

EMPIRICAL PAPER

Wearable Biosensors for Remote Monitoring and Early Detection of Cardiovascular Diseases: A Systematic Literature Review

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Abstract

Purpose: The current state of wearable biosensors for remote monitoring and early cardiovascular disease (CVD) detection is examined in this systematic literature review, which also highlights the technological advancements, clinical applicability, and implementation difficulties of these devices.

Methodology: A thorough search for peer-reviewed research published between 2020 and 2025 was carried out using PRISMA guidelines across Scopus and Web of Science. A total of thirty studies met the inclusion criteria. The PROBAST tool was used to evaluate the risk of bias in the data that was extracted on device type, biosensors, monitored parameters, clinical settings, and methodological quality.

Results: Wearable biosensors have shown considerable promise in monitoring metrics like blood pressure, heart rate, and electrocardiogram. Diagnostic accuracy has increased due to integration with machine learning algorithms; some models have over 90% accuracy in identifying conditions like hypertension and atrial fibrillation. However, only a small percentage of studies included clinical validation; most were restricted to simulations or prototype evaluations. Motion artefacts, data security, power constraints, and a lack of standardisation are some of the main obstacles.

Novelty and Contribution: This review provides a current evaluation of wearable CVD monitoring technologies by synthesising recent developments in biosensor miniaturisation, multi-modal sensing, and AI-driven analytics. It shows that hospital-based diagnostics are gradually giving way to ongoing, individualised health monitoring.

Implications: Wearable biosensors have considerable potential to improve early intervention, lessen healthcare costs, and facilitate remote care models. Additional clinical validation, regulatory alignment, and strong integration into healthcare infrastructures are necessary to realise this potential.

Keywords: Wearable Biosensors; Remote Monitoring; Early Detection; Systematic Literature Review; Cardiovascular Disease

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1 Introduction

Cardiovascular diseases (CVDs) remain the leading cause of morbidity and mortality worldwide, representing a major global public health concern (Li et al., 2025). The Global Burden of Disease Study 2019 estimated that 523.2 million people were living with CVD that year, a 26% increase from 1990 (Roth et al., 2020) with CVD-related deaths rising by nearly 19% between 2010 and 2020. The economic burden is similarly substantial, costing the European economy more than €200 billion annually (Zhu et al., 2025), despite slow progress in implementing cost-effective therapies globally (Mendis et al., 2022). CVD risk factors are broadly divided into non-modifiable factors (age, gender, genetics) and modifiable factors, including hypertension, elevated cholesterol, smoking, poor diet, obesity, physical inactivity, and elevated fasting blood sugar (Frieden & Jaffe, 2018). Notably, more than 80% of CVD cases occur in low- and moderate-sociodemographic-index (SDI) countries, underscoring the interplay between socioeconomic determinants and cardiovascular health (Yusuf et al., 2020; Li et al., 2025). The WHO projects that CVD, already the leading cause of premature mortality for decades, will kill over 23.6 million people annually by 2030 (Baghdadi et al., 2023).

Early detection, identifying a condition or risk factor before symptoms manifest allows for timely intervention and can significantly alter disease trajectory, particularly for myocardial infarction and coronary artery disease (Nair et al., 2024; Almansouri et al., 2024). Continuous monitoring of diagnosed or at-risk patients further supports clinicians in tracking disease progression, evaluating treatment efficacy, and adjusting therapy to prevent complications and hospitalisation (Nair et al., 2024). However, traditional monitoring tools such as blood pressure cuffs, ECGs, and sphygmomanometers while informative, are limited in their capacity for continuous data collection and frequent, convenient use (Welsh et al., 2024; Zhu et al., 2024). These limitations have motivated the development of new techniques to improve prediction and interpretation of disease progression (Lin et al., 2025).

Wearable technology has emerged to address these gaps, enabling real-time, non-invasive monitoring of vital indicators outside clinical settings and supporting early detection of arrhythmias and asymptomatic conditions such as atrial fibrillation (Almansouri et al., 2024; Sims et al., 2020). Early-generation devices, however, carry notable drawbacks: standard ECGs require correct electrode placement and are too bulky for continuous long-term use (Khan et al., 2025), while PPG-based smartwatches despite improvements in mobility, AI-driven accuracy, and arrhythmia detection (Smith & Maisrikrod, 2025) remain vulnerable to motion artefacts, calibration drift, and reduced clinical-grade precision over time (Gruwez et al., 2021). Additional concerns include the risk of inaccurate diagnoses, heightened patient anxiety, and increased costs associated with decentralised monitoring and alerts.

CVDs cause approximately 18 million deaths worldwide annually and remain the leading cause of death globally (Razeeb et al., 2019). Because early detection and continuous monitoring can prevent complications, reduce hospitalisation, and improve survival (Anbuselvam et al., 2024), wearable biosensors have become transformative tools for non-invasive, real-time monitoring of cardiovascular metrics such as blood pressure, heart rate, ECG, and biochemical indicators (Chen et al., 2021). Given the rapid growth of wearable technologies and the expanding body of research in this domain, a systematic review and synthesis of the existing literature is urgently needed. Accordingly, this systematic literature review addresses the following research questions:

- What types of wearable biosensors are currently used in CVD monitoring?
- What physiological parameters are monitored (e.g., heart rate, ECG, BP)?
- What are the technological and clinical outcomes of using wearable biosensors?
- What challenges and limitations exist in current research?

2 Materials and Methods

Meta-analyses and systematic reviews are crucial instruments and methods for correctly, precisely, and consistently summing the data gleaned from the literature. Many academics advise using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) standard standards, which are used in this systematic review (Page et al., 2021). For every item on the checklist pertaining to research backgrounds, development, explanations, and justifications, PRISMA offers thorough review criteria that reviewers can adhere to in order to guarantee that the review procedures and meta-analysis are genuine and open (Zobair et al., 2023). The study was registered on the PROSPERO website with ID PROSPERO 2025 CRD420251170090 (<https://www.crd.york.ac.uk/PROSPERO/view/CRD420251170090>).

2.1 Search Source and Search Strategy

In accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria, a search was conducted in the Web of Science and Scopus databases. Additionally, a manual Google Scholar search was carried out as complementary search using the same keywords combination used in the two databases. Only peer-reviewed journals published between 2020 and 2025 were included in the search strategy for the targeted papers. Keyword combinations such as "wearable biosensors," "wearable devices," "cardiovascular disease," "CVD," "remote monitoring," and "early detection" were included in the search terms. When combined with Boolean operators like "AND" and "OR," the keywords are utilised. Only articles written in English were included in the study. The titles and abstracts were manually reviewed after duplicates were eliminated. After a full-text assessment, the papers that were judged relevant were evaluated for eligibility using predetermined inclusion and exclusion criteria.

2.2 Eligibility and Inclusion Criteria

Strictly peer-reviewed English-language journal papers pertaining to the primary body of research were included in this review (inclusion criteria); duplicates and unrelated materials were not (exclusion criteria). Additionally, studies that solely used wearable biosensors for the monitoring and detection of cardiovascular disease were included in this review. Studies that had no direct bearing on the identification and tracking of cardiovascular illness, however, were not taken into account. Notably, peer-reviewed publications were included in this review. In order to get the most pertinent items for analysis and synthesis, the writers conducted three rounds of screening and filtering procedures, excluding all extraneous publications, book chapters, conference papers, and research notes. Figure 1 shows the flow diagram for PRISMA.

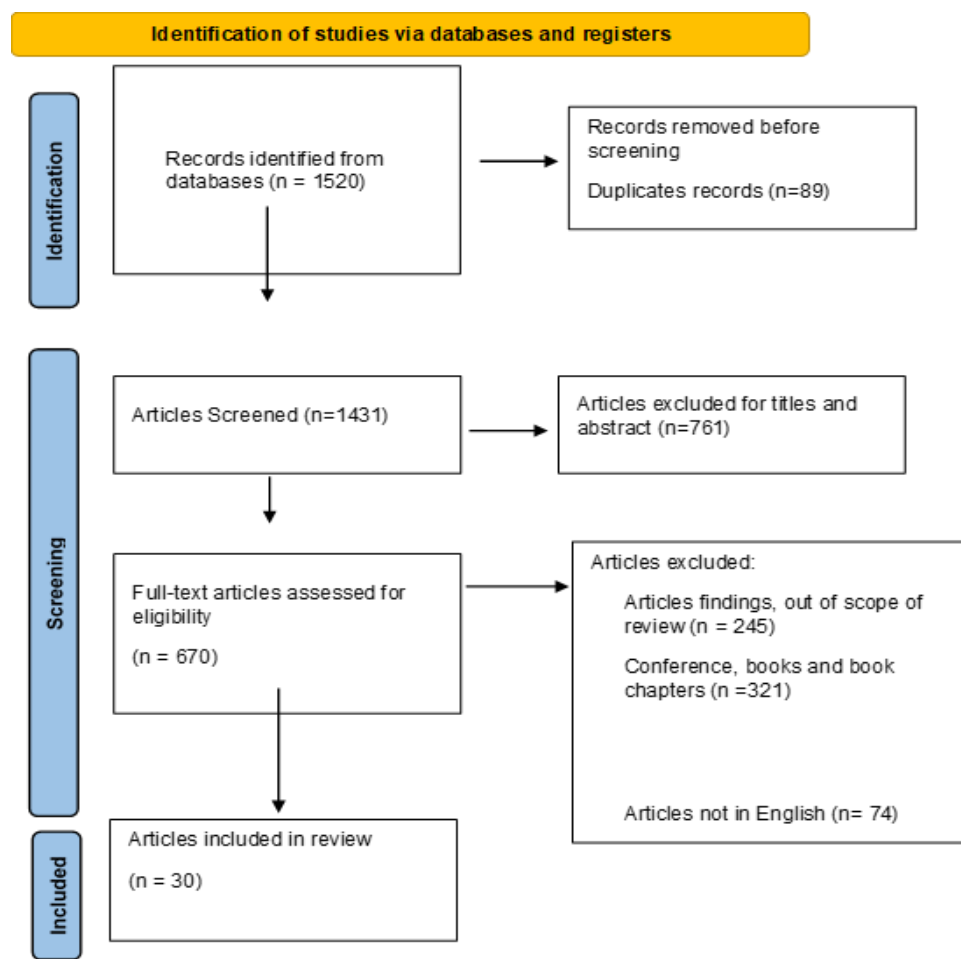


Figure 1 PRISMA flow diagram

Table 1 Inclusion and exclusion criteria table

Category	Inclusion	Exclusion
Year	2020 -2025	Below 2020
Language	English	Non-English
Device	Wearable biosensors	Non-wearable device
Article type	Peer-reviewed articles	Book, book chapters, conference, repositories
Disease	Cardiovascular disease	Non-cardiovascular diseases.

2.3 Data Extraction

As indicated in table 2 (supplementary file, S1), we gathered the following information from all included studies: year of publication, authors, country of research, study type, wearable device type, biosensors utilised, physiological parameters monitored, targeted CVD, sample size, and technology employed.

2.4 Risk of Bias

We used the Prediction Model Risk of Bias Assessment Tool (PROBAST) to evaluate the methodological quality of the prediction model studies that were part of this review (Wolff et al., 2019). It evaluates risk of bias and applicability of studies that develop, validate, or update a prediction model, assessed across four domains, participants, predictors, outcome, and analysis (Tewarie et al., 2021).

3 Results

There were 1520 distinct studies found in the search. 670 studies were included for full-text review after being screened first by title and abstract and then by full text. Thirty of these papers were included in the qualitative synthesis after meeting our inclusion criteria. Three articles (Khan et al., 2025; Terada et al., 2025; Babar et al., 2023) are themselves reviews or evaluate the biosensor literature rather than primary empirical work, while 27 of these studies design, test, or deploy a wearable device/algorithm for CVD detection. The prognostic models that are included were created between 2020 and 2025.

3.1 Study Characteristics

There is a clear trend towards more research activity in wearable biosensor technology for the detection of cardiovascular disease, according to the temporal analysis of publication years. The data shows a distinct acceleration pattern, with the most recent years seeing a sharp increase in research output. With only one study published in 2020 and 2021, respectively, the distribution exhibits little activity in the early years of the analysis period. In 2022, there was a gradual increase to four studies. With five studies published in 2023 a 25% increase from the year before the research momentum increased substantially. With eight publications in 2024 a 60% increase from 2023 this upward trajectory continued even more sharply. The highest publication output occurred in 2025, when eleven studies were published, accounting for more than one-third of all the studies in the dataset and a 37.5% increase from 2024.

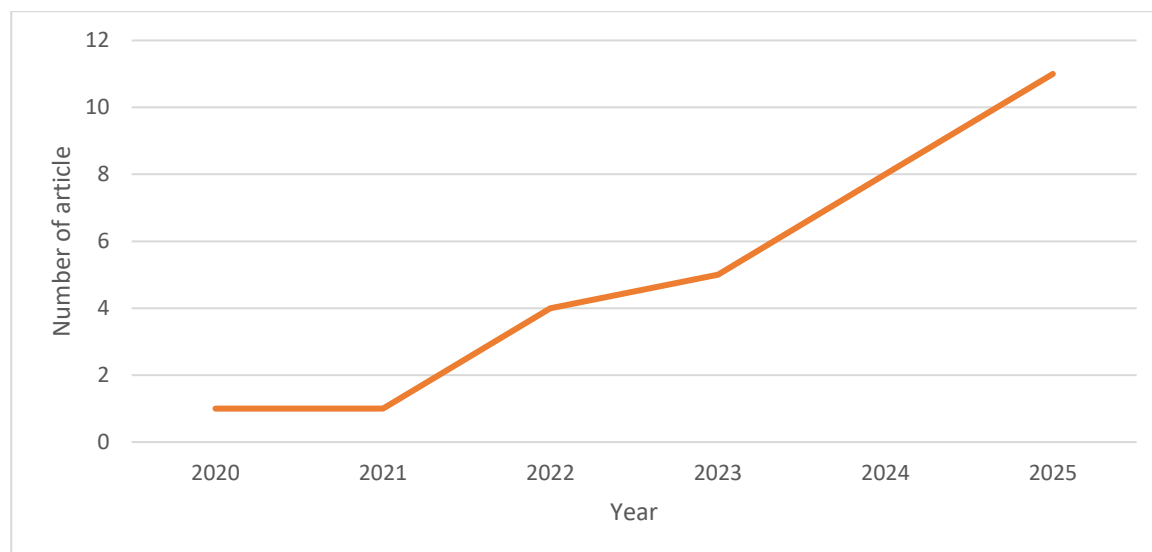


Figure 2 Publication by year of reviewed articles.

China is the leading contributor to the field, according to the geographic analysis, which shows a notable concentration of research activities among a small number of nations. With seven studies, or 23.3% of the total research output, China leads all countries. The United States comes in second with five studies (16.7%). With three studies (10%), Japan comes in third place, while a number of other nations make smaller contributions. Thirteen distinct countries are represented in the research landscape, demonstrating the data's impressive geographic diversity. However, given that 50% of all research output comes from the top three nations (China, the United States, and Japan), this seeming diversity conceals a significant concentration. Ten additional nations share the remaining research, each contributing one to two studies. Furthermore, one study shows that the USA and UK are working together, suggesting that cross-border research collaborations are starting to form (Shim et al., 2024). While South Korea, Greece, Taiwan, Kazakhstan, Turkey, and India each contribute one study, countries like Italy have two, indicating growing interest and capability development in these areas. However, no nation was mentioned in the other studies.

Out of thirty studies, only eight (26.7%) offered precise numerical data on sample size. The data shows significant variation in study scale among the eight studies that did report numerical sample sizes. With a mean sample size of 322 participants and a standard deviation of 233.39, the sample sizes vary from a minimum of 44 participants (Mitropoulos et al., 2024) to a maximum of 721 participants (Pasli et al., 2024). According to the median sample size of 294 participants, the majority of research involving human subjects is carried out on a moderate scale. The majority of the 22 unreported studies (73.3%) used algorithmic validation with public datasets (Khan et al., 2025; Terada et al., 2025; Babar et al., 2023) or prototype testing (Maan et al., 2025; Liang et al., 2025; Wang et al., 2022). The smallest clinical validation ($n=44$) assessed a graphene-based patch for hypertension (Mitropoulos et al., 2024), while the largest ($n=721$) concentrated on atrial fibrillation detection in multi-centre trials (Pasli et al., 2024).

Each study in the dataset focuses on a different facet of cardiovascular health monitoring, and there are thirty distinct targeted cardiovascular diseases or conditions. Targeted conditions range from specific conditions like atrial fibrillation (Pasli et al., 2024; Babar et al., 2023), heart failure (Terada et al., 2025; Spaccarotella et al., 2022), and coronary heart disease (Terada et al., 2025) to more general categories like cardiovascular risk assessment and general cardiovascular monitoring. Some research focuses on well-defined clinical conditions like hypertension (Chen et al., 2025; Gong et al., 2025; Mitropoulos et al., 2024) and myocardial infarction (Zang et al., 2025), while others address newer topics like metabolic syndrome (Shim et al., 2024; Staffini et al., 2023) and sleep apnea-related cardiovascular risk (Hayano et al., 2024). Both acute and chronic cardiovascular conditions are included in the diversity. Myocardial ischaemia (Maan et al., 2025) and potentially fatal arrhythmias (Zang et al., 2025) are examples of acute conditions, whereas hypertension, heart failure, and coronary artery disease are examples of chronic conditions. The potential of wearable biosensors in preventive medicine is also acknowledged by a number of studies that discuss cardiovascular risk factors and prevention techniques.

Twenty-five distinct study types were found among the thirty studies, demonstrating the remarkable diversity in study types and methodological approaches revealed by the analysis. Eleven studies use prototype evaluation, which is the most prevalent study type. The variety of research methodologies used in this field is illustrated by the remaining study types. Prospective monitoring trials, observational studies, and randomised controlled trials are examples of clinical research methodologies. The creation and assessment of algorithms, the creation and verification of AI models, and experimental research utilising simulation datasets are examples of technology-focused methodologies. The multidisciplinary character of wearable biosensor research for cardiovascular applications is reflected in a number of study types. Prototype and clinical study (Pasli et al., 2024) and RCT and model evaluation (Chen et al., 2025) are two examples of categories that show attempts to integrate clinical validation with technology development.

3.2 Technological Aspects

A broad range of form factors, including both consumer electronics and specialised prototypes, are present in the included studies. While some research projects developed their own wearable platforms, others used commercial smartwatches and fitness bands, such as the Apple Watch, Fitbit, and Garmin (Pasli et al., 2024; Spaccarotella et al., 2022; Lubitz et al., 2022). One example is a flexible optical fibre watchband for blood pressure monitoring (Chen et al., 2025), a wireless chest electronic tattoo with integrated ECG and seismocardiography (SCG) sensors (Bhattacharya et al., 2024), and wearable electrocardiographic clothing that integrates ECG electrodes across the torso (He et al., 2025). In addition, wearable patches and multi-sensor wristbands were popular. For example, one study used a dual-PPG wristwatch with temperature and pressure sensors to continuously estimate blood pressure (Wang et al., 2023). Other kinds of devices included IoT-assisted single-lead ECG modules that could be monitored remotely, head-mounted or limb sensors (such as those that capture pulse waves at the wrist and fingertip), and piezoelectric pulse-detection wristbands (Ali et al., 2021).

The biosensing techniques used in each study were equally diverse. To record cardiac signals, electrical biosensors—mainly ECG electrodes—were widely employed. For example, Wang et al. (2022) integrated ECG electrodes with multi-wavelength photoplethysmography (PPG) in a wrist wearable, and Zang et al. (2025) combined standard ECG electrodes with a PZT-based heart sound sensor (phonocardiogram). Optical sensors were widely used, and many devices included oximetry or PPG. Single-lead ECG and optical PPG sensors were available on Fitbits and Apple Watches right out of the box. PPG sensors were used in custom wearables to measure oxygen saturation (SpO₂) or heart rate. Multi-wavelength pulse oximetry and fibre-optic blood pressure sensors were two more optical innovations (Marinari et al., 2022).

Proprietary signal-processing pipelines for feature extraction and noise reduction were reported in numerous studies. Liang et al. (2025), for instance, used empirical mode decomposition and wavelet techniques to denoise radial pulse wave signals. Several others extracted cardiac time intervals using empirical mode decomposition or adaptive thresholding. Ensemble models and deep neural networks were popular at the machine learning end. Most often, convolutional neural networks (CNNs) were trained for regression or classification: Hasumi et al. (2025) used a CNN to classify the severity of heart failure from a single-lead ECG with 91.6% accuracy, and Chen et al. (2025) estimated systolic/diastolic blood pressure from optical sensor data using a 1D ResNet. Hybrid architectures also surfaced: for real-time heart rate prediction from PPG, Maan et al. (2025) integrated CNN layers with bidirectional LSTMs and attention mechanisms. Additional machine learning models were also used, including Random Forest and decision tree classifiers for identifying arrhythmias or hypertension, support vector machines for multi-parameter vitals estimation, and Bayesian optimisation or gradient boosting for fine-tuning model parameters. Additionally, specialised frameworks emerged, including a β -VAE (variational autoencoder) + BiLSTM model for sleep-related heart rate anomaly detection and a "Prior-to-Attention" network for transmembrane potential reconstruction (Staffini et al., 2023). Table 2 lists the 27 empirical studies' wearable device type, biosensors, parameters measured, technology, and clinical settings.

Table 2. Type of wearable device

Author(s) (Year)	Wearable Device Type	Biosensor(s) Used	Physiological Parameters Monitored	Technology Used (e.g., AI/ML)	Clinical Setting (Yes/No)
Zang et al. (2025)	Wearable system with integrated ECG and PCG	ECG electrodes, PZT heart sound sensor	ECG, PCG, derived metrics (EMD, LVET, PEP)	Signal processing algorithms	No
Hasumi et al. (2025)	Apple Watch (Wearable ECG device)	Single-lead ECG	ECG signals	Convolutional Neural Network (CNN)	No
Hsiao et al. (2025)	Wrist-worn multi- modal device	PPG (2x), Bioimpedance (2x)	Blood Pressure (systolic, diastolic)	Random Forest Regression (RFR)	No
Khan et al. (2025)	Various (Hybrid Sensor Devices)	Magnetic sensors, Optical sensors (PPG)	Blood volume changes, Pulse rate	Multi-sensor data fusion (no AI/ML mentioned)	No
Chen et al. (2025)	Optical microfibre intelligent watchband	Fibre optic sensor (SMMF)	Systolic & Diastolic Blood Pressure	Residual Neural Network (1D- ResNet)	No
Terada et al. (2025)	Consumer-grade wearable devices (e.g., smartwatches, fitness trackers)	HR, rhythm, accelerometer	Heart rate, rhythm, step count, VO ₂ peak, exercise adherence	No specific mention	No
Maan et al. (2025)	Wristband-type wearable	PPG sensor	Heart Rate	CNN-Bi-LSTM- Attention, Bayesian Optimisation	No
He et al. (2025)	Wearable electrocardiographic clothing (ECGI- based)	ECG electrodes for BSP measurement	Transmembrane potential (TMP), Body Surface Potential (BSP)	Priori-to- Attention Network (P2AN) with cross- attention & normalisation	No
Gong et al. (2025)	Wrist-worn wearable device	ECG, PPG	ECG and PPG signal features	Causal inference + Machine Learning	No
Bhattacharya et al. (2024)	Wireless chest e- tattoo	ECG, SCG sensors	ECG, SCG, CTIs (LVET, PEP)	FAD framework (NMLS filtering, EMD)	No
Liang et al. (2025)	Wearable pulse detection system	Flexible piezoelectric sensor	Radio pulse wave	ICEEMDAN, WPD, cubic spline, adaptive threshold detection	No

Mun et al. (2024)	Consumer wearable (unspecified)	Heart rate sensor	All-day HR, sleeping HR, minimum HR, inactive HR, HR dip	No specific AI/ML mentioned	No
Mitropoulos et al. (2024)	Wearable device for telerehab	Heart rate sensor, motion sensor	Heart rate (%HRpeak), RPE, affect ratings	Real-time telerehab & telecoaching	Yes
Shim et al. (2024)	Consumer-grade wearable devices	Accelerometers, motion sensors	Circadian rhythmicity, physical activity	Statistical modelling, predictive analytics	No
Hayano et al. (2024)	Wristwatch wearable device	IMU (triaxial accelerometer & gyroscope)	Respiratory frequency (via motion signals)	Signal processing algorithm, threshold-based detection	Yes
Chen et al. (2024)	Garmin smart watch	Optical HR sensor (PPG)	Resting heart rate	PCA, linear mixed models, distributed lag nonlinear models	No
Alimbayeva et al. (2024)	Wearable ECG device (ADS1298 + STM32L151xD)	ECG electrodes	ECG, BP, cholesterol	AI/ML (CNN, SVM, RF, XGBoost, Isolation Forest)	Yes
Andersen & Carlsen (2024)	Apple Watch; Reveal LINQ ILR	Optical HR sensor; Accelerometer; ECG (ILR)	HR, HRV, physical activity time	Custom EHR integration (no AI)	Yes
Pasli et al. (2024)	Apple Watch	Single-lead ECG sensor	Heart rate, ECG rhythms	None	Yes
Wang et al. (2023)	Wrist-worn wearable with dual PPG sensors	Dual photoplethysmography (PPG) sensors, interface pressure & temperature sensors	Blood pressure, pulse waveform, cardiac output	Machine Learning (signal fusion, LOSO)	No
Zhan et al. (2023)	Low-cost wearable signal detection system	PRV sensor from pulsation signal	Pulse Rate Variability (PRV)	Decision Trees (AI/ML), FPE algorithm	No
Yan et al. (2023)	Lab-developed wearable for pulse wave capture	Pulse wave sensors (wrist & fingertip)	Pulse waves, microcirculation parameters	Random Forest, SMA algorithm	No
Babar et al. (2023)	Smartwatches, wearable patches	PPG sensor, single-lead ECG	Heart rhythm (AF detection)	Not specified	No
Staffini et al. (2023)	Wristband-style smartwatch	Optical HR sensor	Heart rate	β -VAE, BiLSTM, anomaly detection models	No

Lubitz et al. (2022)	Fitbit wrist-worn device	Optical PPG sensor	Pulse rate via PPG; ECG (for confirmation)	PPG-based detection algorithm	No
Marinari et al. (2022)	Wrist-worn device (BrOxy M)	Optical biosensor (Pulse oximeter)	SpO ₂ , Heart Rate (HR)	None	No
Wang et al. (2022)	Lightweight, integrated wearable multimodal sensor	ECG electrodes, 2-wavelength PPG sensors	ECG, heart rate, SpO ₂ , SBP, DBP, PTT	Support Vector Machine (SVM)	No
Spaccarotella et al. (2022)	Apple Watch Series 6	Pulse oximeter (SpO ₂ sensor)	SpO ₂ , Heart Rate	Non explicitly mentioned	Yes
Ali et al. (2021)	IoT-assisted single-channel ECG monitor	ECG electrodes, RLD circuit	ECG, heart rate	IoT, Bluetooth, cloud database	No
Li et al. (2020)	Wearable BP wristband with optical fibre	Optical fibre + PDMS + Ag diaphragm	Blood pressure (SBP, DBP), PTT	Signal processing (no AI/ML)	Yes

AF = Atrial Fibrillation; Ag = Silver; AI = Artificial Intelligence; BiLSTM = Bidirectional Long Short-Term Memory; BP = Blood Pressure; BSP = Body Surface Potential; CNN = Convolutional Neural Network; CTIs = Cardiac Time Intervals; DBP = Diastolic Blood Pressure; ECG = Electrocardiogram; ECGI = Electrocardiographic Imaging; EHR = Electronic Health Record; EMD = Empirical Mode Decomposition; FAD = Frequency-Adaptive Denoising; FPE = Fast Permutation Entropy; HR = Heart Rate; HRV = Heart Rate Variability; HRpeak = Peak Heart Rate; ICEEMDAN = Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise; ILR = Implantable Loop Recorder; IMU = Inertial Measurement Unit; IoT = Internet of Things; LOSO = Leave-One-Subject-Out; LVET = Left Ventricular Ejection Time; ML = Machine Learning; NMLS = Neighbourhood Majority Label Smoothing; PCA = Principal Component Analysis; PCG = Phonocardiogram; PDMS = Polydimethylsiloxane; PEP = Pre-Ejection Period; PPG = Photoplethysmography; PRV = Pulse Rate Variability; PTT = Pulse Transit Time; PZT = Lead Zirconate Titanate; RF = Random Forest; RFR = Random Forest Regression; RLD = Right Leg Drive; RPE = Rating of Perceived Exertion; SBP = Systolic Blood Pressure; SCG = Seismocardiography; SMMF = Single-Mode Microfibre; SMA = Slime Mould Algorithm; SpO₂ = Peripheral Capillary Oxygen Saturation; SVM = Support Vector Machine; TMP = Transmembrane Potential; VO_{2peak} = Peak Oxygen Uptake; WPD = Wavelet Packet Decomposition; XGBoost = Extreme Gradient Boosting; β -VAE = Beta Variational Autoencoder; 1D-ResNet = One-Dimensional Residual Neural Network.

Only a small percentage of the studies were carried out on actual patient populations or in clinical settings. As shown in the 'Clinical Setting' column of Table 2, only 8 of the 30 included studies (26.7%) were conducted in a clinical setting, while the remaining 22 (73.3%) relied on simulations, prototype testing, or public-dataset evaluation. Many of them were simulations or prototype/evaluation studies conducted on healthy subjects. For instance, Gong et al. (2025) trained an ML model for hypertension detection using a public dataset (n=405), and Zang et al. (2025) assessed signal quality in 40 cases (healthy vs. CHD) without real-world deployment. On the other hand, clinical trials or real patients were used in some studies. High compliance and safety were found in a randomised feasibility trial (n=44) conducted by Mitropoulos et al. (2024) of a wearable tele-rehabilitation device in patients who had suffered myocardial infarction. In 122 patients with suspected sleep apnoea, Hayano et al. (2024) compared a wrist motion sensor algorithm to polysomnography. Andersen & Carlsen (2024) used an Apple Watch and loop recorder to prospectively monitor 40 patients with pulmonary hypertension. According to Pasli et al. (2024), 721 emergency patients used Apple Watch ECGs to assess their rhythm. Limited clinical samples were enrolled in other studies (e.g., 323 subjects for the classification of coronary/hypertension, 132 subjects for the detection of arrhythmias, and 16 patients in a BP estimation trial). Large-scale remote monitoring studies were also observed; for example, Shim et al. (2024) used data from 80,000 wearable users to create a circadian ageing biomarker 34, and Lubitz et al. (2022) tracked 455, 699 Fitbit users for atrial fibrillation screening 33.

3.3 Benefits of Biosensor Wearable Devices for Cardiovascular Disease Detection

Numerous studies showed that conditions like atrial fibrillation, hypertension, and heart failure could be identified with continuous monitoring. Hasumi et al. (2025), for instance, used a CNN-based model with single-lead ECG data from an Apple Watch to classify the severity of heart failure with 91.6% accuracy, allowing for non-invasive at-home diagnostics. A similar 98.2% positive predictive value (PPV) for atrial fibrillation detection using PPG data from Fitbit devices across a large sample ($n=455,699$) was reported by Lubitz et al. (2022), demonstrating the scalability and practicality of wearable AF screening. With accuracy levels that meet AAMI and BHS standards, wearables such as the optical microfibre intelligent watchband created by Chen et al. (2025) showed promise in replacing conventional sphygmomanometers for the screening of hypertension.

Alimbayeva et al. (2024) used a suite of AI models (CNN, SVM, XGBoost, and Isolation Forest) to analyse ECG data, detecting cardiac anomalies with 92.6% accuracy and highlighting the predictive power of wearable-based AI systems. Staffini et al. (2023) also showed that deep learning is feasible for anomaly detection in sleep-related heart rate using a β -VAE + BiLSTM model embedded within smartwatch devices. All of these studies combined machine learning (ML) and signal processing algorithms to transform raw sensor data into clinically actionable predictions.

Wearable technology fills care gaps by enabling long-term, real-time physiological monitoring in the home, particularly in remote or underdeveloped areas. According to the Mitropoulos et al. (2024) telerehabilitation trial, wearable-guided exercise after myocardial infarction was safe, feasible, and linked to high compliance (91.6%). In a similar vein, Andersen & Carlsen (2024) monitored patients with pulmonary hypertension by integrating smartwatch data with electronic health records, which decreased the risk of hospitalisation while improving patient engagement.

3.4 Challenges of Biosensor Wearable Devices for Cardiovascular Disease Detection

Despite the high baseline accuracy of many wearables, signal quality can be deteriorated by outside variables like motion artefacts, perspiration, skin tone, and ambient temperature. Bhattacharya et al. (2024) observed that while filtering techniques (FAD framework) increased robustness, SCG signal quality was extremely sensitive to movement. Similar to this, Wang et al. (2023) found that environmental factors like perspiration and movement caused their wristband-based blood pressure monitor to perform worse. Data accuracy was also found to be impacted by sensor placement and device variability, particularly in consumer-grade devices. Although they noted the need for increased sensitivity for clinical thresholds, Hayano et al. (2024) found a correlation ($r = 0.84$) between polysomnography and wrist IMU-derived respiratory rate.

Significant worries about data privacy and cybersecurity are raised by the growing use of AI/ML and cloud-based data processing. Few studies specifically addressed secure data handling, despite the fact that many used cloud-enabled wearable platforms, such as IoT-ECG in Ali et al., 2021. Strong encryption procedures and regulatory compliance are essential when integrating wearable data into health systems, especially under GDPR, HIPAA, or comparable frameworks, according to Andersen & Carlsen (2024).

Continuous monitoring is limited by battery limitations, especially in wrist-worn devices where power capacity is constrained by compact form factors. Battery life is a major drawback of Apple Watch-based monitoring systems, according to Andersen & Carlsen (2024). Furthermore, unless low-power architectures are used, such as GSMD in Maan et al., 2025, computationally demanding algorithms like CNNs and LSTMs increase energy demands and impair real-time use.

The majority of studies lack extensive clinical validation and are still in the prototype or simulation stages. For instance, Zang et al. (2025) only used a single-centre pilot with 40 cases to test their ECG-PCG device. Several studies, such as Li et al. (2020) and Wang et al. (2022), validated algorithms on limited samples or healthy subjects only, and Gong et al. (2025) used public datasets instead of real-time monitoring.

3.5 Risk of Bias

The PROBAST tool was used to evaluate the risk of bias. Out of the 30 studies, 27 were evaluated using PROBAST. The remaining three studies (Khan et al., 2025; Terada et al., 2025; Babar et al., 2023) were excluded from the PROBAST assessment because they are literature evaluations of biosensor applications in CVD detection rather than primary studies developing or validating a prediction model, and therefore fall outside PROBAST's intended scope.

These studies included observational/clinical validation studies, machine learning-based prediction model evaluations, and prototype development, among other wearable device applications. Nine (33%) of the 27 studies had a low overall risk of bias, whereas 14 (52%) had a high risk rating. Inadequate methodological detail resulted in unclear ratings for the remaining 4 studies (15%). Large-scale, real-world data and structured model development pipelines were common in the least risky studies (Hasumi et al., 2025; Lubitz et al., 2022; Mitropoulos et al., 2024). However, because of their early design phases, simulation-only studies (He et al., 2025) and prototype evaluations (e.g., Zang et al., 2025; Ali et al., 2021) were more likely to show high bias.

Another key worry was applicability to actual healthcare environments. The generalisability of studies carried out solely in lab or simulation settings (He et al., 2025; Zhan et al., 2023) and prototype-only evaluations (Zang et al., 2025; Marinari et al., 2022) was restricted. On the other hand, research that used a variety of patient samples and placed the biosensors in actual or nearly real clinical settings (e.g., Spaccarotella et al., 2022; Andersen & Carlsen, 2024; Mitropoulos et al., 2024) was judged to have minimal applicability issues. The assessment's outcome is available in the supplemental file (S2).

4 Discussion

This case report presents a rare instance of sporadic intraabdominal desmoid-type fibromatosis in a 49-year-old Nigerian male who presented with a massive abdominal mass measuring approximately 40 × 30 × 20 cm.

Despite the absence of immunohistochemistry, histopathological examination of the resected specimen revealed long sweeping fascicles of uniform spindle cells with minimal cytological atypia, confirming the diagnosis of desmoid-type fibromatosis. Intraoperative findings demonstrated that the tumor, though appearing non-infiltrative on preoperative imaging, was firmly adherent to the terminal ileum, cecum, ascending colon, and proximal transverse colon, necessitating en bloc resection with right hemicolectomy and ileotransverse anastomosis. The patient achieved an uneventful postoperative recovery and was discharged on postoperative day six, demonstrating favourable short-term outcomes following surgical intervention.

The reviewed studies show that sensor modalities involve distinct trade-offs rather than one dominant approach. ECG-based systems offer the highest diagnostic specificity — Hasumi et al. (2025) achieved 91.6% accuracy classifying heart failure severity from single-lead ECG — but remain sensitive to motion and electrode placement. PPG-based systems scale more easily to consumer devices and population-level screening, as shown by Lubitz et al.'s (2022) 98.2% PPV for atrial fibrillation across 455,699 Fitbit users, though at some cost to precision. Optical fibre and pulse-wave sensors targeting blood pressure achieve competitive but variable accuracy: Chen et al. (2025) met AAMI standards (± 4.58 mmHg) with a fibre-optic watchband, while Wang et al. (2023) reached a somewhat wider ± 6 mmHg using multi-optical fusion. Multimodal/hybrid systems address single-sensor limitations directly — Zang et al. (2025) combined ECG with phonocardiogram to achieve high signal quality (ECG SNR 44.13 dB, PCG SNR 30.04 dB), and Bhattacharya et al. (2024) paired ECG with seismocardiography to maintain accurate cardiac-timing extraction even during motion. Overall, ECG offers precision, PPG offers scalability, and multimodal fusion offers the strongest robustness against motion artefacts — but typically at greater device complexity and cost.

Deep learning models feature prominently in interpreting wearable data. Hasumi et al. (2025) trained a CNN on single-lead ECG data to classify heart failure severity with 91.6% accuracy, while Chen et al. (2025) used a 1D-ResNet on fibre-optic pulse data to meet clinical BP accuracy standards, and Maan et al. (2025) combined CNN-BiLSTM-attention architecture to estimate heart rate from PPG with a 2.42 BPM mean absolute error. Newer analytical approaches are also emerging: Gong et al. (2025) applied causal inference to ECG/PPG features for hypertension prediction (89% accuracy, improving on correlational methods), and Staffini et al. (2023) used a β -VAE-BiLSTM model to detect sleep-related heart-rate anomalies more effectively than conventional algorithms. Signal-processing innovations complement these models, Zhan et al.'s (2023) Fast Permutation Entropy algorithm classified arrhythmias at 85.4% accuracy while running 211× faster than standard methods, and Bhattacharya et al. (2024) combined narrowband filtering with median-label smoothing to reduce motion noise in ECG/SCG signals, reflecting a broader emphasis across the literature on artefact reduction alongside model accuracy.

Clinical validation lags behind technological advancements. These wearables have only been tested in a small number of clinical trials and real-world environments. Only two of the studies we reviewed were randomised controlled trials. According to an RCT of online cardiac telerehabilitation after MI (44 patients), Mitropoulos et al. (2024) found that

home-based rehab using a wearable heart-rate/motion system was safe, feasible, and had 91.6% adherence with no adverse events. The patient experience was also positive, and the results were comparable to those of gym-based rehab. CR. In an 8-subject study, Staffini et al. (2023) discovered that a smartwatch wristband model could accurately identify nocturnal heart-rate abnormalities linked to the risk of metabolic syndrome. Shim et al. (2024), on the other hand, retrospectively examined 80,000 adults wearing accelerometer-equipped devices to determine a circadian "CosinorAge" biomarker predictive of mortality and disease risk. The majority of studies, however, were observational or prototype evaluations. Afib detection has been demonstrated to be possible with large-scale remote monitoring: consumer PPG-ECG algorithms have been shown to screen for atrial fibrillation at scale by Lubitz et al. (2022) and Pasli et al. (2024). Pasli (n=721) found 94% heart-rate agreement with ECG in ED patients, indicating wearables' usefulness in AF triage, and Lubitz's (n≈455,000) Fitbit study achieved a PPV of 98.2% for the new AF detection file-ezhptnddkkzsmmyubee2osc. These results from a large cohort support earlier research on smartwatch AF screening.

Two important themes that came to light were patient usability and health-system integration. Patients can easily adopt wearables in structured programmes, as demonstrated by the high compliance in Mitropoulos's telerehab trial. In order to empower patients and lower hospitalisation rates, Andersen & Carlsen (2024) integrated heart-rate data with electronic health records and showed continuous smartwatch monitoring in patients with pulmonary hypertension. Other studies also reported positive user experiences and engagement. User-friendly interfaces built into consumer devices (Apple Watch, Fitbit, and Garmin) improve adherence. But there are still practical challenges. According to Andersen et al., battery life and the requirement for frequent charging may restrict continuous monitoring, and motion, skin contact, and wrist position can all affect sensor accuracy. According to Terada et al. (2025), wearables typically increase clinical outcomes and engagement in cardiac rehabilitation settings, but their efficacy can be compromised by usability problems like calibration and data quality. Furthermore, Shim et al. (2024) note that cross-population biomarker comparisons are difficult due to variations across device brands and algorithms. Integration on the systems side is still in its infancy; real-time data pipelines have only been used in a small number of studies. Others propose telemedicine frameworks (e.g., remote coaching combined with wearables) as logical next steps, while Andersen's project demonstrated that it is possible to stream smartwatch data into the EHR for clinical monitoring.

Our results show new directions while generally agreeing with previous research trends. In line with earlier reviews, we discover that wearable CVD monitors provide continuous tracking and improved engagement when compared to conventional approaches (Chen et al., 2024). Previous studies (such as the original Apple Heart Study) demonstrated the efficacy of optical PPG and ECG wearables for rhythm monitoring, and our findings support the high accuracy of PPG-based AF detection (e.g. Lubitz 2022). The emphasis on using AI to speed up data analysis is also consistent with the expanding body of research on machine learning in cardiology. Researchers are now integrating novel materials (nanomembranes, optical fibres) and combining modalities (ECG+SCG, multi-wavelength PPG), in contrast to earlier studies that frequently tested single-signal wearables (e.g., standalone ECG patches or wristband PPG). Examples of these innovative designs, which were mostly nonexistent in the literature only a few years ago, are documented in our review. Examples include fibre-optic watches, e-tattoos, and multimodal wristbands. Comparably, many of the more recent works use deep learning and ensemble models (CNNs, RNNs, VAE, causal ML), reflecting advancements in computation and data availability, whereas the foundational studies used traditional algorithms. The requirement for larger, more varied cohorts and clinically meaningful endpoints, however, are universal problems that have persisted throughout time. According to our review and previous analyses, the majority of devices are still in the prototype stage, with only a small number of large RCTs (Scholte et al., 2024).

All of the evidence points to the need for more work before wearable biosensors can be widely used in practice, even though engineering advancements like miniaturisation, multimodality, and AI-enhanced sensing are accelerating. Large-scale validation, standardised protocols, and regulatory approval are necessary to close the gap between promising prototypes and validated clinical tools, as stressed by Scholte et al. (2024) and others. Future research should evaluate these devices' effects on clinical outcomes and test them in representative patient populations. To fully utilise the potential of remote monitoring, integration with electronic medical records and telehealth platforms will be essential. Transforming current innovations into practical applications will require addressing enduring problems with motion artefacts, user variability, data security, and equity of access. Though multidisciplinary cooperation will be required to transform wearable biosensors into efficient, evidence-based instruments for the early detection and treatment of cardiovascular disease, the reviewed studies show impressive technological advancements overall.

5 Discussion and Future Directions

The recent developments, uses, and restrictions of wearable biosensors in the early detection and remote monitoring of cardiovascular diseases (CVDs) were examined in this comprehensive review of the literature. The results point to an increasing amount of data demonstrating the clinical utility of wearable biosensors in monitoring physiological parameters with real-time feedback and high patient compliance, including blood pressure, oxygen saturation, heart rate, and ECG. Continuous, non-invasive, and personalised health monitoring is made possible by these devices, which is especially important for long-term disease management and the early detection of CVD events. According to the review, wearable biosensors have the potential to revolutionise cardiovascular care by increasing the precision of diagnoses, facilitating prompt interventions, and enhancing patient outcomes. Predictive analytics and remote doctor engagement are made possible by combining wearable technology with wireless communication and artificial intelligence. However, issues like sensor accuracy, data privacy, standardisation, and integration with current healthcare systems continue to be major obstacles to broad adoption.

To confirm the long-term efficacy and clinical results of wearable biosensors, future studies should concentrate on multi-centre clinical trials. Additionally, it is necessary to improve device comfort and miniaturisation, create more reliable anomaly detection algorithms, and guarantee fair access for a variety of demographics. Furthermore, fostering acceptance and trust between patients and healthcare providers will require addressing ethical and regulatory issues.

The implications are that desmoid tumors should be considered in the differential diagnosis of large abdominal masses in sub-Saharan Africa, and surgical resection remains a viable and effective treatment where advanced diagnostics and systemic therapies are unavailable. However, delayed presentation and limited diagnostic capacity remain significant barriers. Strengthening pathology services, clinician awareness, and long-term surveillance is essential for improving outcomes in similar settings.

Limitations

In the context of its methodology, scope, and evidence synthesis, a number of limitations must be noted, even though this systematic literature review provides insightful information about the state of wearable biosensors for cardiovascular disease (CVD) monitoring and early detection. It was impossible to perform a meta-analysis or use quantitative synthesis techniques due to the heterogeneity of the reviewed articles. Rather, the review mostly relied on qualitative analysis, which restricts the findings' statistical inference and generalisability even though it provides rich descriptive detail. Additionally, only 26.7% (8/30) of included studies reported explicit sample sizes, limiting the ability to assess statistical power, generalisability, and cross-study comparability of the reported diagnostic accuracies. Furthermore, by limiting the review to studies conducted between 2020 and 2025, it only includes the most recent technological advancements without placing them in the larger historical context of wearable biosensors. Consequently, the development trajectory, small-scale innovations, and comparisons with early-stage technologies are only mentioned in passing.

Conflict of Interest

The authors declare that there is no conflict of interest.

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