

Olawade, David B., Aderinto, Nicholas,

Clement David-Olawade, Aanuoluwapo, Egbon, Eghosasere, Adereni, Temitope, Popoola, Mayowa Racheal and Tiwari, Ritika ORCID logoORCID: https://orcid.org/0000-0002-5078-8989 (2025) Integrating AI-driven wearable devices and biometric data into stroke risk assessment: A review of opportunities and challenges. Clinical Neurology and Neurosurgery, 249. p. 108689.

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Contents lists available at [ScienceDirect](www.sciencedirect.com/science/journal/03038467)

Clinical Neurology and Neurosurgery

journal homepage: www.elsevier.com/locate/clineuro

Review Article

Integrating AI-driven wearable devices and biometric data into stroke risk assessment: A review of opportunities and challenges

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ARTICLE INFO

Keywords: Stroke risk assessment Wearable technology Biometric data Artificial intelligence Continuous monitoring

ABSTRACT

Stroke is a leading cause of morbidity and mortality worldwide, and early detection of risk factors is critical for prevention and improved outcomes. Traditional stroke risk assessments, relying on sporadic clinical visits, fail to capture dynamic changes in risk factors such as hypertension and atrial fibrillation (AF). Wearable technology (devices), combined with biometric data analysis, offers a transformative approach by enabling continuous monitoring of physiological parameters. This narrative review was conducted using a systematic approach to identify and analyze peer-reviewed articles, reports, and case studies from reputable scientific databases. The search strategy focused on articles published between 2010 till date using pre-determined keywords. Relevant studies were selected based on their focus on wearable devices and AI-driven technologies in stroke prevention, diagnosis, and rehabilitation. The selected literature was categorized thematically to explore applications, opportunities, challenges, and future directions. The review explores the current landscape of wearable devices in stroke risk assessment, focusing on their role in early detection, personalized care, and integration into clinical practice. The review highlights the opportunities presented by continuous monitoring and predictive analytics, where AI-driven algorithms can analyze biometric data to provide tailored interventions. Personalized stroke risk assessments, powered by machine learning, enable dynamic and individualized care plans. Furthermore, the integration of wearable technology with telemedicine facilitates remote patient monitoring and rehabilitation, particularly in underserved areas. Despite these advances, challenges remain. Issues such as data accuracy, privacy concerns, and the integration of wearables into healthcare systems must be addressed to fully realize their potential. As wearable technology evolves, its application in stroke care could revolutionize prevention, diagnosis, and rehabilitation, improving patient outcomes and reducing the global burden of stroke.

1. Introduction

Stroke remains one of the most pressing global health challenges, ranking as the second leading cause of death and a primary contributor to long-term disability $[1,2]$. Each year, more than 15 million people suffer from a stroke, with five million fatalities and another five million left permanently disabled, placing a substantial burden on healthcare systems worldwide [\[3\]](#page-8-0). Stroke-related impairments, such as cognitive,

motor, and speech dysfunction, not only diminish quality of life but also contribute significantly to the global loss of disability-adjusted life years (DALYs) [4–[6\].](#page-8-0) Ischemic strokes, caused by blockages in cerebral blood vessels, account for approximately 87 % of all cases, with the remainder being hemorrhagic strokes resulting from vessel rupture [\[7\].](#page-8-0) The sudden and unpredictable nature of stroke, combined with the narrow therapeutic window for effective intervention, underscores the urgent need for enhanced risk monitoring and early prevention strategies to mitigate

<https://doi.org/10.1016/j.clineuro.2024.108689>

Received 12 November 2024; Received in revised form 4 December 2024; Accepted 9 December 2024

Available online 10 December 2024

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its devastating impact [\[8\].](#page-8-0)

Atrial fibrillation (AF) is one of the most significant modifiable risk factors for stroke, strongly associated with increased morbidity and mortality in ischemic and cardioembolic stroke patients [\[9,10\]](#page-8-0). Ischemic strokes in patients with AF tend to be more severe and frequently involve cortical locations, which are recognized as potential risk factors for post-stroke complications such as seizures and epilepsy [\[11\]](#page-8-0). Evidence indicates that the rate of early post-ischemic stroke seizures ranges from 2 % to 33 %, with late seizure rates varying between 3 % and 67 %. Post-stroke epilepsy, defined as recurrent late seizures, occurs in approximately 2–4 % of patients and is more likely in those who experience late seizures [\[12\]](#page-8-0). These complications, coupled with AF's contribution to stroke severity, highlight the critical need for early detection and management to prevent exacerbation of neurological outcomes and improve overall patient prognosis.

One of the most effective ways to reduce stroke incidence and improve outcomes is through early identification of risk factors, enabling timely intervention $[6,13,14]$. Established stroke risk factors, including hypertension, atrial fibrillation (AF), diabetes, smoking, physical inactivity, and obesity, are well-documented, but many remain undiagnosed or inadequately managed, especially among asymptomatic individuals [\[15\]](#page-8-0). The sporadic nature of traditional healthcare visits often means that stroke risk factors, such as episodic high blood pressure or intermittent heart arrhythmias, may go unnoticed until they culminate in a cerebrovascular event. This reactive approach to stroke management limits the potential for early interventions that could significantly lower the risk of stroke and improve patient outcomes.

Standard stroke risk assessments, like the Framingham Stroke Risk Profile, offer valuable predictive frameworks based on long-term, static factors such as age, gender, cholesterol levels, and smoking history [\[13,](#page-8-0) [16\].](#page-8-0) However, these tools are typically based on data collected during infrequent clinical assessments and do not account for the day-to-day or even minute-to-minute variability in physiological markers that might indicate an elevated stroke risk [\[16\]](#page-8-0). For example, hypertension—the most significant modifiable risk factor for stroke—may go undetected in individuals who only exhibit elevated readings intermittently or outside of clinical settings [\[16\]](#page-8-0). This includes patients with "white coat hypertension," where blood pressure readings are artificially elevated in medical settings but normal at home, or "masked hypertension," where clinical readings appear normal but are elevated in everyday conditions [\[17\]](#page-8-0).

Wearable technology offers an innovative solution to this gap in stroke risk monitoring by enabling continuous, non-invasive data collection in real-world environments $[18,19]$. Devices such as smartwatches, fitness trackers, and specialized wearable health monitors are now equipped with sensors capable of measuring vital physiological parameters that are closely linked to stroke risk [\[19\]](#page-8-0). These devices provide real-time monitoring of metrics such as heart rate variability (HRV), blood pressure, physical activity levels, oxygen saturation, and even sleep quality, delivering a more comprehensive and dynamic view of an individual's health status [\[20](#page-8-0)–22]. By capturing data around the clock, wearables provide insight into the fluctuations in these parameters that may precede a stroke, offering opportunities for earlier detection and preventive care [\[23\]](#page-8-0).

One of the most compelling examples of wearable technology's potential in stroke risk assessment is its ability to monitor heart rhythm abnormalities, particularly atrial fibrillation (AF), which is a wellknown precursor to ischemic stroke [\[22,24,25\].](#page-8-0) Devices like the Apple Watch, Fitbit series, Samsung Galaxy Watch and other fitness trackers are now equipped with sensors capable of detecting irregular heart rhythms in real-time, which can then be analyzed by algorithms to identify potential AF episodes [\[22,26\]](#page-8-0). This continuous monitoring could allow for earlier diagnosis and timely treatment, reducing the likelihood of stroke in high-risk individuals [\[24\].](#page-8-0) Similarly, wearable blood pressure monitors, such as those developed by Omron and Withings, can track blood pressure continuously, enabling the detection of persistent hypertension or sudden spikes that could indicate an imminent risk of stroke [\[22,27\]](#page-8-0).

The data generated by wearable devices goes beyond simple monitoring; when integrated with advanced machine learning algorithms and big data analytics, it provides a powerful tool for stroke prediction [\[28\]](#page-8-0). Machine learning models can analyze the vast amounts of biometric data generated by wearables, identifying patterns and correlations that are not readily apparent to the human eye [\[25\].](#page-8-0) These algorithms can process not only historical data but also dynamic, real-time data streams, offering personalized stroke risk assessments that evolve as new data is collected [\[25\].](#page-8-0) This allows healthcare providers to move beyond traditional, static risk models and develop adaptive, personalized care plans tailored to the specific physiological characteristics of each patient [\[25,28\].](#page-8-0)

In addition to heart rhythm and blood pressure monitoring, wearable devices also track other key stroke risk factors, such as physical inactivity and poor sleep quality [\[21,22,25\]](#page-8-0). Sedentary behavior and lack of physical activity are associated with a higher risk of stroke, and many wearables now include activity tracking features that encourage users to meet daily movement goals, promoting cardiovascular health [\[29,30\]](#page-8-0). Furthermore, sleep quality has been increasingly recognized as an important factor in stroke prevention, with conditions linked to increased stroke risk $[31-33]$. Wearables equipped with pulse oximetry sensors can detect drops in blood oxygen levels during sleep, a key indicator of sleep apnea, allowing for early diagnosis and intervention [\[34\]](#page-9-0).

Despite the significant opportunities that wearable technology presents for stroke risk assessment, there are several challenges that must be addressed to fully realize its potential [\[18\]](#page-8-0). Data accuracy remains a key concern, as not all consumer-grade wearable devices are validated to the same standard as clinical-grade equipment [\[35,36\].](#page-9-0) For example, while wearable ECG monitors can detect irregular heart rhythms, their accuracy may vary compared to traditional medical devices used in clinical settings. Additionally, the vast amounts of data generated by wearables raise important questions about data privacy, security, and ownership [\[37\]](#page-9-0). Ensuring that patients' health data is protected and used appropriately is critical for the widespread adoption of wearable technology in healthcare [\[37\].](#page-9-0)

Moreover, the integration of wearable technology into existing healthcare systems presents a logistical challenge [\[35\].](#page-9-0) While the continuous data generated by wearables can provide valuable insights, integrating this data into electronic health records (EHRs) and ensuring that it is accessible to healthcare providers in a meaningful way is not yet fully realized [\[35\].](#page-9-0) Additionally, healthcare providers need to be trained in interpreting and acting upon the data generated by wearable devices, which represents a significant shift from traditional methods of stroke risk assessment.

There is a growing concern in the inability of current diagnostic methods to continuously monitor individuals for these fluctuating stroke risk factors, leading to missed opportunities for early detection and timely intervention [\[38\]](#page-9-0). The growing availability of wearable technology and biometric data collection presents a compelling solution, offering the potential to track real-time health metrics and provide personalized, preventive care outside of clinical settings [\[18,19,39\]](#page-8-0). However, despite the promise of these technologies, significant challenges related to data accuracy, integration into clinical practice, and data privacy remain unresolved [\[28,35\]](#page-8-0). The objective of this review is to assess the current state of wearable technology in stroke risk assessment, explore its opportunities for enhancing early detection and personalized treatment, and examine the challenges that must be addressed to fully realize its potential in clinical practice.

This narrative review employed a critical approach to identify, analyze, and synthesize relevant literature on the integration of wearable technology and biometric data in stroke risk assessment. The search was conducted in reputable databases, including PubMed, Scopus, and IEEE Xplore, focusing on studies published between 2010 till date.

Keywords such as "stroke risk assessment," "wearable technology," "atrial fibrillation," and "artificial intelligence" guided the search strategy. Articles were screened based on inclusion criteria, such as relevance to wearable devices and stroke risk factors, and exclusion criteria, such as non-peer-reviewed sources and non-English publications. Relevant studies were thematically categorized to explore applications, opportunities, challenges, and future directions. This methodology ensured a comprehensive evaluation of the role of wearable technology and artificial intelligence in advancing stroke prevention and care.

2. Wearable technology and biometric data in stroke risk assessment

The integration of wearable technology into stroke risk assessment has transformed the way individuals and healthcare providers monitor and manage stroke risk factors [\[19,40\]](#page-8-0)**.** Traditionally, stroke risk assessments relied on intermittent clinical visits and diagnostic tools, providing only a fragmented view of an individual's health status [\[41\]](#page-9-0). This approach often misses the dynamic fluctuations in risk factors such as blood pressure and heart rhythm that occur outside of clinical settings [\[17\]](#page-8-0). However, wearable devices offer a new solution by enabling continuous, real-time monitoring of critical physiological parameters, such as heart rate, blood pressure, physical activity, and sleep patterns [\[19,28,39\].](#page-8-0) These devices generate vast amounts of biometric data that can be analyzed using advanced algorithms to provide actionable insights into stroke risk, making it possible to detect problems early and intervene promptly [\[28\]](#page-8-0). Table 1 below summarizes the different applications of wearable technology in stroke care, highlighting the AI tools and applications that enhance continuous monitoring, personalized care, and remote patient management.

2.1. Overview of wearable devices for stroke risk monitoring

The proliferation of wearable technology has introduced a wide range of devices capable of monitoring key physiological parameters associated with stroke risk [\[19\]](#page-8-0). Smartwatches and fitness trackers have become popular tools for health monitoring due to their widespread accessibility and ease of use [\[21\]](#page-8-0). Devices like the Apple Watch and Fitbit can track heart rate, physical activity, and sleep patterns, providing users with continuous feedback on their overall health [\[21\]](#page-8-0). In recent years, these devices have evolved to include advanced features, such as electrocardiogram (ECG) monitoring, which allows for the detection of irregular heart rhythms, particularly atrial fibrillation (AF) [\[46,47\].](#page-9-0) AF is a well-known risk factor for stroke, and its detection through wearable technology has been shown to facilitate early medical intervention [\[48\]](#page-9-0). Studies have demonstrated that devices like the Apple Watch are capable of identifying AF episodes with high accuracy, potentially reducing the risk of stroke for individuals who may not display any symptoms of the condition [\[42\].](#page-9-0)

Blood pressure monitors are another important category of wearable devices in stroke risk assessment [\[49\]](#page-9-0). Hypertension is the most significant modifiable risk factor for stroke, and its continuous monitoring is essential for effective management [\[49\]](#page-9-0). Traditional blood pressure measurements taken in clinical settings may not capture fluctuating patterns that occur throughout the day, leading to misdiagnosis or underdiagnosis of hypertension. Wearable blood pressure monitors, such as those offered by Omron and Withings, provide a non-invasive way to continuously track systolic and diastolic blood pressure in real-time [\[17,](#page-8-0) [22,27\]](#page-8-0). This allows for early detection of elevated blood pressure levels, enabling timely interventions that could prevent strokes from occurring [\[27\]](#page-8-0).

Wearable electrocardiogram (ECG) and cardiac monitors are also crucial in detecting arrhythmias, such as atrial fibrillation, that significantly increase the risk of stroke [\[47\]](#page-9-0). Continuous ECG monitoring via devices like KardiaMobile and Withings ECG provides real-time heart rhythm analysis, allowing for the early detection of irregularities that **Table 1**

AI applications and tools in stroke care using wearable technology.

Opportunities in stroke care	Wearable technology	AI application/ tool used	Description
Continuous Monitoring and Early Detection [42]	Smartwatches (e. g., Apple Watch, Fitbit); Wearable ECG monitors	AI-driven ECG analysis algorithms	Continuous monitoring for atrial fibrillation (AF) and other irregular heart rhythms, enabling early detection and intervention.
Continuous	Wearable blood	Machine	Continuous
Monitoring and	pressure monitors	learning-based	monitoring of
Early Detection [17, 22, 27]	(e.g., Omron HeartGuide, Withings BPM)	blood pressure tracking	systolic and diastolic blood pressure, detecting white coat or masked hypertension, enabling early intervention.
Personalized	Smartwatches,	Predictive	AI algorithms
Stroke Risk Assessment [28]	Fitness Trackers. ECG monitors	algorithms for risk profiling	analyze real-time data on heart rate, blood pressure, activity, and sleep patterns to generate individualized stroke risk profiles.
Integration with	Wearable sensors	Remote patient	AI enables real-
Telemedicine [28.43]	(e.g., heart rate monitors, activity trackers)	monitoring platforms	time data transmission to healthcare providers, allowing remote monitoring and timely adjustments in care plans.
Rehabilitation [44, 45]	Wearable activity monitors, AI- enhanced VR platforms	AI-based adaptive therapy algorithms	AI tracks patient recovery and adjusts rehabilitation programs in real time, ensuring customized therapy regimens.

may not be captured during periodic medical exams. These devices are particularly valuable for individuals who experience intermittent episodes of AF, which can be challenging to diagnose without continuous monitoring. In addition to heart and blood pressure monitoring, wearable devices that track oxygen saturation and respiratory rate have shown promise in stroke risk management [\[20,50\].](#page-8-0) Sleep apnea, a condition characterized by pauses in breathing during sleep, is emerging as a significant risk factor for stroke [31–[33,51\]](#page-9-0). Wearable devices equipped with pulse oximeters can monitor blood oxygen levels and detect sleep apnea events, enabling early diagnosis and treatment, which may help reduce stroke risk in affected individuals [\[34\]](#page-9-0). These devices offer a comprehensive approach to monitoring the physiological parameters most closely associated with stroke risk [\[34\].](#page-9-0) [Fig. 1](#page-4-0) demonstrates how different wearable technologies work together to provide a comprehensive approach to stroke risk monitoring.

2.2. Key biometrics for stroke risk assessment

Several key biometric parameters can be measured using wearable devices, all of which play a significant role in assessing stroke risk [\[18\]](#page-8-0). Blood pressure, for instance, is one of the most critical factors in stroke prevention [\[18\].](#page-8-0) Continuous monitoring of blood pressure through wearable devices allows for the early detection of hypertension, making

Fig. 1. Various types of wearable devices utilized for monitoring stroke risk. These devices contribute to stroke risk assessment, which can lead to early intervention.

it possible to intervene with lifestyle changes or medications before the condition leads to a stroke [\[49\]](#page-9-0). Real-time blood pressure monitoring provides a more accurate picture of an individual's cardiovascular health compared to periodic readings taken in clinical settings, which may miss short-term spikes or fluctuations [\[17\].](#page-8-0)

Heart rate variability (HRV) and ECG data are also pivotal in stroke risk assessment, particularly for detecting atrial fibrillation [\[52\]](#page-9-0). AF is a leading cause of ischemic stroke, and wearable devices equipped with ECG sensors can monitor heart rhythms continuously [\[28\].](#page-8-0) By detecting abnormal heart rhythms early, these devices enable prompt medical intervention, such as the administration of anticoagulants, which significantly reduce the risk of stroke [\[53\]](#page-9-0). Wearable devices like the Apple Watch, KardiaMobile, and other ECG-capable trackers have demonstrated high sensitivity and specificity in detecting AF, proving to be valuable tools in stroke prevention [\[54\]](#page-9-0).

Physical activity levels are another important factor in stroke risk [\[55\]](#page-9-0). Sedentary behavior is strongly associated with increased stroke risk, and fitness trackers are designed to monitor daily activity levels and encourage users to engage in regular physical exercise [\[56\]](#page-9-0). By tracking metrics such as steps taken, calories burned, and hours spent active, these devices can help users maintain a healthy lifestyle, which is crucial in reducing the risk of stroke $[21]$. Sleep patterns, including the detection of sleep apnea, are emerging as critical biomarkers for stroke risk [\[57\]](#page-9-0). Wearable devices that track sleep duration and quality, as well as those equipped with pulse oximetry, can detect abnormalities such as sleep apnea, which has been linked to increased stroke risk [\[34\]](#page-9-0). The ability to identify sleep disturbances in real-time allows for earlier intervention and management of sleep disorders, contributing to overall stroke prevention [\[33\].](#page-9-0)

Furthermore, Arterial hypertension is the primary modifiable risk factor for stroke and is particularly associated with the lacunar infarction subtype of ischemic stroke. Lacunar infarctions are small, deep cerebral infarcts caused by occlusion of small penetrating arteries, and their pathophysiology, prognosis, and clinical features are distinct from other acute stroke subtypes [\[58,59\]](#page-9-0). According to Arboix et al. [\[60\]](#page-9-0), while lacunar syndromes are highly suggestive of lacunar infarctions, 16.6 % of cases of lacunar syndrome are not due to lacunar infarcts. This study emphasizes the importance of distinguishing lacunar infarctions from other stroke subtypes, particularly in patients presenting with atrial fibrillation, sensorimotor symptoms, and sudden onset [\[60\].](#page-9-0) The findings underscore the need for accurate hypertension management, especially in patients predisposed to lacunar strokes, to mitigate the risk of both typical lacunar infarctions and other small vessel-related stroke syndromes [\[60\]](#page-9-0). This highlights the critical role of continuous blood pressure monitoring via wearable technology in stroke prevention strategies targeting lacunar infarction.

2.3. Real-time data analysis and predictive algorithms

One of the most significant advantages of wearable technology in stroke risk assessment is its ability to generate continuous, real-time data [\[28\]](#page-8-0). The vast amount of biometric data collected by wearables can be analyzed using machine learning algorithms to detect subtle patterns and trends that may be indicative of an elevated stroke risk [\[28\].](#page-8-0) For instance, AI algorithms can analyze heart rate variability and ECG data to predict the likelihood of an atrial fibrillation episode $[24,28]$. These predictive models use real-time inputs from wearables, such as blood pressure and activity data, to provide a more dynamic and comprehensive stroke risk assessment compared to traditional methods, which often rely on isolated measurements taken during clinical visits [\[28\].](#page-8-0)

By integrating multiple biometric data streams—such as heart rate, blood pressure, physical activity, and sleep patterns—machine learning algorithms can provide healthcare professionals with a holistic view of a patient's cardiovascular health [\[22\].](#page-8-0) This comprehensive assessment allows for more accurate predictions of stroke risk, enabling early interventions that could prevent the occurrence of strokes [\[22\]](#page-8-0). Additionally, wearable devices equipped with AI capabilities can offer personalized recommendations to users, such as lifestyle changes or medication adjustments, based on real-time health data, thereby empowering individuals to take a proactive role in managing their stroke risk [\[25\].](#page-8-0)

3. Opportunities in stroke care using wearable technology

Wearable technology has emerged as a pivotal innovation in healthcare, particularly in the prevention and management of stroke [\[19\]](#page-8-0). Its ability to provide continuous monitoring of vital health parameters, coupled with real-time data analysis, presents numerous opportunities for improving stroke care outcomes [\[18\]](#page-8-0). By enabling early detection, personalizing stroke risk assessments, and integrating with telemedicine platforms, wearable devices hold the potential to transform stroke prevention, diagnosis, and recovery [\[19,28\].](#page-8-0) These opportunities underscore the growing role of wearable technology in revolutionizing the landscape of stroke care [\[28\].](#page-8-0)

3.1. Continuous monitoring and early detection

One of the most significant advantages of wearable technology in stroke care is the capability for continuous monitoring over extended periods [\[22\].](#page-8-0) This is particularly valuable for identifying stroke risk factors like hypertension and atrial fibrillation (AF), which may be intermittent or asymptomatic $[48]$. Many individuals with AF, for example, may be unaware of their condition due to the absence of noticeable symptoms, putting them at heightened risk for ischemic stroke. Wearable ECG devices, such as smartwatches equipped with ECG sensors, can continuously monitor heart rhythms and detect irregularities before they become symptomatic $[48,61]$. This allows for timely interventions, such as the initiation of anticoagulant therapy, which can significantly reduce the risk of stroke [\[48,61\]](#page-9-0).

Similarly, continuous blood pressure monitoring offers a critical advantage for individuals at risk of stroke due to hypertension [\[62,63\]](#page-9-0). Traditional blood pressure measurements are typically taken in clinical settings and may not capture fluctuations in blood pressure that occur throughout the day [\[17,41\]](#page-8-0). Wearable blood pressure monitors enable real-time tracking, helping to identify conditions like "white coat hypertension," where blood pressure is elevated during clinical visits but normal at home, or "masked hypertension," where blood pressure remains high outside the clinic but appears normal during doctor visits [\[17\]](#page-8-0). Early detection of these conditions through continuous monitoring allows for earlier treatment, thereby lowering the risk of stroke [\[17,22,](#page-8-0) [27\].](#page-8-0)

3.2. Personalized stroke risk assessment

Wearable devices also enable personalized stroke risk assessments by capturing individual biometric data and analyzing it in real-time [20–[22\]](#page-8-0). Using machine learning algorithms, wearable technology can generate dynamic risk profiles tailored to each user's unique physiological and behavioral patterns [\[19,28,39\]](#page-8-0). This personalized approach allows for more accurate predictions and interventions compared to traditional risk models, which are often based on static demographic and clinical data. For instance, a wearable device could continuously track multiple factors, such as sustained elevated blood pressure, recurrent AF episodes, levels of physical activity, and sleep quality $[28,61]$. This combination of data points can then be processed by machine learning algorithms to produce a personalized stroke risk score, which accounts for the interactions between these variables [\[64\].](#page-9-0) Based on this dynamic risk profile, customized intervention plans can be created, which may include lifestyle changes, medication adjustments, or more intensive clinical monitoring [\[25\]](#page-8-0). By continuously updating the risk assessment with real-time data, wearable technology ensures that stroke prevention strategies remain responsive to the individual's evolving health status [\[18\]](#page-8-0).

While wearable technology and AI offer transformative potential for personalized stroke risk assessment, socio-economic barriers remain significant challenges to their widespread adoption. The high cost of advanced wearable devices, such as smartwatches with ECG capabilities or continuous blood pressure monitors, may place them out of reach for individuals in low-income settings [\[65,66\]](#page-9-0). Additionally, limited access to the internet and smartphones in underserved regions restricts the ability to use these technologies, as many wearable devices rely on app-based integrations for data analysis and monitoring. Health literacy is another critical barrier; individuals with limited understanding of health technologies may struggle to interpret data or take appropriate action based on alerts from wearable devices [\[67\].](#page-9-0) Furthermore, disparities in healthcare infrastructure, particularly in rural areas, limit the integration of wearable data into clinical workflows, reducing the potential impact of these tools in such settings [\[68\].](#page-9-0) Addressing these socio-economic barriers will require collaborative efforts, including cost reduction strategies, initiatives to improve digital and health literacy, and policy reforms to ensure equitable access to these life-saving technologies. These steps are essential to maximize the benefits of personalized stroke risk assessment and ensure its reach across diverse populations.

3.3. Integration with telemedicine and remote healthcare

Wearable devices, when integrated with telemedicine platforms, have the potential to significantly address disparities in healthcare delivery, particularly in underserved regions [\[28\].](#page-8-0) These technologies enable real-time monitoring of stroke risk factors, such as blood pressure and atrial fibrillation, without requiring frequent in-person visits to healthcare facilities [\[69,70\]](#page-9-0). This is especially critical in rural or low-resource settings, where access to specialized stroke care may be limited. By transmitting data from wearable devices to telemedicine systems, healthcare providers can remotely monitor patients, provide timely interventions, and adjust treatment plans based on real-time data. Furthermore, wearables empower patients by providing them with accessible tools to track their own health metrics, promoting proactive health management. Programs that subsidize wearable devices or implement community-based telemedicine hubs could amplify these benefits, ensuring that patients in underserved areas have access to the same life-saving technologies as those in urban centers. Addressing these disparities requires collaborative efforts between healthcare providers, policymakers, and technology developers to create scalable and equitable solutions for stroke prevention and care.

For stroke survivors, wearable devices offer the potential to play a crucial role in recovery and the prevention of secondary strokes [\[45\]](#page-9-0). Recovery from stroke often requires close monitoring of physical activity, blood pressure, and heart health to ensure that complications are avoided and that patients are adhering to rehabilitation protocols. By transmitting data directly to healthcare providers, wearable devices allow for ongoing assessments of the patient's recovery progress and enable timely adjustments to rehabilitation programs, medications, or lifestyle recommendations [\[71\]](#page-9-0). This real-time feedback loop between the patient and the healthcare provider can enhance the overall effectiveness of stroke rehabilitation and prevent secondary strokes, which are common among stroke survivors [\[72\]](#page-9-0).

4. AI in stroke follow-up and rehabilitation

Artificial intelligence (AI) has become a game-changer in the field of stroke rehabilitation and follow-up care [\[73\].](#page-9-0) By harnessing the power of AI-driven systems, healthcare providers can now offer more effective and personalized stroke recovery programs [\[73\].](#page-9-0) Wearable devices, enhanced with AI algorithms, enable continuous monitoring of patients after a stroke, facilitating the detection of complications, supporting rehabilitation, and predicting recovery outcomes [\[74\]](#page-9-0). The integration of AI with telemedicine, predictive analytics, and personalized rehabilitation plans has transformed stroke follow-up, ensuring that patients receive timely interventions and tailored therapies, thereby improving their chances of recovery [\[44\].](#page-9-0)

4.1. Remote monitoring and predictive analytics

AI-driven systems have proven especially valuable in the realm of post-stroke care by allowing for remote monitoring and predictive analytics [\[73\].](#page-9-0) Wearable devices equipped with AI can continuously monitor vital signs and detect early warning signs of stroke recurrence or complications, such as atrial fibrillation, which often increases the likelihood of a secondary stroke [\[42\]](#page-9-0). These AI-enhanced wearables generate real-time data that is sent directly to healthcare providers, who receive immediate alerts if abnormalities or dangerous trends are detected [\[28\].](#page-8-0) This real-time, continuous monitoring can prompt early interventions, potentially preventing further damage and reducing the need for hospital readmissions [\[28\].](#page-8-0) For stroke survivors, this kind of vigilant care ensures that potential risks are mitigated, leading to a safer and more stable recovery process.

Predictive analytics, driven by AI, has further enhanced the ability of clinicians to forecast recovery trajectories for stroke patients [\[73\].](#page-9-0) Using data collected from wearable sensors, AI-powered platforms analyze

patterns in a patient's performance and progress, allowing for more accurate predictions regarding recovery timelines [\[28,73\].](#page-8-0) These predictions help healthcare providers tailor rehabilitation programs to the specific needs of each patient, ensuring that they receive the most appropriate therapies at every stage of recovery [\[73\].](#page-9-0) This level of precision in predicting patient outcomes ensures that clinicians can intervene promptly when necessary and optimize the rehabilitation plan to support long-term recovery [\[73,75\].](#page-9-0)

4.2. Personalized rehabilitation programs

AI is playing a pivotal role in transforming stroke rehabilitation by enabling highly personalized recovery plans [\[73\].](#page-9-0) Wearable sensors can collect data on a patient's motor abilities, cognitive function, and overall physical progress [\[71\]](#page-9-0). AI algorithms analyze this data to develop individualized therapy regimens that are specifically designed to meet the unique needs of each patient $[71,72]$. As the patient engages in rehabilitation exercises, AI-driven platforms monitor their performance and continuously adapt the rehabilitation plan [\[72\]](#page-9-0). This dynamic approach ensures that patients are always challenged at an appropriate level, keeping them engaged in the recovery process while avoiding frustration or plateauing [\[71\]](#page-9-0).

In addition to traditional rehabilitation methods, AI-enhanced virtual reality (VR) platforms are gaining traction as a promising tool in stroke recovery [\[76\].](#page-9-0) These immersive environments encourage patients to participate in interactive exercises that target motor skills, balance, and coordination, which are often impaired following a stroke [\[76\]](#page-9-0). AI algorithms integrated into these VR platforms can assess the patient's performance in real time, adjusting the difficulty of the exercises based on progress and abilities [\[77\]](#page-9-0). By tracking patient data and adapting tasks in real time, these AI-powered VR systems ensure that patients remain motivated, engaged, and consistently challenged throughout their recovery journey, promoting continuous improvement in motor function [\[77\]](#page-9-0). Fig. 2 emphasizes the integration of AI-enhanced virtual reality (VR) platforms that provide immersive, interactive exercises tailored to improve motor skills, balance, and coordination during recovery. This comprehensive approach ensures continuous engagement and optimal challenge levels for patients throughout their rehabilitation journey.

5. Future directions and innovations

The evolution of wearable technology and artificial intelligence (AI)

in stroke care is poised to revolutionize the field further $[28]$. By integrating multiple data sources, enhancing predictive analytics, and advancing towards autonomous health monitoring systems, the future holds tremendous potential for even more personalized, timely, and effective stroke prevention and management strategies [\[78\].](#page-9-0) These advancements will not only improve the accuracy of stroke risk assessments but also streamline interventions, making healthcare more responsive to individual needs and dynamic health changes [\[25,28\]](#page-8-0). [Table 2](#page-7-0) summarizes future innovations in wearable technology for stroke care, highlighting the role of AI applications and tools in multi-modal data integration, predictive analytics, and autonomous health monitoring systems. [Table 2](#page-7-0) also outlines the potential impact of these advancements, which are poised to improve stroke prevention and management through more accurate risk assessments and proactive, real-time interventions.

5.1. Multi-modal data integration

One of the most promising future directions for wearable technology in stroke risk assessment is the integration of multiple data sources into a unified platform [\[18\].](#page-8-0) Currently, wearables primarily focus on physiological data such as heart rate, blood pressure, and activity levels [\[18\]](#page-8-0). However, the integration of additional data types—such as genetic information, lifestyle habits, environmental factors, and detailed clinical records—will provide a more holistic understanding of an individual's health status [\[79\]](#page-9-0). Genetic information, for instance, can help identify inherited predispositions to stroke, while lifestyle data can offer insights into behavioral risk factors like diet, sleep, and exercise [\[80\].](#page-9-0)

AI algorithms will play a crucial role in processing this multi-modal data [\[18\]](#page-8-0). By combining diverse datasets, AI systems will be able to generate even more accurate and personalized stroke risk assessments [\[18\]](#page-8-0). These integrated models will enable healthcare providers to detect subtle interactions between genetic predispositions, behavioral factors, and real-time biometric data, allowing for earlier and more targeted interventions [\[81\]](#page-9-0). This personalized, data-driven approach will help clinicians not only assess current stroke risk but also anticipate future health challenges, providing more effective prevention strategies tailored to each individual [\[18\].](#page-8-0)

5.2. Advanced predictive analytics

As AI and machine learning algorithms continue to advance, more sophisticated predictive models will emerge, capable of forecasting

Fig. 2. AI-driven personalized rehabilitation programs for stroke recovery. The figure illustrates the components of AI-driven personalized rehabilitation programs for stroke patients. It highlights the process of data collection through wearable sensors, the analysis of this data by AI algorithms to create individualized therapy regimens, and the dynamic adaptation of rehabilitation plans based on real-time performance monitoring.

Table 2

Future directions and innovations in wearable technology for stroke risk assessment.

stroke risk with greater precision than ever before [\[82\]](#page-9-0). Current models already analyze relationships between various biometric parameters such as blood pressure, heart rate variability, and activity levels, but future systems will take these predictions to the next level by incorporating more complex interactions between larger datasets [\[83\]](#page-9-0). AI will be able to identify nuanced patterns that indicate elevated stroke risk, even when traditional risk factors appear within normal ranges [\[82\].](#page-9-0) For example, AI might detect subtle shifts in heart rate variability that signal impending atrial fibrillation or use long-term data trends to predict hypertension flare-ups [\[83\]](#page-9-0). These advanced predictive models will provide clinicians with actionable insights, allowing them to intervene preemptively with lifestyle changes, medications, or other preventive measures before the risk escalates into an acute stroke event [\[83\]](#page-9-0)**.** This ability to predict and prevent strokes earlier will drastically improve patient outcomes, reducing both the incidence of strokes and the severity of their impact [\[83\]](#page-9-0).

5.3. Autonomous health monitoring systems

A significant innovation in wearable technology lies in the development of fully autonomous health monitoring systems [\[35,71\].](#page-9-0) These systems would not only detect stroke risk in real-time but also initiate preventive or corrective measures automatically, without requiring constant human oversight [\[35\]](#page-9-0). For instance, a wearable device that continuously tracks blood pressure could autonomously adjust medication dosing based on real-time readings, ensuring that blood pressure stays within a safe range and reducing the risk of stroke [\[25,28\]](#page-8-0).

Autonomous systems could also recommend specific lifestyle changes based on an individual's real-time data [\[84\]](#page-10-0). For example, if a wearable device detects a pattern of sedentary behavior and elevated blood pressure, it might recommend increased physical activity, dietary adjustments, or stress-reduction techniques to lower stroke risk [\[29\]](#page-8-0). These systems would operate as a proactive health companion, providing real-time, personalized interventions that adapt to the user's changing health needs [\[25,28,29\].](#page-8-0) Furthermore, autonomous systems will likely integrate with telemedicine platforms, allowing healthcare providers to remotely monitor these automatic adjustments and intervene when necessary [\[28\].](#page-8-0) By reducing the need for constant in-person check-ups, these systems could increase access to preventive stroke care, particularly for individuals living in remote or underserved areas [\[20,](#page-8-0)

[28\].](#page-8-0) This integration of wearable technology, AI, and autonomous systems represents the future of stroke prevention—where technology acts not only as a diagnostic tool but also as a decision-maker, improving outcomes through timely, data-driven interventions [\[28\]](#page-8-0).

5.4. Integrating AI-driven wearable services for acute ischemic stroke subtypes

The integration of AI-driven wearable devices and biometric data into stroke risk assessment offers exciting potential for tailoring strategies to the distinct characteristics of acute ischemic stroke subtypes. Acute ischemic strokes, including large artery atherosclerosis, cardioembolic, and lacunar subtypes, differ significantly in their pathophysiology, distribution of risk factors, stroke severity, and clinical outcomes [\[58\]](#page-9-0). For example, lacunar strokes are often associated with chronic hypertension and small vessel disease, while cardioembolic strokes are closely linked to atrial fibrillation [\[85\].](#page-10-0) AI-powered wearables, such as continuous blood pressure monitors and ECG devices, could provide subtype-specific insights by capturing and analyzing real-time data relevant to these differing etiologies.

Future research should explore how wearable technology can aid in distinguishing between stroke subtypes by integrating multi-modal data, such as genetic, hemodynamic, and environmental factors, into machine learning algorithms. These AI systems could enhance early detection, improve the precision of risk stratification, and guide targeted prevention strategies, particularly for populations predisposed to specific subtypes. By addressing the unique pathophysiological mechanisms, this approach has the potential to transform personalized stroke care, leading to improved outcomes across all ischemic stroke subtypes.

6. Limitations of this review

This narrative review has several limitations that should be acknowledged. First, the study relies on literature published between 2010 till date, which may have excluded relevant earlier studies that could provide additional context or historical perspectives on the development of wearable technology in stroke care. Second, the review primarily includes articles published in English, potentially introducing language bias and overlooking valuable research published in other languages. Third, as a narrative review, the study does not employ

quantitative synthesis methods such as meta-analysis, which limits the ability to statistically assess the efficacy of wearable technologies and AI applications in stroke risk assessment. Fourth, the heterogeneity of the included studies—in terms of study design, population characteristics, types of wearable devices, and outcomes measured—may affect the generalizability of the conclusions drawn. Additionally, there is a possibility of publication bias, as studies with positive findings are more likely to be published than those with negative results. Lastly, the rapidly evolving nature of wearable technology and artificial intelligence means that newer developments may have emerged since the completion of this review, potentially limiting the timeliness of the findings. Future research should address these limitations by including broader search strategies, incorporating studies from multiple languages, employing systematic review methodologies, and conducting quantitative analyses to provide more robust and generalizable evidence on the effectiveness of wearable technology and AI in stroke risk assessment and management.

7. Conclusion

Wearable technology and the integration of biometric data present a transformative opportunity for enhancing stroke risk assessment and delivering more personalized care. The ability of these devices to continuously monitor key physiological parameters, such as heart rate, blood pressure, and physical activity, coupled with the predictive power of machine learning algorithms, has the potential to revolutionize how stroke risk is detected and managed. Early detection of risk factors, such as hypertension and atrial fibrillation, allows for timely interventions that can significantly reduce the likelihood of stroke. Furthermore, personalized care plans based on real-time data offer a more tailored approach to stroke prevention and rehabilitation, improving patient outcomes and quality of life. However, several challenges must be addressed to fully realize the potential of wearable technology in stroke care. Issues related to data accuracy, especially with consumer-grade devices, can impact the reliability of these systems. Privacy and data security concerns are also paramount, given the sensitive nature of continuous health monitoring. Additionally, integrating wearable technology into existing healthcare infrastructures and ensuring that healthcare providers can effectively utilize the data remains a challenge. Overcoming these obstacles will be crucial for unlocking the full potential of wearable devices and artificial intelligence in revolutionizing stroke prevention, diagnosis, and rehabilitation, ultimately reducing the global burden of stroke and improving patient outcomes.

CRediT authorship contribution statement

Aanuoluwapo Clement David-Olawade: Writing – review & editing, Writing – original draft, Project administration, Formal analysis, Conceptualization. **Eghosasere Egbon:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Temitope Adereni:** Writing – review & editing, Writing – original draft. **Mayowa Popoola:** Writing – original draft, Visualization, Validation. **Ritika Tiwari:** Writing – review & editing, Writing – original draft, Supervision, Methodology. **David Bamidele Olawade:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Nicholas Aderinto:** Writing – review & editing, Writing – original draft, Validation, Project administration, Investigation, Conceptualization.

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