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Design and Implementation of mHealth-Based Early Warning Systems for Heart Disease: A Scoping Review

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Abstract

Cardiovascular diseases (CVDs) remain the leading cause of mortality globally, with sub-Saharan Africa including Uganda experiencing a growing burden due to limited access to early detection and specialist care. In response, mobile health (mHealth) technologies have emerged as promising tools to support early cardiac risk detection and intervention, especially in low-resource settings.

Following Arksey and O'Malley's scoping review framework with enhancements a systematic search was conducted across five databases from January 2000 to April 2025. Studies were screened and selected based on predefined inclusion criteria, and data were charted across design elements, outcomes, and implementation contexts. Thematic analysis was applied to synthesize findings.

Sixteen studies met the inclusion criteria. mHealth-based EWS frequently incorporate wearable sensors, mobile apps, and AI-driven analytics for real-time monitoring and risk prediction. While user-centered design enhances acceptability, clinical efficacy evidence is mixed and scalability remains under-explored. AI/ML integration shows promise in improving prediction and personalization, but challenges persist around interoperability and health system integration.

mHealth-based early warning systems hold significant potential to address cardiovascular care gaps in resource-limited settings. To maximize impact, future interventions should prioritize clinical validation, adaptive AI integration, and sustainable scale-up models tailored to local infrastructure and user needs. These insights are critical for guiding policymakers, developers, and researchers toward more effective digital health strategies for CVD prevention.

A. Introduction

Cardiovascular diseases (CVDs), including heart disease, are the leading cause of mortality globally, accounting for approximately 20.5 million deaths annually representing 32% of all global deaths [1]. Low- and middle-income countries (LMICs) bear more than 75% of this burden, with sub-Saharan Africa experiencing a rapidly growing share of CVD-related morbidity and mortality [2]. In Africa, CVDs now contribute to more than 13% of total deaths, with projections indicating a sharp increase due to urbanization, lifestyle shifts, and limited access to early diagnosis and treatment[3]. In Uganda, heart disease accounts for roughly 10% of adult hospital admissions and ranks among the top five causes of mortality[4]. However, efforts toward early detection and preventive care are significantly hindered by systemic constraints particularly in rural areas, where over 70% of the population resides and health infrastructure is minimal [5]. These factors highlight the urgent need for scalable, low-cost solutions for early cardiovascular screening and risk detection in low-resource contexts.

A critical gap exists in these environments, where access to advanced medical equipment and specialized health professionals is severely limited. Sub-Saharan Africa has fewer than 1 cardiologists per 100,000 people compared to over 70 per 100,000 in high-income countries [6]. Uganda, with a population of over 45 million, has fewer than 50 practicing cardiologists nationwide, resulting in a cardiologist-to-population ratio of approximately 1:900,000, mostly concentrated in urban referral hospitals [7]. This severe shortage limits access to timely cardiac diagnosis and treatment for the majority of the population. In such settings, wearable and mobile health (mHealth) technologies offer a promising solution for extending basic cardiac screening to frontline workers and communities. For instance, phonocardiogram (PCG) analysis via digital stethoscopes connected to mobile devices can enable non-specialist health workers to detect abnormal heart sounds and refer high-risk patients [8]. Similarly, wearable electrocardiogram (ECG) systems can monitor cardiac rhythms continuously and transmit alerts to remote providers when abnormalities are detected bridging critical gaps in diagnosis and early intervention even in the absence of traditional healthcare infrastructure [9].

Mobile health (mHealth) is defined as the use of mobile devices and wireless technologies to support healthcare delivery. mHealth has gained global traction as an innovative solution for improving health outcomes, particularly in under-resourced settings [10]. The widespread penetration of mobile phones, combined with improvements in wearable sensors, cloud computing, and artificial intelligence, has catalyzed the development of mHealth-based early warning systems (EWS) for heart disease [11]. These systems offer a cost-effective means of real-time health monitoring, patient engagement, and risk prediction, often integrating data collection, analysis, and alert mechanisms to support clinical decision-making. Despite the increasing interest and investment in mHealth technologies for cardiac care, the implementation landscape of early warning systems remains fragmented. There is considerable heterogeneity in system design, technological capabilities, user engagement models, and evidence of clinical effectiveness. Furthermore, much of the existing literature focuses on pilot interventions, with limited insights into scalability, interoperability, sustainability, or the contextual factors influencing success.

To address this gap, we conducted a scoping review to map and synthesize the current evidence on the design and implementation of mHealth-based early warning systems for heart disease. This review seeks to (i) identify the types of mHealth interventions utilized in cardiac EWS, (ii) examine their design characteristics, implementation strategies, and technological frameworks, and (iii) evaluate their reported outcomes in terms of feasibility, accuracy, patient uptake, and integration into existing health systems. The findings aim to inform policy, practice, and future research toward more equitable and scalable mHealth solutions for heart disease prevention and management.

B. Research Method

B.1 Scoping review methodology

This study employs a scoping review methodology based on the framework established by Arksey and O'Malley [12], with refinements from the Joanna Briggs Institute [13]. Scoping reviews are particularly appropriate for examining complex, heterogeneous fields where technologies are rapidly evolving as is the case with mHealth-based early warning systems for cardiac conditions. This approach allows for a systematic mapping of existing evidence, identification of key technological trends, and exploration of critical research gaps. A structured five-step process was undertaken: (1) identification of the research questions; (2) systematic search for relevant literature; (3) application of inclusion and exclusion criteria to select studies; (4) data extraction and charting of key characteristics; and (5) synthesis and reporting of findings. Special attention was given to the role of AI/ML in improving detection accuracy, personalization, and system responsiveness, especially in low-resource settings.

B.2 Identification of the Research Questions

The three research questions were deliberately developed to explore both foundational and frontier aspects of early warning systems. This review is guided by the following research questions:

1. What are the key design components (e.g., sensors, algorithms, user interfaces) of mHealth-based early warning systems for heart disease?
2. How are these systems evaluated in terms of clinical efficacy, usability, and scalability?
3. How can artificial intelligence (AI) and machine learning (ML) be integrated into early warning systems to enhance predictive performance and adaptability?

The first question focuses on system design elements, such as sensor configurations, algorithms, and user interface design, across both wearable and mobile platforms. The second examines how these systems are validated and implemented, emphasizing outcomes related to clinical efficacy, end-user usability, and scalability in diverse settings. The third expands the scope to include AI and machine learning, probing how these technologies are currently being incorporated or could be optimized to improve predictive modeling, risk stratification, and adaptive system behavior. Eligible studies included those addressing early detection of cardiac events or deterioration through mHealth-based tools, encompassing both traditional and innovative approaches. This included hospital-based early warning scores, mobile apps, wearable ECG monitors, phonocardiogram systems, biomarker detection platforms, and AI-powered decision support systems.

B.3 Identification of Relevant Literature

A comprehensive literature search was conducted From January to April 2025, supported by trained research assistants. Search terms were derived from the three research questions and refined using a preliminary scan of relevant literature on Google Scholar (excluded from final results due to reproducibility concerns). Boolean operators and truncation techniques were applied to ensure breadth. The search strategy targeted four key conceptual domains: Cardiac conditions (e.g., “cardiac event,” “myocardial infarction,” “rheumatic heart disease”) Early warning and risk detection (e.g., “early warning score,” “predictive monitoring,” “risk stratification”) Technology platforms (e.g., “wearable devices,” “mobile health,” “ECG,” “phonocardiography,” “biosensors”) Advanced analytics and context (e.g., “machine learning,” “artificial intelligence,” “resource-limited,” “remote monitoring”). The final search was applied to five databases: PubMed/MEDLINE, ACM, Science Direct, IEEE Xplore, and Google Scholar. Inclusion criteria were: English-language, peer-reviewed articles (original studies, reviews, or clinical trials) published between January 2000 and April 2025, focusing on early warning systems for cardiac conditions, particularly those incorporating mobile, wearable, or AI-enhanced technologies.

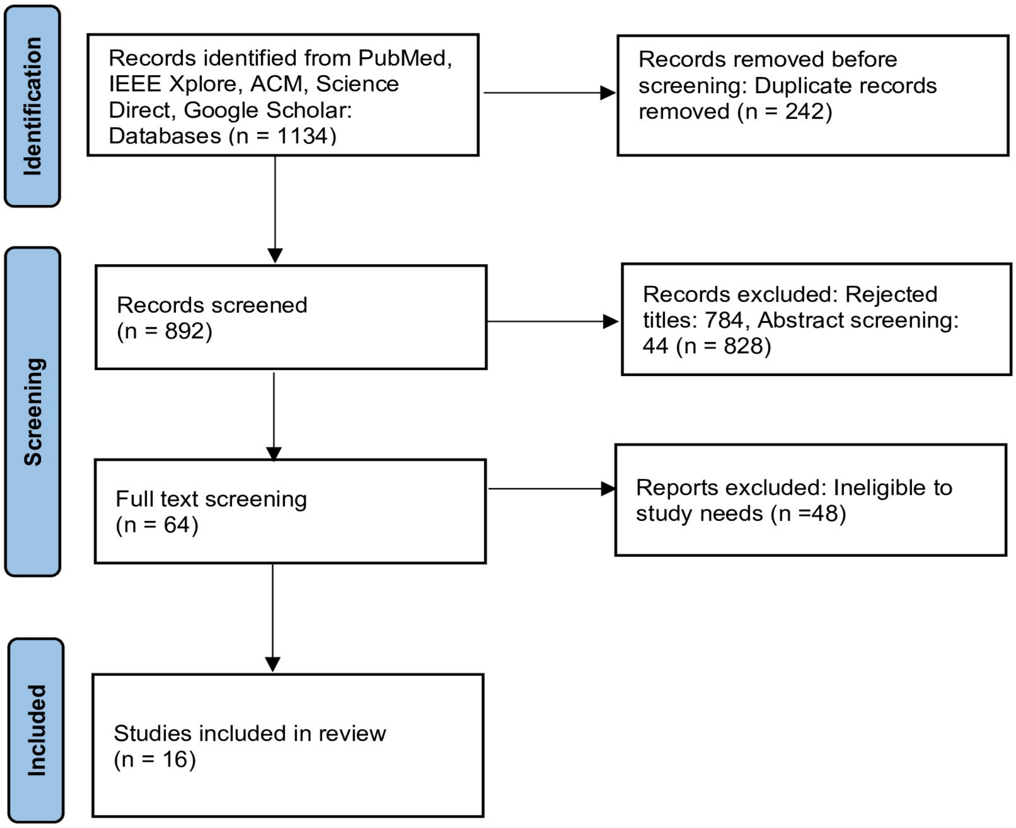

Figure 1. Inclusion and Eclusion criteria

B.4 Study Selection

The search yielded 1,134 initial results. After removing 242 duplicates, 892 unique records remained. Titles, abstracts, and keywords were screened for relevance; 64 full-text articles were reviewed in-depth by two independent reviewers. Discrepancies were resolved through consensus. Sixteen (16) articles met the inclusion criteria as shownin Figure 1 above. Exclusions included studies focused on treatment, non-cardiac early warning systems, and theoretical or conceptual papers lacking empirical evidence. This rigorous filtering ensured that only studies directly relevant to the three research questions were retained.

B.5 Charting the Data

Using a standardized charting form, data were extracted across several domains: authorship, year and location of study; cardiac condition targeted; type and design of early warning system; use of AI or machine learning; study design and population; outcome measures (clinical efficacy, usability, scalability); and implementation setting. This approach enabled both descriptive and comparative analysis aligned with the guiding questions. These are presented in table 1 below:

Table 1. Articles that met the inclusion criteria

Author, year, Ref	Key findings	Gap
Armand et al. (2023), [14]	A low-cost IoT system effectively monitored cardiovascular patients remotely, proving feasible, accurate, and user-friendly in Cameroon.	Lacked ECG integration, robust security, and large-scale validation, limiting comprehensive cardiovascular monitoring and deployment readiness.
Chauhan et al. (2025), [15]	Many cardiovascular health apps and wearables exist, but only a few deliver meaningful value for both patients and clinicians.	Apps lack robust evidence, sex-specific tailoring, and clinical workflow integration; wearables show better evidence but still limited clinician benefit
Chavez-Ecos et al. (2024), [16]	Only about one-third of reviewed cardiovascular risk-assessment apps met "good" or better quality/functionality standards.	The majority of apps are misaligned with validated risk-tools and not tailored for healthcare-professional use.
Cruz-Ramos et al. (2022), [17]	Most mHealth apps support arrhythmia, heart failure or coronary disease; main features are recommendations, reminders, parameter monitoring	Apps lack full functionality, interoperability, psychological health and family-inclusion features, and strong privacy/data protections.
Elsayed, et al. (2017), [18]	mHealth offers significant opportunity in developing countries by reaching underserved populations via mobile phone-based services.	Growth remains slow due to infrastructure, funding, scalability, and sustainability challenges in low-resource settings
SMS Islam et al. (2025), [19]	Health professionals and cardiovascular-disease patients view mHealth lifestyle-support apps as feasible but face significant implementation obstacles.	Persistent barriers include limited digital literacy, workflow integration issues, and inadequate tailoring to patient- and provider-perspectives.
Jevin et al. (2023), [20]	A distributed agent-based model using association rules and machine-learning (Random Forest) achieved high accuracy for heart disease prediction.	The study uses a small dataset and lacks clinical validation and exploration of real-world implementation in health systems.
Khan et al.	The machine-learning model	The work relies on a

(2020), [21]	using a Random Forest classifier achieved about 90 % accuracy in predicting cardiovascular disease.	relatively small dataset and lacks validation in diverse clinical settings or integration into real-world healthcare workflows.
Lu et al. (2020), [22]	Wearable health devices are increasingly used for monitoring, chronic disease management, diagnosis/treatment and rehabilitation in health-care settings	Major barriers include poor device usability, privacy/security concerns, lack of industry standards and technical bottlenecks.
Molina-Recio et al. (2020), [23]	Proposes a structured four-session user-centred design methodology involving users, IT and healthcare professionals for mHealth apps	Requires empirical validation of the methodology through real-world app development and measurement of adherence/clinical outcomes.
Nagavelli et al. (2022), [24]	Survey of machine-learning methods shows rising accuracy in heart disease detection models, across classifiers and feature-selection techniques.	Many models lack large, diverse datasets, real-world clinical validation and reporting of explainability or deployment readiness.
Ni et al. (2024), [25]	Mobile app–based interventions significantly reduced heart-failure-related hospitalisations and improved quality of life.	No significant effect on mortality or self-care; evidence certainty remains low and studies lack long-term data.
Schorr et al. (2021), [26]	Mobile health technologies hold strong potential for supporting behavior change and medication adherence in older adults with cardiovascular disease.	Evidence is limited by small study sizes, lack of diversity, and unclear which mHealth interventions are most effective in older adult CVD populations.
Sharma et al. (2024), [27]	A design-science approach produced a mobile ML app for early cardiovascular disease risk detection accessible to Fijian populations.	The application lacks large-scale real-world validation, long-term user evaluation, and local healthcare system integration.
Tundjungsari et al. (2018), [28]	HCD-developed mobile app helped users record lifestyle behaviours, and scored	It lacks clinical expert validation of accuracy, real-world outcome data,

	above-average on attractiveness, clarity, efficiency and stimulation.	and long-term user engagement evidence.
Vu et al. (2024), [29]	A mobile-phone based system with lightweight neural network "IConNet" detects abnormal heart sounds without extra equipment or server dependency.	Early-stage work; lacks extensive real-world deployment, large diverse datasets and explainability of model decisions.

B.6 Collating, Summarizing, and Reporting the Findings

Findings were synthesized narratively and organized into thematic categories reflecting the three research questions. Descriptive results summarize publication trends, geographic distribution, and healthcare settings. Thematic analysis identified four major clusters: 1) Design architecture of early warning systems including hardware (e.g., sensors), software (e.g., signal processing, mobile apps), and interface components; 2) Evaluation of clinical efficacy, usability, and scalability focusing on validation studies, real-world deployment, and user feedback; 3) AI and machine learning integration detailing applications in predictive modeling, anomaly detection, personalization, and adaptive thresholds; 4) Implementation in low-resource settings exploring affordability, infrastructure challenges, and localization of technologies. These findings map the current landscape of mHealth-based cardiac early warning systems, with an emphasis on the technological, clinical, and contextual factors critical to their future development and deployment.

C. Results

C.1 Key Design Components of mHealth-Based Early Warning Systems for Heart Disease

1. Sensors and Devices

The reviewed studies consistently highlight the central role of physiological sensors in mHealth-based early warning systems for cardiovascular disease (CVD). Commonly integrated sensors include heart rate monitors, blood pressure cuffs, electrocardiogram (ECG) sensors, respiration and activity trackers, and body temperature monitors. These sensors are typically embedded in wearable devices such as chest straps, smartwatches, smartbands, wearable ECG T-shirts, and portable ECG recorders. Less frequent but notable devices include SpO_2 pulse oximeters, mobile stethoscopes, smartphone cameras, and advanced telemetry devices like the Hitoe Transmitter 01. These tools enable continuous monitoring and real-time data collection, feeding into early detection mechanisms.

2. Data Processing and Algorithmic Approaches

Data collected by sensors is processed using a range of computational techniques, including both traditional statistical methods and advanced artificial intelligence (AI). Machine learning (ML) methods dominate the analytical landscape, with supervised and unsupervised learning models applied for classification, clustering, and regression tasks. Common algorithms include Support Vector Machines (SVM), k-Nearest Neighbors, Decision Trees, Naïve Bayes, Logistic Regression, Artificial Neural Networks (ANN), and ensemble models like XGBoost. Feature selection algorithms such as Relief, Minimal Redundancy Maximal Relevance (mRMR), and Least Absolute Shrinkage and Selection Operator (LASSO) are employed to enhance predictive efficiency. In certain applications, neural networks analyze audio signals from heart sound recordings for anomaly detection.

3. User Interfaces and Application Design

Smartphones are the predominant platform for user interaction, hosting mobile applications that display physiological data, facilitate self-reporting, and enable communication with healthcare providers. Some systems extend functionality through web portals that connect patients with lab workers and cardiologists. App design emphasizes usability, intuitive navigation, and adherence-supporting features such as visual cues, color-coded alerts, and graphical data input. A user-centered or human-centered design approach is consistently advocated to improve adoption and engagement, particularly through iterative feedback from both patients and healthcare professionals.

4. Functionalities

Key functionalities in early warning systems include real-time alerts triggered by abnormal physiological readings, medication reminders, symptom reporting, risk tracking, and tailored health recommendations. Advanced systems also facilitate remote monitoring, allowing clinicians to assess patient data in real time. Some platforms enable users to estimate their risk for CVD using models like the Framingham Risk Score and receive evidence-based guidance accordingly. Integration with wearable technologies supports seamless data transmission for continuous health surveillance.

C.2 Evaluation of Clinical Efficacy, Usability, and Scalability

1. Clinical Efficacy

While several studies document the potential health benefits of mHealth interventions for heart disease prevention and management, robust clinical validation remains limited. Randomized controlled trials (RCTs) and pilot studies report mixed results; for example, while some applications improved physiological indicators like VO_2 max or medication adherence, others such as MyHeartMate showed minimal impact on behavior change or cardiovascular risk profiles. A gap persists in the scientific validation of many commercial mHealth applications, with wearable devices generally exhibiting stronger evidence bases and regulatory certifications.

2. Usability and Acceptability

Usability is a recurring theme in both the development and evaluation phases. User resistance, limited digital literacy, and perceived complexity are commonly reported barriers. Evaluative tools such as the Mobile App Rating Scale (MARS) are employed to assess quality, functionality, aesthetics, and engagement. Systematic reviews reveal that user-centered development strategies significantly enhance both patient and clinician acceptance. Customization options, clear visual design, and streamlined navigation are important for improving app adoption, particularly among older adults and underserved populations.

3. Scalability and System Integration

Although scalability is infrequently evaluated systematically, studies frequently reference it as a critical design consideration. Low-cost mobile platforms and the ubiquity of smartphones facilitate broad dissemination, especially in low-resource settings. However, significant challenges remain, particularly regarding system interoperability with Electronic Medical Records (EMRs), user onboarding, clinician training, and sustained engagement. The capacity to handle large-scale, real-time data inputs is also central to ensuring functional scalability and long-term integration into clinical workflows.

4. Enhancing Predictive Performance

AI and ML algorithms are instrumental in improving the predictive capacity of early warning systems. These technologies enable the development of personalized risk models that predict the onset or progression of heart disease based on real-time or historical patient data. ML classifiers such as SVM, Decision Trees, and neural networks are trained to recognize patterns in physiological signals and generate timely alerts. Hybrid models and ensemble learning techniques have demonstrated high sensitivity and specificity in several studies, contributing to more accurate and timely detection.

5. Supporting Adaptability and Personalization

Beyond prediction, AI and ML support dynamic system adaptability by analyzing large and diverse data streams. This allows for tailored feedback, proactive intervention recommendations, and user-specific risk stratification. Systems leveraging AI can evolve with accumulated data, improving their accuracy and contextual relevance over time. Integration with Internet of Things (IoT) infrastructure enables real-time data collection from wearables, further enhancing predictive accuracy. This transition from reactive to proactive healthcare supports continuous, personalized care delivery.

D. Discussion

The development of an effective mHealth-based early warning system (EWS) for cardiovascular disease (CVD) necessitates a thoughtful and multi-dimensional design process that incorporates clinical relevance, technological feasibility, and user-centeredness. The synthesis of evidence in this review highlights several interdependent design considerations that underpin the efficacy, usability, and acceptability of such systems.

At the core of effective mHealth solutions lies the principle of user-centered design (UCD), which prioritizes the needs, preferences, and contextual realities of end users primarily patients and healthcare providers. Studies consistently emphasize that involving stakeholders early and continuously in the design process can lead to more usable, acceptable, and impactful systems. The use of qualitative methods, such as in-depth interviews and focus groups, can capture nuanced insights into users' digital literacy levels, prior experiences with technology, and expectations from mHealth interventions. In particular, considerations related to personalization, comfort, and interface simplicity are vital for sustained engagement, especially among older adults or populations with limited health and digital literacy.

An essential function of an mHealth-based EWS is the accurate assessment and prediction of cardiovascular risk. This functionality can be enabled through the integration of traditional risk scoring models, such as the Framingham risk score, alongside machine learning algorithms capable of handling high-dimensional and diverse datasets. Predictive models should be calibrated using both clinical (e.g., blood pressure, cholesterol levels) and non-clinical data (e.g., physical activity, dietary habits), ensuring a holistic view of patient risk. The HeartCare+ app exemplifies this approach, offering a 10-year risk estimate for hard coronary heart diseases. However, the broader implementation of such models necessitates rigorous validation against real-world clinical outcomes and adaptability to various demographic and geographic contexts.

Effective mHealth early warning systems must incorporate capabilities for real-time monitoring of vital physiological parameters, including heart rate, blood pressure, and symptoms of heart failure. These can be collected either through self-reports or automatically via wearable devices using wireless technologies like Bluetooth. Alerts and notifications triggered by abnormal readings are critical for the early detection of clinical deterioration. These alerts should be customizable in terms of threshold settings and notification channels, thereby reducing alarm fatigue and increasing clinical utility. Moreover, reminders for medication adherence and daily self-monitoring reinforce patient compliance and can prevent avoidable exacerbations.

Providing timely and personalized feedback is pivotal to the behavioral and clinical impact of mHealth systems. Based on risk assessments or monitored data, the system should generate actionable insights ranging from dietary and exercise advice to medication adjustments aligned with evidence-based clinical guidelines. Feedback mechanisms should be intelligible to users of varying literacy levels and, where appropriate, include motivational content or gamified features to reinforce engagement. This aligns with a preventive care model where digital tools support users in managing their health proactively.

Several barriers to the adoption and sustained use of mHealth EWS were identified, and addressing these challenges is essential for real-world implementation. First, the scientific validity and trustworthiness of mHealth apps remain a key concern for both clinicians and patients. This necessitates the grounding of system functionalities in validated clinical protocols and the conduct of rigorous usability and efficacy trials. Second, digital literacy limitations, particularly among elderly or rural populations, call for simplified interfaces, larger font sizes, and intuitive navigation. Third, cost and accessibility considerations must be taken into account to avoid exacerbating health inequities, particularly in low-resource settings. Strategies such as open-source development, public-private partnerships, and subsidized device distribution could help mitigate these concerns.

Security and privacy remain fundamental to user trust and legal compliance. Concerns around the unauthorized access to personal health information must be addressed through robust encryption, user authentication protocols, and transparent privacy policies. Additionally, the lack of interoperability with existing clinical systems, such as electronic medical records (EMRs), limits the utility of mHealth apps within integrated care workflows. Future systems should prioritize standards-based data exchange and enable bidirectional communication between patients and providers, facilitating continuity of care.

Finally, special attention should be given to tailoring mHealth systems for vulnerable populations such as the elderly, who may experience sensory, cognitive, or motor limitations that affect technology use. Furthermore, social influences such as family support, community norms, and caregiver involvement should be considered in both the design and deployment of these tools. Adaptive and inclusive design strategies can ensure that mHealth interventions do not inadvertently exclude the very populations that may benefit the most from early detection and prevention of CVD.

E. Conclusion

This review underscores the growing potential of mHealth-based early warning systems (EWS) to support the early detection, prevention, and management of cardiovascular disease through continuous monitoring, intelligent data analysis, and user-centered system design. The findings demonstrate that effective EWS rely on the integration of reliable wearable sensors, robust data processing pipelines, and advanced AI- and ML-driven predictive models capable of generating timely and personalized risk assessments. Smartphones serve as a central interface, enabling real-time feedback, alerts, and communication between patients and healthcare providers, while supporting adherence to preventive and therapeutic interventions.

Despite these technological advances, the evidence also highlights persistent gaps in clinical validation, long-term efficacy, and large-scale implementation. Many systems remain insufficiently evaluated through rigorous trials, limiting their credibility and adoption in routine clinical practice. Usability, digital literacy, and accessibility continue to shape user engagement, reinforcing the importance of human-centered design approaches that account for diverse populations and contextual constraints. Moreover, challenges related to interoperability, data privacy, and system scalability must be addressed to ensure sustainable integration into healthcare infrastructures.

Overall, mHealth-based EWS represent a promising shift toward proactive and personalized cardiovascular care. Future efforts should prioritize clinical validation, inclusive design, and seamless system integration to translate technological innovation into measurable and equitable health outcomes.

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