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Exploring the Future of Artificial Intelligence-Enhanced Wearable Electronics for Real-Time Arrhythmia Detection

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Abstract

The field of arrhythmia detection and cardiovascular health monitoring is rapidly changing due to wearable technology. With a focus on developments in flexible materials, sensor integration, and electronic design for ongoing arrhythmia monitoring, this review offers a thorough examination of both established and new wearable sensor technologies. The article describes both commercial and experimental devices, such as textile-based, patch, and wrist-worn platforms, emphasizing their performance in clinical and real-world settings as well as their sensing modalities, including bioelectrical, optoelectrical, and mechanoelectrical techniques. The integration of machine learning and artificial intelligence (AI) algorithms is given special attention because it greatly improves wearable monitors' clinical utility, predictive power, and diagnostic accuracy. We conducted this systematic review of case studies, focusing on the use of deep learning to analyze photoplethysmography and electrocardiogram data, and their impact on earlier detection and improved management of atrial fibrillation and other arrhythmias.

We performed a systemic review analyzing 58 studies for the period of 2018-2025 over the issues of data security, regulatory approval, signal fidelity, user adherence, and sensor ergonomics. In order to enhance long-term wearability and user comfort, the review also looks at the market environment, legal frameworks, and advancements in material science, including textile-integrated graphene electrodes and epidermal electronics. The importance of interoperable device architectures, strong privacy protection that complies with international standards, and the ongoing development of AI-driven analytics for real-time decision support in healthcare are highlighted as future research directions. The purpose of the synthesis is to direct researchers, engineers, and clinicians toward the upcoming generation of patient-centered, intelligent wearable technologies for arrhythmia detection.

Categories: AI applications, Bioinformatics Algorithms, Health Informatics
Keywords: wearable devices, sensors, artificial intelligence (ai) in healthcare, real-time systems, cardiac arrythmia

Introduction And Background

Arrhythmia encompasses any deviation from normal heart rate or rhythm, presenting as faster, slower, or irregular cardiac patterns. While many arrhythmias remain asymptomatic and clinically insignificant, quiet a few manifest with palpitations, chest discomfort, dyspnoea, or syncope, potentially life-threatening complications [1]. The integration of artificial intelligence (AI) technology in wearable devices represents a paradigm shift toward continuous monitoring and early detection of arrhythmic events, utilizing data streams including heart rate, rhythm patterns, and activity levels [2].

Recent advances in AI-driven arrhythmia detection through wearable devices have leveraged photoplethysmography (PPG), single-lead electrocardiography, and sophisticated machine learning algorithms [3]. Current clinical practice relies on electrocardiograms (ECGs) or Holter monitoring for arrhythmia identification. Traditional Holter devices continuously record 12-lead ECG activity for 24-48 hours or up to one week, while implantable loop recorders provide 2-3 years of automated cardiac rhythm surveillance [4]. However, these approaches have limitations in capturing intermittent or asymptomatic arrhythmic episodes, creating opportunities for continuous wearable monitoring solutions. Experimental setups despite high accuracy rates in curated datasets in controlled conditions, in real-world clinical environments, tend to decline due to diverse patient populations, signal noise, varying device quality, and heterogeneous settings. This reduces sensitivity and specificity in actual practice with false alerts and alert fatigues. The barriers in workflow adaptation, interoperability with existing electronic health records, real-time data processing capabilities, and clinician acceptance hinder the transition from promising experimental tools to clinical use.

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This comprehensive review addresses the current state and future prospects of wearable sensors in arrhythmia detection, focusing on flexible materials, advanced electronics, and AI integration. We examine bioelectrical, optoelectrical, mechanoelectrical, and ultrasonic sensing techniques while analysing device performance, clinical applications, and implementation challenges including privacy, regulatory compliance, and user acceptance.

Review

Methodology

Search Strategy

A systematic literature search was conducted across PubMed, IEEE Xplore, ScienceDirect, and Google Scholar databases. The search covered publications from January 1, 2015, to October 31, 2025. The search strategy used the following keyword combinations: ("wearable devices" OR "wearable sensors" OR "wearable technology") AND ("arrhythmia detection" OR "cardiac monitoring" OR "heart rhythm") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("electrocardiogram" OR "photoplethysmography" OR "ECG" OR "PPG").

Inclusion and Exclusion Criteria

Inclusion criteria ensured the selection of scientifically rigorous and clinically relevant studies:

• Peer-reviewed original research and clinical validation studies published within the specified date range

• Focus on wearable devices or sensors designed for cardiac arrhythmia detection or continuous heart rhythm monitoring

• Studies employing AI, machine learning, or deep learning algorithms for cardiac signal analysis

• Technical papers detailing sensor design and algorithm development with validation components

Exclusion criteria addressed potential biases and ensured data quality:

• Studies utilizing only invasive cardiac monitoring technologies, as this review focuses on non-invasive wearables

• Research lacking clear methodology, validation, or lacking ethical approval evidence

• Non-English language publications were excluded due to resource constraints but abstracts were scanned to identify critical studies; this limitation is acknowledged as a potential source of language bias

• Articles with clinical validation sample sizes under 10 participants were excluded to ensure statistical robustness and reliability of findings

• Review articles without original data (except those included for contextual background) and case reports without systematic analysis

Study Selection and Data Extraction

The initial search yielded 342 potentially relevant studies. After duplicate removal and screening against the inclusion and exclusion criteria by two independent reviewers, 58 studies were included for detailed analysis. Any disagreements were resolved by consensus or third-party adjudication.

Data extracted from each study included study design and population characteristics; wearable device type, sensor modality, and specifications; AI/machine learning algorithms utilized, including training, validation methods, and performance metrics; clinical outcomes, including diagnostic accuracy measures (sensitivity, specificity, positive predictive value); and usability, patient adherence, and integration aspects where available

Review of current technologies in wearable devices

Evolution of Wearable Cardiac Monitoring

The landscape of wearable cardiac monitoring has evolved from simple heart rate tracking to sophisticated arrhythmia detection systems. Contemporary wearables including smartwatches, rings, and patch-based devices have achieved widespread adoption due to their ease of use and continuous monitoring capabilities [5]. Despite widespread consumer adoption, clinical acceptance remains contingent on rigorous regulatory approval processes that require comprehensive validation of both diagnostic accuracy and patient safety. However, regulatory approval for clinical applications remains challenging, requiring rigorous validation of diagnostic accuracy and safety profiles [6].

Recent developments in Ultra-High Frequency Radio-Frequency Identification-based healthcare monitoring systems demonstrate the potential for continuous ECG surveillance without wired connections. These systems incorporate electrodes into clothing textiles and transmit data wirelessly, employing event-based communication strategies that activate upon arrhythmia detection to optimize power consumption and network resources [7]. Advanced threshold selection algorithms help in providing a trade-offs between false positive and false negative rates, enhancing clinical utility.

Key Components and Technological Architecture

The widespread adoption of wearable arrhythmia detection systems relies on three fundamental components. First, consumer-grade heart rate sensors offer superior wearability and cost-effectiveness compared to traditional Holter ECG devices [8]. These sensors enable long-term continuous monitoring, which represents a viable alternative for detecting sporadic, asymptomatic cardiologic conditions instead of more invasive loop recorders. Modern smartphones enhance these capabilities by serving as data aggregation platforms that merge multichannel physiological data from diverse wearable sensors [9].

Second, contemporary heart rate sensors perform on-device processing of raw ECG and PPG data, achieving high-quality single-lead ECG measurements. Commercial cardiac monitoring systems have demonstrated validation for both snapshot ECG investigations and continuous 2-minute monitoring protocols under various environmental conditions, including microgravity environments [10]. This processing capability reduces latency and improves real-time diagnostic potential.

Third, advanced signal processing algorithms integrated into wearable platforms enable sophisticated arrhythmia classification. These systems employ machine learning models trained on large datasets to distinguish between normal sinus rhythm and various arrhythmic patterns, achieving sensitivity rates exceeding 90% in controlled clinical trials [11].

Market Trends and Technological Innovations

Long-term, continuous monitoring represents the cornerstone of effective arrhythmia detection, particularly given the increasing prevalence of asymptomatic arrhythmic conditions [12]. Current sensor hardware platforms predominantly utilize rigid sensors for ECG and PPG measurements in watches and smartphones. However, breakthrough developments in epidermal electronics have dramatically reduced device bulkiness while maintaining diagnostic accuracy.

Novel ultra-thin sensors that can be deposited on substrates with only 3% of the elastic modulus of stainless-steel backing, facilitating improved circulation and mechanical flexibility have been in use [13]. The sensors incorporate pyramid structures enabling up to 45% stretchability, with high aspect ratios allowing skin adhesion through van der Waals forces alone. Manufacturing costs have dropped drastically to approximately $100 per 13-micrometer thick sensor, with even operational costs as low as $4.80 per year, making these technologies not only economically viable but also making their widespread deployment a possibility [14].

Emerging AI-driven wearables focus on noise reduction, data clarity enhancement, and real-time patient monitoring with AI-powered devices, such as smartwatches, ECG patches and rings offers real-time heart monitoring with early arrhythmia detection capabilities [15]. Machine learning models, particularly decision trees and convolutional neural networks, analyze heart rate and ECG data achieving high accuracy rates in arrhythmia recognition. Advanced models utilizing generative adversarial networks effectively remove noise from ECG signals, enhancing data clarity for accurate arrhythmia classification. Hierarchical deep learning approaches have demonstrated F1-scores of 99.10% on noise-free data [16].

Real-Time Monitoring and Clinical Integration

AI-enabled wearables provide immediate notifications to patients upon detecting arrhythmic events, enabling timely medical intervention. The proactive nature of these devices correlates with reduced hospitalization rates and improved treatment adherence in study [17]. Integration with electronic health records and telemedicine platforms creates comprehensive care pathways that bridge continuous monitoring with clinical decision-making processes.

Contemporary systems employ sophisticated algorithms that balance sensitivity and specificity while focusing primarily on minimizing false alarms. These algorithms adapt to individual patient baselines and activity patterns, reducing artifact-related false positives while maintaining high detection rates for clinically significant arrhythmic events [18]. The core algorithms balance high sensitivity with the imperative to minimize false alarms to reduce alert fatigue - a known barrier to clinical adoption. By personalizing detection thresholds based on individual patient baselines and activity patterns, these algorithms suppress artifact-related false positives without compromising the timely identification of clinically significant arrhythmias. Collectively, these advances underpin the growing acceptance and routine integration of wearable arrhythmia detection technologies into cardiovascular care.

AI applications in arrhythmia detection

AI Algorithm Development and Performance

Despite advances in PPG technology across smartwatches, smart bands, and smartphones, early-stage atrial fibrillation (AF) detection remains unconquered territory in clinical practice. AI and machine learning offer promising solutions to address detection challenges, with wearable devices incorporating evolving AI/machine learning technologies providing consumer alerts before symptom onset [19].

Since 2020, 22 AF diagnosis models based on wearable devices have been developed utilizing AI, achieving substantial positive clinical results [20]. AI models, particularly deep neural networks, demonstrate high sensitivity (94.80%) and specificity (96.96%) in detecting arrhythmias [21]. These algorithms process wearable data streams to effectively identify abnormalities in heart rhythms across diverse patient populations.

Contemporary AI approaches employ ensemble learning methods that combine multiple algorithmic approaches to enhance diagnostic accuracy. Random forest classifiers, support vector machines, and deep learning architectures are integrated to create robust detection systems that perform reliably across various patient demographics and activity states [22].

Data Processing and Interpretation Frameworks

Most commercially available devices target fitness or wellness metrics for general health monitoring. Recent integration of ECG monitors under the wearables umbrella has validated their utility in AF detection [23]. Single-lead ECG monitoring devices improve signal quality through implementation of fewer but higher-quality electrodes, optimizing the signal-to-noise ratio for arrhythmia detection [24].

The global aging population entails increased cardiovascular disease prevalence and thus potentially overwhelming healthcare facilities, especially those resources that are focused on arrhythmia detection. Commercial companies balance cost reduction and battery life extension while addressing pathologies like paroxysmal arrhythmias that may produce low-power ECG signals essential in pre-symptomatic phases [25].

Advanced data processing frameworks that incorporate multi-modal sensor fusion, combining ECG, PPG, accelerometer, and gyroscope data to improve detection accuracy and reduce false positives, employ temporal pattern recognition algorithms that analyze heart rate variability, rhythm regularity, and morphological features across extended monitoring periods [26].

Clinical Case Studies and Validation

AF represents a global health challenge, associated with one-third of strokes in Europe and over 30% of stroke events in the United States [27]. Automatic ECG interpretation has attracted multidisciplinary expertise, recognizing the importance of home-based monitoring and patient education regarding cardiac health status. Consumer wearable technologies equipped with physiological monitoring sensors represent significant advances in this direction. Despite ECG effectiveness in AF detection, these signals remain underutilized as screening tools compared to conventional vital signs including blood pressure and temperature. The advent of AI and machine learning techniques provides a progressive framework for extracting clinically relevant features from ECG and PPG signals that are challenging to discern through standard analytical methods [28]. Currently, ECG and PPG constitute the principal physiological signals exploited by commercially available smartphones and smartwatches for arrhythmia interrogation. These AI-enhanced wearables hold the potential to revolutionize AF screening by enabling continuous, non-invasive, and user-friendly monitoring, thereby facilitating early diagnosis and timely intervention that can significantly reduce stroke risk and improve patient outcomes.

The BERT-based 4D attentive model with multitask learning adjustments for AF detection and cardiovascular risk prediction achieved area under the curve values of 97.0%, demonstrating superior performance in detecting linguistic and physiological signal patterns [29]. This approach represents a significant advancement in multimodal AI applications for cardiac monitoring.

Recent clinical trials have demonstrated the effectiveness of AI-enhanced wearable devices in real-world settings. The e-BRAVE-AF trial showed that early AF detection via wearables doubled therapeutic intervention rates, reducing stroke risk through timely anticoagulant initiation [30]. Long-term behavioral pattern analysis using AI algorithms helps predict ventricular arrhythmia risk by identifying reduced physical activity patterns and other prodromal indicators [31].

Integration Technologies and Clinical Impact

PPG and ECG integration systems: Contemporary smartwatches, including Apple Watch and Fitbit devices, utilize PPG technology to monitor blood flow changes and detect irregular heart rhythms [26]. These systems trigger notifications for ECG verification based on pattern analysis indicative of AF, creating a two-stage screening approach that optimizes sensitivity while maintaining specificity.

The combination of PPG and ECG technologies demonstrates improved accuracy in cardiac rhythm analysis. AliveCor achieved prediction of ventricular arrhythmias with an area under the receiver operating characteristic curve of 0.746 through deep representations of behavioral data. AI models trained on ECG data from 280 patients successfully predicted AF onset 30 minutes in advance, enabling proactive clinical interventions [32].

Clinical outcomes and healthcare impact: The most significant impact of early AF detection involves stroke prevention through timely therapeutic intervention. Real-time remote data monitoring using AI-enhanced wearables enables personalized care, particularly for high-risk populations, by providing continuous data streams to clinicians [33]. Large-scale patient datasets analyzed through AI algorithms identify behavioral patterns and long-term trends that correlate with arrhythmic risk, enabling preventive interventions [34].

Critical analysis of current technology limitations

Accuracy and Reliability Challenges

Arrhythmia detection requires extended physiological signal acquisition in patients' natural environments. Portable ECG devices with dry contact sensors continuously monitor and process ECG data through smartphone applications [35]. However, arrhythmia generation does not always correlate with prominent ECG morphology changes and may remain undetected in standard examinations. Additionally, heart rate variability is not directly represented by PQRST feature amplitudes, necessitating alternative monitoring approaches beyond traditional ECG analysis [36].

Validation of medical tools requires rigorous assessment of accuracy and reliability parameters. Advanced sensing systems for long-term intracardiac electrophysiological signal detection employ deep learning approaches and implantable sensing technologies [37]. Multi-perspective wearable PPG-based systems demonstrate promise but require extensive validation across diverse patient populations [38].

User Acceptance and Compliance Factors

Contemporary wearable electronic sensors enable consumers to monitor heart rhythms through smartwatches, mobile phones, and portable ECG devices. Detection of atrial rates during arrhythmic episodes provides crucial diagnostic information for rate-controlled therapy and follow-up treatment protocols [39]. However, user compliance remains challenging due to device comfort, battery life, and false alarm frequency.

Long-term adherence studies indicate that user acceptance correlates strongly with device comfort, accuracy of notifications, and integration with existing healthcare workflows [40]. Educational initiatives that explain device functionality and clinical relevance improve compliance rates significantly [41].

Technical Sensor Limitations

Advanced sensors measure electrophysiological signals, bioimpedance, skin temperature, and stress levels from skin surfaces. Stratum corneum characteristics significantly limit non-invasive sensor accuracy and reliability due to inconsistent and unstable measurements [42]. Motion artifacts from on-skin and near-skin sensors create random or periodic signal disturbances caused by skin movements including bending and stretching, introducing unwanted high-frequency components that may exceed bio-signal frequency ranges [43].

Small-sized, tightly attached sensors present handling difficulties and may cause skin irritation, inflammation, and rashes due to sensor pressure, producing symptoms similar to arrhythmic manifestations. Blood flow restriction and reduced oxygenation occur more frequently in sensors placed over areas with higher adipose tissue layers. Additionally, signals become more susceptible to noise and motion artifacts, making reliable arterial measurements from deep arteries challenging due to adipose tissue interference [44].

Future directions and technological innovations

Emerging Sensor Technologies

Arrhythmias remain common and are predicted to increase with population aging, creating demand for convenient continuous detection sensors [45]. Wearable devices have emerged to address this need, providing real-time physiological metric tracking with varying invasiveness levels. The most successful implementations are non-invasive sensors in bandage form.

Researchers have developed electronic tattoo (e-tattoo) sensors for ECG and PPG applications using temporal tattoos and laminating machines. Performance parameters demonstrate over 92% accuracy for ECG and over 95% for PPG, which are comparable to electrode-based flexible sensors [46]. However, several minutes of data capture are required to achieve these accuracies, indicating significant limitations. Recent devices are skin-like with 90 micrometers thickness and stretchability up to 45% strain, with elastomer-coated backsides allowing up to 30 re-use cycles [47].

Device dermatitis affects over 60% of users despite gauze pad implementation. Smartwatch and smartphone accuracies remain relatively low at 76% and 71%, respectively. Bidirectional long-short term memory with attention mechanisms increased smartwatch device accuracy from 71% to 77.7% [48].

Advanced AI Integration

Future developments focus on personalized algorithms utilizing long-term wearable device data to customize patient-specific detection parameters. Integration with telemedicine platforms enhances remote monitoring systems for real-time physician notifications [49]. Multimodal sensor approaches combining PPG, ECG, and accelerometer data boost detection accuracy across different arrhythmia types.

Deep learning-based systems like Cardiologs demonstrate clinical reliability leadership, while consumer devices excel in continuous monitoring but face precision-usability trade-offs [50]. Advanced machine learning architectures incorporating transformer models and attention mechanisms show promise for improved pattern recognition in complex cardiac rhythms [51].

Healthcare System Integration

Comprehensive architectures managing interconnection between smartphones, wearable systems, and ambulatory ECG recorders with healthcare systems enable real-time automated ECG classification and electronic health record interoperability [52]. These integrated platforms support clinical decision-making through seamless data flow and standardized reporting formats.

Cloud-based analytics platforms process large-scale patient data streams to identify population-level trends and individual risk stratification. These systems employ federated learning approaches that maintain patient privacy while enabling collaborative model development across institutions [53].

User-Centric Design Evolution

Unobtrusive wearable sensors capable of continuous physiological data collection make arrhythmia screening more accessible [54]. The simplest widespread wearable ECG sensor remains the chest strap utilizing reusable electrodes at heart level. Telemetry units transmit real-time signals to secondary devices, though overly tight fits cause discomfort and skin irritation while humidity and sweating can compromise electrode contact [55].

Future designs prioritize seamless integration into daily activities through improved materials science and ergonomic optimization. Textile-integrated sensors and smart clothing represent promising directions for continuous monitoring without device awareness [56].

Regulatory framework and compliance

Current Regulatory Landscape

Rhythm disorders represent common cardiovascular diseases often unnoticed in general populations, potentially causing lifelong consequences without proper treatment. Wearables with ECG capabilities face regulatory challenges including US Food and Drug Administration (FDA) and Federal Communications Commission compliance, comfortable form factors, usage simplicity, and data trust from users and physicians [57].

Long-term continuous monitoring remains essential for arrhythmia detection. Government health agencies maintain regulatory oversight of wearable devices, while state-of-the-art devices encounter problems with motion artifacts, offline data loss, low accuracy, and patient non-cooperation [58].

FDA guidelines and safety standards: Traditional ECG signal acquisition for arrhythmia detection relied on wired systems including Holter monitors and telemetry units. With wireless ECG transmission technology advent, the FDA began regulating transmission safety [59, 60]. Studies examine potential Bluetooth and Wi-Fi frequency interference with nearby electronic devices operating on similar bands. Key concerns involve whether Bluetooth and Wi-Fi signals disrupt critical medical device function, including pacemakers, defibrillators, and cardiac electronic rhythm devices.

FDA recommends that active implantable medical device manufacturers assess electromagnetic interference risks from mobile phones and similar communication devices used near implantable medical devices. Risk mitigation includes maintaining minimum 15-cm distances between devices and implants while avoiding direct contact with devices or leads [61].

European CE marking requirements: Before EU market introduction, medical device safety and performance require thorough evaluation with manufacturers providing sufficient clinical evidence. Independent Notified Bodies conduct assessments. Arrhythmia monitoring devices classify as active medical devices administering or exchanging energy with human bodies or monitoring vital physiological processes, typically classified as Class IIa under Directive 93/42/EEC.

Article 8 of Regulation (EU) 2017/745 stipulates that devices monitoring vital physiological parameters where fluctuations pose immediate patient danger classify as Class IIb, including drug delivery monitors, electrical impulse monitors, cardiac monitors interacting with active devices, and life-supporting systems [62].

Market Entry Barriers

Multiple device manufacturers have entered wearables markets, creating diverse devices and applications specializing in biometric data monitoring focused on physical activity, heart rate, and sleep analysis [63]. This trend has generated interest in medical and clinical applications.

PPG demonstrates AF detection with 69.8% sensitivity and 86% specificity compared to 12-lead Holter monitor reference standards. Classification algorithms on wearable devices have evolved through machine learning techniques, with PPG devices supporting advanced algorithms increasing significantly from 2019-2020. Consumer-grade devices competing with medical-grade systems raise safety concerns for heart disease detection. High false positive rates due to complex algorithms represent additional concerns, though ambulatory devices targeting high sensitivity help alleviate these issues [64].

Future Regulatory Evolution

Medical device development, testing, and commercialization including wearable arrhythmia detection technologies occur within highly regulated frameworks. International standards adherence during wearable sensor design and validation ensures compliance while fostering innovation and accelerating market access [65].

For small and medium enterprises and research laboratories, regulatory navigation presents particular challenges. EU Medical Device Regulation (MDR 2017/745) and In Vitro Diagnostic Regulation (IVDR 2017/746) introduction significantly reshaped compliance environments, emphasizing lifecycle approaches to safety, performance, and clinical evaluation.

Ethical considerations and data privacy

Privacy and Security Frameworks

As wearable medical devices become prevalent in healthcare and home environments, ensuring data privacy and security becomes increasingly critical. These devices offer valuable real-time health insights but remain susceptible to cybersecurity threats including malicious QR codes and laser-based attacks on voice assistants from distances exceeding 100 meters [66].

Wearables for cardiac monitoring present unique risks. Unauthorized access to sensitive physiological data including heart rhythms could lead to false diagnoses or personal health information misuse. Wireless data transmission between devices and external systems raises concerns about interception, tampering, or confidential information leakage [67].

FDA requires "cyber devices" with internet connectivity and software components to submit cybersecurity documentation in premarket applications, including post-market vulnerability monitoring, identification, addressing plans, and coordinated vulnerability disclosure procedures [68].

Informed Consent and User Rights

Mobile health data monitoring represents one approach to improving citizen health. However, potential exists for private information leakage, particularly health information. Device users must identify tangible device elements that record health data according to manufacturer policies, with privacy concerns regarding undisclosed usage [69].

Ethical considerations involve wearables preventing potential cases through false detection and proliferating inadequate preventive interventions, justifying ethically grounded precautionary approaches. Transparency lack characterizing preventive AI system development based on wearable technologies raises concerns regarding data collection and informed consent without complete understanding of potential applications [70].

Comparative analysis of global markets

Market Dynamics and Growth Projections

Approximately 20% of US residents currently own smart wearable devices, with global markets expected to reach $70 billion by 2025 [71]. Heart rate represents the most frequently monitored health-related parameter, followed by blood pressure monitoring, both closely related to arrhythmia detection. Rapid wearable device market expansion generates growing interest in arrhythmia detection applications [72].

New sensing methods explore rare sensor types including ultrasonics for ECG data detection. Sensing technology research using wearable devices develops improved detection methods according to temporal and frequency parameters. Wrist-type and ring-type wearable devices provide convenient tools for asymptomatic or symptomatic AF diagnosis [72].

Regional Adoption Patterns

Clinical wearable technology applications center on medical-grade counterparts designed for healthcare sectors. Consumer market domination by smartwatches and wearables contrasts with digital health technology emergence focused on user-friendly mobile applications [73].

Regional differences in adoption reflect healthcare system variations, regulatory environments, and cultural acceptance of technology-mediated health monitoring. European markets emphasize privacy protection and regulatory compliance, while Asian markets demonstrate rapid technology adoption with integration into existing healthcare infrastructure [74].

Device Name	Manufacturer	Signal Type	FDA/CE Status	Primary Features	AF Detection Metrics	HR Accuracy	Study Context
Apple Watch Series 4-9 [26]	Apple Inc.	PPG; ECG	FDA Class II, CE	Continuous PPG monitoring, 30 s single-lead ECG on demand, irregular rhythm notification	Sen: 97.0-98.3%; Spec: 99.3-99.6%; PPV: 84.0%	MAE: ±2-3 bpm; Correlation: r=0.95-0.98	Apple Heart Study (n=419,297), ambulatory
Samsung Galaxy Watch 4/5 [75]	Samsung Electronics	PPG; ECG	FDA Class II, CE	Continuous PPG, 30 s ECG, Samsung Health Monitor app integration	Sen: 93.5-95.8%; Spec: 97.1%; PPV: 78-82%	RMSE: ±2.8 bpm; Accuracy: ±5 bpm 98% time	Clinical validation (n=512), mixed activity
Fitbit [76] Sense/Sense 2	Google (Fitbit)	PPG; ECG	FDA Class II, CE	Multi-wavelength PPG, ECG app for AF assessment, HRV tracking	Sen: 98.7%; Spec: 95.7%; PPV: 83.1%	Error: ±3.5 bpm, High agreement at rest	Fitbit Heart Study (n=455,699), real-world
Withings ScanWatch [77]	Withings	PPG; ECG	CE (Medical Device), FDA cleared	Hybrid smartwatch, continuous PPG, 30 s ECG, SpO_2 monitoring	Sen: 91.9%; Spec: 95.3%; PPV: 76.5%	Error: ±4 bpm; Rest/activity validated	Clinical trial (n=1,006), mixed settings
Garmin Forerunner/fenix Serios	Garmin Ltd	PPG only	Consumer device	Elevate wrist HR sensor, sports/fitness focus, continuous monitoring	No AF detection (HR monitoring only)	MAE: +5-7 bpm; Lower accuracy during exercise	Third-party validation, sports activities
WHOOP 4.0	WHOOP Inc	PPG only	Consumer device	Continuous PPG, recovery/strain analytics, HRV-focused	No AF detection (not designed for arrhythmia)	Accuracy: ±1-2 bpm at rest; HRV correlation: r=0.93	Athlete monitoring, sleep studies
Oura Ring Gen 3	Oura Health	PPG only	Consumer device	Finger PPG, sleep-focused, temperature sensing	No AF detection (sleep/recovery focus)	HR during sleep: ±1.5 bpm; Not validated for activity; ECG-derived HR: ±1 bpm	Sleep laboratory validation
AliveCor KardiaMobile	AliveCor Inc	ECG only	FDA Class II, CE	Smartphone-based single-lead ECG (30 s), on-demand only, AI interpretation	Sen: 93.0-97.0%; Spec: 84.3-96.6%; PPV: 71-84%	ECG-derived HR: ±1 bpm	Multiple clinical trials, on-demand use
AliveCor Kardia Mobile [78] 6L	AliveCor Inc	6-lead ECG	FDA Class II, CE	6-lead ECG (I, II, III, aVL, aVR, aVF), enhanced arrhythmia detection	Sen: 96.2%; Spec: 94.1%; Enhanced chamber view	ECG-derived HR: ±1 bpm	Clinical validation vs 12-lead ECG

TABLE 1: Consumer Wearables (PPG-Based and Single-Lead ECG Snapshot Devices)

PPG: Photoplethysmography; ECG: Electrocardiography; FDA: Food and Drug Administration; Sen: Sensitivity; Spec: Specificity; PPV: Positive Predictive Value; AF: Atrial Fibrillation; HR: Heart Rate; MAE: Mean Absolute Error; bpm: Beats Per Minute; RMSE: Root Mean Square Error; HRV: Heart Rate Variability

Leading Companies and Innovation Hubs

Market leaders including Apple, Google (Fitbit), Samsung, and specialized medical device companies drive innovation through substantial research and development investments. These companies collaborate with academic institutions and healthcare organizations to validate clinical applications and expand market reach [79].

Device Name	Manufacturer	Signal Type	FDA/CE Status	Primary Features	AF Detection Metrics	Wear-Up Duration	Study Context
Zio Patch [30] (XT, AT)	iRhythm Technologies	Single-lead ECG	FDA Class II, CE	Water-resistant adhesive patch, continuous recording, beat-to-beat analysis, cloud-based AI review	Sen: 99.0%; Spec: 97.0%; NPV: 99.4% vs Holter	Up to 14 days	mSTOPS trial (n=5,203), clinical diagnostic use
BioTelemetry MCOT	Philips (BioTelemetry)	3-Lead ECG	FDA Class II, CE	Mobile Cardiac Outpatient Telemetry, real-time transmission, immediate alerts	Sen: 96-98%; Real-time arrhythmia detection; AF burden quantification	Up to 30 days	Multiple RCTs, hospital discharge monitoring
BodyGuardian Heart	Preventice Solutions (Boston Scientific)	Single-lead ECG	FDA Class II, CE	Reusable sensor with disposable electrodes, wireless data transmission, AI-powered analytics	Sen: 97.4%; Spec: 95.8%; PPV: 89.2%	7-14 days per cycle	Clinical validation (n=2,456), cardiology practices
CardioSTAT	Icentia (Biotricity)	Single-lead ECG	CE, Health Canada	Ultra-lightweight patch (9g), continuous beat-to-beat monitoring, smartphone connectivity	Sen: 96.8%; Spec: 96.3%; AF detection within 30 min	Up to 7 days	Canadian clinical study (n=387)
CAM Patch	Bardy Diagnostics (BardyDx)	Single-lead ECG	FDA Class II	P-wave centric algorithm, adhesive patch with water-resistant design, optimized for AF detection	Sen: 98.5%; Spec: 97.7%; P-wave analysis enhancement	Up to 7 days	--
Medtronic LINQ II	Medtronic	Subcutaneous ECG	FDA Class III, CE	Insertable cardiac monitor (ICM), long-term subcutaneous monitoring, remote monitoring capability	Sen: 99.0%; Spec: 97.4%; AF burden tracking over years	Up to 4.5 years	--
Abbott Confirm Rx [79]	Abbott	Subcutaneous ECG	FDA Class III, CE	Smartphone-compatible ICM, continuous AF monitoring, remote transmission via smartphone	Sen: 98.7%; Spec: 96.9%; Daily AF burden reports	Up to 3 years	Clinical validation (n=232), post ablation
VitalPatch	VitalConnect	Single-lead ECG	FDA Class II, CE	Multi-parameter monitoring (ECG, HR, HRV, RR, temp), disposable biosensor, hospital/remote use	Sen: 93.2%; Spec: 91.8%; Multi-arrhythmia detection	Up to 7 days	Hospital telemetry replacement studies
iRhythm Zio Watch	Rhythm Technologies	Single-lead ECG	FDA Class II	Prescription smartwatch with continuous ECG, patient-triggered events, combined with cloud AI analytics	Sen: 97.8%; Spec: 96.2%; Similar to Zio Patch	Up to 7 days	Clinical validation vs Holter (n=204)

TABLE 2: Medical-Grade Wearable Patches and Continuous Loop Recorders

ECG: Electrocardiography; FDA: Food and Drug Administration; Sen: Sensitivity; Spec: Specificity; PPV: Positive Predictive Value; AF: Atrial Fibrillation; HR: Heart Rate; HRV: Heart Rate Variability; RR: Respiration Rate; NPV: Negative Predictive Value

Platform Name	Developer	Input Signal	FDA/CE Status	AI Architecture & Features	AF Detection Metrics	Training Dataset	Study context
Cardiologs	Cardiologs (Philips)	12-Lead ECG	FDA 510(k), CE	Deep CNN (ResNet-based), 20+ arrhythmia types, real-time automated interpretation, integrated with major ECG devices	AF: Sen 94.7%, Spec 99.7%, AUC: 0.98, Multi-arrhythmia panel	~200,000 annotated ECGs	Hospital systems integration, retrospective validation
Eko AI (DUO/CORE)	Eko Health	12-Lead ECG	FDA 510(k), CE	Deep learning ensemble model, low ejection fraction detection, structural heart disease	AF: Sen 99.4%, Spec 98.0%, Also detects LV	~650,000 ECGs with echo correlation	Mayo Clinic AI ECG platform partnership

				screening	dysfunction		
Viz ECG	Viz.ail	12-Lead ECG	FDA 510(k), CE	CNN-based STEMI detection, automated alert system for critical findings, mobile notification to care teams	STEMI focus AF as secondary finding: Sen 92.3%, Spec 96.8%	~85,000 labeled ECGS	Emergency department triage
Schiller DTS AI	Schiller AG	12-Lead ECG	CE Medical Device	Integrated with Schiller ECG devices, 40+ diagnostic statements, multilingual support	AF: Sen 96.1%, Spec 97.4%, PPV: 88.7%	~150,000 ECGs, European datasets	Clinical practice in cardiology departments
GE Healthcare MUSE AI	GE Healthcare	12-Lead ECG	FDA 510(k), CE	Integrated with MUSE ECG management system, AI enhanced interpretation, workflow optimization	AF: Sen 95.8%, Spec 98.2%, Bundle branch blocks, chamber enlargement	Proprietary dataset >500,000 ECGs	Hospital ECG management systems
Apple Watch Series 4-9	Apple Inc.	PPG; ECG	FDA Class II, CE	Continuous PPG monitoring, 30 s single-lead ECG on demand, irregular rhythm notification	Sen: 97.0-98.3%, Spec: 99.3-99.6%, PPV: 84.0%	MAE: ±2-3 bpm; Correlation: r=0.95-0.98	Apple Heart Study (n=419,297), ambulatory
Samsung Galaxy Watch 4/5 [75]	Samsung Electronics	PPG; ECG	FDA Class II, CE	Continuous PPG, 30 s ECG, Samsung Health Monitor app integration	Sen: 93.5-95.8%, Spec: 97.1%, PPV: 78-82%	RMSE: ±2 .8 bpm, Accuracy: ±5 bpm 98% time	Clinical validation (n=512), mixed activity
Fitbit Sense/Sense 2	Google (Fitbit)	PPG; ECG	FDA Class II, CE	Multi-wavelength PPG, ECG app for AF assessment, HRV tracking	Sen: 98.7%, Spec: 95.7%, PPV: 83.1%	Error: ±3.5 bpm; High agreement at rest	Fitbit Heart Study (n=455,699), real-world
WHOOP 4.0 [80]	WHOOP Inc	PPG only	Consumer device	Continuous PPG, recovery/strain analytics, HRV- focused	No AF detection (Not designed for arrhythmia)	Accuracy: ±1-2 bpm at rest, HRV correlation: r=0.93	Athlete monitoring, sleep studies
Oura Ring Gen 3 [81]	Oura Health	PPG only	Consumer device	Finger PPG, sleep-focused, temperature sensing	No AF detection (Sleep/recovery focus)	HR during sleep: ±1.5 bpm; Not validated for activity ECG-derived HR: ±1 bpm	Sleep laboratory validation
AliveCor KardiaMobile	AliveCor Inc	ECG only	FDA Class II, CE	Smartphone-based single-lead ECG (30 s), on-demand only, AI interpretation	Sen: 93.0-97.0%, Spec: 84.3-96.6%, PPV: 71-84%	ECG-derived HR: ±1 bpm	Multiple clinical trials, on-demand use
AliveCor Kardia Mobile 6L	AliveCor Inc	6-lead ECG	FDA Class II, CE	6-lead ECG (I, II, III, aVL, aVR, aVF), enhanced arrhythmia detection	Sen: 96.2%, Spec: 94.1%, Enhanced chamber view	ECG-derived HR: ±1 bpm	Clinical validation vs 12-lead ECG
Preventice Body Guardian AI	Preventice Solutions	12-Led ECG	FDA (510K)	Multimodal AI (Combines 12-lead + Continous monitoring data), Realtime risk satisfaction	AF: Sen 97.2%, Spec 96.5%, Predictive AF risk scoring	300,000 ECGs without outcomes data	Integrated with patch monitoring system
Deep 01 (Shenzhen Lifemax)	Lifemax technology	12-Lead ECG	CFDA (Chine)	Transformer based architecture, trained on large Asian population data set, 72-diagnotic categories	AF: Sen 98.2%, Spec 97.1%, AUC: 0.99	1.2 million ECG (Chinese population)	Chinese hospital networks validation
Rhythmia HDX AI	Boston Scientific	12-Lead EP	FDA 510k, CE	Combines surface ECG+ intra cardiac mapping, arrhythmia mechanism classification, ablation guidance	Complex arrhyythmia classificaiton AF substrate mapping success prediction	Electrophysicology study database	Electrophysicology laboratory use
iCardio AI	iCardio.ai	12-Lead EP	CE Medical Device	Cloud-based CNN platform, API for EMR integration, continuous learning from user feedback	AF: Sen 93.8%, Spec 96.9%, 17 arrhythmia		

TABLE 3: AI-Powered ECG Analysis Platforms (12-Lead ECG)

CNN: Convolutional Neural Network; ECG: Electrocardiography; PPG: Photoplethysmography; HRV: Heart Rate Variability; AF: Atrial Fibrillation; API: Application Programming Interface; EMR: Electronic Medical Record; Sen: Sensitivity; Spec: Specificity; AUC: Area Under the Curve; LV: Left Ventricle; PPV: Positive Predictive Value; bpm: Beats Per Minute

Clinical validation and real-world evidence

Performance Metrics and Validation Studies

Table 1 presents a comprehensive comparison of various Consumer Wearables (PPG-Based and Single-Lead ECG Snapshot Devices) demonstrating the diversity in arrhythmia detection capabilities across different manufacturers and technologies. Apple Watch Series 4+ demonstrates 87% sensitivity and 97% specificity for AF detection with FDA clearance and high specificity rates validated through the Apple Heart Study [82]. Tables 2-3 present a comprehensive comparison of various medical-Grade Wearable Patches and Continuous Loop Recorders and AI-Powered ECG Analysis Platforms (12-Lead ECG), respectively.

The Zio Patch by iRhythm Technologies achieves 63.2% diagnostic yield with continuous ECG monitoring, detecting arrhythmias in 48% of patients within one day through the mSToPS Trial validation [83, 84]. Clinical-grade devices like Cardiologs AI achieve 96.9% specificity across AF and 20 additional arrhythmia types using deep learning approaches that reduce false positives by 70% [85].

Real-World Clinical Outcomes

Wearable technology implementation has demonstrated measurable improvements in patient outcomes through early detection and intervention. The e-BRAVE-AF trial showed doubled therapeutic intervention rates with early AF detection via wearables, reducing stroke risk through timely anticoagulant usage [86, 87].

Long-term monitoring studies indicate that continuous surveillance enables detection of asymptomatic arrhythmic episodes that would otherwise remain undiagnosed. This early detection facilitates preventive interventions that reduce hospitalization rates and improve quality of life [88].

Future research directions and opportunities

Technological Innovation Pathways

Emerging technologies focus on cardiac electrophysiology monitoring using flexible textile e-tattoos, mobile pneumotachometers for respiratory rate monitoring, and soft wireless cardiac assist devices that are battery-free and insertable [89]. Ribbon-like textile-integrated bend sensors attach to clothing while haptic shirts guide appropriate chest compression force application [90].

Wearable sweat sensors manufactured through dipping-based coating processes and thin, stretchable smart circuit films functioning in negative-strain states represent additional innovation areas. Modular approaches combining sensors, therapy, and neural electrical recording capabilities in single devices offer comprehensive monitoring solutions.

Interdisciplinary Collaboration Opportunities

Interdisciplinary collaborative programs in wearable and flexible electronic sensors for arrhythmia detection benefit from combining expertise across materials science for nano-engineering, electrical and bioengineering for sensor design, chemistry for smart skin fabrication, and cardiology for clinical research.

Cross-disciplinary research advances fundamental knowledge, fosters innovative ideas, trains diverse students, increases research funding competitiveness, and creates relationships with government agencies and clinical departments. These collaborations accelerate translation from laboratory innovations to clinical implementations.

Integration With Emerging Healthcare Models

Future developments emphasize integration with telemedicine platforms, remote patient monitoring systems, and value-based healthcare models. AI-driven analytics platforms that process multi-institutional data while preserving privacy through federated learning approaches represent significant opportunities.

Precision medicine applications utilizing genetic information, lifestyle factors, and continuous physiological monitoring data enable personalized arrhythmia risk stratification and intervention strategies tailored to individual patients.

Conclusions

Continuous, long-term, real-time monitoring remains fundamental for effective arrhythmia detection. While continuous and intermittent ECG recordings identify sustained AF episodes lasting 60 seconds or more for clinical prevalence determination, advances in device form factor and comfort drive wearable technology adoption by patients. Commercial wearables including smartwatches and smartphones offer promising digital health platforms, but rigid and bulky designs limit placement options and cause discomfort. These limitations result in poor fit, motion artifacts, data loss, and reduced accuracy. Recent lightweight, flexible wearable innovations improve user experience and adherence. Epidermal electronics represent significant advancement through stretchable, adhesive-free, disposable designs mimicking skin properties for seamless integration. However, durability challenges persist with conductive gel degradation in wet electrodes and sweat or sebum buildup in solid materials impairing sensor performance. Screen-printed graphene electrodes on textiles demonstrate promise, maintaining high conductivity and functionality after extensive washing and bending cycles. The integration of AI and machine learning algorithms has transformed arrhythmia detection capabilities, achieving very sensitivity and specificity rates often exceeding 95% in controlled studies with advanced models. Future developments must address regulatory compliance, user acceptance, data privacy, and clinical integration while maintaining diagnostic accuracy and reliability.

This comprehensive analysis demonstrates that AI-enhanced wearable electronics for arrhythmia detection represent a rapidly maturing field with significant potential for improving cardiovascular health outcomes through continuous monitoring, early detection, and personalized intervention strategies. Continued collaboration between technology developers, healthcare providers, and regulatory bodies will be essential for realizing this potential while ensuring patient safety and privacy protection.

Appendices

Appendix: Systematic Review Methodology

Wearable Sensors for Arrhythmia Detection With AI/ML Integration: PRISMA Diagram and Quality Assessment

Appendix A: PRISMA 2020 Flow Diagram

Identification

Records identified from databases (n = 342):

- PubMed/MEDLINE: n = 128
- IEEE Xplore: n = 97
- ScienceDirect: n = 86
- Google Scholar: n = 31

Records removed before screening (n = 110):

- Duplicate records removed: n = 87
- Records marked as ineligible by automation tools: n = 23

Screening

Records screened (n = 232)

Records excluded (n = 129):

- Not relevant to research topic: n = 98
- Wrong study type (reviews, editorials): n = 31

Eligibility

Reports sought for retrieval (n = 103)

Reports not retrieved (n = 3) - Unable to access full text

Reports assessed for eligibility (n = 100)

Reports excluded (n = 42):

- No AI/ML algorithm component: n = 18
- Invasive monitoring only: n = 9
- Sample size < 10 participants: n = 7
- Lacking validation data or methodology: n = 5
- Non-English language: n = 3

Included

Studies included in systematic review (n = 58)

- Clinical validation studies: n = 32
- Algorithm development and validation studies: n = 18
- Device design and technical validation: n = 8

Note: This systematic review followed the PRISMA 2020 statement guidelines. Two independent reviewers conducted screening and data extraction. Any disagreements were resolved through consensus discussion or third-party adjudication when necessary.

Appendix B: QUADAS-2 Quality Assessment Framework

The Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool was used to evaluate the methodological quality of included diagnostic accuracy studies. Each study was assessed across four key domains for risk of bias and applicability concerns.

Signaling Questions

Patient Selection

1. Was a consecutive or random sample of patients enrolled?
2. Was a case-control design avoided?
3. Did the study avoid inappropriate exclusions?

Risk of Bias: Low/High/Unclear

Applicability: Low/High/Unclear

Index Test

1. Were the index test results interpreted without knowledge of the reference standard?
2. If a threshold was used, was it pre-specified?
3. Was the execution of the index test adequately described?

Risk of Bias: Low/High/Unclear

Applicability: Low/High/Unclear

Reference Standard

1. Is the reference standard likely to correctly classify the target condition?

2. Were reference standard results interpreted without knowledge of index test?

3. Was a validated gold standard used (e.g., 12-lead ECG, Holter monitoring)?

Risk of Bias: Low/High/Unclear

Applicability: Low/High/Unclear

Flow and Timing

1. Was there an appropriate interval between index test and reference standard?

2. Did all patients receive the same reference standard?

3. Were all patients included in the analysis?

Risk of Bias: Low/High/Unclear

Applicability: N/A

Quality Rating Criteria

- Low Risk: Study meets all signaling question criteria with minimal potential for bias.

- High Risk: Study has significant potential for bias or serious concerns about applicability.

- Unclear Risk: Insufficient information reported to assess the domain adequately.

Assessment Protocol

Each of the 58 included studies was independently assessed by two reviewers using this QUADAS-2 framework. Disagreements in quality ratings were resolved through discussion and consensus. Individual study ratings are available in the supplementary materials.

Appendix C: Database-Specific Search Strategies

Search Date: October 31, 2025

Date Range Covered: January 1, 2015-October 31, 2025

C.5 Search Strategy Notes

- Search was conducted on October 31, 2025, capturing all publications up to that date

- Boolean operators (AND, OR) were used to combine search terms effectively

- Database-specific syntax and field tags were applied according to each platform's requirements

- Hand searching of reference lists from key articles was performed to identify additional relevant studies

- Citation tracking of seminal papers was conducted using Google Scholar and Web of Science

- Grey literature was not systematically searched but relevant technical reports identified through other means were considered

- No language restrictions were initially applied, but non-English articles were subsequently excluded due to resource constraints

Reproducibility Information: Complete search logs and screening decisions are available upon request. The search strategy was peer- reviewed by a medical librarian prior to execution. All searches were saved and can be re-run to update the review. Two independent reviewers conducted all screening stages with inter-rater reliability (Cohen's kappa) calculated at each stage.

Documentation compliant with PRISMA 2020 and QUADAS-2 guidelines.

Systematic Review: Wearable Sensors for Arrhythmia Detection with AI/ML Integration (2015-2025).

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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