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Wearable IoT Devices for Chronic Disease Monitoring: Sensors, Data Transmission, and Machine Learning Inference

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Abstract- The increasing prevalence of chronic diseases has intensified the demand for healthcare solutions capable of supporting continuous, personalised, and cost-effective patient management beyond traditional clinical settings. Wearable Internet of Things (IoT) devices have emerged as a promising technology by integrating physiological sensors, wireless communication, and intelligent data analytics to enable real-time remote monitoring of patients. This narrative literature review critically examines recent advances in wearable IoT devices for chronic disease monitoring, with a particular focus on sensing technologies, data transmission mechanisms, and machine learning inference. The review synthesises evidence from contemporary peer-reviewed literature to examine how wearable sensors capture physiological signals, how IoT communication technologies facilitate secure and reliable data exchange, and how machine learning algorithms transform raw health data into clinically meaningful insights. The review highlights the roles of key wearable sensors, including electrocardiography (ECG), photoplethysmography (PPG), continuous glucose monitoring, accelerometers, and pulse oximetry, in monitoring chronic conditions such as cardiovascular disease, diabetes mellitus, chronic obstructive pulmonary disease, and neurological disorders. It further compares wireless communication technologies, including Bluetooth Low Energy (BLE), Wi-Fi, Zigbee, Narrowband IoT (NB-IoT), Long Range (LoRa), and fifth-generation (5G) networks, with respect to their suitability for remote healthcare applications. In addition, the review discusses the growing contribution of traditional machine learning, deep learning, edge artificial intelligence, and explainable artificial intelligence in supporting early disease detection, risk prediction, and clinical decision-making. Finally, current challenges—including interoperability, data privacy, cybersecurity, energy efficiency, and clinical validation—are critically discussed alongside emerging research directions. By integrating recent developments across sensing, communication, and intelligent analytics, this review provides a comprehensive overview of wearable IoT technologies and their potential to advance remote patient monitoring and personalised chronic disease management.

I. INTRODUCTION

Chronic diseases, also referred to as non-communicable diseases (NCDs), represent one of the most significant public health challenges of the twenty-first century. Characterised by their long duration and slow progression, conditions such as cardiovascular disease, diabetes mellitus, chronic respiratory diseases, chronic kidney disease, and neurological disorders require continuous monitoring and long-term clinical management rather than short-term treatment (Guo et al., 2021; Jafleh et al., 2024). According to the World Health Organization (WHO), NCDs were responsible for approximately 43 million deaths in 2021, accounting for about 75% of all non-pandemic-related deaths worldwide. Cardiovascular diseases remain the leading cause of NCD mortality, followed by cancer, chronic respiratory diseases, and diabetes, with a large proportion of premature deaths occurring in low- and middle-income countries where healthcare resources are often constrained (World Health Organization, 2025). These trends continue to place substantial pressure on healthcare systems through increasing hospital admissions, long-term treatment costs, and growing demands for continuous patient care.

Conventional approaches to chronic disease management are primarily based on periodic clinical consultations and intermittent physiological measurements. Although these methods remain fundamental for diagnosis and treatment planning, they frequently provide only isolated snapshots of a patient's health status and may fail to detect gradual

physiological deterioration occurring between clinical visits (Guo et al., 2021; Tegegne et al., 2026). Furthermore, traditional monitoring often depends on patient self-reporting, which may be affected by inconsistent measurement practices, recall bias, or poor adherence to prescribed monitoring routines. As a result, clinically significant changes may remain undetected until patients present with severe symptoms requiring urgent medical intervention. These limitations have driven increasing interest in technologies capable of supporting continuous, real-time health monitoring outside traditional healthcare environments (Tan et al., 2024; Uddin & Koo, 2024).
Rapid advances in the Internet of Things (IoT) have fundamentally changed the way healthcare data are collected, transmitted, and analysed. Within healthcare, the Internet of Medical Things (IoMT) has enabled the development of interconnected medical devices capable of continuously monitoring physiological parameters while facilitating communication between patients, healthcare professionals, and digital health platforms (Islam et al., 2015; Dang et al., 2019). Wearable IoT devices—including smartwatches, fitness bands, smart patches, and continuous glucose monitoring systems—integrate miniaturised sensors with wireless communication technologies to collect physiological data in real time (Majumder et al., 2017; Di Rienzo & Mukkamala, 2021). Parameters such as heart rate, electrocardiography (ECG), photoplethysmography (PPG), blood oxygen saturation (SpO_2), blood glucose, respiratory rate, body temperature, and physical activity can now be monitored continuously during normal daily activities, providing clinicians with longitudinal health information that was previously difficult to obtain using conventional healthcare models (Andrade et al., 2024; Tegegne et al., 2026).

The value of wearable IoT technologies extends beyond continuous data collection. Advances in wireless communication technologies, including Bluetooth Low Energy (BLE), Wi-Fi, Narrowband IoT (NB-IoT), Long Range (LoRa), and fifth-generation (5G) mobile networks, have enabled reliable transmission of physiological data to smartphones, edge computing devices, and cloud-based healthcare platforms (Islam et al., 2015; Uddin & Koo, 2024). At the same time, developments in artificial intelligence (AI) and machine learning (ML) have enabled these large volumes of physiological data to be transformed into clinically meaningful information. Modern ML algorithms can detect abnormal physiological patterns, estimate disease risk, predict disease progression, and support evidence-based clinical decision-making, thereby shifting healthcare from reactive treatment towards predictive and personalised care (Rajkomar et al., 2019; Xiao et al., 2024).

These technological developments have significantly expanded the capabilities of remote patient monitoring (RPM), allowing healthcare professionals to supervise patients beyond hospital settings while improving continuity of care. Continuous monitoring may facilitate earlier detection of disease deterioration, reduce unnecessary hospital admissions, encourage patient engagement in self-management, and improve access to healthcare for individuals living in rural or underserved communities (Tan et al., 2024; Uddin & Koo, 2024). International organisations have also recognised the growing importance of digital health technologies, highlighting their potential to improve healthcare delivery while reducing the burden of chronic diseases on healthcare systems (World Health Organization & International Telecommunication Union, 2024).

Despite the rapid evolution of wearable healthcare technologies, several challenges continue to limit their widespread clinical adoption. Wearable sensors remain susceptible to motion artefacts, environmental interference, and battery limitations, while heterogeneous communication protocols and proprietary platforms complicate interoperability between devices and healthcare information systems (Patel et al., 2012; Majumder et al., 2017). In addition, concerns regarding data privacy, cybersecurity, algorithm transparency, regulatory compliance, and clinical validation continue to influence the deployment of wearable IoT systems in routine healthcare practice (Jian et al., 2024; Xiao et al., 2024). These challenges demonstrate that successful implementation requires not only technological innovation but also robust governance,

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multidisciplinary collaboration, and user-centred system design.

Although numerous review articles have examined wearable sensors, IoT-enabled healthcare, remote patient monitoring, or machine learning individually, relatively few narrative reviews integrate these three fundamental components—wearable sensing technologies, data transmission mechanisms, and machine learning inference—within a single comprehensive framework for chronic disease monitoring (Guo et al., 2021; Uddin & Koo, 2024; Tegegne et al., 2026). Given the rapid pace of innovation across these interconnected fields, there is a need for an updated synthesis that critically examines recent technological developments, identifies current challenges, and highlights future research opportunities.

Accordingly, this narrative literature review synthesises recent advances in wearable IoT devices for chronic disease monitoring, with particular emphasis on wearable sensors, wireless data transmission technologies, and machine learning inference. The review discusses the technological foundations of wearable IoT systems, evaluates the principal sensing and communication technologies currently employed in chronic disease management, examines the role of machine learning in transforming physiological data into actionable clinical insights, and analyses the major challenges and emerging research directions shaping the future of intelligent remote healthcare.

II. FUNDAMENTALS OF WEARABLE IOT SYSTEMS

Wearable Internet of Things (IoT) systems have emerged as a cornerstone of modern digital healthcare by integrating wearable sensing technologies, wireless communication, cloud and edge computing, and intelligent data analytics into a connected healthcare ecosystem. These technologies enable the continuous acquisition, transmission, processing, and interpretation of physiological data, allowing healthcare professionals to monitor patients beyond conventional clinical settings and facilitate proactive disease management (Islam et al., 2015; Guo et al., 2021; Uddin & Koo, 2024). Unlike traditional healthcare models that rely on episodic clinical assessments, wearable IoT systems support continuous monitoring and real-time clinical decision-making, thereby improving the management of chronic diseases through timely intervention and personalised care (Majumder et al., 2017; Jafleh et al., 2024). Understanding the fundamental concepts underpinning wearable IoT technologies is essential for appreciating how these systems support remote patient monitoring and intelligent healthcare delivery.

2.1 Chronic Disease Monitoring

Chronic diseases are long-term medical conditions that typically progress slowly and require continuous clinical management to minimise complications and improve patients' quality of life. Conditions including cardiovascular disease, diabetes mellitus, chronic obstructive pulmonary disease (COPD), chronic kidney disease, and neurological disorders account for a substantial proportion of global morbidity and mortality (World Health Organization, 2025). Unlike acute illnesses, chronic diseases often exhibit gradual physiological changes that may remain undetected when patients are assessed only during periodic clinical consultations. Consequently, conventional healthcare approaches based on intermittent measurements may fail to identify early signs of disease progression or deterioration (Guo et al., 2021).

Continuous health monitoring has therefore become an important strategy for improving chronic disease management. By collecting physiological data over extended periods, clinicians can observe longitudinal health trends, detect subtle physiological abnormalities, and intervene before severe complications develop (Majumder et al., 2017; Tegegne et al., 2025). Recent advances in wearable sensing technologies have made long-term monitoring increasingly practical by enabling physiological measurements to be collected continuously during normal daily activities rather than exclusively within hospitals or outpatient clinics (Di Rienzo & Mukkamala, 2021; Jafleh et al., 2024). This transition from episodic to continuous monitoring represents one of the most significant developments in digital healthcare, supporting more

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proactive, personalised, and patient-centred models of chronic disease management.

2.2 Internet of Things in Healthcare

The Internet of Things (IoT) refers to a network of interconnected devices capable of sensing, communicating, and exchanging information through wired or wireless communication networks. Within healthcare, this paradigm has evolved into the Internet of Medical Things (IoMT), an ecosystem comprising wearable sensors, medical devices, smartphones, cloud platforms, and healthcare information systems that operate collaboratively to support patient care (Islam et al., 2015; Dang et al., 2019). Through continuous connectivity, IoMT enables the automatic acquisition and transmission of physiological data with minimal human intervention, facilitating remote clinical supervision and evidence-based healthcare delivery.

The integration of IoT into healthcare has fundamentally changed how physiological information is collected and utilised. Rather than relying solely on hospital-based monitoring, wearable IoT devices enable continuous observation of patients in home and community settings, improving healthcare accessibility while reducing unnecessary hospital visits (Andrade et al., 2024; Uddin & Koo, 2024). Furthermore, integration with cloud computing provides scalable storage and processing capabilities, while artificial intelligence enables intelligent analysis of continuously acquired physiological data. Together, these technologies support predictive healthcare, early disease detection, and personalised clinical decision-making, illustrating the transformative potential of IoMT within modern healthcare systems (Aceto et al., 2020; Jafleh et al., 2024).

2.3 Wearable IoT System Architecture

A wearable IoT healthcare system typically consists of several interconnected layers that collectively support intelligent health monitoring. The sensing layer includes wearable devices equipped with physiological sensors such as electrocardiography (ECG), photoplethysmography (PPG), accelerometers, pulse oximeters, temperature sensors, and continuous glucose monitoring systems. These sensors continuously acquire physiological information relevant to chronic disease management (Majumder et al., 2017; Guo et al., 2021).

The communication layer is responsible for transmitting physiological data using wireless technologies including Bluetooth Low Energy (BLE), Wi-Fi, Zigbee, Long Range (LoRa), Narrowband IoT (NB-IoT), and fifth-generation (5G) mobile networks. The choice of communication protocol depends on factors such as transmission range, energy consumption, bandwidth, latency, and application requirements (Uddin & Koo, 2024).

Following transmission, physiological data are processed within edge or cloud computing environments where signal processing, secure storage, feature extraction, and machine learning inference are performed. Increasingly, edge computing is being adopted to reduce latency, improve response times, and enhance privacy by processing data closer to the patient (Xiao et al., 2024). Finally, the application layer presents analysed information through mobile health applications, clinician dashboards, telemedicine platforms, or electronic health records, enabling healthcare professionals to make informed clinical decisions while allowing patients to participate actively in managing their own health (Di Rienzo & Mukkamala, 2021). This layered architecture forms the technological foundation of modern wearable healthcare systems and enables scalable, secure, and intelligent remote patient monitoring.

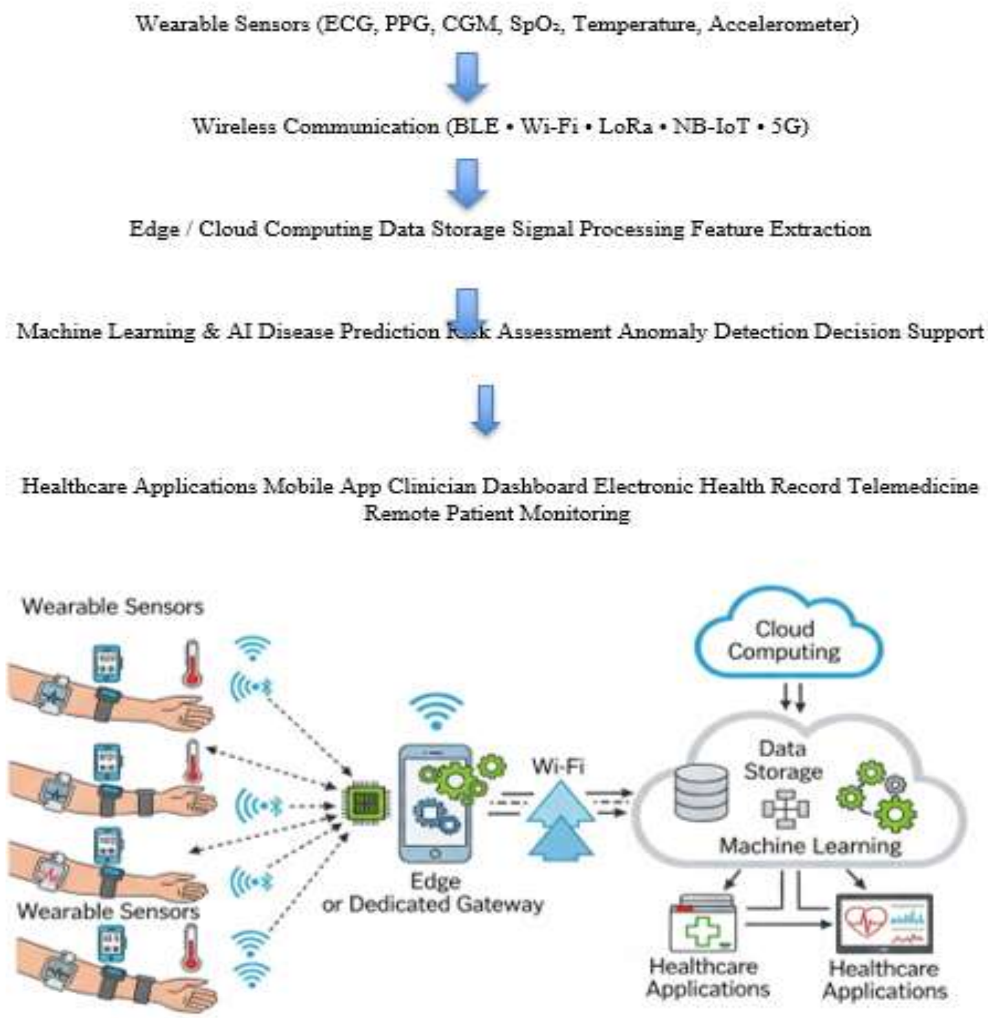

Figure 1. General architecture of a wearable IoT system for chronic disease monitoring

2.4 Remote Patient Monitoring

Remote Patient Monitoring (RPM) represents one of the most significant clinical applications of wearable IoT technologies. By continuously collecting physiological information outside traditional healthcare environments, RPM enables clinicians to monitor patients remotely, identify early signs of disease deterioration, and intervene before complications become severe (Tan et al., 2024; Uddin & Koo, 2024). Continuous access to physiological information also promotes patient engagement, improves adherence to treatment plans, and facilitates more personalised approaches to chronic disease management.

Recent advances in cloud computing, edge computing, and artificial intelligence have further enhanced RPM by enabling near real-time analysis of physiological signals, automated risk assessment, and intelligent clinical alerts. These capabilities have demonstrated considerable potential to reduce hospital admissions, improve clinical outcomes, and expand access to healthcare services, particularly for patients residing in rural or underserved communities (World Health Organization & International Telecommunication Union, 2024; Jafleh et al., 2024). Nevertheless, several challenges continue to influence the large-scale implementation of RPM, including interoperability, cybersecurity, patient privacy, regulatory compliance, and long-term patient adherence (Jian et al., 2024). Addressing these challenges will be essential for ensuring the safe, reliable, and sustainable integration of wearable IoT technologies into routine clinical practice.

Collectively, these fundamental concepts demonstrate how wearable IoT systems integrate sensing technologies, wireless communication, distributed computing, and intelligent analytics to support continuous chronic disease monitoring. This technological foundation underpins the operation of modern wearable healthcare platforms and provides the basis for understanding the wearable sensing technologies discussed in the following section.

III. WEARABLE SENSORS FOR CHRONIC DISEASE MONITORING

Wearable sensors constitute the foundation of wearable Internet of Things (IoT) systems because they enable the continuous acquisition of physiological and behavioural data that support remote patient monitoring and clinical decision-making. Recent advances in microelectronics, flexible materials, wireless communication, and low-power computing have facilitated the development of lightweight, non-invasive, and energy-efficient sensors capable of monitoring patients during normal daily activities. Unlike conventional clinical measurements obtained during periodic hospital visits, wearable sensors generate continuous longitudinal data, allowing clinicians to observe disease progression, evaluate treatment effectiveness, and detect early physiological abnormalities. These capabilities have significantly expanded the role of wearable technologies in managing chronic diseases, particularly cardiovascular disease, diabetes mellitus, chronic obstructive pulmonary disease (COPD), neurological disorders, and other long-term conditions requiring continuous surveillance.

Although wearable sensing technologies have improved substantially, no single sensor can comprehensively assess an individual's health status. Consequently, modern wearable healthcare systems increasingly employ multimodal sensing, combining multiple physiological measurements to improve diagnostic accuracy and reduce the limitations associated with individual sensors. The following sections review the principal sensing technologies currently used in wearable IoT systems for chronic disease monitoring.

3.1 Cardiovascular Sensors: Electrocardiography (ECG) and Photoplethysmography (PPG)

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for approximately 17.9 million deaths annually and representing a major contributor to the global burden of chronic disease (World Health Organization, 2025). Effective management of cardiovascular conditions relies heavily on the early detection of physiological abnormalities such as cardiac arrhythmias, changes in heart rate, reduced blood oxygen saturation, and altered cardiac function. Consequently, wearable cardiovascular sensors have become one of the most mature and widely adopted applications of wearable Internet of Things (IoT) technologies, enabling continuous, non-invasive monitoring of cardiovascular health outside conventional clinical environments (Guo et al., 2021; Jafleh et al., 2024).

Electrocardiography (ECG) remains the clinical gold standard for assessing the electrical activity of the heart. Traditional ECG monitoring has historically been restricted to hospitals or short-term ambulatory devices such as Holter monitors. However, recent advances in wearable electronics have enabled lightweight ECG sensors to be incorporated into smartwatches, adhesive chest patches, smart garments, and portable cardiac monitors, allowing continuous monitoring during normal daily activities (Patel et al., 2012; Di Rienzo & Mukkamala, 2021). Continuous wearable ECG monitoring provides clinicians with longitudinal cardiac data that can reveal transient arrhythmias or other abnormalities that may be missed during brief clinical examinations.

The integration of artificial intelligence with wearable ECG systems has further enhanced their clinical utility. Machine learning algorithms can analyse continuous ECG recordings to detect abnormal cardiac rhythms, classify arrhythmias, estimate cardiovascular risk, and support clinical decision-making with high levels of accuracy. Recent studies have demonstrated that deep learning models can achieve diagnostic performance comparable to expert cardiologists for specific arrhythmia classification tasks, highlighting the growing role of AI-assisted ECG interpretation in remote healthcare (Rajkomar et al., 2019). These advances have contributed to the increasing adoption of wearable ECG technologies in both clinical practice and home-based remote patient monitoring programmes.

In addition to ECG, photoplethysmography (PPG) has emerged as one of the most widely implemented sensing technologies in commercial wearable devices. PPG is an optical sensing technique that estimates changes in blood volume within peripheral blood vessels by measuring variations in reflected or transmitted light. Because PPG sensors require only light-emitting diodes and photodetectors, they can be integrated easily into wrist-worn devices such as smartwatches and fitness trackers, making them particularly attractive for continuous cardiovascular monitoring (Knight et al., 2023; Charlton et al., 2022). Modern wearable PPG systems are capable of continuously measuring heart rate, heart rate variability, pulse wave characteristics, and blood oxygen saturation (SpO_2), providing valuable physiological information for both clinical and consumer health applications.

Although wearable PPG technology offers significant advantages in terms of comfort, affordability, and long-term usability, several limitations remain. Signal quality may be degraded by motion artefacts, variations in skin pigmentation, ambient light interference, poor sensor placement, and reduced peripheral blood perfusion, all of which can affect measurement accuracy during daily activities (Knight et al., 2023). Consequently, researchers continue to investigate advanced signal-processing algorithms and machine learning techniques capable of improving noise reduction and enhancing the reliability of wearable PPG measurements under real-world conditions.

Recent advances have increasingly combined ECG and PPG measurements within multimodal wearable systems. Integrating electrical and optical cardiovascular signals enables more comprehensive assessment of cardiovascular function while improving robustness and diagnostic accuracy. Multimodal sensing also supports the estimation of additional physiological parameters, including pulse transit time, arterial stiffness, and cuffless blood pressure, which may further enhance chronic cardiovascular disease management (Charlton et al., 2022; Vo & Trinh, 2024). This convergence of wearable sensing technologies, wireless connectivity, and artificial intelligence demonstrates the continuing evolution of cardiovascular monitoring from episodic clinical assessment towards continuous, intelligent, and personalised healthcare.

3.2 Metabolic Sensors: Continuous Glucose Monitoring

Continuous glucose monitoring (CGM) has transformed diabetes management by enabling real-time assessment of glucose concentrations without the need for repeated finger-prick testing. Unlike conventional self-monitoring, which provides only intermittent measurements, CGM systems continuously monitor glucose levels in interstitial fluid, allowing clinicians and patients to observe glucose trends, identify episodes of hypoglycaemia and hyperglycaemia, and evaluate responses to medication, diet, and physical activity (Battelino et al., 2023; American Diabetes Association, 2024).

Modern CGM devices employ minimally invasive electrochemical biosensors that transmit glucose measurements wirelessly to smartphones, insulin pumps, or dedicated monitoring devices. The availability of continuous physiological data supports more personalised diabetes management and has contributed to improved glycaemic control and greater patient engagement in self-care (Kim et al., 2019; Vo & Trinh, 2024). Furthermore, integration with machine learning algorithms enables prediction of future glucose fluctuations, supporting early intervention and advancing the development of automated insulin delivery systems.

Despite these advantages, several challenges remain. Current CGM devices measure glucose in interstitial fluid rather than directly in blood, resulting in a physiological lag during periods of rapid glucose change. Additional limitations include device cost, periodic sensor replacement, and skin irritation (Battelino et al., 2023). To overcome these challenges, researchers are investigating non-invasive metabolic sensing technologies based on sweat, saliva, tears, and other biofluids. Flexible biosensors and wearable microfluidic platforms have shown considerable promise for improving patient comfort and expanding long-term metabolic monitoring, although further clinical validation is required before widespread adoption can be achieved (Heikenfeld et al., 2019; Chen et al., 2023).

3.3 Motion and Activity Sensors

Accelerometers and gyroscopes are among the most widely used wearable sensors for monitoring physical activity, mobility, posture, gait, and fall risk. Accelerometers measure linear acceleration, whereas gyroscopes measure angular velocity, enabling comprehensive assessment of body movement during daily activities. These sensors are commonly integrated into smartwatches, smartphones, wearable bands, and rehabilitation devices because they are compact, energy-efficient, and capable of continuously collecting movement data (Patel et al., 2012; Majumder et al., 2017).

Motion and activity sensors have become particularly valuable in the management of neurological disorders such as Parkinson's disease, where alterations in gait, tremor, balance, and movement patterns provide important indicators of disease progression. They are also widely applied in fall detection among older adults, stroke rehabilitation, physical activity assessment, and monitoring treatment outcomes. Beyond neurological disorders, objective measurement of physical activity supports the management of obesity, cardiovascular disease, and diabetes by enabling clinicians to evaluate exercise behaviour and lifestyle interventions more accurately (Guo et al., 2021; Jafleh et al., 2024).

Recent advances in artificial intelligence have further enhanced the capabilities of wearable motion sensors. Machine learning algorithms can analyse accelerometer and gyroscope data to recognise daily activities, detect abnormal movement patterns, and identify clinically significant behavioural changes automatically. These intelligent monitoring systems improve the accuracy of activity recognition while enabling earlier intervention for patients experiencing functional decline (Vo & Trinh, 2024).

Despite these advantages, interpreting movement data remains challenging because measurement accuracy can be influenced by sensor orientation, device placement, individual movement patterns, and environmental factors. Consequently, ongoing research focuses on improving sensor calibration, signal-processing techniques, and machine learning algorithms to enhance the reliability of wearable motion sensing under real-world conditions (Patel et al., 2012; Guo et al., 2021).

3.4 Physiological Sensors

In addition to cardiovascular and metabolic monitoring, wearable IoT devices increasingly incorporate physiological sensors capable of measuring blood oxygen saturation (SpO_2), body temperature, respiratory rate, and blood pressure. These sensors provide complementary physiological information that supports continuous assessment of patient health and facilitates the early detection of disease deterioration, particularly among individuals with chronic respiratory and cardiovascular conditions (Guo et al., 2021; Di Rienzo & Mukkamala, 2021).

Pulse oximeters estimate arterial oxygen saturation using photoplethysmography (PPG) and have become essential for monitoring patients with chronic respiratory diseases such as chronic obstructive pulmonary disease (COPD). Continuous SpO_2 monitoring enables clinicians to identify declining respiratory function, detect hypoxaemia at an early stage, and initiate timely clinical intervention. Similarly, wearable temperature sensors provide valuable information regarding infection, inflammation, and general physiological status. Although temperature alone is rarely sufficient for chronic disease management, combining it with other physiological measurements improves clinical interpretation and enhances remote patient monitoring (Knight et al., 2023; Vo & Trinh, 2024).

Wearable blood pressure monitoring has also evolved considerably, progressing from conventional cuff-

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based measurements towards cuffless approaches that combine ECG, PPG, and pulse transit time analysis. These emerging techniques offer the potential for continuous and non-invasive blood pressure monitoring, although further clinical validation is required before they can replace conventional sphygmomanometers in routine practice (Charlton et al., 2022).

A notable trend in wearable healthcare is the integration of multiple physiological sensors within a single device. By combining measurements such as SpO_2, temperature, respiratory rate, heart rate, and blood pressure, multimodal sensing systems provide a more comprehensive assessment of patient health than individual sensors alone. This integrated approach improves diagnostic accuracy, supports personalised chronic disease management, and forms the foundation for intelligent wearable healthcare platforms that combine continuous sensing with machine learning and remote patient monitoring (Kim et al., 2019; Guo et al., 2021).

3.5 Emerging Wearable Sensors

Recent advances in materials science, flexible electronics, and nanotechnology have accelerated the development of next-generation wearable sensors that are more comfortable, accurate, and suitable for long-term health monitoring. Flexible electronic patches, smart textiles, electronic skin (e-skin), and wearable biochemical sensors are expanding the range of physiological and biochemical information that can be collected continuously while improving user comfort and device wearability (Kim et al., 2019; Rodrigues et al., 2020).

Among these emerging technologies, wearable biochemical sensors have attracted considerable research interest because they enable non-invasive monitoring of biomarkers in biofluids such as sweat, saliva, tears, and interstitial fluid. These sensors can measure clinically relevant analytes including glucose, lactate, electrolytes, cortisol, and other metabolites, providing valuable insights into metabolic status, hydration, stress, and disease progression. Such capabilities have the potential to complement conventional physiological monitoring and support more comprehensive chronic disease management (Heikenfeld et al., 2019; Chen et al., 2023; Vo & Trinh, 2024).

Artificial intelligence is expected to play an increasingly important role in these emerging sensing technologies by enabling adaptive signal processing, multimodal data fusion, and personalised interpretation of physiological measurements. Combined with advances in low-power electronics, flexible materials, and energy-efficient hardware, these developments are expected to improve the accuracy, usability, and clinical value of future wearable healthcare systems (Kim et al., 2019; Vo & Trinh, 2024).

Despite their considerable potential, many emerging wearable sensors remain at the prototype or early clinical evaluation stage. Challenges related to sensor stability, analytical accuracy, large-scale manufacturing, regulatory approval, and long-term clinical validation must be addressed before these technologies can be widely adopted in routine healthcare. Nevertheless, continued advances in biosensing, flexible electronics, and artificial intelligence are expected to expand the capabilities of wearable IoT systems and support the next generation of intelligent, personalised chronic disease monitoring (Rodrigues et al., 2020; Chen et al., 2023).

Overall, wearable sensing technologies have evolved from simple fitness-tracking devices into sophisticated medical platforms capable of supporting continuous chronic disease monitoring. ECG and PPG sensors remain central to cardiovascular assessment, continuous glucose monitoring has transformed diabetes management, motion sensors provide objective evaluation of mobility and neurological function, and multimodal physiological sensing enhances comprehensive patient assessment. As wearable sensors continue to evolve, their effectiveness will increasingly depend on the reliable transmission of physiological data to healthcare platforms for storage, analysis, and clinical decision-making. Consequently, the following section examines the wireless communication technologies that enable secure and

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efficient data transmission within wearable IoT healthcare systems.

Table 1. Comparison of wearable sensors used in chronic disease monitoring

Sensor	Physiological parameter	Chronic disease applications	Advantages	Limitations
ECG	Cardiac electrical activity	Arrhythmia, heart disease	High diagnostic accuracy	Motion artefacts, skin contact
PPG	Heart rate, SpO_2	Cardiovascular disease	Low cost, non-invasive	Sensitive to motion and ambient light
CGM	Glucose concentration	Diabetes	Continuous glucose trends	Calibration, cost
Accelerometer/ Gyroscope	Movement and gait	Parkinson's disease, rehabilitation	Low power, activity monitoring	Placement sensitivity
Pulse Oximeter	Oxygen saturation	COPD, respiratory disease	Continuous oxygen monitoring	Reduced accuracy in some conditions
Temperature Sensor	Body temperature	General physiological monitoring	Simple, low power	Limited diagnostic value alone

IV. DATA TRANSMISSION TECHNOLOGIES

The effectiveness of wearable Internet of Things (IoT) systems depends not only on the acquisition of physiological data but also on the reliable transmission of these data to healthcare providers for analysis and clinical decision-making. Continuous health monitoring generates large volumes of physiological information that must be transferred efficiently, securely, and with minimal delay. Consequently, wireless communication technologies form a critical component of wearable healthcare systems by connecting wearable sensors with smartphones, edge devices, cloud platforms, and healthcare information systems (Islam et al., 2015; Uddin & Koo, 2024). The selection of an appropriate communication technology depends on transmission range, energy consumption, bandwidth, latency, reliability, scalability, and security requirements. Since no single wireless protocol satisfies every clinical scenario, modern wearable IoT systems increasingly employ hybrid communication architectures that combine multiple technologies to optimise performance.

Bluetooth Low Energy (BLE) is the most widely adopted communication protocol for wearable healthcare because of its low power consumption and seamless compatibility with smartphones and wearable devices. BLE enables physiological measurements collected by wearable sensors to be transmitted over short distances while preserving battery life, making it particularly suitable for

smartwatches, fitness trackers, and continuous glucose monitoring systems that require prolonged operation (Uddin & Koo, 2024; Andrade et al., 2024). Despite these advantages, BLE has a relatively limited communication range and generally depends on nearby gateway devices, such as smartphones, to support remote healthcare applications.

Wi-Fi provides substantially greater bandwidth than BLE and is therefore well suited to transmitting larger volumes of physiological data, firmware updates, and multimedia healthcare information. Hospitals and healthcare facilities commonly utilise Wi-Fi networks because they support high-speed communication between wearable devices, electronic health records, and clinical information systems. However, Wi-Fi consumes considerably more energy than BLE, reducing its suitability for battery-powered wearable devices intended for continuous long-term monitoring (Islam et al., 2015; Aceto et al., 2020). Consequently, Wi-Fi is primarily employed in environments where reliable network infrastructure and power availability are less restrictive.

For applications requiring communication across wider geographical areas, Low-Power Wide-Area Network (LPWAN) technologies such as Long Range (LoRa) and Narrowband IoT (NB-IoT) have emerged as attractive alternatives. These technologies provide extended communication distances while maintaining relatively low energy consumption, making them particularly valuable for remote patient monitoring in rural or underserved regions. Although LoRa and NB-IoT support lower transmission rates than Wi-Fi, they are well suited to wearable healthcare because physiological measurements generally comprise relatively small packets of sensor data transmitted at regular intervals rather than continuous high-bandwidth streams (Uddin & Koo, 2024). Their ability to support long battery life further enhances their suitability for long-term chronic disease monitoring.

The introduction of fifth-generation (5G) mobile communication has further expanded the capabilities of wearable IoT healthcare systems by providing ultra-low latency, high data throughput, and improved network reliability. These characteristics support healthcare applications requiring rapid transmission of physiological information, including telemedicine, emergency response systems, and near real-time monitoring of high-risk patients. Furthermore, 5G supports significantly larger numbers of connected devices than previous mobile communication technologies, making it well suited to future smart hospitals and large-scale digital healthcare ecosystems. Nevertheless, widespread deployment remains constrained by infrastructure costs, network availability, and higher energy requirements compared with lower-power communication protocols (Aceto et al., 2020).

Beyond communication performance, cybersecurity remains a fundamental requirement for wearable healthcare systems. Physiological information collected by wearable devices constitutes highly sensitive personal health data and therefore requires robust protection during transmission and storage. Modern wearable IoT platforms employ encryption, authentication protocols, secure communication channels, and access-control mechanisms to maintain the confidentiality, integrity, and availability of patient information. However, the increasing number of interconnected medical devices also expands the potential attack surface for cyber threats, including unauthorised access, data breaches, and insecure communication protocols (Jian et al., 2024). Consequently, cybersecurity should be considered an integral component of communication system design rather than an additional feature implemented after deployment.

Selecting an appropriate communication technology therefore requires balancing multiple technical and clinical requirements rather than simply choosing the protocol with the highest transmission speed. BLE remains the preferred solution for short-range wearable communication because of its exceptional energy efficiency, whereas Wi-Fi provides higher bandwidth for hospital environments. LoRa and NB-IoT extend monitoring capabilities across large geographical regions while preserving battery life, whereas 5G enables emerging healthcare applications that demand low latency and high reliability. Increasingly, hybrid communication architectures combine these technologies to improve flexibility, scalability, and resilience within wearable healthcare systems.

Ultimately, reliable data transmission transforms wearable physiological measurements into clinically actionable information. Regardless of the sensing technology employed, delayed, incomplete, or insecure communication may compromise clinical decision-making and reduce the effectiveness of remote patient monitoring. As wearable healthcare systems continue to evolve, future communication infrastructures will increasingly integrate low-power wireless technologies, edge computing, artificial intelligence, and next-generation mobile networks to deliver secure, intelligent, and continuous healthcare connectivity. Once physiological data have been transmitted successfully, the next challenge lies in extracting clinically meaningful insights from these data through machine learning inference, which is discussed in the following section.

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Table 2. Comparison of Wireless Communication Technologies for Wearable IoT Healthcare

Technology	Typical Range	Power Consumption	Bandwidth	Typical Healthcare Applications	Strengths	Limitations
Bluetooth Low Energy (BLE)	Short	Very Low	Moderate	Smartwatches, fitness trackers, CGM	Energy efficient, widely supported	Limited range
Wi-Fi	Medium	High	High	Hospital monitoring, clinical networks	High throughput	High power consumption
LoRa	Long	Very Low	Low	Rural remote monitoring	Long range, long battery life	Low data rate
NB-IoT	Long	Low	Moderate	Nationwide remote patient monitoring	Reliable cellular coverage	Network dependency
5G	Wide area	Moderate–High	Very High	Telemedicine, emergency monitoring	Low latency, high capacity	Infrastructure cost

V. MACHINE LEARNING INFERENCE

The rapid growth of wearable Internet of Things (IoT) technologies has resulted in the continuous generation of large volumes of physiological and behavioural data. Although wearable sensors effectively collect information such as heart rate, electrocardiography (ECG), blood glucose, blood oxygen saturation (SpO_2), physical activity, and sleep patterns, these raw measurements require intelligent analysis to provide meaningful clinical insights. Machine learning (ML) has therefore become a fundamental component of wearable healthcare systems by enabling automated interpretation of physiological signals, early detection of abnormalities, prediction of disease progression, and clinical decision support (Rajkomar et al., 2019; Xiao et al., 2024). Rather than replacing clinicians, ML assists healthcare professionals by identifying complex patterns within continuous health data that may not be readily recognised through manual analysis.

Machine learning inference refers to the application of a trained model to new data in order to generate predictions or classifications. Within wearable IoT systems, physiological signals are first pre-processed to remove noise, reduce motion artefacts, and extract relevant features before being analysed by trained ML models. The resulting predictions may identify clinically significant events such as cardiac arrhythmias, abnormal glucose trends, falls, or respiratory deterioration, enabling continuous monitoring systems to generate alerts, estimate risk, and support timely clinical intervention (Guo et al., 2021; Jafleh et al., 2024).

Traditional supervised machine learning algorithms remain widely used because they provide reliable predictive performance while requiring relatively modest computational resources. Decision trees, random forests, support vector machines (SVMs), and k-nearest neighbours (k-NN) have been successfully applied to classify physiological signals, detect falls, recognise physical activities, and predict disease risk. These algorithms are particularly valuable in healthcare because they often provide greater interpretability than more complex deep learning models while maintaining competitive performance across many clinical applications (Rajkomar et al., 2019).

Recent advances in deep learning have further expanded the analytical capabilities of wearable healthcare systems. Convolutional neural networks (CNNs) automatically learn discriminative features from physiological signals such as ECG and photoplethysmography (PPG), while long short-term memory (LSTM) networks are well suited to analysing sequential physiological data because they capture temporal dependencies over time. These approaches have demonstrated promising results in arrhythmia detection, glucose prediction, sleep analysis, and activity recognition. However, deep learning models generally require larger training datasets and greater computational resources, limiting direct deployment on resource-constrained wearable devices (Xiao et al., 2024).

The location where inference is performed has also become an important design consideration. Traditionally, physiological data were transmitted to cloud platforms for analysis because cloud computing provides substantial processing power and storage capacity. More recently, edge artificial intelligence (Edge AI) has emerged as an attractive alternative by performing inference closer to the data source on smartphones, gateway devices, or edge computing platforms. Edge AI reduces communication latency, decreases bandwidth requirements, enhances data privacy, and enables faster responses for time-critical applications such as fall detection and cardiac monitoring. Consequently, hybrid edge–cloud architectures are increasingly adopted to balance computational performance, scalability, and privacy (Xu et al., 2022; Uddin & Koo, 2024).

Researchers are also increasingly investigating explainable artificial intelligence (XAI) and federated learning to improve the trustworthiness of AI-assisted healthcare. Explainable AI enhances transparency by providing interpretable explanations for model predictions, thereby increasing clinician confidence and supporting regulatory requirements. Federated learning enables ML models to be trained collaboratively across multiple devices without transferring sensitive patient data to a central server, improving privacy while maintaining predictive performance (Xu et al., 2022).

Despite significant progress, several challenges continue to influence the implementation of ML within wearable IoT systems. Model performance depends heavily on the quality and diversity of training data, while physiological signals are frequently affected by motion artefacts, missing values, environmental interference, and inter-patient variability. In addition, algorithmic bias, limited interpretability, computational constraints, and the need for rigorous clinical validation remain important barriers to widespread adoption (Rajkomar et al., 2019; Xiao et al., 2024).

Overall, machine learning has transformed wearable IoT systems from passive monitoring platforms into intelligent healthcare technologies capable of supporting early disease detection, predictive analytics, and personalised clinical decision-making. Continued advances in lightweight deep learning, Edge AI, explainable AI, and privacy-preserving learning are expected to further improve the accuracy, efficiency, and clinical reliability of wearable healthcare systems, supporting the next generation of intelligent remote patient monitoring.

VI. CLINICAL APPLICATIONS

Wearable Internet of Things (IoT) technologies have significantly expanded the scope of chronic disease management by enabling continuous physiological monitoring, remote patient supervision, and intelligent clinical decision support. Through the integration of wearable sensors, wireless communication, and machine learning, these systems have shifted healthcare from episodic assessment towards continuous, data-driven care. Across a range of chronic diseases, wearable IoT technologies facilitate early disease detection, monitor disease progression, support personalised treatment, and improve patient engagement, ultimately contributing to better clinical outcomes (Guo et al., 2021; Jafleh et al., 2024).

6.1 cardiovascular disease

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Cardiovascular disease remains the leading cause of death globally, making it one of the most important application areas for wearable IoT technologies (World Health Organization, 2025). Wearable devices equipped with electrocardiography (ECG) and photoplethysmography (PPG) sensors enable continuous monitoring of heart rhythm, heart rate, heart rate variability, and blood oxygen saturation. Combined with machine learning, these physiological signals can be analysed to detect cardiac arrhythmias, identify abnormal heart rhythms, and provide early warning of clinical deterioration. Continuous monitoring is particularly valuable for patients with intermittent cardiac abnormalities that may not be detected during routine clinical examinations, supporting earlier intervention and reducing avoidable hospital admissions (Charlton et al., 2022; Rajkomar et al., 2019).

6.2 Diabetes Mellitus

Wearable continuous glucose monitoring (CGM) systems have transformed diabetes management by providing continuous assessment of glucose concentrations throughout the day. Unlike conventional finger-prick testing, CGM devices allow clinicians and patients to observe glucose trends, identify episodes of hypoglycaemia and hyperglycaemia, and evaluate treatment effectiveness in real time. Machine learning further enhances diabetes management by predicting future glucose fluctuations, supporting personalised insulin therapy, and improving patient self-management through automated alerts and decision support (Battelino et al., 2023; American Diabetes Association, 2024). These advances have contributed to improved glycaemic control and greater patient engagement in diabetes care.

6.3 Chronic Respiratory Diseases

Wearable IoT technologies are increasingly used to monitor patients with chronic respiratory diseases such as chronic obstructive pulmonary disease (COPD). Pulse oximeters, respiratory sensors, and activity monitors continuously measure blood oxygen saturation (SpO_2), respiratory rate, and physical activity, enabling clinicians to detect declining respiratory function before severe exacerbations occur. Remote monitoring also supports home-based disease management by reducing unnecessary hospital visits while allowing timely clinical intervention when abnormal physiological changes are identified (Uddin & Koo, 2024; Guo et al., 2021). These capabilities are particularly beneficial for older adults and patients living in rural or underserved communities.

6.4 Neurological Disorders

Wearable motion sensors, including accelerometers and gyroscopes, have become valuable tools for monitoring neurological disorders such as Parkinson's disease. Continuous assessment of gait, tremor, posture, and mobility provides objective information regarding disease progression that complements conventional neurological examinations. Machine learning algorithms further improve clinical assessment by identifying subtle changes in movement patterns, evaluating treatment response, and supporting rehabilitation programmes. Beyond Parkinson's disease, wearable sensors have demonstrated considerable potential in stroke rehabilitation and the monitoring of other neurological conditions affecting balance and mobility (Patel et al., 2012; Majumder et al., 2017).

6.5 Towards Personalised Chronic Disease Management

Although wearable IoT technologies have demonstrated significant benefits across individual chronic diseases, their greatest potential lies in supporting personalised healthcare. By integrating continuous physiological monitoring with artificial intelligence, clinicians can move beyond standardised treatment approaches towards interventions tailored to each patient's physiological characteristics and disease trajectory. Multimodal wearable systems that combine cardiovascular, metabolic, respiratory, and behavioural data provide a more comprehensive understanding of patient health than individual measurements alone. As edge computing, explainable artificial intelligence, and next-generation communication networks continue to mature, wearable IoT systems are expected to deliver increasingly accurate predictions, earlier clinical interventions, and more efficient healthcare delivery. Nevertheless, widespread implementation will depend on continued improvements in

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interoperability, clinical validation, cybersecurity, data privacy, and patient acceptance (Xiao et al., 2024; Jian et al., 2024).

Collectively, these clinical applications demonstrate that wearable IoT technologies have evolved beyond consumer health-tracking devices into clinically relevant platforms for chronic disease management. Their ability to integrate continuous sensing, reliable wireless communication, and intelligent data analysis provides healthcare professionals with richer clinical information while empowering patients to participate more actively in managing their own health. As these technologies continue to advance, they are expected to play an increasingly important role in delivering predictive, preventive, and personalised healthcare.

Table 3. Clinical Applications of Wearable IoT Technologies

Chronic disease	Wearable sensors	Physiological parameters	Machine learning application	Clinical benefits
Cardiovascular disease	ECG, PPG	Heart rate, ECG, SpO_2	Arrhythmia detection, cardiovascular risk prediction	Early diagnosis, continuous monitoring, reduced hospital admissions
Diabetes mellitus	Continuous glucose monitor (CGM)	Glucose concentration	Glucose prediction, insulin optimisation	Improved glycaemic control, personalised diabetes management
Chronic respiratory disease (COPD)	Pulse oximeter, respiratory sensor, activity monitor	SpO_2, respiratory rate, activity level	Exacerbation prediction, respiratory deterioration detection	Early intervention, reduced hospital visits
Neurological disorders (e.g., Parkinson's disease)	Accelerometer, gyroscope	Gait, tremor, posture, balance	Activity recognition, disease progression monitoring	Improved rehabilitation and functional assessment
Multiple chronic conditions	Multimodal wearable platform	Cardiovascular, metabolic, respiratory and behavioural data	Personalised risk prediction and clinical decision support	Precision medicine, comprehensive remote patient monitoring

VII. CHALLENGES

Despite the significant advances in wearable Internet of Things (IoT) technologies for chronic disease monitoring, several technical, clinical, organisational, and ethical challenges continue to limit their widespread adoption. Although wearable sensors, wireless communication technologies, and machine learning algorithms have demonstrated considerable potential to improve remote patient monitoring and personalised healthcare, their successful implementation depends on addressing issues related to data quality, energy efficiency, interoperability, cybersecurity, artificial intelligence, and patient acceptance (Guo et al., 2021; Jafleh et al., 2024). Overcoming these challenges is essential to ensure that wearable IoT systems can be integrated safely, effectively, and sustainably into routine healthcare practice.

One of the primary challenges is maintaining the accuracy and reliability of physiological measurements obtained from wearable sensors. Unlike hospital-based medical equipment that operates under controlled conditions, wearable devices function in dynamic real-world environments where motion artefacts, poor sensor placement, perspiration, environmental interference, and individual physiological differences may affect signal quality. Inaccurate or incomplete physiological

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measurements can reduce the performance of machine learning models and increase the likelihood of false alarms or missed clinical events. Consequently, improving sensor robustness, signal processing techniques, and calibration methods remains an important research priority (Majumder et al., 2017; Di Rienzo & Mukkamala, 2021).

Energy efficiency represents another major engineering challenge. Wearable devices are expected to operate continuously while maintaining compact designs and user comfort. However, continuous sensing, wireless communication, and on-device computation consume considerable battery power, limiting operational lifetime and increasing the need for frequent charging. Researchers are therefore investigating low-power communication protocols, energy-efficient hardware, lightweight machine learning models, and energy harvesting technologies to extend battery life without compromising monitoring performance (Uddin & Koo, 2024).

Interoperability also remains a significant barrier to large-scale deployment. Wearable healthcare ecosystems comprise devices from multiple manufacturers that frequently employ proprietary communication protocols, data formats, and software platforms. This lack of standardisation complicates the seamless exchange of information between wearable devices, mobile applications, hospital information systems, and electronic health records. Improving interoperability through the adoption of common communication standards and digital health frameworks is essential for reducing implementation costs and supporting efficient integration into clinical workflows (Aceto et al., 2020).

Protecting patient privacy and ensuring cybersecurity are equally critical challenges. Wearable devices continuously collect highly sensitive physiological and behavioural information that is transmitted across wireless networks and often stored in cloud-based infrastructures. These distributed environments increase exposure to cyber threats, including unauthorised access, data interception, device compromise, and ransomware attacks. Although encryption, authentication protocols, and secure communication mechanisms have strengthened the security of wearable healthcare systems, maintaining the confidentiality, integrity, and availability of patient data remains a major concern for developers, healthcare providers, and regulators (Jian et al., 2024).

The growing integration of artificial intelligence introduces additional clinical and ethical considerations. Machine learning models rely heavily on high-quality and representative training datasets, and algorithms developed using limited or biased data may perform poorly when applied to different patient populations. Furthermore, many deep learning models function as "black boxes," making it difficult for clinicians to understand how predictions are generated. These limitations have stimulated increasing interest in explainable artificial intelligence (XAI), which seeks to improve model transparency, strengthen clinician trust, and support regulatory approval of AI-assisted clinical decision support systems (Rajkomar et al., 2019; Xiao et al., 2024).

Finally, successful implementation depends on patient acceptance, rigorous clinical validation, and supportive regulatory frameworks. Long-term adherence is influenced by factors such as device comfort, usability, affordability, digital literacy, and confidence in technology. At the same time, many wearable devices and artificial intelligence models have demonstrated promising results only under controlled research conditions and require further evaluation across diverse patient populations and real-world healthcare environments. Establishing clinical effectiveness, safety, and cost-effectiveness will require close collaboration among clinicians, engineers, computer scientists, healthcare organisations, industry, and regulatory authorities (World Health Organization & International Telecommunication Union, 2024; Jafleh et al., 2024).

Addressing these challenges will be fundamental to the continued evolution of wearable IoT technologies. Continued advances in sensor design, low-power communication, cybersecurity, explainable artificial intelligence, interoperability standards, and clinical validation are expected to strengthen the reliability and scalability of wearable healthcare systems. These developments will provide

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the foundation for the future research directions discussed in the following section.

VIII. FUTURE RESEARCH

Wearable Internet of Things (IoT) technologies have advanced rapidly over the past decade, yet significant opportunities remain to improve their clinical effectiveness, scalability, and integration into healthcare systems. Future research is expected to focus on enhancing sensing accuracy, reducing energy consumption, improving wireless communication, strengthening artificial intelligence (AI), and addressing interoperability and security challenges. As healthcare continues to shift towards predictive, preventive, and personalised care, the next generation of wearable IoT systems is expected to become increasingly intelligent, autonomous, and seamlessly integrated into routine clinical practice (Guo et al., 2021; Jafleh et al., 2024).

One important research direction is the development of next-generation wearable sensors capable of providing more comprehensive and reliable physiological monitoring. Advances in flexible electronics, smart textiles, electronic skin (e-skin), and wearable biochemical sensors are enabling devices that are lighter, more comfortable, and suitable for long-term use. Researchers are also investigating non-invasive sensing technologies capable of monitoring biomarkers through sweat, saliva, tears, and interstitial fluid, reducing reliance on invasive sampling while expanding the range of physiological information available for chronic disease management (Heikenfeld et al., 2019; Kim et al., 2019; Chen et al., 2023).

Artificial intelligence is expected to play an increasingly central role in wearable healthcare. Future research is likely to focus on lightweight machine learning models capable of performing inference directly on wearable devices or nearby edge computing platforms. Edge AI reduces communication latency, lowers bandwidth requirements, and enhances data privacy by limiting the transmission of sensitive physiological information to remote cloud servers. At the same time, explainable artificial intelligence (XAI) and federated learning are expected to improve model transparency, clinician trust, and privacy-preserving collaborative learning, making AI-assisted healthcare systems more reliable and clinically acceptable (Xu et al., 2022; Xiao et al., 2024).

Future communication infrastructures will also influence the evolution of wearable healthcare systems. Although Bluetooth Low Energy (BLE), Wi-Fi, Long Range (LoRa), Narrowband IoT (NB-IoT), and fifth-generation (5G) networks currently support many wearable healthcare applications, future research is expected to explore sixth-generation (6G) communication, ultra-low-power networking, and adaptive communication protocols capable of supporting larger numbers of connected medical devices with improved reliability and lower energy consumption (Aceto et al., 2020; Uddin & Koo, 2024).

Another promising direction is the integration of multimodal sensing and digital twins into chronic disease management. Rather than relying on individual physiological measurements, future wearable systems are expected to combine cardiovascular, metabolic, respiratory, behavioural, and environmental data to generate comprehensive digital representations of patient health. These digital twins may enable simulation of disease progression, evaluation of treatment strategies, and more personalised clinical decision-making before interventions are implemented in real-world settings, supporting the broader goals of precision medicine (Vo & Trinh, 2024).

Future research should also prioritise interoperability, standardisation, and clinical validation. The adoption of common communication standards, interoperable data formats, and open software architectures will facilitate seamless integration between wearable devices, electronic health records, telemedicine platforms, and clinical decision-support systems. Equally important is the need for large-scale multicentre clinical studies involving diverse patient populations to establish the long-term effectiveness, safety, reliability, and cost-effectiveness of wearable IoT technologies. Incorporating clinicians, patients, engineers, healthcare organisations, and policymakers throughout the development process will help ensure that future wearable systems address genuine clinical needs while remaining accessible, secure, and user-centred (World Health Organization & International Telecommunication Union, 2024).

Overall, the future of wearable IoT technologies lies in the convergence of advanced sensing, intelligent analytics, secure communication, and personalised healthcare. Continued progress in flexible electronics, artificial intelligence, multimodal sensing, digital twins, and next-generation communication networks is expected to overcome many of the current limitations identified throughout this review. Achieving this vision will require interdisciplinary collaboration, rigorous clinical validation, and internationally accepted standards to ensure that technological innovation translates into meaningful improvements in chronic disease prevention, monitoring, and management.

IX. CONCLUSION

The growing global burden of chronic diseases continues to place significant pressure on healthcare systems, highlighting the need for innovative approaches that support continuous, efficient, and patient-centred care. Wearable Internet of Things (IoT) technologies have emerged as a transformative solution by combining wearable sensing technologies, wireless communication networks, and intelligent data analytics to enable continuous remote monitoring and personalised disease management. This narrative review has examined the three fundamental pillars underpinning wearable IoT systems—wearable sensors, data transmission technologies, and machine learning inference—and demonstrated how their convergence is reshaping chronic disease monitoring and modern healthcare delivery.

The review highlighted the important role of wearable sensors in continuously capturing physiological and behavioural information relevant to chronic disease management. Technologies including electrocardiography (ECG), photoplethysmography (PPG), continuous glucose monitoring, motion sensors, pulse oximeters, and multimodal physiological sensors have substantially improved the ability to monitor patients beyond conventional clinical settings. Equally important, advances in wireless communication technologies such as Bluetooth Low Energy (BLE), Wi-Fi, Long Range (LoRa), Narrowband IoT (NB-IoT), and fifth-generation (5G) networks have enabled secure and reliable transmission of physiological data to healthcare platforms. These communication capabilities, combined with advances in machine learning, have transformed wearable healthcare systems from passive data collection tools into intelligent platforms capable of supporting early disease detection, predictive analytics, risk stratification, and clinical decision support.

Despite these technological advances, several barriers continue to limit widespread clinical implementation. Challenges relating to sensor accuracy, battery life, interoperability, cybersecurity, patient privacy, clinical validation, regulatory compliance, and long-term user adherence must be addressed before wearable IoT technologies can achieve routine large-scale adoption. Furthermore, ensuring that artificial intelligence models are transparent, reliable, unbiased, and clinically interpretable will be essential for strengthening clinician confidence and facilitating regulatory acceptance of AI-assisted healthcare systems.

The review also demonstrates that the future of wearable healthcare extends beyond incremental improvements in individual technologies. Emerging developments in flexible electronics, wearable biochemical sensors, Edge AI, explainable artificial intelligence, multimodal sensing, digital twins, and next-generation communication networks have the potential to further improve the accuracy, efficiency, and accessibility of chronic disease management. However, technological innovation alone will not be sufficient. Continued collaboration among clinicians, engineers, computer scientists, healthcare organisations, policymakers, regulators, and industry will be necessary to develop secure, interoperable, clinically validated, and patient-centred wearable healthcare ecosystems.

In conclusion, wearable IoT technologies represent a significant advancement towards intelligent, connected, and personalised healthcare. By integrating continuous physiological sensing, reliable wireless communication, and advanced machine learning inference, these systems have the potential to improve early diagnosis, support proactive clinical intervention, enhance patient engagement, and optimise long-term chronic disease management. As research continues to address the remaining technical and clinical challenges, wearable IoT technologies are expected to play an increasingly important role in advancing remote patient monitoring, precision medicine, and the future delivery of digital healthcare.

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