

Artificial Intelligence-driven Real-time Monitoring of Cardiovascular Conditions with Wearable Devices: A Scoping Review

Ali Abedi, Anshul Verma, Dherya Jain, Jathushan Kaetheeswaran, Cynthia Chui,
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Abstract

Background: Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for 18 million deaths annually. Early detection and prediction of cardiovascular conditions are essential for timely intervention and improved patient outcomes. Wearable devices offer a promising, non-invasive solution for continuous monitoring of cardiovascular signals, vital signs, and physical activity. However, the large data volumes generated by these devices and the rapid fluctuations in cardiovascular signals necessitate advanced Artificial Intelligence (AI) techniques for real-time analysis and effective clinical decision-making.

Objective: The objective of this scoping review is to identify the main challenges of AI-driven platforms for real-time cardiovascular condition monitoring with wearable devices and explore potential solutions. Additionally, this review aims to examine how AI algorithms and deployment pipelines are optimized to enable real-time cardiovascular condition monitoring.

Methods: A comprehensive search was conducted in the following electronic databases: MEDLINE(R) ALL (Ovid), Embase (Ovid), Cochrane Central Register of Controlled Trials (Ovid), Web of Science Core Collection (Clarivate), IEEE Xplore, and ACM Digital Library, yielding 2,385 unique records. Inclusion criteria focused on studies that utilized wearable devices for participant data collection and applied AI algorithms for real-time analysis to detect or predict cardiovascular events and diseases. After title and abstract screening, 153 articles remained, and following a full-text review, 19 studies met the inclusion criteria.

Results: The findings indicate that despite the promise of AI and wearable devices, research on real-time cardiovascular monitoring remains limited and lacks comprehensive validation. Most studies relied on publicly available wearable datasets rather than real-world validation with recruited participants in community settings. Studies that deployed AI algorithms in real-time frequently failed to report operational characteristics and challenges. ECG-based wearable sensors were the most frequently used devices, primarily in hospital settings. A variety of AI techniques, ranging from traditional machine learning to lightweight deep learning algorithms, were deployed either on wearable devices or via cloud-based processing.

Conclusions: Robust, interdisciplinary research is needed to harness the full potential of AI-driven, real-time cardiovascular health management using wearable devices. This includes the development and validation of scalable solutions for continuous community-based deployment. Furthermore, real-world challenges such as participant compliance, hardware and connectivity constraints, and AI model optimization for real-time continuous monitoring must be carefully addressed.

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Review

Artificial Intelligence-driven Real-time Monitoring of Cardiovascular Conditions with Wearable Devices: A Scoping Review

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Abstract

Background: Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for 18 million deaths annually. Early detection and prediction of cardiovascular conditions are essential for timely intervention and improved patient outcomes. Wearable devices offer a promising, non-invasive solution for continuous monitoring of cardiovascular signals, vital signs, and physical activity. However, the large data volumes generated by these devices and the rapid fluctuations in cardiovascular signals necessitate advanced Artificial Intelligence (AI) techniques for real-time analysis and effective clinical decision-making.

Objective: The objective of this scoping review is to identify the main challenges of AI-driven platforms for real-time cardiovascular condition monitoring with wearable devices and explore potential solutions. Additionally, this review aims to examine how AI algorithms and deployment pipelines are optimized to enable real-time cardiovascular condition monitoring.

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Results: The findings indicate that despite the promise of AI and wearable devices, research on real-time cardiovascular monitoring remains limited and lacks comprehensive validation. Most studies relied on publicly available wearable datasets rather than real-world validation with recruited participants in community settings. Studies that deployed AI algorithms in real-time frequently failed to report operational characteristics and challenges. ECG-based wearable sensors were the most frequently used devices, primarily in hospital settings. A variety of AI techniques, ranging from traditional machine learning to lightweight deep learning algorithms, were deployed either on wearable devices or via cloud-based processing.

Conclusions: Robust, interdisciplinary research is needed to harness the full potential of AI-driven, real-time cardiovascular health management using wearable devices. This includes the development and validation of scalable solutions for continuous community-based deployment. Furthermore, real-world challenges such as participant compliance, hardware and connectivity constraints, and AI model optimization for real-time continuous monitoring must be carefully addressed.

Keywords: Cardiovascular Diseases; Artificial Intelligence; Real-time Monitoring; Continuous Monitoring; Wearable Devices; Machine Learning; Deep Learning; Smartwatches;

Electrocardiography (ECG); Atrial Fibrillation.

Introduction

Cardiovascular diseases (CVDs) continue to be the leading cause of mortality worldwide, causing over 18 million deaths each year [1]. The number of deaths attributed to CVDs has increased significantly over the past decades, rising by 53.7% from 12.1 million in 1990 to 18.6 million in 2019 [2]. This trend is expected to continue, with an estimated 35.6 million cardiovascular deaths by 2050, an increase of 90% compared to 2025 [2]. This escalating trend underscores the urgent need for comprehensive prevention and management strategies to address the global impact of CVDs.

Early detection and prediction of CVDs and cardiovascular events are critical for reducing the morbidity and mortality associated with these conditions [3], [4], [5]. CVDs, such as coronary artery disease, hypertensive heart disease, and cardiomyopathies, often develop silently over years, with patients exhibiting minimal or no symptoms until a significant event occurs [6]. Identifying risks at an early stage allows for timely intervention, lifestyle modifications, and treatment, which can dramatically reduce the likelihood of severe outcomes [7]. Real-time predictive detection of cardiovascular events, such as heart attacks, cardiac arrest, and strokes, is particularly essential because it provides actionable insights during critical windows when interventions can have the greatest impact. Delays in recognizing and responding to subtle physiological changes can mean the difference between prevention and a life-threatening event [8], [9].

Wearable devices equipped with sensors for continuous monitoring of vital signs such as heart rate, blood pressure, and oxygen saturation offer the potential to identify abnormal patterns indicative of cardiovascular stress or disease [10]. These devices enable remote monitoring for people in the community, allowing healthcare providers to track patients' health in real-time and intervene promptly, even outside of clinical settings. Coupled with artificial intelligence (AI), these devices can analyze large amounts of data in real-time, detecting and predicting potential cardiovascular events before they occur [9]. Advanced machine-learning and deep-learning techniques play a critical role in processing and interpreting the large and complex data captured by wearable devices, identifying subtle patterns and trends that may go unnoticed by human observation. Their ability to learn from historical data and continuously improve predictions ensures timely and accurate alerts, enabling healthcare providers to intervene before critical events unfold, thereby reducing the risk of adverse outcomes [9].

An AI-driven, wearable-sensor-based platform for real-time cardiovascular monitoring can be equipped with single or multimodal sensors to collect various data, including electrocardiogram (ECG), photoplethysmogram (PPG), heart rate, blood pressure, and mobility indicators. This data is analyzed by AI algorithms, trained on historical datasets and optimized for real-time inference. Depending on the system's design, these algorithms can run either directly on wearable devices or on cloud servers (requiring data transfer). Analysis results are then communicated to clinicians, participants, or caregivers, enabling timely interventions to prevent or reduce adverse cardiovascular outcomes.

By prioritizing early detection and prediction, healthcare systems can shift focus from reactive to proactive care, reducing hospitalizations, improving health outcomes, and patients' quality of life, and lowering healthcare costs [11]. Ultimately, early intervention is the foundation of effective CVD management and a pathway to saving millions of lives annually [3], [4], [5].

Related Reviews

Table 1 summarizes recent reviews on the applications of wearable devices and AI algorithms for real-time cardiovascular monitoring [10], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], as well as relevant reviews in the broader domain of healthcare monitoring [23], [24], [25]. While previous reviews about cardiovascular monitoring addressed one or two concepts, wearable

devices [10], [12], [13], [14], [15], [16], [17], [20], [21], [22], AI [18], [18], [20], [21], [22], [25], or real-time monitoring [10], [23], [24], [25], none comprehensively covered all three. Additionally, reviews on real-time monitoring in general healthcare [23], [24], [25] lack a specific focus on the detection and prediction of cardiovascular conditions. Most of these reviews included studies that utilized pre-collected public datasets for developing AI algorithms, which do not deal with the real-world challenges of deploying AI for real-time monitoring.

Research Questions

AI [18], [20], [21], [22], [25] plays a crucial role in processing data from wearable devices [10], [12], [13], [14], [15], [16], [17], [20], [21], [22] facilitating real-time [10], [23], [24], [25] detection, prediction, and diagnosis of cardiovascular conditions. This empowers clinicians to intervene swiftly, helping to prevent or mitigate adverse outcomes, reduce hospitalizations and mortality, and improve patient quality of life. In this paper, a scoping review was conducted to systematically map the current body of research on AI-driven platforms using wearable sensors for real-time cardiovascular monitoring and to identify knowledge gaps and associated challenges. The scoping review was guided by the following research questions: (1) What are the main challenges of AI-driven platforms for real-time cardiovascular condition monitoring with wearable devices, and how can they be addressed? (2) How are AI algorithms and deployment pipelines optimized to enable real-time cardiovascular condition monitoring?

Table 1. A comparison between this scoping review and previous related reviews, sorted by the inclusion of focus on cardiovascular diseases (CVD), real-time, artificial intelligence (AI), and wearable concepts. Notably, this review is the only one that integrates all four concepts comprehensively.

Review	Year	CVD	Real-time	AI	Wearable
Albahri et al. [23]	2018	✗	✓	✗	✗
Uddin et al. [24]	2024	✗	✓	✗	✗
Paganelli et al. [25]	2022	✗	✓	✓	✗
Bogar et al. [12]	2024	✓	✗	✗	✓
Ho et al. [13]	2024	✓	✗	✗	✓
Duncker et al. [14]	2021	✓	✗	✗	✓
Bayoumy et al. [15]	2021	✓	✗	✗	✓
Nazarian et al. [16]	2021	✓	✗	✗	✓
Scholte et al. [17]	2024	✓	✗	✗	✓
Ahsan et al. [18]	2022	✓	✗	✓	✗
Safdar et al. [19]	2018	✓	✗	✓	✗
Lee et al. [20]	2022	✓	✗	✓	✓
Huang et al. [21]	2022	✓	✗	✓	✓
Moshawrab et al. [22]	2023	✓	✗	✓	✓
Lin et al. [10]	2021	✓	✓	✗	✓
This review	2025	✓	✓	✓	✓

Methods Design

This study employed a scoping review methodology to address the broad scope of the research questions, the diversity of the studies and populations, and the absence of previously conducted comprehensive reviews [26], [27]. The scoping review followed the framework outlined by Arksey and O'Malley [26] and was reported in compliance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

[27].

Eligibility Criteria

Inclusion Criteria

Peer-reviewed journal and conference articles written in English, including quantitative, qualitative, and mixed-method studies, were considered for inclusion. To be eligible, studies had to describe either the development of a new research platform or a commercial platform, or the use of an existing platform for AI-driven real-time monitoring of cardiovascular conditions through wearable devices. The platform was required to meet all four criteria outlined below:

- It must collect continuous data from adult participants using wearable sensing devices.
- It must be AI-driven, incorporating machine learning and/or deep learning algorithms to analyze wearable data.
- The AI algorithms must perform data analysis and inference-making in real-time or near real-time.
- The inferences made by AI algorithms must involve detecting, predicting, forecasting, or diagnosing cardiovascular conditions, diseases, or events. Studies could also look at other comorbidities, such as diabetes, in addition to CVD.

Using the SPICE framework [28], the setting; population; intervention; comparison; and evaluation criteria were identified as participants' homes, nursing homes, or hospitals; adult participants; monitoring (predicting or detecting) any cardiovascular condition; real-time AI algorithms; and the accuracy and latency of real-time AI algorithms, respectively.

Exclusion Criteria

Non-peer-reviewed and non-English publications or resources were excluded. Studies were excluded if they:

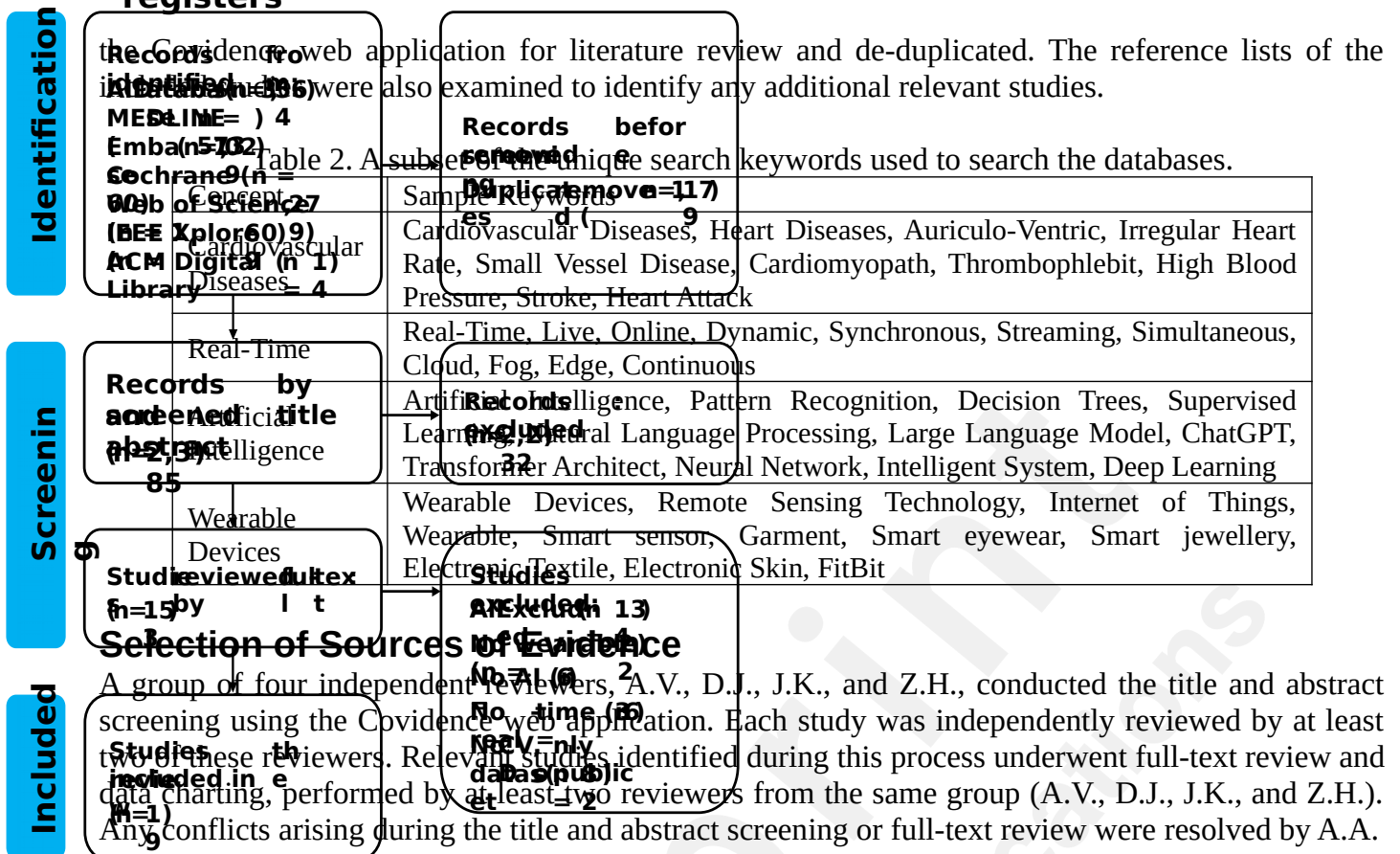
- did not use a platform in which wearable sensor devices were used for data collection from adult participants,
- did not use AI algorithms for wearable sensor data analysis,
- perform offline data analysis, or
- only evaluated their platform on wearable sensor datasets already collected, such as publicly available datasets.

If one or more of the above criteria were met, studies were excluded.

Information Sources and Search Strategy

To identify relevant studies, a comprehensive literature search was designed in collaboration with an Information Specialist (C.C.) and further refined through team discussions. A.A. and A.V. initially provided C.C. with a list of keywords and 20 target articles that needed to be retrieved from the search. Following this, C.C., A.A., and A.V. collaboratively refined the keyword list and developed a search strategy using a combination of subject headings and text words for Medline, which was subsequently translated to other databases. The search strategy consisted of four concepts: wearable devices, cardiovascular diseases, AI algorithms, and real-time data analysis. The search was conducted in the following electronic bibliographic databases: MEDLINE(R) ALL (Ovid), Embase (Ovid), Cochrane Central Register of Controlled Trials (Ovid), Web of Science Core Collection (Clarivate), Institute of Electrical and Electronics Engineers (IEEE) Xplore, and Association for Computing Machinery (ACM) Digital Library, covering records from inception to July 5, 2024. Search filters were used to remove studies on children and animals when possible. The results were limited to the English language. Table 2 provides a subset of unique search keywords used for database queries. The complete search strategy and associated keywords for databases are detailed in Supplementary Table 1. The search results were exported as RIS files, consolidated, imported into

Identification of studies via databases and registers



Data Charting Process and Data Items

To address the research questions for this scoping review, a data charting form was designed to extract relevant information from the reviewed studies. The form consisted of five sections: (i) study characteristics, participants, and settings, as well as cardiovascular condition under monitoring, (ii) study aims, methodologies, and key findings, (iii) characteristics of wearable devices, (iv) characteristics of real-time AI algorithms, (v) robustness analysis of AI algorithms.

Synthesis of Results

To address the research questions, a descriptive analysis was performed, followed by a narrative summary of relevant study characteristics presented using tables. Studies were analyzed based on the data characteristics outlined above. Due to the heterogeneity in populations, CVDs, outcome measurement tools, and measurement times, a meta-analysis was not conducted [29].

Results

Selection of Sources of Evidence

Figure 1 illustrates the PRISMA flow diagram, which describes the study selection process. Upon removing duplicates, a total of 2,385 studies were identified through comprehensive literature searches of electronic databases. Following title and abstract screening, 2,232 studies were excluded, and 153 full-text studies were retrieved for full-text review. Among these 153 studies, 134 were excluded due to the absence of any one or more of the four aforementioned inclusion criteria. This resulted in the inclusion of 19 studies.

Figure 1. PRISMA flow diagram for the scoping review. Of the 2,385 unique titles and abstracts initially screened, 153 full-text studies were further evaluated, resulting in 19

studies being included in the scoping review.

Characteristics of Sources of Evidence

Tables 3–5, Table 6(a) and (b), and Table 7(a) and (b) present the five aforementioned categories of data items for the studies included in this scoping review. A ‘—’ in the tables indicates that the respective item was not mentioned or discussed in the paper.

Characteristics of Studies

As outlined in Table 3, the included studies ($n = 19$) were published between 2010 and 2024, with the majority, 17 (89.5%), published between 2019 and 2024 [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], highlighting the increasing shift toward real-time AI solutions for monitoring cardiovascular conditions. Among the included studies, 5 (26.3%) were conducted in the United States [32], [40], [44], [45], [47], 4 (21.1%) in Taiwan [33], [35], [36], [48], 3 (15.8%) in China [31], [34], [46], 2 (10.5%) in India [37], [43], and 1 (5.3%) each in Japan [30], Turkey [38], Pakistan [39], Bangladesh [41], and Sri Lanka [42]. Of the included studies, 14 (73.7%) were journal articles, while five (26.3%) were peer-reviewed conference publications.

Characteristics of Participants

One of the inclusion criteria for this scoping review was that the selected studies must have involved the collection of data from adult participants specifically for monitoring cardiovascular conditions. Consequently, a significant number of studies were excluded during the title and abstract screening, as well as the full-text review ($n = 82$). The majority of these excluded studies focused on the development and evaluation of AI algorithms or AI-driven platforms for cardiovascular condition monitoring using publicly available datasets, such as the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Arrhythmia Database [49]. Such studies, while valuable for algorithmic advancements, do not provide insights into the feasibility and practical challenges associated with deploying AI models for real-time cardiovascular condition monitoring in real-world settings.

The included studies generally lacked comprehensive details regarding the demographic information of participants whose data was collected and analyzed for cardiovascular condition monitoring. Notably, as can be seen in Table 3, five out of the nineteen included studies did not provide any participant demographic information [31], [33], [34], [43], [47]. A highly variable number of participants was reported in the 14 studies that disclosed participant counts, ranging from as few as two participants [38] to as many as 350 participants [46] with a mean and standard deviation of 84.14 and 92.69, respectively. For studies that reported sex distribution, the balance varied. Some studies included more females [30], [32], [46], while others reported more males [40], [44], [45]. Age ranges also varied significantly across studies, with the youngest participants reported having a mean age of 33.2 years [30] and the oldest having a mean age of 72.1 years [45].

Depending on the study design, some studies included only healthy participants [30], others included only participants with CVD [31], [32], [33], [34], [35], [36], [37], [40], [41], [42], [43], [44], [45], [46], [47], and a few included a mixed population of both healthy participants and participants with CVD [38], [39], [48]. With the exception of Colombage et al. [42], who monitored participants with both heart failure and diabetes, all other studies focused exclusively on monitoring one or more cardiovascular conditions without accounting for comorbidities beyond CVDs.

Characteristics of Study Settings

Unexpectedly, with the exception of a few studies [32], [43], [44], [45], which reported study durations of one, two, four, and sixteen weeks, the other studies involved data collection lasting only

for one day [30], [33], [46] or a single session [35], [40], [48]. Additionally, while three studies were conducted in home settings [30], [32], [41], all other studies took place in hospital environments [33], [34], [35], [36], [37], [38], [39], [40], [46], [47], [48].

As outlined in Table 3, in 84.2% ($n = 16$) of the 19 studies, the cardiovascular conditions under monitoring predominantly involved the detection of various types of cardiac arrhythmias, with a primary focus on atrial fibrillation (AF) [30], [31], [32], [33], [34], [35], [36], [38], [41], [43], [44], [45], [46], [47], [48]. Among these, two studies additionally measured the AF burden [32], [44], and one study aimed to predict AF by detecting early warnings or the onset of AF [46]. One study concentrated on the measurement of Left Ventricular Ejection Fraction (LVEF) [40]. Additionally, two studies focused on detecting heart disease [37] and heart failure [42], while one study investigated the prediction of cardiac arrest [39].

Characteristics of Wearable Devices

Depending on the data modalities required for AI-driven cardiovascular condition monitoring, primarily ECG data, a variety of wearable devices were employed in the included studies. As outlined in Table 5, the studies either developed custom hardware sensors or utilized commercially available wearable devices, such as Polar [30], Samsung [32], Xiaomi [42], Verily [44], and Apple [45] smartwatches. Typically, studies that collected data over extended periods (at least one week) relied on commercial smartwatches suitable for everyday use, whereas those conducted in controlled laboratory settings used custom-built hardware wearable sensors [33], [34], [35], [36], [37], [38], [39], [40], [48].

Seven out of 19 studies (36.8%) utilized only ECG signals [31], [33], [34], [36], [43], [46], [48], while another seven studies (36.8%) incorporated ECG signals along with additional physiological or motion signals, such as PPG, acceleration, blood pressure, galvanic skin response, skin temperature, and oxygen saturation [32], [39], [40], [41], [44], [45], [47]. Other studies exclusively employed non-ECG signals, such as PPG [35], heart rate, skin temperature, and acceleration [37], or electrical signals from skin-muscle interfaces [38]. The data collection frequency ranged from 1 Hz [30] to 1200 Hz [33]. Either raw signals or features extracted from signals were input to AI models for analysis.

Of the 19 included studies, 6 (31.6%) deployed AI models directly on wearable devices for data analysis and inference [31], [36], [37], [40], [45], [48]. Other studies transferred wearable sensor data to a cloud for AI-based analysis [32], [33], [39], [41], [42], [43], while a few utilized a hybrid approach, deploying AI models on both wearable devices and the cloud [35], [44].

Characteristics of AI Algorithms

As outlined in Table 6, except for two studies that performed prediction tasks, one predicting the early warning or onset of AF [46] and another predicting the risk of cardiac arrest [39], all other studies focused on detection. While the terms “detection” and “prediction” are often used interchangeably in the literature, this paper distinguishes between them. While detection refers to making inferences about the current timestamp based on the data collected at the current timestamp, prediction involves making inferences about future timestamps based on the data collected at the current timestamp.

In 73.7% ($n = 14$) of the 19 studies, the primary focus of cardiovascular condition monitoring was the detection of various types of cardiac arrhythmias, with an emphasis on AF [30], [31], [32], [33], [34], [35], [36], [38], [41], [44], [45], [46], [47], [48]. Among these, two studies also measured AF burden [32], [44], and one study aimed to predict AF by detecting early warnings or onset [46]. One study focused on the measurement of LVEF [40], while two studies addressed the detection of heart disease [37] and heart failure [42], and one investigated the prediction of cardiac arrest [39].

Except for one study employing supervised AI models for a regression task to measure LVEF [40], all other studies utilized supervised AI models for classification. These classification tasks varied, including binary classifications (e.g., normal vs. abnormal cardiovascular conditions) [31], [32], [37], [38], [42], [43], [44], [45] and categorical classifications distinguishing between multiple cardiovascular conditions [30], [33], [34], [36], [39], [41], [46], [47], [48].

The included studies did not develop novel AI models but instead employed pre-existing machine learning and deep learning models. The machine-learning models applied included rule-based classifiers, logistic regression, decision tree, k-nearest neighbor, random forest, gradient-boosting machines, support vector machine, feed-forward neural networks, and hidden Markov model [30], [32], [36], [37], [39], [42], [47], [48]. The deep-learning models primarily comprised low-complexity 1D or 2D Convolutional Neural Networks (CNNs) [31], [33], [34], [35], [38], [40], [43], [45], [46], with a few studies incorporating architectures such as residual layers [44] and attention mechanisms [41].

The annotation of wearable sensor data for supervised AI model development was predominantly performed by cardiologists in most studies. However, some studies utilized public datasets, such as the MIT-BIH Arrhythmia Database [49], for training AI models, which were subsequently tested on data collected from their study participants [30], [31], [33], [37], [41], [45], [47].

Depending on the specific task, a variety of evaluation metrics were employed to assess the performance of AI algorithms, with accuracy being the most commonly used. The reported accuracies were high, reaching up to 98%.

Synthesis of Results

Research Question 1: What are the main challenges of AI-driven platforms for real-time cardiovascular condition monitoring with wearable devices, and how can they be addressed?

Several challenges associated with AI-driven platforms for real-time cardiovascular condition monitoring using wearable devices were identified. In this section, these challenges are discussed, along with the strategies proposed in the reviewed studies, specifically those that addressed or examined potential solutions, to mitigate their impact and enhance performance for cardiovascular condition monitoring.

Latency in decision-making—A significant limitation of deploying AI-driven platforms for real-time cardiovascular monitoring is the delay in making inferences about cardiovascular conditions. This delay arises from computational latency, or *inference time*, which refers to the time required for machine-learning and deep-learning models to extract features and analyze data using pre-trained algorithms. Additionally, some platforms implement near real-time inference, where data analysis occurs intermittently rather than continuously. This strategic delay, or reduced *inference frequency*, stems from two primary factors: computational burden and design trade-offs by platform developers. Near real-time analysis is often employed to balance clinical relevance with computational efficiency, reducing battery consumption and minimizing Internet data usage when data transfer is required for cloud-based processing. This is especially critical for wearable devices, as battery depletion leads to data gaps and interrupted monitoring. For example, Zhu et al.'s platform [32] processes data in five-minute intervals to address these trade-offs. However, they noted that such intervals are insufficient to capture brief arrhythmic episodes that occur within shorter timeframes, presenting a significant limitation.

As outlined in Table 6, AI inference times varied widely in the included studies, ranging from milliseconds to several seconds, depending on the platform and implementation. The fastest reported inference time was 100 milliseconds [46], followed by times under a second [30], [31], [47], 1.5–2.5 seconds [39], less than 5 seconds [33], and under 6 seconds [48]. Inference frequencies, which often correspond to the size of data window lengths, also differed significantly in the included

studies. These include processing every second [30], [47], every 5 seconds [45], and every 15 seconds [46]. These variations highlight the trade-offs AI platform developers must consider, balancing real-time responsiveness, computational demands, and energy efficiency on wearable and cloud-based platforms.

Motion artifacts—Motion artifacts are a significant challenge in wearable-based cardiovascular monitoring, particularly for ECG and PPG-based platforms, as they introduce noise that disrupts the detection of true physiological signals. Commonly caused by user movements or improper sensor-skin contact during everyday activities or dynamic conditions such as exercise, these artifacts degrade the signal-to-noise ratio and often overlap with the frequency range of cardiac signals [32]. This overlap complicates the differentiation between true heart rhythms and noise, compromising accurate rhythm detection and increasing the likelihood of missed detections. Additionally, preprocessing to filter motion artifacts and noise introduces further latencies, particularly during periods of high physical activity when signal corruption is prevalent.

Participant compliance—Adherence and participant compliance remain critical challenges in wearable-based cardiovascular monitoring. Participants often face difficulties consistently recharging the device on time, wearing it, and maintaining proper sensor-skin contact, which is essential for obtaining reliable PPG and ECG data. While features such as battery recharge reminders and sensor contact monitors can help notify users of low battery or improper device wear, compliance rates have shown significant variability [32]. Notifications must also be limited to prevent overwhelming participants, which can sometimes delay necessary corrections. Additionally, adherence variability has been linked to demographic differences and individual behaviors, underscoring the importance of developing personalized notification systems to improve compliance [32].

Battery life—Battery life is a critical challenge in wearable-based monitoring, as the need for frequent charging directly impacts usability and participant adherence. While notifications can remind users to recharge devices, particularly to ensure the collection of overnight data, maintaining consistent compliance remains difficult. Participants often forget or neglect to charge or wear the device regularly, resulting in data gaps that undermine the system's ability to provide effective continuous monitoring.

Internet and Bluetooth Connection—Maintaining reliable Internet and Bluetooth connections is a significant challenge for wearable-based monitoring systems, especially for platforms requiring data transfer to the cloud for AI-based analysis or to a base device, such as a smartphone or computer, acting as a hub. Interruptions or instability in these connections can lead to delays, data loss, or incomplete uploads, compromising the system's effectiveness and accuracy.

Zhu et al. [32] demonstrated that the deployment of AI models for real-time cardiovascular monitoring using wearable devices is feasible, achieving high sensitivity (87.8%) and specificity (97.4%) for AF detection. However, challenges such as noise handling, user adherence, limited battery life, and integration of diverse arrhythmias must be addressed to ensure effective and scalable real-time monitoring solutions. Pramukantoro et al. [30] demonstrated the feasibility of real-time AI deployment for cardiovascular monitoring using the Polar H10 wearable device. The classifiers achieved inference times under one second, enabling continuous and efficient monitoring. Additionally, reliable Bluetooth Low Energy (BLE) connections ensured seamless data transmission, with strong Received Signal Strength Indicator (RSSI) values confirming effective communication over practical distances. However, other challenges, such as motion artifacts, participant compliance, and battery life, were not addressed. Hu et al. [47] addressed motion artifacts by integrating accelerometer data to classify user activity and differentiate artifacts from true ECG signals. To enhance battery life, the wearable sensor node incorporated energy-efficient hardware and low-power Bluetooth modules, enabling 24-hour monitoring with a 500 mAh battery. Reliable data transmission was ensured through BLE to a smartphone gateway, where AI-based analyses were conducted. Ye et al. [31] handled battery life in their wearable cardiac arrhythmia monitoring

processor with ultra-low-power design and optimized motion artifact management by reconstructing multi-cycle ECG segments to retain correlation features. In Nguyen et al.'s platform [35], motion artifacts were addressed through a hybrid deep neural network, where a 1D CNN filtered out low-quality PPG signals caused by motion or ambient light interference, ensuring that only reliable data were forwarded to a 2D CNN for the primary task of AF detection. Poh et al. [44] highlighted participant compliance, reporting a median device wear time of 18.3 hours daily. Compliance was supported by automated notifications prompting users to perform ECG acquisitions when AF was detected through continuous PPG. These notifications encouraged consistent use and improved data quality for continuous monitoring in real-world ambulatory environments.

Research Question 2: How are AI algorithms and deployment pipelines optimized to enable real-time cardiovascular condition monitoring?

Methods for optimizing AI algorithms and deployment pipelines to enable real-time cardiovascular condition monitoring are examined in this section. Strategies proposed in the reviewed studies, particularly those that explored optimization techniques, are discussed in relation to their effectiveness in improving platform performance, computational efficiency, and real-world applicability.

Zhu et al. [32] optimized their AI algorithm for real-time inference through a hybrid decision model that combined machine learning classifiers for clean data with statistical heuristics for noisy data. Advanced signal preprocessing techniques, including noise filtering and motion artifact detection, enhanced robustness during real-world use. The model processed five-minute data intervals to balance computational efficiency with accuracy, achieving 87.8% sensitivity and 97.4% specificity for AF detection. The deployment process integrated lightweight on-device algorithms capable of real-time analysis using PPG and accelerometer data. For extended capabilities, the system supported cloud-based connectivity for advanced processing and storage. The design focused on efficient data handling and real-time inference while minimizing computational and energy demands, enabling seamless monitoring in diverse settings. Pramukantoro et al. [30] demonstrated the use of lightweight machine learning models, enabling inference times under one second for real-time cardiovascular monitoring. Data transfer was facilitated through BLE from the Polar H10 wearable to a local middleware system, where analysis was performed efficiently. Hu et al. [47] optimized AI deployment by running arrhythmia classification algorithms on a smartphone gateway rather than a wearable device. The smartphone processed ECG data transmitted via Bluetooth, enabling real-time inference through a layered hidden Markov model, reducing computational demands on the wearable and enhancing overall system efficiency and scalability. Ye et al. [31] leveraged an event-driven neural network architecture, which activates data analysis only when specific signal thresholds are met, achieving a 0.2-second response time and reducing energy consumption to 842 nW in classification mode. The deployment process in the platform introduced by Lin et al. [33] utilized a wearable ECG device with BLE to transmit real-time data to a smartphone application, which provided immediate classification of ECG signals as normal or abnormal. For detailed analysis, the data was transmitted to a cloud server via Wi-Fi or mobile Internet, enabling remote, high-precision classification and storage in a cloud database. This two-tiered system ensured seamless integration of on-device and cloud-based inference. Nguyen et al. [35] employed a 1D CNN deployed on the wearable device for quality assessment, which evaluated PPG signals in real-time to determine if they met the required standards for further analysis, while a 2D CNN in the cloud performed the main task of AF detection. Mary et al. [43] employed Modular Linear Discriminant Analysis (MLDA) for dimensionality reduction in their ECG classification platform. MLDA extracted the most relevant shape, texture, and statistical features from ECG signals, reducing dimensionality while retaining critical information. This process enhanced their deep neural network's efficiency and accuracy in real-time analysis.

Discussion

In this scoping review, we identified nineteen studies that reported the development or utilization of platforms incorporating wearable devices and AI algorithms for real-time cardiovascular condition monitoring. These studies employed various sensors to collect data across multiple modalities, which were subsequently analyzed by AI algorithms to detect or predict cardiovascular conditions. The reviewed studies demonstrated the feasibility of their platforms, reporting high accuracies and low latencies for AI models in recognizing cardiovascular outcomes. However, our findings underscore a critical need for further research to evaluate the performance of real-time AI algorithms for cardiovascular monitoring in real-world settings.

Limitations and Future Recommendations

Platform Validation in Real-world Settings

A wearable sensor platform designed to monitor cardiovascular conditions, particularly those critical enough to risk rehospitalization or death if unmanaged, requires rigorous performance evaluation. Furthermore, its validation in real-world settings is essential before being implemented for clinical use with participants. This is especially important when the platform is intended for continuous use in community settings, where it must reliably operate over extended periods. The need for validation becomes even more critical when the platform aims to provide real-time inferences about cardiovascular conditions, as this demands high accuracy, low latency, participant compliance, and reliability under dynamic, real-world conditions. There is a significant gap in the current research literature regarding the validation of proposed platforms in real-world settings, highlighting the need for further studies to assess and improve their performance, reliability, and scalability under practical conditions.

Lack of evaluation on real-world participants—Hundreds of records (out of 2,358 unique records extracted from databases) were excluded after title and abstract screening, and 82 (out of 153) records were excluded following full-text review because these studies only evaluated their platforms on publicly available datasets, such as subsets of the MIT-BIH dataset [49], without recruiting participants or collecting data in real-world settings. Such evaluations do not ensure the platform's effectiveness on real participants. For example, a deep-learning model with large numbers of parameters might achieve high accuracy for AF detection but exhibit high latency, making it unsuitable for real-time applications. Similarly, custom-designed ECG hardware [33], [34], [35], [36], [37], [38] may acquire high-accuracy signals with robust noise resistance in lab settings but fail to provide the comfort necessary for participants to wear continuously in community settings.

Lack of evaluation in real-world environments—Only three of the included studies evaluated their platforms on participants living in community settings, while the others were assessed using data collected from participants in hospital or laboratory environments. Without evaluating platforms in community settings, where wearable devices are worn by participants without supervision from clinicians or researchers, it is impossible to fully understand the challenges and usability of the platforms. These challenges, as outlined in response to the first research question, include latency in decision-making, motion artifacts, participant compliance, battery life, and Internet and Bluetooth connectivity, all of which are critical for real-world implementation. The evaluation is crucial, as the majority of critical cardiovascular events, such as cardiac arrest or stroke, occur outside of hospitals, often in community settings [50].

Lack of platform usability, acceptability, and adherence validation and co-designing—The reviewed studies did not evaluate their platforms in terms of usability, acceptability, and adherence from the perspectives of participants, including patients wearing the devices, caregivers, and clinicians [51], [52]. Factors such as the shape, size, and weight of the wearable devices, the adherence of patients to consistently wearing the devices, the alerts and notifications (e.g., a cardiac

arrest alert) displayed on the devices or sent to caregivers and clinicians, the frequency of alerts, and the user interface of associated smartphone or web applications, require co-design with all stakeholders [53], [54]. After deployment, the usability, acceptability, and adherence to the platforms must be assessed, and based on feedback from stakeholders, the platforms should be iteratively refined and improved.

Limitations in the Development and Validation of Robust AI Algorithms

Most of the included studies used traditional machine-learning models, such as decision trees or lightweight 1D or 2D CNNs. This is due to the fact that the models should be able to make inferences in real time. However, many more recent models have been proposed, suitable to be used for ECG and PPG data analysis, such as Transformers [55]. These advanced models offer improved accuracy and the ability to capture long-range dependencies in sequential data, making them highly effective for detecting patterns in physiological signals. Despite their advantages, their computational complexity often makes them less suitable for deployment in real-time scenarios without optimization. Optimization techniques such as quantization, pruning, and knowledge distillation can significantly reduce model size and computational demands [56], enabling their use in resource-constrained settings. The literature should explore the use of these advanced models with proper optimization to balance accuracy, latency, and efficiency. Furthermore, future studies should validate these optimized models on platforms designed for real-world settings to ensure their suitability for real-time cardiovascular condition monitoring. Such models are often deployed on cloud services rather than edge devices due to their computational demands. The reviewed studies lacked the use of modern cloud resources designed specifically for AI deployment, which offer low latency, high reliability, and scalability [57]. These resources are ideal for real-time cardiovascular condition monitoring, where accuracy and speed are critical. Examples include Google Cloud Vertex AI for streamlined model development and deployment, Amazon Web Services SageMaker for scalable training and inference, and Microsoft Azure AI for comprehensive AI solutions, all of which can significantly enhance the efficiency and scalability of cardiovascular monitoring platforms.

Table 3. Baseline characteristics of the included studies, including study characteristics, participants, and settings, as well as cardiovascular condition under monitoring.

Study				Study Participants			Study Setting		
Reference	Year	Type	Country	Females– Males	Age	Disease	Condition Under Monitoring	Study Setting	Study Duration
Lin et al. [48]	2010	Journal	Taiwan	30 in total	71.4 (50–89)	Atrial fibrillation	Atrial fibrillation and other rhythm disorders	Hospital	6 minutes
Hu et al. [47]	2012	Journal	USA	—	—	Arrhythmias	Arrhythmias	—	—
Lin et al. [33]	2019	Conf.	Taiwan	—	—	Arrhythmias	Arrhythmias	Hospital	24 hours
Lin et al. [36]	2019	Conf.	Taiwan	40 in total	—	Arrhythmias	Arrhythmias	Hospital	—
Wasserlauf et al. [45]	2019	Journal	USA	9–17	72.1 (7.2)	Atrial fibrillation	Atrial fibrillation	Hospital	110 days
Zhu et al. [32]	2021	Journal	USA	35–6	69.3 (10.9)	Atrial fibrillation and healthy	Atrial fibrillation and burden estimation	Home	28 days
Fu et al. [34]	2021	Journal	China	—	—	Various CVDs	Arrhythmias and rhythm abnormalities	Hospital	—
Ergen et al. [38]	2021	Journal	Turkey	2 in total	—	Atrial fibrillation and healthy	Atrial fibrillation and heart rate monitoring	Lab	—

Pramukantoro et al. [30]	2022	Journal	Japan	4–2	33.2 (3.2)	Healthy	Heartbeat classification into normal vs. abnormal	Home	24 hours
Nguyen et al. [35]	2022	Journal	Taiwan	40 in total	—	Variants of AF	Atrial fibrillation and rhythm analysis	Hospital	5 minutes
Jenifer et al. [37]	2022	Conf.	India	20 in total	—	General heart disease	Heart disease	Lab	—
Colombage et al. [42]	2022	Conf.	Sri Lanka	134 in total	—	91 heart failure patients & 43 healthy	Severity levels of heart failure	Hospital	—
Ye et al. [31]	2023	Conf.	China	—	—	Arrhythmias	Arrhythmia	—	—
Howard et al. [40]	2023	Journal	USA	27–54	53 (16)	Varied cardiac pathologies	Left Ventricular Ejection Fraction	Lab	3 minutes
Islam et al. [41]	2023	Journal	Bangladesh	22 in total	—	Arrhythmias	Heart rate and arrhythmias	Home	—
Mary et al. [43]	2023	Journal	India	—	—	Arrhythmias	Arrhythmias	—	7 days
Poh et al. [44]	2023	Journal	USA	50–61	65 (11)	Atrial fibrillation	Atrial fibrillation	Hospital	14 days
Gavidia et al. [46]	2024	Journal	China	189–161	66.5 (14.5)	Atrial fibrillation	Sinus rhythm to atrial fibrillation	Hospital	24 hours
Hannan et al. [39]	2024	Journal	Pakistan	149 in total	49.7 (8.2)	Cardiac Arrest	Cardiac arrest risk	Hospital	—

Table 4. Aims, methodologies, and key findings of the included studies.

Reference	Aim	Methodology	Key Findings
Lin et al. [48]	To develop and evaluate a wearable, wireless, real-time tele-cardiology platform for detecting atrial fibrillation and other rhythm abnormalities with built-in emergency alerts.	Patients were monitored using a lightweight wireless three-lead ECG device with disposable electrodes. The platform processed ECG signals locally using an expert platform and transmitted abnormal data to a remote server via wireless communication.	The platform demonstrated strong performance in detecting atrial fibrillation, enabling early identification, remote monitoring, and real-time emergency alerts.
Hu et al. [47]	To develop a real-time platform for continuous monitoring and classification of cardiac arrhythmias	Utilized wearable ECG sensors and a layered hidden Markov model to classify arrhythmias based on real-time ECG features and motion data.	Achieved high accuracy in arrhythmia detection and demonstrated the platform's reliability in real-time applications.
Lin et al. [33]	To develop and validate an AI-driven IoT wearable platform for real-time ECG monitoring and arrhythmia detection using a cloud-integrated CNN model.	Clinical trials were conducted at Tainan Hospital with ECG data collected using a single-lead wearable patch. Preprocessing included noise and baseline drift removal, followed by a CNN-based arrhythmia classification algorithm.	Demonstrated reliable real-time arrhythmia detection and classification across clinical trial data and the MIT-BIH database.
Lin et al. [36]	To develop an AI-driven IoT wearable ECG patch for real-time arrhythmia analysis using decision tree algorithms.	Data were collected from participants using a wearable ECG patch, with features extracted and analyzed through a decision tree model for arrhythmia detection.	The platform demonstrated reliable arrhythmia detection with efficient real-time performance, supporting its potential for clinical and remote health monitoring.
Wasserlauf et al. [45]	To evaluate the performance of a smartwatch combined with a deep learning algorithm for detecting and quantifying AF episodes and duration compared to an insertable cardiac monitor.	A convolutional neural network was trained and validated on participants with implanted cardiac monitors. Participants wore both an AF-sensing smartwatch and an implanted monitor simultaneously. Data included heart rate, activity level, and ECG recordings.	The system exhibited high sensitivity for AF detection, effectively identifying longer episodes and total AF duration. While the Positive Predictive Value was moderate, it demonstrated strong potential for

	(ICM).	collected in real-world conditions.	continuous, noninvasive AF monitoring.
Zhu et al. [32]	To develop and validate wearable-based algorithms for detecting atrial fibrillation and estimating AF burden during daily activities.	Multiple groups, including patients undergoing elective cardioversion, were monitored using wearables. ECGs patches served as reference data, while a machine learning algorithm analyzed PPG and accelerometer signals to detect AF and estimate its burden.	Achieved high sensitivity and specificity for AF detection across diverse populations and settings, with reliable AF burden estimation over daily activities.
Fu et al. [34]	To develop an AI-enhanced mobile platform for cardiovascular health management with real-time ECG monitoring and diagnosis capabilities.	ECG data were collected using a custom-designed portable ECG device, processed using deep learning models combining CNN and RNN, and deployed on the Tencent Cloud for real-time diagnosis. Data were annotated and revised by cardiologists.	The AI platform demonstrated high diagnostic accuracy and improved real-time ECG analysis for cardiovascular health management.
Ergen et al. [38]	To develop a graphene aerogel-based nano-tattoo for robust heart rate and atrial fibrillation detection during extreme upper-extremity motions.	A nano-tattoo sensor platform was developed using graphene aerogel and boron nitride materials. AI-based neural networks processed electrical signals for real-time detection of heart rate and atrial fibrillation.	The device showed high performance in reducing noise and detecting atrial fibrillation during various motion activities, achieving significant improvement compared to traditional PPG sensors.

Table 4 (Continued)

Pramukantoro et al. [30]	The study aimed to create a platform for ongoing, real-time tracking of heartbeat patterns to distinguish between regular and irregular beats. It aimed to aid in the early identification of heart-related conditions by recognizing differences in heartbeat features across various medically important categories during daily activities.	The study included healthy individuals monitored at home during regular daily activities. Data collection centered on heartbeat timing, categorizing it as either regular or irregular. Participants were observed for a brief period of 20 to 30 minutes to test the platform in real-life conditions.	The platform showed strong reliability in identifying and categorizing heartbeat patterns, achieving high accuracy in differentiating regular and irregular heartbeats. It delivered timely predictions, enabling continuous tracking during daily activities, emphasizing its potential for early detection and management of heart conditions in medical practice.
Nguyen et al. [35]	To create a deep learning model using PPG data for real-time AF detection and rhythm quality evaluation.	Data from multiple subjects were collected using PPG sensors and analyzed with deep learning models for rhythm quality assessment and AF detection.	The model demonstrated strong performance in AF detection and rhythm quality assessment, ensuring reliable monitoring and analysis.
Jenifer et al. [37]	To design an edge-based IoT device for heart disease prediction, reducing latency and ensuring data privacy.	Data from temperature, pulse rate, and motion sensors were processed on a Raspberry Pi using a decision tree model trained on a public dataset. Predictions were displayed on a connected OLED screen.	The platform demonstrated reliable performance on data from recruited subjects, ensuring effective monitoring and analysis.
Colombage et al. [42]	To develop a real-time detection platform for heart failure, heart failure severity, diabetes, and diabetes types using smartwatch data and user-provided information.	Data collected via smartwatch (e.g., heart rate, blood pressure, respiratory rate) and user inputs (e.g., age, family history). Machine learning models trained on public datasets to predict heart failure, severity, diabetes, and diabetes types. Predictions made using Logistic Regression and Random Forest models deployed on a cloud.	The models demonstrated strong predictive performance for heart failure, severity assessment, and diabetes classification, with validation on local patient datasets confirming their reliability in real-world applications.
Ye et al. [31]	To develop a low-power, real-time wearable cardiac arrhythmia monitoring processor that balances generalization performance with computational efficiency.	The study used an event-driven architecture to process ECG signals, including QRS localization, multi-cycle heartbeat reconstruction, and classification into arrhythmia classes via a neural network. Data was processed locally on a wearable device for real-time monitoring.	The processor demonstrated high sensitivity and reliable detection for heartbeat localization, abnormal beat identification, and arrhythmia classification. It operated with minimal power consumption (842 nW).
Howard et al.	To evaluate the accuracy of a	Simultaneous CPS measurements.	CPS LVEF measurements

[40]	wearable biosensor platform (CPS) using machine learning for automated real-time measurement of Left Ventricular Ejection Fraction (LVEF).	CPS platform involved acoustic and ECG sensors to collect data processed by a regression-based neural network. Evaluation included intraoperator and interoperator variability assessments.	demonstrated strong performance. The model showed high discrimination for LVEF thresholds, with minimal variability between and within operators.
Islam et al. [41]	To develop a deep learning-based IoT framework for remote health monitoring and early detection of health issues in real-time, enabling proactive healthcare.	Data collection via IoT sensors (ECG, heart rate, oxygen saturation, body temperature). Data transmitted to a server via Message Queuing Telemetry Transport protocol. Pre-trained CNN with attention layers classifies health issues and generates reports.	The system effectively classified multiple arrhythmias and detected fever, enabling real-time monitoring with timely alerts for abnormalities.

Table 4 (Continued)

Mary et al. [43]	To develop a wearable IoT platform for real-time ECG monitoring and classification of normal versus abnormal heartbeats using adaptive deep neural networks (ADNN).	Data collected from wearable sensors via Wi-Fi. ECG signals were preprocessed using denoising, heartbeat alignment, and data standardization. Feature extraction performed using Modular Linear Discriminant Analysis (MLDA). Classification performed using Adaptive Deep Neural Networks (ADNN), trained on time-domain and automatically extracted features.	The platform effectively detected abnormal ECG signals with high accuracy. The proposed ADNN model outperformed other classification methods, demonstrating superior performance in ECG analysis.
Poh et al. [44]	To validate the performance of a wrist-worn device for detecting AF and estimating AF burden using a PPG-based algorithm.	Prospective, multicenter study where participants wore both a wrist-worn Study Watch and a reference patch ECG device simultaneously.	The wrist-worn device demonstrated strong performance in detecting AF, with high sensitivity and specificity, while providing accurate AF burden estimation compared to reference ECG.
Gavidia et al. [46]	To develop a deep learning model for predicting atrial fibrillation onset at least 30 minutes in advance, enabling early intervention and reducing emergency healthcare demands.	Analysis of 24-hour Holter ECG data, developing a convolutional neural network for continuous monitoring and validating on external datasets from Argentina and France.	The deep learning models successfully predicted AF onset approximately 30 minutes in advance, demonstrating strong performance and generalizability across external cohorts.
Hannan et al. [39]	To develop an IoT-based wearable platform for real-time cardiac arrest monitoring and prediction, reducing response time and enabling remote supervision via an Android application.	Real-time data collection from wearable IoT sensors. Preprocessing, feature extraction, and classification using machine-learning models. Comparison of real-time data with trained models. Alerts transmitted via Android applications to patients and caregivers.	The Random Forest algorithm effectively predicted cardiac arrest, ensuring timely alerts with minimal delay through a hybrid IoT-cloud architecture.

Table 5. Characteristics of wearable devices in the included studies.

Reference	Type	Model	Data modalities	Data collection frequency	Data transfer frequency	AI algorithm deployed on wearable device	AI inference delivery
Lin et al. [48]	Wireless three-lead ECG device.	Custom-built	ECG	512 Hz	Every 6 seconds	Yes	Delivered to a smartphone or transmitted to a remote server for display and alerts
Hu et al. [47]	Wearable ECG sensor	iBoSen	ECG, acceleration	ECG 100 Hz, acceleration 10 Hz	—	No (on a smartphone)	Results displayed on a smartphone for real-time visualization and

							notification
Lin et al. [33]	Single-lead ECG patch	Custom-built	ECG	1200 Hz	Real-time	No (on the cloud)	Results displayed on a smartphone and a web application

Table 5 (Continued)

Lin et al. [36]	Wearable ECG patch.	Custom-built	ECG	—	—	Yes	Results displayed locally on a local computer
Wasserlauf et al. [45]	Smartwatch with ECG sensor	Apple Watch Series 2 paired with KardiaBand	Heart rate, activity level, ECG	Every 5 seconds	—	Yes	Notifications prompting ECG recordings displayed on the smartwatch.
Zhu et al. [32]	Smartwatch and ECG patch.	Samsung Galaxy Watch 2, Active BioTel ePatch	PPG, acceleration, and ECG	PPG and acceleration 25 Hz, ECG continuous	Real-time	No (on the cloud)	Decisions displayed on a smartphone and a cloud in real-time
Fu et al. [34]	Portable single-lead ECG device.	Custom-built	ECG	125 Hz	Real-time	No (on the cloud)	Results sent back to a smartphone application for user display
Ergen et al. [38]	Aerogel-based nano-tattoo.	Custom-built	Electrical signals from skin-muscle interfaces.	—	—	—	—
Pramukantoro et al. [30]	Chest strap	Polar H10	Heart rate	1 Hz	1 Hz	No	Real-time middleware on a local computer
Nguyen et al. [35]	PPG sensor patch.	Custom-built	PPG	500 Hz	—	Yes, 1D-CNN on device, 2D-CNN on the cloud	—
Jenifer et al. [37]	IoT-based wearable sensor module.	Custom-built	Heart rate, temperature, acceleration	Every 10 minutes	—	Yes	Results displayed locally on an OLED screen
Colombage et al. [42]	Smartwatch	Mi Smart Band 6	Blood pressure, heart rate, respiratory rate, body temperature, calories burned	Every hour	Real-time	No (on the cloud)	Results delivered to users via smartphone and web applications for real-time monitoring and alerts
Ye et al. [31]	Wearable ECG sensors.	—	ECG	Event-driven based on amplitude thresholds	—	Yes	On the wearable device
Howard et al. [40]	Acoustic biosensors with ECG.	CPS (Cardiac Performance System)	Cardiac acoustic signals and ECG	Continuous	—	Yes	Displayed on the CPS patient monitor in real time
Islam et al. [41]	IoT-based sensors.	MAX30100 (pulse oximeter), AD8232 (ECG), MLX90614 (body temperature)	ECG, heart rate, SPO2, body temperature	Real-time	Real-time	No (on the cloud)	Alerts and reports delivered via a smartphone application to patients and healthcare providers

Table 5 (Continued)

Mary et al. [43]	Wearable sensors integrated into a Body Area Sensor Network	—	ECG	Continuous	Real-time	No (on the cloud)	Real-time data and alerts delivered to health monitoring personnel via a mobile device or computer interface.
Poh et al. [44]	Study Watch (wrist-worn)	Verily	ECG, PPG	Every 15 minutes	—	Yes	Alerts for irregular pulse and instructions to record ECG delivered via watch vibrations and screen notifications.
Gavidia et al. [46]	Smartwatches and fitness bands capable of measuring R-to-R intervals.	—	Heart rate	Every 15 seconds	—	—	—
Hannan et al. [39]	IoT-based wearable system with multiple sensors.	Custom-built	ECG, Galvanic Skin Response, temperature sensor, SPO2	—	Real-time	No (on the cloud)	Alerts delivered to caregivers and patients via an Android smartphone application

Table 6 (a). Characteristics of AI algorithms in the included studies.

Reference	Outcome type	Outcome	Task	Output	Annotation	Features/Raw Data
Lin et al. [48]	Detection	AF	Classification	Classes (Normal, AF, Tachycardia, Bradycardia, Asystole, Wide QRS)	Annotated by cardiologists	R-R intervals, QRS durations, RR intervals features
Hu et al. [47]	Detection	Arrhythmias	Classification	Classes (Normal, PVC, APC, Invalid)	Used MIT-BIH	ECG, acceleration signals
Lin et al. [33]	Detection	Arrhythmias	Classification	Classes (Normal, AF, AFL, VFib)	Used MIT-BIH	ECG
Lin et al. [36]	Detection	Arrhythmias	Classification	Classes (Normal, AF, VT)	Annotated by cardiologists	ECG features: RR intervals, QRS width, and signal morphology characteristics.
Wasserlauf et al. [45]	Detection	AF	Classification	Classes (AF or Non-AF)	—	ECG, heart rate, motion index derived from pedometer data
Zhu et al. [32]	Detection	AF and AF burden	Classification	Classes (Normal, AF)	Annotated using clinical ground truth provided by BioTel ePatch recordings	PPG features: signal quality, heart rate variability, pulse irregularity metrics; acceleration features: motion artifacts, activity levels
Fu et al. [34]	Detection	Arrhythmias	Classification	Classes (AF, VT, BBB, Normal)	Annotated by cardiologists	ECG

Table 6 (a) (Continued)

Ergen et al. [38]	Detection	AF	Classification	Classes (AF, Normal)	—	Skin-muscle interface electrical signals during motion.
Pramukantoro et al. [30]	Detection	Heartbeat types	Classification	Classes (normal, supraventricular ectopic, ventricular fusion, unknown)	Used the MIT-BIH public dataset	RR intervals and statistical features from RR intervals

Nguyen et al. [35]	Detection	AF and rhythm quality	Classification	Classes (Normal, AF)	Annotated by cardiologists	PPG features: waveform shape, rhythm irregularities, and signal quality metrics
Jenifer et al. [37]	Detection	Heart disease status (normal or abnormal conditions)	Classification	Classes (Normal, Abnormal)	Used a public dataset from Kaggle	Pulse rate, body temperature, acceleration
Colombage et al. [42]	Detection	Heart failure and heart failure severity	Classification	Classes (heart failure: Yes/No; heart failure severity: Type II, Type III)	Used a public dataset	Resting blood pressure, maximum heart rate, body temperature, respiratory rate, calories burned, blood sugar levels, fasting blood sugar levels
Ye et al. [31]	Detection	Arrhythmias and abnormal heartbeats	Classification	Classes (Normal, Abnormal)	Used MIT-BIH	ECG features: QRS complex localization, RR intervals, QRS durations, window accumulation features
Howard et al. [40]	Detection	Left ventricular ejection fraction (LVEF)	Regression	Continuous regression values (ejection fraction as a percentage).	—	Acoustic signals: Temporal, amplitude-based, and spectral features derived from heart sound signals ECG signals: Timing information for segmenting acoustic signals.
Islam et al. [41]	Detection	Arrhythmias and fever conditions	Classification	Classes (Normal beat, Supraventricular premature beat, etc.)	Used MIT-BIH	ECG signals, and heart rate measurement. SPO2, body temperature
Mary et al. [43]	Detection	Abnormal ECG signals	Classification	Classes (Normal, Abnormal)	—	Morphology of ECG waves, pattern details in the ECG signal, mean, standard deviation, signal intensities and gray-level properties.
Poh et al. [44]	Detection	AF and AF burden	Classification	Classes (AF, Non-AF, Unanalyzable, Not enough data/off-wrist)	Annotated by cardiologists	PPG: Heart rate variability and inter-beat intervals. ECG: Single-lead waveform features
Gavidia et al. [46]	Prediction	Early warning of AF	Classification	Classes (Sinus Rhythm, Pre-AF, and AF).	Annotated by cardiologists	RR intervals derived from ECG data
Hannan et al. [39]	Prediction	Risk of cardiac arrest	Classification	Classes (Less Critical, More Critical, Normal)	—	ECG, galvanic skin response, body temperature, SPO2

Table 6 (b). Characteristics of AI algorithms in the included studies.

Reference	Features selection	Machine-learning/deep-learning	Algorithms	Performance	inference frequency	inference time	Deployed where
Lin et al. [48]	—	Machine	Expert rule-based System	Sensitivity: 94.56%; Positive Predictive Value: 99.39%	Every seconds	Less than 6 seconds	On the wearable device
Hu et al. [47]	—	Machine	Layered Hidden Markov Model	Accuracy: 99.20%	Less than 1 second	Less than 1 second	On a smartphone
Lin et al. [33]	—	Deep	Convolutional Neural Network (CNN)	Accuracy: 94.96%	Real-time	Less than 5 seconds	On the cloud

Lin et al. [36]	—	Machine	Decision tree	—	Real-time	—	On the wearable device
Wasserlauf et al. [45]	—	Deep	CNN	Sensitivity: 97.5%	Real-time, based on 5-6 second data inputs.	—	On the wearable device
Zhu et al. [32]	—	Machine	Gradient-boosted decision trees	Specificity: 97.00%; Positive Predictive Value: 96.00%	—	—	On the cloud
Fu et al. [34]	—	Deep	CNN and recurrent neural network	AUC-ROC > 0.98	Real-time	—	On the cloud
Ergen et al. [38]	—	Deep	Neural network	—	Real-time	—	—
Pramukantoro et al. [30]	—	Machine	Decision tree, random forest, k-nearest neighbor, support vector machine, neural network	Accuracy: 99.67%	1 Hz	Less than 1 second	On a local computer
Nguyen et al. [35]	—	Deep	1D and 2D CNN	Sensitivity: 96.82%; Specificity: 98.86%	Real-time.	—	1D-CNN on device, 2D-CNN on the cloud
Jenifer et al. [37]	—	Machine	Decision tree	Accuracy: 95.00%	Real-time.	—	On the wearable device
Colombage et al. [42]	—	Machine	Logistic regression, random forest	F1-Score: 0.72	Real-time	—	On the cloud
Ye et al. [31]	—	Deep	Neural network	Accuracy: 93.30%	0.2 seconds	0.2 seconds	On the wearable device

Table 6 (b) (Continued)

Howard et al. [40]	—	Deep	Neural network	AUC-ROC: 97.40%	Real-time	—	On the wearable device
Islam et al. [41]	—	Deep	CNN with attention layers	Accuracy: 98.20%	Real-time	—	On the cloud
Mary et al. [43]	Modular Linear Discriminant Analysis for dimensionality reduction	Deep	CNN	Sensitivity: 98.10%; Accuracy: 98.10%	Real-time	—	On the cloud
Poh et al. [44]	—	Deep	CNN	Sensitivity: 96.10%; Specificity: 98.10%	Real-time	—	On the wearable device
Gavidia et al. [46]	—	Deep	CNN	Accuracy: 83.00%	Every 15 seconds	100 milliseconds	—
Hannan et al.	—	Machine	Random forest,	Accuracy: 97.81%	Real-time	2.5 seconds	On the cloud

[39]			support vector machine, AdaBoost				
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Table 7 (a). Robustness analysis of the AI algorithms in the included studies.

Reference	Input perturbations and alterations	Input perturbations and alterations	Missing data	Label noise
Lin et al. [48]	Preprocessing uses band-pass and notch filters to eliminate noise and artifacts.	Preprocessing uses band-pass and notch filters to eliminate noise and artifacts.	The QRS detection algorithm employs dynamic thresholding to detect missing beats.	Data were annotated by experienced cardiologists to maintain high-quality labels.
Hu et al. [47]	The circuit minimizes noise from impedance and capacitance changes, with built-in motion artifact handling via accelerometer data.	The circuit minimizes noise from impedance and capacitance changes, with built-in motion artifact handling via accelerometer data.	—	Relied on high-quality labels from the MIT-BIH Arrhythmia Database.
Lin et al. [33]	Noise reduction is achieved using an 8-point moving average filter, with baseline drift corrected through polynomial fitting.	Noise reduction is achieved using an 8-point moving average filter, with baseline drift corrected through polynomial fitting.	—	Relied on high-quality annotations from the MIT-BIH dataset.
Lin et al. [36]	Preprocessing utilizes low-pass and high-pass Butterworth filters along with notch filters to eliminate noise and artifacts.	Preprocessing utilizes low-pass and high-pass Butterworth filters along with notch filters to eliminate noise and artifacts.	—	Relied on high-quality annotations from the MIT-BIH dataset.

Table 7 (a) (Continued)

Wasserlauf et al. [45]	Motion index calculation was incorporated into the model to account for motion artifacts.	The system managed missing data by including only continuous, time-synchronized inputs and discarding intervals lacking sufficient data for analysis.	The system managed missing data by including only continuous, time-synchronized inputs and discarding intervals lacking sufficient data for analysis.	Annotations were based on validated automated ECG classification algorithms to reduce uncertainty in training labels.
Zhu et al. [32]	Preprocessing employs a bandpass filter to remove frequencies outside the heartbeat spectrum, a motion detection block for artifact reduction, and a sensor contact monitor to ensure signal quality.	Preprocessing employs a bandpass filter to remove frequencies outside the heartbeat spectrum, a motion detection block for artifact reduction, and a sensor contact monitor to ensure signal quality.	—	The study utilized clinically validated annotations from ECG recordings reviewed by board-certified cardiologists and certified ECG technicians.
Fu et al. [34]	Low-pass and high-pass filters remove noise and baseline drift during preprocessing, while a notch filter eliminates artifacts.	Low-pass and high-pass filters remove noise and baseline drift during preprocessing, while a notch filter eliminates artifacts.	—	At least two cardiologists manually annotated and validated each label to ensure accuracy.
Ergen et al. [38]	Graphene aerogel-based nano-tattoos and AI algorithms minimize noise and motion artifacts, ensuring reliable signal acquisition during	Graphene aerogel-based nano-tattoos and AI algorithms minimize noise and motion artifacts, ensuring reliable signal	—	—

	movement.	acquisition during movement.		
Pramukantoro et al. [30]	—	—	RR intervals were calculated using past data to compensate for missing future data.	Relied on high-quality annotations from the MIT-BIH dataset.
Nguyen et al. [35]	A 4th-order Butterworth bandpass filter is used to denoise and eliminate motion artifacts from the PPG signal.	A 4th-order Butterworth bandpass filter is used to denoise and eliminate motion artifacts from the PPG signal.	—	Cardiologists validated data annotations to ensure high-quality labels.
Jenifer et al. [37]	—	—	—	Trained on a publicly validated dataset (Kaggle) to ensure reliable labels.
Colombage et al. [42]	Users were instructed to remain at rest during blood pressure measurements to minimize artifacts.	—	—	Publicly available datasets with labeled data from trusted sources were used for model training, reducing uncertainty in labels.
Ye et al. [31]	An event-driven architecture manages variable sampling and minimizes noise.	An event-driven architecture manages variable sampling and minimizes noise.	—	Relied on high-quality annotations from the MIT-BIH Arrhythmia Database

Table 7 (a) (Continued)

Howard et al. [40]	Acoustic signals undergo preprocessing with filtering techniques to reduce low- and high-frequency interference from motion, speech, or environmental noise.	—	—	Ground truth labels were performed by experienced echo cardiographers.
Islam et al. [41]	ECG signals are preprocessed using a bandpass filter (0.5–100 Hz) for noise removal, resampled to 125 Hz, and normalized for consistent feature extraction.	—	—	Relied on high-quality annotations from the MIT-BIH dataset.
Mary et al. [43]	ECG image preprocessing includes noise reduction, heartbeat alignment, and data standardization to minimize signal acquisition errors and measurement inconsistencies.	—	—	Labels were validated using a combination of manually extracted time-domain features and model-extracted features, ensuring consistency and accuracy.
Poh et al. [44]	Unanalyzable signal periods due to motion and peripheral circulation were excluded.	The model excluded unanalyzable intervals and redundancy in continuous monitoring to ensure sufficient data for decision-making.	The model excluded unanalyzable intervals and redundancy in continuous monitoring to ensure sufficient data for decision-making.	Certified cardio graphic technicians and electrophysiologist triple-reviewed annotations to minimize labeling errors during training.
Gavidia et al. [46]	Preprocessing utilizes a band-pass filter and the Pan-Tompkins algorithm to reduce noise and improve signal quality.	—	—	Labels for AF were assigned by cardiologists to minimize errors.
Hannan et al. [39]	Preprocessing includes data cleaning and anomaly removal to minimize the impact of noisy or	—	—	Biomarkers recorded from tertiary hospitals ensure reliability in measurement standards.

	inconsistent sensor data.			
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Table 7 (b). Robustness analysis of the AI algorithms in the included studies.

Reference	Imbalanced data	Feature selection and extraction	Model specification and learning	External data and domain shift	Adversarial attacks
Lin et al. [48]	—	Focused on R-R intervals, RRI variability, and QRS durations, robust to signal variations.	Threshold-based expert system with parameters tuned to handle variations in ECG patterns.	—	—
Hu et al. [47]	Weighted metrics for evaluation; no specific balancing technique mentioned.	Used predefined ECG and accelerometer features to ensure consistency across physical states.	Incorporated a layered Hidden Markov Model for adaptive classification.	—	—

Table 7 (b) (Continued)

Lin et al. [33]	—	Predefined preprocessing pipeline with noise and baseline correction to enhance input reliability.	Lightweight CNN with hyperparameter tuning based on experimental tests.	Validated with clinical trials from patients in a hospital environment as well as MIT-BIH database.	—
Lin et al. [36]	—	Focused on R-R intervals, PR intervals, and P-wave duration, and P-peak location, robust to motion artifacts or other signal variations.	Optimization of decision tree depth using cross-validation to prevent overfitting while maintaining high classification accuracy	Updating decision tree coefficients based on user-specific ECG data uploaded to the cloud server, adapting to individual variations. System has been used in 40 human trials at time of publication.	—
Wasserlauf et al. [45]	—	Features were extracted in fixed time intervals, ensuring robustness to noise and variability in input signals during preprocessing. Additionally, intervals with missing ECG data were discarded	The CNN architecture included dropout layers and batch normalization to ensure generalization and reduce overfitting during training.	—	—
Zhu et al. [32]	Decision thresholds were set with an emphasis on classification due to cohort's prior history of AF diagnosis or at-risk status.	Focused on key PPG and accelerometer features like heart rate variability, inter-beat interval, and motion compensation metrics to ensure robustness.	Decision thresholds validated on prior development datasets.	Algorithms were validated on diverse cohorts prior to large-scale study, including healthy participants and AF patients in free-living and clinical settings.	—
Fu et al. [34]	—	ECG measurements done using QRS complex detection and evaluated using case studies.	Combined CNN and RNN layers optimized for time-series and spatial feature learning.	—	—
Ergen et al. [38]	—	Direct signal processing from the nano-tattoo ensures robust feature extraction against	Neural networks optimized for motion-resistant PPG signal analysis.	—	—

		motion artifacts.			
Pramukantoro et al. [30]	Applied oversampling techniques like SMOTE	Used predefined low-complexity RR interval features.	Evaluated multiple algorithms to optimize for simplicity and real-time efficiency but hyperparameter selection not explained	Validated on unseen healthy male and female participants of varying ages during inter-patient evaluation	

Table 7 (b) (Continued)

Nguyen et al. [35]		1D-CNN is trained using expert labelled PPG data and then used for signal quality assessment to ensure features are only extracted from reliable PPG signals.	Combined CNN models (1D-CNN for quality assessment and 2D-CNN for detection) optimized for real-time and cloud-based processing.		
Jenifer et al. [37]		Direct use of sensor-derived features (pulse rate, temperature, and accelerometer data) for consistent variability management.	The decision tree classifier was optimized for lightweight computation on an edge device.		
Colombage et al. [42]	SMOTE was applied to balance classes in the datasets during training.	Features were selected based on their collectability through the smartwatch or user inputs to reflect wearable conditions.			
Ye et al. [31]	Multi-cycle heartbeat reconstruction to reduce imbalance between normal and abnormal beats	Multi-cycle heartbeat reconstruction to preserve RR features and QRS features and reduce variability.	Utilized a simplified neural network structure optimized for low-power hardware with fixed-point quantization but no mention of hyperparameter selection and tuning		
Howard et al. [40]		Features were extracted from acoustic and ECG signals based on their strong correlation with LVEF, ensuring reliability across conditions.	The model was locked and pre-trained with a wide range of predefined regression-based neural network architecture to prevent variability during deployment and ensure consistent performance.	The platform was tested on a diverse population with a wide range of LVEF values (20%-80%), various cardiac conditions, and belonging to 3 different clinical settings to ensure generalizability.	
Islam et al. [41]		The attention layer in the CNN focuses on the most informative signal regions, improving robustness to variability in feature extraction.	The model parameters, such as filter sizes, dropout rates, and learning rates, were fine-tuned using grid search to improve consistency and performance across different data inputs.		
Mary et al. [43]		Modular Linear Discriminant Analysis (MLDA) was employed to extract and prioritize the most essential features, reducing the impact of variability and irrelevant features.	The Adaptive Deep Neural Network (ADNN) architecture was designed with multiple nonlinear layers to improve robustness and increase the model's capacity to generalize across data.		

Table 7 (b) (Continued)

Poh et al. [44]		Features were extracted from physiological		The model was evaluated across	
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		signals (e.g., PPG and ECG) and validated under different activity levels and skin tones to ensure reliability.		diverse populations, activity levels, and Fitzpatrick skin tone categories to address domain shift.	
Gavidia et al. [46]		Simplification to R-to-R intervals, extracted directly from ECG data, to ensure consistency and robustness across diverse wearable devices.	Use of cross-validation during CNN model training to tune optimal threshold and moving average for tradeoff between sensitivity and specificity.	Validation on external datasets from Argentina and France to assess generalizability across different populations and care settings	
Hannan et al. [39]		Use of domain-specific features (e.g., ECG, SPO2, GSR, pulse rate) to improve feature reliability and relevance.	Comparison of multiple machine learning algorithms (Random Forest, SVM, AdaBoost) to select the best-performing model (Random Forest) based on accuracy and error rate.		

Balendran et al. [58] conducted a scoping review to explore robustness concepts in the application of machine learning models in healthcare. They identified eight key robustness concepts, which are detailed below and outlined in Table 7, highlighting whether they were addressed in the reviewed studies.

Input perturbations and alterations—Perturbations such as noise in data collected from wearable devices (e.g., ECG and PPG) are often caused by motion artifacts due to body movements. These alterations were addressed in the methodologies of the reviewed studies, including applying signal processing techniques such as filtering, using acceleration data to compensate for motion, or analyzing ECG and PPG signals only when motion artifacts were absent. However, the extent to which the reviewed studies addressed these artifacts was limited to the methodology level, without comprehensively validating their platforms against the full range of alterations that can occur continuously in everyday life.

Missing data—Missing input data, such as robustness to random and non-random data missingness, is a critical challenge in AI-driven platforms relying on wearable devices. Missing data frequently occurs due to various reasons, including participants not wearing the devices, devices being out of charge, or lack of Internet/Bluetooth connectivity [59], [60]. However, the reviewed studies did not address this robustness concept on their proposed platforms. To minimize missing data, participant adherence must be improved by encouraging consistent wearing, regular charging, and maintaining Internet/Bluetooth connectivity for wearable devices. Additionally, when missing data occurs, imputation strategies [61] should be employed to mitigate its negative impact on the performance of AI algorithms [62].

Label noise—Label noise refers to the uncertainty or inaccuracies in the labels used to train AI models, such as inconsistencies arising from differing expert opinions [63]. Some of the reviewed studies used publicly available datasets to train their AI models and then applied these trained models for cardiovascular condition monitoring on their recruited participants. However, these studies failed to examine label noise caused by discrepancies between the public datasets and the participant-collected data. For example, Pramukantoro et al. [30] trained their models on the MIT-BIH dataset [49] collected in a hospital setting and deployed them for monitoring participants in home environments. Additionally, while some studies reported annotating their datasets with cardiologists, they did not provide detailed information about the annotation protocols [64], such as inter-rater agreement among annotators, or analyze how annotation variability impacted dataset quality and AI

model performance.

Imbalanced data—Imbalanced data refers to scenarios where samples from one or more classes are significantly underrepresented compared to others [65]. This issue is critical when the minority class represents important events, such as the occurrence of cardiac arrest versus non-occurrence, or in regression problems, where underrepresented values, such as very low heart rates, are of interest. If left unaddressed, AI models trained on such data are prone to overfitting to the majority class, resulting in the failure to detect or predict crucial cardiac events [66]. While a few studies acknowledged and addressed this issue using techniques such as the Synthetic Minority Oversampling Technique (SMOTE) or weighted loss functions favoring minority classes [30], [31], [32], [47], the majority of the included studies failed to discuss or mitigate this challenge, limiting the robustness of their models.

Feature selection—Using feature selection techniques on features extracted from wearable data allows models to focus on the most significant and relevant features for inference in cardiovascular conditions [67]. Selecting the most important features and removing redundant ones enhances model generalizability and reduces overfitting. Additionally, reducing the number of features helps avoid the curse of dimensionality, making AI pipelines lighter and more efficient for real-time inference. Among the reviewed studies, none explicitly implemented feature selection techniques; instead, they used either raw sensor data or extracted features directly as input to AI models. One study utilized attention mechanisms in CNNs [41], enabling the network to focus on specific portions of input data or features that were more effective at distinguishing between classes.

Model specification and learning—It pertains to robustness against variability arising from the selection, parameterization, and training of AI models [68]. A few of the included studies addressed this robustness concept by employing various techniques. For instance, some studies utilized multiple machine-learning algorithms or different versions of the same algorithm to enhance platform robustness against model type and parameter variability. Others implemented cross-validation techniques during the development and validation phases of their AI algorithms to ensure stability and reliability in their performance.

External data and domain shift—This robustness concept involves evaluating a model's performance across diverse populations, tasks, and care settings, such as different environments, age groups, sexes, and ethnicities [69], [70]. It is linked to bias, as models trained on homogeneous datasets may not generalize well to underrepresented groups [70]. Ensuring robustness helps mitigate bias and improve fairness and reliability in real-world applications. The distribution and diversity of demographics varied across the reviewed studies. Among those that reported demographic information, the data is often imbalanced, introducing bias into AI models that skew inferences toward majority age groups, sexes, ethnicities, or health conditions. It is crucial to include a representative proportion of demographics during the training process, ensuring alignment with the populations where the AI models will be deployed in real-world settings.

Adversarial attacks—Adversarial attacks involve deliberate alterations to input data to manipulate the predictions of a model [71]. In wearable cardiovascular monitoring, such attacks could subtly distort ECG or PPG signals, leading to misclassification of arrhythmias or missed detection of conditions such as atrial fibrillation. These small changes, invisible to humans, can severely impact model performance. To mitigate such vulnerabilities, techniques such as adversarial training, where models are exposed to adversarial examples during training, or input preprocessing methods, such as signal denoising, can be employed [72].

Strategies should be adopted by platform developers to ensure platform security and protect participants' privacy. The reviewed studies that deployed AI models on the cloud reported using encrypted data transfer processes and storing data on Health Insurance Portability and Accountability Act (HIPAA)-compliant cloud servers where the AI models were deployed. Beyond these measures, advanced techniques such as federated learning or split learning with differential privacy could be

employed [73]. These distributed learning approaches remove the need for transferring raw data from local devices to cloud servers. Instead, AI models are trained and deployed through a collaborative process between the cloud and wearable devices, sharing only models or model splits, thereby significantly enhancing platform privacy.

Other Limitations

Among all cardiovascular conditions requiring real-time monitoring, the included studies addressed only a limited subset, with most focusing on AF detection. Critical conditions, such as stroke, remain unexamined. Unexpectedly, many studies failed to report essential methodological details, such as complete demographic information of participants or even the number of participants evaluated. Additionally, critical information such as study duration, data collection frequency and duration, frequency of data transfer to the cloud, and the inference frequency of AI models was often missing.

The field exhibits significant inconsistencies in the use of AI algorithms for wearable data analysis and cardiovascular condition monitoring. While the ideal scenario involves continuous data collection, analysis, and inference-making, this is hindered by practical limitations, including battery life, Internet connectivity, and participant compliance. Consequently, a trade-off must be established between these constraints and the minimum frequency required for effective cardiovascular monitoring. Multi-disciplinary collaborations between cardiovascular specialists and platform engineers are essential to determine the optimal inference frequency for various cardiovascular conditions, which would differ significantly between applications such as AF detection, cardiac arrest detection, or cardiac arrest prediction.

This review follows a systematic and reproducible process guided by a well-established scoping review framework. The search strategy was developed in collaboration with a Library Sciences Expert to ensure a comprehensive exploration of relevant literature. Furthermore, the review covers studies from the inception of this technology to the present, capturing a broad scope of pertinent research. However, some limitations should be noted. Non-English language articles were excluded, which may have resulted in the omission of additional relevant studies. Additionally, the heterogeneity in outcome measurement tools, assessment timelines, patient populations, and randomization methods across the included studies limited the ability to perform a meta-analysis.

Conclusions

AI-powered platforms integrated with wearable devices hold great promise for revolutionizing real-time cardiovascular condition monitoring in community settings. These platforms leverage AI algorithms to analyze data from wearable sensors, enabling early detection and management of critical conditions such as cardiac arrest and AF. Detected outcomes can be reported to clinicians and caregivers to facilitate timely interventions. However, most studies included in this scoping review validated their platforms in controlled hospital settings and over short durations, limiting insights into their performance and challenges in real world, continuous use within community environments. The reviewed studies primarily utilized traditional machine-learning algorithms, often deployed on cloud servers for inference. However, comprehensive validation of these AI models under real-world conditions was limited, with several robustness concepts, such as resilience to noise, dataset bias, and adversarial attacks, remaining unaddressed. Additionally, inconsistencies were observed in key platform parameters, including the frequency of data collection and inference making, which are critical for real-time monitoring. Significant gaps also include the lack of validation for usability, adherence, and robustness across diverse populations. Issues such as participant compliance, battery life, and co-designing platforms with stakeholders further require deeper exploration to ensure practicality and reliability. Ethical and privacy concerns associated with continuous monitoring and data collection in home settings also demand attention. Addressing these challenges will require interdisciplinary collaboration among AI developers, clinicians, and engineers to refine and enhance

the usability, reliability, and effectiveness of these platforms for cardiovascular condition monitoring in real-world scenarios.

Author Contributions Statement

A.A. and S.S.K. developed the research questions. A.A. designed the review framework and protocol, building on an initial version conceived by S.S.K. and M.L. C.C. conducted the systematic database search. A.A. led the review process, including title and abstract screening, full-text review, and data extraction, and also refined the data extraction tables. A.A. drafted all manuscript sections. A.V. contributed to developing the review protocol. A.V., D.J., and J.K. participated in title and abstract screening, full-text review, and data extraction. Additionally, they helped prepare the data extraction tables included in the manuscript. All authors reviewed the manuscript.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

Abbreviations

AF: atrial fibrillation

AI: artificial intelligence

BLE: Bluetooth Low Energy

CNN: Convolutional Neural Network

CVD: cardiovascular diseases

ECG: electrocardiogram

IEEE: Institute of Electrical and Electronics Engineers

LVEF: Left Ventricular Ejection Fraction

MIT-BIH: Massachusetts Institute of Technology-Beth Israel Hospital

MLDA: Modular Linear Discriminant Analysis

PPG: photoplethysmogram

Data Availability

No data is associated with this paper.

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Supplementary Files

Supplementary Table 1. Search strategy and associated keywords.

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