provided more conclusive diagnoses compared to manufacturers' algorithms, underscoring its reliability for patients utilizing wearable technology in remote care scenarios.

Further advancements are highlighted in the work of [100], where AI is embedded within wearable medical sensors to enhance clinical decision-making, personalize medical interventions, and improve diagnostic accuracy. This study also discusses ongoing challenges and future opportunities associated with deploying advanced AI-enabled technologies to ensure reliable remote patient care.

Additionally, the research conducted by [101] presents an improved ensemble method for the efficient diagnosis of diabetes mellitus. By employing parallel and sequential ensemble ML approaches alongside feature selection techniques, the study achieved 100% classification accuracy, demonstrating the potential of AI-enhanced wearable technologies in facilitating accurate and reliable remote health monitoring.

AI-based solutions for accessibility for diverse populations in wearable technology for remote patient care

AI-powered accessibility solutions in wearable devices for remote patient care play a vital role to make sure that the technology is usable and valuable by diverse populations including people with all abilities, backgrounds and health conditions. The study of [102] presents propose AI models known as deep learning and knowledge graphs to improve remote healthcare access. It addresses the various challenges during analysis of text data for heterogeneous populations, it utilizes the potential to refine diagnostics and treatment of subjects through computational analytics and the cognitive extraction of knowledge insights. Another study of [103] presents machine learning representation via artificial neural networks, decision trees, random forests, and naive Bayes for remote patient monitoring, bridging accessibility through IoT technologies and human-centric design. The study of the authors [104] presented various AI approaches, including federated learning and explainable AI, that promote accessibility in wearable technology for heterogeneous populations through personalized predictions and recommendations and improved remote patient care through individualized interventions as well as data-driven insights.

AI-based solutions for workload and training for providers in wearable technology for remote patient care

AI-based solutions are playing a vital role in reducing the burden on human resources and the training of healthcare providers leveraging wearable technology in remote care. With the increasing availability of wearable technologies in clinical practice, providers are tasked with interpreting large volumes of data while ensuring high-quality care. The study of [105] presented a semantical approach on vernacular language medical chatbots to improve healthcare accessibility for heterogeneous populations. Another study of presents [106] Presented a AI models that can recognize neural signals to seamlessly interact with wearable devices, thus enhancing accessibility in remote patient care for diverse populations. This approach is designed to eliminate the requirement of controllers, gestures, and voice commands. The paper of the authors [107] have proposed an AI-based smart stretcher system which consists of various AI-based sensors and microcontrollers, improves patient access from remote locations by galvanized preparations at the hospital's intensive care unit.

AI-based solutions for data management and overload in wearable technology for remote patient care

AI-based solutions are important in addressing data management challenges and data overload in wearable technology used for remote patient care. Wearable devices produce a massive amount of real-time data, and if health providers do not have better AI solutions in place to understand this data, the amount, complexity, and variability of real-time health information may overwhelm them. The study of [108] focused on liver health monitoring, where the HepatoConect system delivers real-time data for personalized dietary recommendations, offering a distinctive approach to disease management. By integrating cutting-edge technologies, these smart solutions transcend traditional healthcare boundaries. The study of [109] describes various machine learning techniques for clinical decision support systems, addressing the problem of data overload in wearable technology by offering personalized recommendations and analysis of users' data, which subsequently results in improving remote patient care through effective data management strategies.

Additionally, the study of [110] explores the integration of AI with blockchain technology for secure and efficient data management in the Internet of Medical Things (IoMT). AI-powered algorithms optimize data processing, enabling real-time analytics and decision-making, while blockchain ensures secure storage and privacy of patient data. The study highlights how AI-driven techniques, such as predictive modeling and automated data structuring, can mitigate data overload challenges in wearable healthcare devices. By leveraging AI and blockchain integration, healthcare providers can enhance data security, patient trust, and interoperability between different medical systems, improving overall healthcare outcomes in remote patient care.

AI-based solutions for technological and infrastructure limitations in rural areas in wearable technology for remote patient care

AI-based solutions can help overcome these technological and infrastructure limitations in rural areas, where healthcare resources and consistent internet connectivity are limited. In context of wearable technology used in remote patient care, AI can serve to advance the field by improving data accessibility, ensuring care delivery more smoothly, and providers can receive additional support. The study of [111] presents that AI-driven solutions are designed to solve technological, and other constraints necessary for infrastructure in the rural domain of society, and they focus primarily on the need for a collaborative effort amongst the stakeholders to enhance the digital infrastructure together with capacity building initiatives needed for remote patient monitoring and healthcare delivery. Another study of the authors [112] propose an AI-based human motion recognition system using Radio Frequency (RF) signals, overcoming the challenges of existing techniques based on wearables in remote patient monitoring, especially in rural regions that struggle to deal with infrastructure development such as charging devices or wearing an external device used for human motion capture. Another study of [113] the authors presents a multi-designed approach, including infrastructure development, training, data management, cost-effective solutions, and regulatory support, to make efficient use of AI facilitating bridging healthcare disparities in rural locations.

AI-based solutions for ethical concerns and trust in wearable technology for remote patient care

AI-based solutions are key in overcoming ethical issues and creating trust in wearable technology for remote patient care. These issues are particularly relevant because most wearable devices collect sensitive personal health data and the ways this data is processed, analyzed and shared can have significant ethical implications. The study of [114] presents homomorphic encryption (HE) and secure multiparty computation (SMPC) to protect patient privacy, along with AI to improve transparency and reliability to address ethical concerns in AI applications related to healthcare. The study of the authors [115] describes on applying ethical principles across the entire AI pipeline of development by using a case-based framework in which fairness, trust, and accountability are included. Wearable technology for remote patient care can be enhanced by "ethics by design" techniques.

What is the impact of AI-powered wearable devices on patient outcomes, engagement, and healthcare provider decision-making in remote care settings?

AI Wearables in remote care settings enhance outcomes, engagement, and provider insights these technologies support ongoing telemetry of vital signs and body parameters, allowing for timely identification of health statuses and disease states and timely response that are most vital in the management of chronic illnesses and one of the most important steps in reducing readmissions. This holds great promise for enhancing patient engagement and adherence to treatment plans by offering personalized feedback and actionable insights that help patients to take an active role in their health [116]. AI-powered analytics provide data-rich insights that improve diagnostic and decision-making support on clinical and evidence-based decision making, particularly in resource-poor and remote settings. Moreover, wearables enhance resource utilization by prioritizing high-risk patients and automating routine tasks, leading to increased efficiency in care delivery [117]. Despite these advantages, several challenges like data privacy issues, algorithmic biases, and integration with existing healthcare systems are still considerable challenges to widespread use. Tackling these challenges can pave the way to unleash the potential of AI-powered wearables in transforming remote care ensuring better patient outcomes, enhanced engagement, and informed clinical decision-making [118].

Impact on patient outcomes

By facilitating continuous monitoring, early diagnosis, and personalized treatment, AI-based wearable devices significantly influence patient outcomes in the healthcare space. IOT devices allows for live monitoring of the body diagnostic parameters like heart rate, blood pressure, glucose levels, and physical activity, which make possible for detecting the abnormalities in time and treating [119]. In addition, it is especially useful in managing chronic diseases such as diabetes, cardiovascular diseases, and chronic obstructive pulmonary disease (COPD), as early detection can help prevent complications and improve long-term prognoses. The data is processed using AI algorithms capable of delivering personalized recommendations that improve approaches to disease management and adherence to treatment guidelines, including modifications in medication dosage or lifestyle [120]. Furthermore, AI-enabled wearables allow for remote patient monitoring, minimizing the number of in-person hospital visits and allowing for real-time monitoring of patients by healthcare providers, even in underserved areas. This function is especially useful in care after hospital discharge since it prevents readmission to hospital by encouraging patients to maintain their treatment plans and facilitating timely interventions when required. Moreover, the incorporation of AI wearables with EHRs provides a holistic perspective on patients' health, promoting accurate diagnosis and customized treatment plans [121]. However, challenges remain, including addressing data privacy issues, minimizing algorithm biases, and ensuring seamless integration with existing healthcare systems, to maximize the potential for AI-powered wearables [122]. Overall, AI-powered wearables make a sizable difference in patient outcome through earlier diagnosis, personalized treatment, and real-time tracking with the end goal of improving health and lowering healthcare expenses.

Impact on patient engagement

Wearable devices that incorporate AI have improved patient engagement, enabling individuals to play an active role in their health management. These devices also allow for immediate access to personal health metrics including heart rates, exercise, sleep health, and glycaemia, enhancing the sense of personal accountability among patients [123]. These AI-integrated wearable devices deliver tailored feedback and actionable insights that act as a motivational factor that drives patients towards healthier lifestyle choices increased exercise, better nutrition, and strict compliance with prescribed medication. The interactive nature of these devices incorporates gamification features such as a step counter and achievement badges to drive patients toward success in meeting their healthcare goals [124]. Moreover, AI Embedded wearables also facilitate stronger patient-doctor dialogue and interaction through continuous data sharing, which enables timely intervention. This continuous engagement helps patients feel more connected to their care, particularly in remote or underserved settings where access to healthcare providers may be limited. The potential for the use of AI wearables to provide personalized health recommendations that are precisely targeted and tailored for an individual based on their unique data significantly improves the patient experience and level of trust in the care process [125]. However, data privacy, and technological literacy over-reliance on devices are challenges overcome to ensure continued engagement. In summary, AI-powered wearables serve as a key component in promoting patient engagement, offering tools for accessible, personalized, and interactive management of health, fostering better health outcomes and a proactive healthcare approach.

Impact on healthcare provider for decision-making

With AI-powered wearable devices, healthcare providers can receive real-time data-driven insights that enhance clinical decision-making, improving accuracy and efficiency. These devices monitor and track vital signs of the patient, such as heart rate, blood pressure, oxygen levels, or glucose levels, in real-time, generating mountains of actionable data [126]. AI algorithms are capable of finding patterns predicting possible health risks and providing warnings of conditions such as arrhythmias, hypoglycemia or worsening chronic diseases, which can allow timely interventions. It helps to mitigate diagnostic uncertainty and aids in evidence-based decision-making, especially in remote care settings where access to physical examinations and in-clinic consultations is constrained [127]. Integrating wearable data with EHRs provides a more holistic, real-time perspective on patient health, enabling better diagnoses and tailored treatment plans. Finally, AI wearables maximize resource utilization by automating routine monitoring tasks and predicting high-risk patients, which enables providers to focus on critical cases and improves workflow efficiency [128]. These devices fill care gaps and increase access to quality care in remote and underserved regions as they allow providers to continuously track patients without necessitating in-person visits. To fully be able to utilize their potential, there is need to overcome the challenges such as data privacy concerns, algorithmic biases and the need for smooth integration in existing healthcare systems need to be tackled AI-based wearable assistance devices have a positive impact in many ways.

This study is based on the assumption that emerging wearable and AI technologies will continue to improve in terms of interoperability, accuracy, and accessibility, and that health systems will gradually integrate these tools into clinical practice. One key lesson learned is the importance of aligning AI capabilities with actual clinical workflows and patient needs to ensure usability and trust. The findings also highlight that ethical, regulatory, and infrastructure barriers must be addressed early in the design of AI-powered wearable solutions. Based on our analysis, future developments should focus on improving EEG signal fidelity, integrating bias detection in AI models, and designing interfaces that support long-term patient engagement. A limitation of this work is its literature-driven approach, which does not include real-world clinical testing or implementation data. Future studies should explore empirical validation and longitudinal effects to assess scalability, user adoption, and measurable outcomes in real healthcare environments.

Conclusion and future directions

Wearable technological devices with artificial intelligence (AI) capabilities have the potential to become game changers for digital health with great importance in remote patient care. These technologies contribute to improved patient outcomes, enhanced engagement, and optimized healthcare delivery by enabling continuous monitoring, personalized interventions, and data-driven decision-making. Breaking through these barriers will involve promising AI-driven solutions like complex encryption, federated learning, and interoperable platforms.

We have discussed the importance of wearable devices in remote patient care, including their applications in continuous health monitoring, chronic disease management, neurological assessment through EEG wearables, and mental health tracking. Additionally, we have addressed the challenges faced by wearable technology, such as data security, interoperability, reliability, and accessibility. The integration of AI plays a vital role in overcoming these challenges, providing enhanced signal processing, noise reduction, predictive analytics, and personalized health recommendations. In this article, we explored various AI approaches, including deep learning, natural language processing, and machine learning models, that enhance the effectiveness of wearable technology in remote healthcare. These AI methods, when integrated with wearable devices, improve diagnostic accuracy, optimize health interventions, and strengthen patient trust through secure data management and real-time monitoring.

Looking ahead, further research should focus on ensuring that AI algorithms are less biased, ethically aligned, and designed to support diverse populations. Strengthened data security frameworks, along with robust regulatory policies, will be critical in safeguarding patient data and ensuring compliance with privacy standards. The seamless integration of wearable technology with existing healthcare infrastructures will be essential to augment clinical workflows and enhance decision-making processes for healthcare professionals.

Moreover, interdisciplinary collaboration between technologists, healthcare providers, and policymakers will be necessary to drive innovation and address the remaining challenges. Long-term studies measuring the effectiveness of AI-enabled wearables on clinical outcomes and healthcare utilization will be essential for proving their efficacy and scalability. While our findings are tailored to remote healthcare, the approaches discussed—such as AI-enhanced monitoring, secure data transmission, and decentralized analytics—may also inspire innovations in adjacent fields like sports medicine, occupational safety, and cognitive enhancement in educational contexts. With the right solutions to these challenges, wearable technology—including advanced biosensors, AI-powered analytics, and secure data management—has the potential to revolutionize remote patient care, making healthcare more accessible, personalized, and effective for patients worldwide.

This research may benefit a wide range of stakeholders. Healthcare providers can apply the findings to improve diagnostic workflows and patient engagement. Policymakers can use the insights to inform privacy regulations, digital health strategies, and equitable access policies. Developers of wearable and AI systems can integrate these recommendations into more secure and scalable designs. Public health organizations may also leverage these frameworks for large-scale remote care delivery. Communication and dissemination will be ensured through academic publications, digital health symposia, collaborations with industry and clinical partners, and open-access presentations at relevant forums.

As next steps, our goal is to develop a prototype system that incorporates the proposed AI-driven components—such as federated learning, blockchain-enabled privacy, and EEG signal processing—and test it within a controlled pilot environment. This will be followed by validation in collaboration with clinical partners, focusing on usability, accuracy, and regulatory compliance. A sustainable plan involves a 6–12 month phase for technical development and simulation, followed by an 18–24 month period for pilot testing and refinement in healthcare settings. The roadmap emphasizes ethical alignment, patient inclusivity, and cost-efficiency, paving the way for broader clinical integration and impact.

Authors' contributions

Yazeed Yasin Ghadi and Syed Faisal Abbas Shah perform the Original Writing Part, Software, and Methodology; Tehseen Mazhar, Mamoon M. Saeed perform the Rewriting, investigation, design Methodology, and Conceptualization; Wajahat Waheed, Wasim Ahmad and Tehseen Mazhar perform related work part and manage results and discussions; Habib Hamam, Yazeed Yasin Ghadi and perform related work part and manage results and discussion; Wajahat Waheed, and Tehseen Mazhar perform Rewriting, design Methodology, and Visualization; Tehseen Mazhar, Mamoon M. Saeed and; Habib Hamam performs Rewriting, design Methodology, and Visualization.

Funding

Not applicable.

Data availability

The data used to support the findings of this study are available from the corresponding authors upon request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Received: 7 March 2025 / Accepted: 30 May 2025

Published online: 21 July 2025

References

1. Korteling J et al (2021) Human-versus artificial intelligence. Front Artif Intell 4:622364
2. Murala DK, Panda SK, Dash SP (2023) MedMetaverse: medical care of chronic disease patients and managing data using artificial intelligence, blockchain, and wearable devices state-of-the-art methodology. IEEE Access 11:138954–138985
3. Senbekov M et al (2020) The recent progress and applications of digital technologies in healthcare: a review. Int J Telemedicine Appl 2020(1):8830200
4. El-Rashidy N et al (2021) Mobile health in remote patient monitoring for chronic diseases: principles, trends, and challenges. Diagnostics 11(4):607
5. Sabio J et al (2024) A scoping review on the use of consumer-grade EEG devices for research. PLoS ONE 19(3):e0291186
6. Lu L et al (2020) Wearable health devices in health care: narrative systematic review. JMIR mHealth uHealth 8(11):e18907
7. Ometov A et al (2021) A survey on wearable technology: history, state-of-the-art and current challenges. Comput Netw 193:108074
8. Haleem A et al (2022) Medical 4.0 technologies for healthcare: features, capabilities, and applications. Internet Things Cyber-Physical Syst 2:12–30
9. Vijayan V et al (2021) Review of wearable devices and data collection considerations for connected health. Sensors 21(16):5589
10. Canali S, Schiaffonati V, Aliverti A (2022) Challenges and recommendations for wearable devices in digital health: data quality, interoperability, health equity, fairness. PLOS Digit Health 1(10):e0000104
11. Niltakan K (2024) Health literacy in the digital age: challenges and opportunities. J Buddh Educ Res (Online) 10(3):110–122
12. Anikwe CV et al (2022) Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect. Expert Syst Appl 202:117362
13. Symvoulidis C et al (2021) Healthcare provision in the cloud: an EHR object Store-based cloud used for emergency. Healthinf 1:435–442
14. Mubeen M, Iqbal MW, Junaid M, Sajjad MH, Naqvi MR, Khan BA, Saeed MM, Tahir MU (2021) Usability evaluation of pandemic health care mobile applications. In: IOP conference series: earth and environmental science, vol 704, no. 1. IOP Publishing, p 012041
15. Selvakumar P et al (2025) Health Services and AI Technologies, in Economic and Political Consequences of AI: Managing Creative Destruction. IGI Global Scientific Publishing, pp 375–394
16. Khan AAR, Ilyas RNM, Meeral MN (2025) Applications of Artificial Intelligence and Internet of Things in Healthcare Industries. In: Evolution of Machine Learning and Internet of Things Applications in Biomedical Engineering. CRC Press, pp 1–17
17. Mavrogiorgou A et al (2019) Internet of medical things (IoMT): acquiring and transforming data into HL7 FHIR through 5G network slicing. Emerg Sci J 3(2):64–77
18. Ayari A, Hamdi H, Alsulbi KA (2024) E-health application in IoMT environment deployed in an edge and cloud computing platforms. Procedia Comput Sci 246:1019–1028

19. Mavrogiorgos K, Kiourtis A, Mavrogiorgou A, Kleftakis S, Kyriazis D (2022) A multi-layer approach for data cleaning in the healthcare domain. In: Proceedings of the 2022 8th international conference on computing and data engineering. pp 22–28
20. Ghadi YY et al (2024) Enhancing patient healthcare with mobile edge computing and 5G: challenges and solutions for secure online health tools. J Cloud Comput 13(1):93
21. Romiti S et al (2020) Artificial intelligence (AI) and cardiovascular diseases: an unexpected alliance. Cardiol Res Pract 2020(1):4972346
22. Widjaja AMN et al (2024) Digital health technologies in improving access to care for underserved populations. J Acad Sci 1(6):738–747
23. Tariq MU (2024) Advanced wearable medical devices and their role in transformative remote health monitoring. In: Transformative approaches to patient literacy and healthcare innovation. IGI Global, pp 308–326
24. Tiwari S, Nahak K, Mishra A (2023) Revolutionizing healthcare: the power of IoT in health monitoring. J Data Acquisition Process 38(2):2416
25. Soon S, Svavarsdottir H, Downey C, Jayne DG (2020) Wearable devices for remote vital signs monitoring in the outpatient setting: an overview of the field. BMJ Innov 6(2)
26. Sana F et al (2020) Wearable devices for ambulatory cardiac monitoring: JACC state-of-the-art review. J Am Coll Cardiol 75(13):1582–1592
27. Prieto-Avalos G et al (2022) Wearable devices for physical monitoring of heart: a review. Biosensors 12(5):292
28. Hare AJ, Chokshi N, Adusumalli S (2021) Novel digital technologies for blood pressure monitoring and hypertension management. Curr Cardiovasc Risk Rep 15(8):11
29. Konstantinidis D et al (2022) Wearable blood pressure measurement devices and new approaches in hypertension management: the digital era. J Hum Hypertens 36(11):945–951
30. Freckmann G (2020) Basics and use of continuous glucose monitoring (CGM) in diabetes therapy. J Lab Med 44(2):71–79
31. Reddy M, Oliver N (2024) The role of real-time continuous glucose monitoring in diabetes management and how it should link to integrated personalized diabetes management. Diabetes Obes Metabolism 26:46–56
32. Sankaran S, Varshitha P, Sai KMS, Reddy PA, Reddy KL (2024) A Comprehensive Review on Wearable Smart Respiratory Monitoring Shirt in COPD Patients. In: 2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS). IEEE, pp 14–18
33. Davis M, Kirwan M, Maclay W, Pappas H (eds) (2022) Closing the care gap with wearable devices: Innovating healthcare with wearable patient monitoring. CRC Press
34. Arora A, Chakraborty P, Bhatia M (2020) Analysis of data from wearable sensors for sleep quality Estimation and prediction using deep learning. Arab J Sci Eng 45:10793–10812
35. Huang Y, Yao K, Zhang Q, Huang X, Chen Z, Zhou Y, Yu X (2024) Bioelectronics for electrical stimulation: materials, devices and biomedical applications. Chem Soc Rev
36. Ouichka O, Echtioui A, Hamam H (2022) Deep learning models for predicting epileptic seizures using iEEG signals. Electronics 11(4):605
37. Pamulaparthyvenkata S, Murugesan P, Gottipalli D, Palanisamy P (2024) AI-Enabled Distributed Healthcare Framework for Secure and Resilient Remote Patient Monitoring. In: 2024 5th International Conference on Smart Electronics and Communication (ICOSEC). IEEE, pp 2034–2041
38. Ali HH, Ali HM, Ali HM, Ali MA, Zaky AF, Touk AA, Darwiche AH, Touk AA (2025) The Role and Limitations of Artificial Intelligence in Combating Infectious Disease Outbreaks. Cureus 17(1)
39. Wong KK (2023) Cybernetical intelligence: engineering cybernetics with machine intelligence. Wiley
40. Salman HA, Kalakech A, Steiti A (2024) Random forest algorithm overview. Babylon J Mach Learn 2024:69–79
41. Alzghaibi H (2025) Barriers to the Utilization of mHealth Applications in Saudi Arabia: Insights from Patients with Chronic Diseases. In: Healthcare, vol 13, no. 6. MDPI, p 665
42. Lu Y, Shi L, Wang Z (2025) Patient mobility in the digital era: how online service information from internet hospitals shapes patients' Cross-Regional healthcare choices. Healthcare. MDPI
43. Shafran-Tikva S, Gabay G, Kagan I (2025) Transformative Insights into Community-Acquired Pressure Injuries Among the Elderly: A Big Data Analysis. In: Healthcare, vol 13, no. 2. Multidisciplinary Digital Publishing Institute, p 153
44. Soori M, Arezoo B, Dastres R (2023) Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cogn Rob 3:54–70
45. Mulukuntla S, Pamulaparthyvenkata S (2022) Realizing the potential of AI in improving health outcomes: strategies for effective implementation. ESP J Eng Technol Advancements 2(3):32–40
46. Jeddi Z, Bohr A (2020) Remote patient monitoring using artificial intelligence. In: Artificial intelligence in healthcare. Academic Press, pp 203–234
47. Huang S-C et al (2020) Fusion of medical imaging and electronic health records using deep learning: a systematic review and implementation guidelines. NPJ Digit Med 3(1):136
48. Ahmed Z et al (2020) Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Database 2020:baaa010
49. Dlamini Z et al (2020) Artificial intelligence (AI) and big data in cancer and precision oncology. Comput Struct Biotechnol J 18:2300–2311
50. Shaik T et al (2023) Remote patient monitoring using artificial intelligence: current state, applications, and challenges. Wiley Interdisciplinary Reviews: Data Min Knowl Discovery 13(2):e1485
51. Kanakaprabha S, Kumar GG, Reddy BP, Raju YR, Rai PCM (2024) Wearable Devices and Health Monitoring: Big Data and AI for Remote Patient Care. Intell Data Anal Bioinform Biomed Syst 291–311
52. Bozyel S et al (2024) Artificial intelligence-based clinical decision support systems in cardiovascular diseases. Anatol J Cardiol 28(2):74
53. Alowais SA et al (2023) Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Med Educ 23(1):689
54. Andras I et al (2020) Artificial intelligence and robotics: a combination that is changing the operating room. World J Urol 38:2359–2366
55. Echtioui A et al (2024) Classification of BCI multiclass motor imagery task based on artificial neural network. Clin EEG Neurosci 55(4):455–464
56. Echtioui A et al (2021) A novel convolutional neural network classification approach of motor-imagery EEG recording based on deep learning. Appl Sci 11(21):9948
57. Dimigen O (2020) Optimizing the ICA-based removal of ocular EEG artifacts from free viewing experiments. NeuroImage 207:116117
58. Sharma A (2025) Securing the future of healthcare: ensuring privacy and security in wearable and implantable medical devices. Security, privacy, and trust in WBANs and E-Healthcare. CRC press, pp 105–125
59. Mkwashi A, Brass I (2022) The future of medical device regulation and standards: dealing with critical challenges for connected, intelligent medical devices. PETRAS Natl Centre Excellent IoT Syst Cybersecurity: Lond 2022:10
60. Chan J (2021) Exploring digital health care: eHealth, mHealth, and librarian opportunities. J Med Libr Association: JMLA 109(3):376
61. Mbunge E, Muchemwa B, Batani J (2022) Are we there yet? Unbundling the potential adoption and integration of telemedicine to improve virtual healthcare services in African health systems. Sens Int 3:100152
62. Kocyigit D et al (2022) Perspectives on the use of digital health technologies in cardiology among specialists from an ESC member country: results from a survey. Eur Heart Journal-Digital Health 3(4):ztac076
63. Lou Z et al (2020) Reviews of wearable healthcare systems: materials, devices and system integration. Mater Sci Engineering: R: Rep 140:100523
64. Chodankar D, Raval TK, Jeyaraj J (2024) The role of remote data capture, wearables, and digital biomarkers in decentralized clinical trials. Perspect Clin Res 15(1):38–41
65. Adepoju O et al (2024) Equity in digital health: assessing access and utilization of remote patient monitoring, medical apps, and wearables in underserved communities. INQUIRY: J Health Care Organ Provis Financing 61:00469580241271137
66. Wicki S et al (2024) Acceptance of digital health technologies in palliative care patients. Palliat Med Rep 5(1):34–42
67. Elkefi S (2024) Supporting patients' workload through wearable devices and mobile health applications, a systematic literature review. Ergonomics 67(7):954–970
68. Burunkaya DK, Keser N, Şimşek E, Bozyel S, Dalgıç Y, Şeker M, Korkmaz Y, Güler A, Çınar T, Ertürk M (2024) Perspectives on the Use of Digital Health Technologies in Cardiology Among Specialists from an ESC Member Country: Results from a Survey. Arch Turk Soc Cardiol/Türk Kardiyol Derneği Arş 52(1)
69. Golpaygani AT, Mehdizadeh AR (2021) Future of wearable health devices: smartwatches VS smart headphones. J Biomedical Phys Eng 11(5):561
70. Abdul S et al (2024) A review of the challenges and opportunities in implementing health informatics in rural healthcare settings. Int Med Sci Res J 4(5):606–631
71. Low C (2020) Harnessing consumer smartphone and wearable sensors for clinical cancer research. NPJ Digit Med 3:140

72. Ramdowar H, Khedo KK, Chooramun N (2024) A comprehensive review of mobile user interfaces in mHealth applications for elderly and the related ageing barriers. Univ Access Inf Soc 23(4):1613–1629
73. Alzahrani S, Daim T, Choo K-KR (2022) Assessment of the blockchain technology adoption for the management of the electronic health record systems. IEEE Trans Eng Manage 70(8):2846–2863
74. Liu P et al (2020) Use of mobile health applications in low-income populations: a prospective study of facilitators and barriers. Circulation: Cardiovasc Qual Outcomes 13(9):e007031
75. Eaton C et al (2024) User engagement with mHealth interventions to promote treatment adherence and self-management in people with chronic health conditions: systematic review. J Med Internet Res 26:e50508
76. Cho S et al (2021) Identifying data quality dimensions for person-generated wearable device data: Multi-method study. JMIR mHealth uHealth 9(12):e31618
77. Tarakji KG et al (2020) Digital health and the care of the patient with arrhythmia: what every electrophysiologist needs to know. Circulation: Arrhythmia Electrophysiol 13(11):e007953
78. Azodo I et al (2020) Opportunities and challenges surrounding the use of data from wearable sensor devices in health care: qualitative interview study. J Med Internet Res 22(10):e19542
79. Sui A et al (2023) Ethical considerations for the use of consumer wearables in health research. Digit Health 9:20552076231153740
80. George AH, Shahul A, George AS (2023) Wearable sensors: A new way to track health and wellness. Partners Univers Int Innov J 1(4):15–34
81. Al-Worafi YM (2023) Technology for Health: Overview. Handbook of Medical and Health Sciences in Developing Countries: Education, Practice, and Research. pp 1–23
82. Gandhi BM et al (2025) Homomorphic encryption and collaborative machine learning for secure healthcare analytics. Secur Priv 8(1):e460
83. Ramoliya F, Darji K, Gupta R, Kakkar R, Tanwar S, Kumari A (2023) Dl-based secure wearable scheme for remote patient data monitoring in healthcare 4.0. In: 2023 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS). IEEE, pp 757–762
84. Yammouri G, Ait Lahcen A (2024) AI-reinforced wearable sensors and intelligent point-of-care tests. J Personalized Med 14(11):1088
85. Kanagamalliga S (2024) Advancements in Remote Heart Monitoring: Wearable Technology and AI-based Approaches for Cardiovascular Disease Detection. In: AI in the Social and Business World: A Comprehensive Approach. Bentham Science Publishers, pp 102–117
86. Marvasti TB et al (2024) Unlocking tomorrow's health care: expanding the clinical scope of wearables by applying artificial intelligence. Can J Cardiol
87. Gopi B et al (2024) Distributed Technologies Using AI/ML Techniques for Healthcare Applications, in Social Innovations in Education, Environment, and Healthcare. IGI Global, pp 375–396
88. Kaliappan S et al (2023) Integrating Wearable Sensor Data and AI for Remote Monitoring and Management of Chronic Respiratory Diseases. In: IEEE International Conference on ICT in Business Industry & Government (ICTBIG). IEEE
89. Cabral AT, Fischer GS, da Rosa Righi R, da Costa CA, Roehrs A, Rigo SJ, Mello B (2024) Providing Interoperability between Wearable Devices and FHIR-based Healthcare Systems. In: Brazilian Symposium on Multimedia and the Web (WebMedia). SBC, pp 410–414
90. Mazhar T, Generative AI et al (2025) IoT, and blockchain in healthcare: application, issues, and solutions. Discover Internet Things 5(1):5
91. Mohanty A, Mohapatra AG, Mohanty SK (2024) Bridging Gaps in Patient Care With AI-Driven IoMT: Intelligent Connectivity and Patient-Centric Results. In: Lightweight Digital Trust Architectures in the Internet of Medical Things (IoMT). IGI Global, pp 213–228
92. Lopez-Perez L et al (2024) Regulatory Frameworks and Validation Strategies for Advancing Artificial Intelligence in Healthcare. In European Medical and Biological Engineering Conference. Springer
93. Patibandla S et al. Validation of artificial intelligence based real time multivitals remote monitoring solution-a clinical study
94. Chaudhari A, Sarode V, Udtewar S, Moharkar L, Patil L, Barreto F (2023) A review of artificial intelligence for predictive healthcare analytics and healthcare IoT applications. In: International Conference on Intelligent Computing and Networking. Springer Nature Singapore, Singapore, pp 555–562
95. Ismail A et al (2024) Advancing patient care with an intelligent and personalized medication engagement system. Information 15(10):609
96. Charfare RH, Desai AU, Keni NN, Nambiar AS, Cherian MM (2024) IoT-AI in Healthcare: A Comprehensive Survey of Current Applications and Innovations. Int J Robot Control Syst 4(3)
97. Kosaraju D Real-Time Cardiac Monitoring: AI Solutions for Continuous Patient Care
98. Momota MMR, Morshed BI (2022) ML algorithms to estimate data reliability metric of ECG from inter-patient data for trustable AI-based cardiac monitors. Smart Health 26:100350
99. Mannhart D et al (2023) Clinical validation of an artificial intelligence algorithm offering cross-platform detection of atrial fibrillation using smart device electrocardiograms. Arch Cardiovasc Dis 116(5):249–257
100. Haick H, Tang N (2021) Artificial intelligence in medical sensors for clinical decisions. ACS Nano 15(3):3557–3567
101. Olorunfemi BO et al (2025) Efficient diagnosis of diabetes mellitus using an improved ensemble method. Sci Rep 15(1):3235
102. Mah PM (2024) Investigating Remote Healthcare Accessibility with AI: Deep Learning and NLP-Based Knowledge Graph for Digitalized Diagnostics. In: Proceedings of the AAAI Symposium Series, vol 4, no. 1. pp 284–292
103. Kadyan S et al (2024) Human-Centric AI Applications for Remote Patient Monitoring, in Blockchain and IoT Approaches for Secure Electronic Health Records (EHR). IGI Global, pp 117–137
104. Ivanovic M, Autexier S, Kokkonidis M (2022) AI approaches in processing and using data in personalized medicine. In: European Conference on Advances in Databases and Information Systems. Springer
105. Singh KR et al (2023) AI powered medical chatbot in vernacular languages. In: 2023 6th International Conference on Recent Trends in Advance Computing (ICRTAC). IEEE
106. Sen S, Datta A (2024) Human-inspired distributed wearable AI. In: Proceedings of the 61st ACM/IEEE Design Automation Conference
107. Valli MM, Sudha S (2023) AI Based Smart Stretcher With Remote Knowledge Communication Via IoT. In: 2023 11th International Conference on Emerging Trends in Engineering & Technology-Signal and Information Processing (ICETET-SIP). IEEE, pp 1–6
108. Coman L-I et al (2024) Smart solutions for diet-related disease management: connected care, remote health monitoring systems, and integrated insights for advanced evaluation. Appl Sci 14(6):2351
109. Khang A (ed) (2024) Driving Smart Medical Diagnosis Through AI-Powered Technologies and Applications. IGI Global
110. Mazhar T et al (2024) Analysis of integration of IoMT with blockchain: issues, challenges and solutions. Discover Internet Things 4(1):1–36
111. Kerketta A, Balasundaram S (2024) Leveraging AI Tools to Bridge the Healthcare Gap in Rural Areas in India. medRxiv 2024-07
112. Song Y et al (2022) Evaluation of deep learning models in contactless human motion detection system for next generation healthcare. Sci Rep 12(1):21592
113. Olugboja A, Agbakwuru EM (2024) Bridging healthcare disparities in rural areas of developing countries: leveraging artificial intelligence for equitable access. In: 2024 International Conference on Artificial Intelligence, Computer, Data Sciences and Applications (ACDSA). IEEE, pp 1–6
114. Jeyaraman M et al (2023) Unraveling the ethical enigma: artificial intelligence in healthcare. Cureus 15(8)
115. Amugongo LM, Kriebitz A, Boch A, Lütge C (2023) Operationalising AI ethics through the agile software development lifecycle: a case study of AI-enabled mobile health applications. AI Ethics 1–8
116. Sultana S et al (2025) Health monitoring through wearables: A systematic review of innovations in cardiovascular disease detection and prevention. Strategic Data Manage Innov 2(01):96–115
117. Maambo M (2023) Assisted artificial intelligence medical diagnosis system for heart disease (Doctoral dissertation, The University of Zambia)
118. Li Y-H et al (2024) Innovation and challenges of artificial intelligence technology in personalized healthcare. Sci Rep 14(1):18994
119. Abdulmalek S, Nasir A, Jabbar WA, Almuhaya MA, Bairagi AK, Khan MAM, Kee SH (2022) IoT-based healthcare-monitoring system towards improving quality of life: A review. In: Healthcare, vol 10, no. 10. MDPI, p 1993
120. Nurani B et al (2025) Artificial intelligence and big data for personalized preventive healthcare: predicting health risks and enhancing patient adherence. Open Access Libr J 12(1):1–17
121. Adeghe EP, Okolo CA, Ojeyinka OT (2024) A review of wearable technology in healthcare: monitoring patient health and enhancing outcomes. OARJ Multidisciplinary Stud 7(01):142–148

122. Lyroi E, Olusegun J, Amizu T, Tayo O (2025) AI-Powered Wearables: Transforming Remote Patient Monitoring
123. Lewczak Z, Mitchell M, Mitchell MG (2024) Wearable Technology and Chronic Illness: Balancing Justice and Care Ethics. Cureus 16(11)
124. Vo D-K, Trinh KTL (2024) Advances in wearable biosensors for healthcare: current trends, applications, and future perspectives. Biosensors 14(11):560
125. Etli D, Djurovic A, Lark J (2024) The future of personalized healthcare: AI-Driven wearables for Real-Time health monitoring and predictive analytics. Curr Res Health Sci 2(2):10–14
126. Patil S, Shankar H (2023) Transforming healthcare: Harnessing the power of AI in the modern era. Int J Multidisciplinary Sci Arts 2(2):60–70
127. Khan AJMOR, Islam SAM, Sarkar A, Islam T, Paul R, Bari MS (2024) Real-time predictive health monitoring using AI-driven wearable sensors: Enhancing early detection and personalized interventions in chronic disease management. Int J Multidisciplinary R
128. Gautam N et al (2022) Artificial intelligence, wearables and remote monitoring for heart failure: current and future applications. Diagnostics 12(12):2964

Publisher's Note