Wearable and Artificial-Intelligence-Enabled Multimodal Systems for Early Detection and Classification of Acute Myocardial Infarction: A Review of the Integration of Clinical, Electrocardiographic, and Echocardiographic Data

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ABSTRACT

Acute myocardial infarction (AMI) — comprising ST-elevation myocardial infarction (STEMI) and non-ST-elevation myocardial infarction (NSTEMI) — remains the leading cause of cardiovascular death worldwide, and rapid, accurate differentiation between its subtypes is essential for time-critical treatment decisions. Conventional diagnosis relies on a combination of clinical assessment, 12-lead electrocardiography (ECG), cardiac biomarkers, and echocardiography, each of which carries recognized diagnostic limitations when used in isolation. Over the past decade, wearable electrocardiographic devices, point-of-care high-sensitivity troponin assays, handheld artificial-intelligence (AI)-assisted echocardiography, and multimodal deep-learning fusion architectures have matured sufficiently to be considered building blocks of an integrated, low-cost diagnostic pathway suitable for emergency, pre-hospital, and resource-constrained settings. This review synthesizes evidence from cardiology, biomedical engineering, and digital-health literature on (i) the epidemiological burden and diagnostic paradigm of AMI, (ii) the diagnostic performance of wearable ECG and point-of-care biomarker technologies, (iii) artificial-intelligence approaches to ECG- and echocardiography-based MI detection, (iv) multimodal data-fusion strategies, and (v) the specific opportunities and gaps relevant to low- and middle-income countries such as Uganda. Across the reviewed literature, deep-learning models applied to single- or multi-lead ECG achieve areas under the receiver-operating-characteristic curve generally exceeding 0.90 for MI detection, wearable smart watch electrocardiograms achieve sensitivities of 83–100% and specificities of 79–100% for arrhythmia and ST-segment change detection under supervised conditions, and point-of-care high-sensitivity troponin assays achieve diagnostic accuracy comparable to central-laboratory assays with substantially shorter turnaround times. However, multimodal fusion of clinical, ECG, and echocardiographic streams into a single wearable STEMI/NSTEMI classifier remains largely unrealized in the peer-reviewed literature, and evidence from sub-Saharan African populations is markedly under-represented. We propose a conceptual framework for an integrated wearable multimodal diagnostic system and outline the technical, clinical, regulatory, and ethical considerations that must be addressed before such systems can be safely deployed in emergency and pre-hospital cardiac care in low-resource settings.

Keywords: Acute myocardial infarction; STEMI; NSTEMI; wearable devices; electrocardiography; echocardiography; artificial intelligence; deep learning; multimodal fusion; point-of-care diagnostics; low- and middle-income countries

INTRODUCTION

Cardiovascular diseases (CVDs) remain the single largest contributor to global mortality. Estimates from the 2023 iteration of the Global Burden of Disease (GBD) study indicate that cardiovascular deaths rose from approximately 13.1 million in 1990 to 19.2 million in 2023, with ischaemic heart disease continuing to account for the largest share of cardiovascular disability-adjusted life-years worldwide (GBD 2023 Cardiovascular Diseases Collaborators, 2025; World Heart Federation, 2023). The World Health Organization similarly reports that CVDs account for roughly one in three deaths globally, with more than three-quarters of these deaths occurring in low- and middle-income countries (LMICs) (WHO, 2023). Ischaemic heart disease, and specifically acute myocardial infarction (AMI), constitutes a substantial share of this burden and its global mortality attributable share has continued to increase over the past three decades (Mensah et al., 2023).

AMI is clinically classified into ST-elevation myocardial infarction (STEMI) and non-ST-elevation myocardial infarction (NSTEMI) according to the Fourth Universal Definition of Myocardial Infarction, primarily on the basis of electrocardiographic findings, cardiac biomarker kinetics, and the extent of coronary occlusion (Thygesen et al., 2018; Thygesen, 2019). STEMI results from complete coronary occlusion and mandates immediate reperfusion therapy, whereas NSTEMI typically reflects partial occlusion and is managed through risk-stratified, biomarker-guided pathways (Byrne et al., 2023; Collet et al., 2020). Because the two subtypes require materially different time-to-treatment targets, rapid and accurate differentiation at first medical contact is one of the central objectives of contemporary acute cardiac care (Byrne et al., 2024; Licordari et al., 2024).

Conventional diagnosis of AMI integrates history and physical examination, 12-lead ECG, high-sensitivity cardiac troponin measurement, and, where available, echocardiography (Zwart et al., 2024). Each modality has well-documented limitations in isolation: the ECG can be normal or non-diagnostic in a substantial proportion of NSTEMI presentations and in early or atypical STEMI (Birnbaum et al., 2020); high-sensitivity troponin assays, although highly specific for myocardial injury, require one or more hours to reach diagnostic thresholds after symptom onset even under optimized 0/1-hour protocols (Koechlin et al., 2024; Clerico et al., 2024); and echocardiography, while valuable for identifying regional wall-motion abnormalities and structural complications, requires equipment and operator expertise that remain scarce outside tertiary centres (Sengupta et al., 2025; Shittu & Quaye, 2025). These constraints are magnified in emergency departments, ambulances, and particularly in low-resource health systems, where cardiologists, sonographers, and central laboratory infrastructure are in short supply (Bloomfield et al., 2013; Keates et al., 2017).

The past decade has seen parallel advances in three technology domains that are individually mature but have rarely been integrated into a single diagnostic pathway for AMI. First, wearable and handheld ECG devices — including consumer smartwatches, adhesive patches, and multichannel handheld recorders — now achieve diagnostic accuracies for arrhythmia and ischaemic ST-segment change detection that approach those of conventional 12-lead systems under supervised conditions (Isenegger et al., 2024; Iqhrammullah et al., 2025; Perez et al., 2019). Second, deep-learning algorithms applied to ECG waveforms, most commonly convolutional neural networks (CNNs) and recurrent architectures, have demonstrated strong discriminative performance for automated MI detection and localization, in several studies matching or exceeding the accuracy of practicing physicians (Acharya et al., 2017; Ribeiro et al., 2020; Xiong et al., 2022). Third, artificial-intelligence-assisted handheld point-of-care ultrasound (POCUS) now allows non-expert operators to acquire and automatically interpret focused cardiac views with diagnostic agreement approaching that of formal echocardiography performed by trained sonographers (Huang et al., 2024; Campbell et al., 2025). Alongside these imaging and signal-processing advances, point-of-care high-sensitivity troponin platforms have narrowed the performance gap with central-laboratory assays while substantially reducing turnaround time (Zalama-Sánchez et al., 2024; Goldberg et al., 2024).

Despite this progress, relatively few studies have attempted to fuse clinical, electrocardiographic, and echocardiographic data streams into a single wearable or point-of-care multimodal system explicitly designed to distinguish STEMI from NSTEMI, and evidence from sub-Saharan African health systems — where the burden of delayed AMI diagnosis is disproportionately high — remains sparse (Minja et al., 2022; Mocumbi, 2012). This review therefore has three objectives: (i) to synthesize current evidence on wearable ECG, point-of-care troponin, and AI-assisted echocardiographic technologies relevant to AMI detection; (ii) to critically appraise the state of multimodal AI fusion approaches for STEMI/NSTEMI classification; and (iii) to identify the technical, clinical, and contextual gaps that must be addressed to translate these technologies into an integrated wearable diagnostic device suitable for resource-constrained emergency and pre-hospital settings such as those in Uganda.

REVIEW METHODOLOGY

This narrative review synthesizes peer-reviewed literature, clinical practice guidelines, and grey literature (WHO and World Heart Federation reports) published predominantly between 2017 and 2026, identified through structured searches of PubMed/MEDLINE, Scopus, IEEE Xplore, and Google Scholar. Search terms combined controlled vocabulary and free-text keywords across four thematic clusters: (i) acute myocardial infarction, STEMI, NSTEMI, diagnosis, universal definition; (ii) wearable electrocardiography, smartwatch, ECG patch, atrial fibrillation, ST-segment; (iii) deep learning, convolutional neural network, artificial intelligence, multimodal fusion, explainable AI; and (iv) point-of-care ultrasound, handheld echocardiography, high-sensitivity troponin, low- and middle-income countries, sub-Saharan Africa. Studies were prioritized for inclusion if they reported diagnostic accuracy metrics (sensitivity, specificity, area under the curve), described a novel wearable or AI architecture relevant to AMI detection, or provided epidemiological or health-systems context relevant to resource-constrained deployment. Reference lists of identified systematic reviews were hand-searched for additional primary studies. Because this is a narrative rather than a systematic review, no formal risk-of-bias scoring or meta-analytic pooling was performed; instead, findings are synthesized thematically and reported ranges are drawn directly from the primary studies and systematic reviews cited.

Epidemiological and Clinical Burden of Acute Myocardial Infarction

Global cardiovascular mortality has risen substantially in absolute terms over the past three decades, driven primarily by population growth and ageing rather than by rising age-standardized risk, which has in fact declined in most regions (GBD 2023 Cardiovascular Diseases Collaborators, 2025). Ischaemic heart disease remains the single largest contributor to cardiovascular death and disability-adjusted life-years globally, and the burden of cardiovascular disease relative to population size remains highest in low- and lower-middle-income settings (World Heart Federation, 2023; WHO, 2023).

In sub-Saharan Africa, the epidemiological transition from communicable to non-communicable disease has accelerated the incidence of acute coronary syndromes, although absolute incidence figures remain lower than in high-income regions and the region continues to carry a disproportionate burden of hypertensive and rheumatic heart disease alongside emerging ischaemic heart disease (Keates et al., 2017; Minja et al., 2022). Health-systems analyses consistently identify shortages of cardiologists, catheterization laboratories, and echocardiography equipment as major contributors to delayed diagnosis and poorer outcomes in the region (Bloomfield et al., 2013; Mocumbi, 2012). Uganda reflects this broader regional pattern: rising prevalence of hypertension, diabetes mellitus, obesity, and urbanization-associated lifestyle change is increasing the incidence of acute coronary syndromes, while cardiac specialist and diagnostic-imaging capacity remains concentrated in a small number of urban referral centres, leaving patients in regional and rural facilities dependent on clinical assessment and basic ECG alone for initial triage.

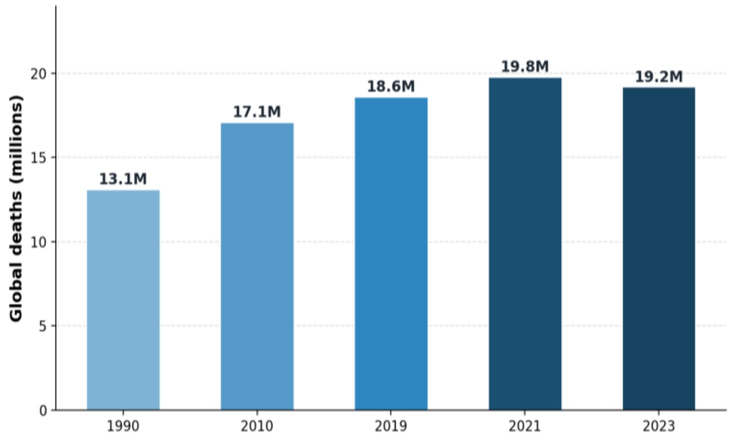

Figure 1. Global cardiovascular disease mortality trend, 1990–2023, compiled from Global Burden of Disease, World Heart Federation, and World Health Organization estimates (GBD 2023 Cardiovascular Diseases Collaborators, 2025; World Heart Federation, 2023; WHO, 2023).

The Conventional Diagnostic Paradigm and Its Limitations

The Fourth Universal Definition of Myocardial Infarction anchors clinical diagnosis in the detection of a rise and/or fall of cardiac troponin with at least one value above the 99th percentile upper reference limit, together with evidence of acute myocardial ischaemia from symptoms, ECG changes, or imaging (Thygesen et al., 2018). The 2023 European Society of Cardiology (ESC) Guidelines for the management of acute coronary syndromes unify STEMI and NSTE-ACS management within a single framework, emphasizing the 'A-C-S' approach — assessing for abnormal ECG, clinical context, and patient stability — at first medical contact (Byrne et al., 2023; Byrne et al., 2024). Table 1 summarizes the principal strengths and limitations of the three core diagnostic modalities.

Table 1. Comparison of Core Diagnostic Modalities for Acute Myocardial Infarction

Modality	Key strengths	Key limitations	Representative sources
12-lead ECG	Rapid, inexpensive, widely available, first-line for STEMI identification	Normal or non-diagnostic in many NSTEMI/early presentations; interpretation variability	Thygesen et al., 2018; Birnbaum et al., 2020
High-sensitivity cardiac troponin	High specificity for myocardial injury; central to 0/1-hour rule-in/rule-out algorithms	Diagnostic elevation may take 1–3 hours after symptom onset; not specific to coronary aetiology	Byrne et al., 2023; Koechlin et al., 2024; Lee et al., 2019
Echocardiography	Identifies regional wall-motion abnormalities, ejection fraction, structural complications	Requires trained operators and dedicated equipment; limited availability outside referral centres	Sengupta et al., 2025; Bloomfield et al., 2013

Wearable Electrocardiographic Technologies

Wearable ECG devices — including wrist-worn smartwatches with embedded single-lead electrodes, adhesive multichannel patches, and photoplethysmography (PPG)-based optical sensors — have progressed from consumer novelty devices to instruments with regulatory clearance for arrhythmia screening. The Apple Heart Study, a large-scale pragmatic trial of over 400,000 participants, demonstrated that a smartwatch-based irregular-pulse notification algorithm identified atrial fibrillation on subsequent ECG-patch monitoring in roughly one-third of notified participants, establishing proof of concept for population-scale passive cardiac screening (Perez et al., 2019).

Subsequent validation studies have refined estimates of diagnostic accuracy. A comparative validation of five commercially available smartwatches against 12-lead ECG in a tertiary electrophysiology cohort found that automated atrial fibrillation detection accuracy varied meaningfully between devices and improved over successive algorithm iterations, though inconclusive-recording rates remained a persistent limitation (Isenegger et al., 2024). Systematic reviews and meta-analyses report smartwatch ECG sensitivity for atrial fibrillation ranging from roughly 83% to 100% and specificity from 79% to 100%, with manual clinician review of borderline tracings improving both parameters relative to automated algorithms alone (Iqhrammullah et al., 2025). Single-lead Apple Watch recordings evaluated against simultaneous 12-lead ECG in patients undergoing cardioversion achieved sensitivity above 93% and specificity approaching 100% for atrial fibrillation identification (Pepplinkhuizen et al., 2022). Comparative work evaluating consumer wearables — including handheld six-lead devices, smartwatch single-lead ECG, and PPG-based smartphone applications — against simultaneous 12-lead reference recordings found broadly comparable discriminative performance across device classes, with device choice in practice driven as much by cost and accessibility as by raw diagnostic accuracy (Wouters et al., 2025).

Beyond atrial fibrillation, several systematic reviews have specifically examined wearable ECG performance for ST-segment change detection relevant to STEMI screening, reporting that multichannel smartwatch reconstructions of ischaemic ST-elevation patterns show high agreement with 12-lead ECG under supervised conditions, although evidence remains limited to small cohorts and controlled settings rather than real-world pre-hospital deployment (Iqhrammullah et al., 2025). Machine-learning post-processing of wearable pulse and ECG data has additionally been applied to postoperative atrial fibrillation detection, achieving algorithm performance approaching that of continuous telemetry review by clinicians (Hiraoka et al., 2022; Inui et al., 2020).

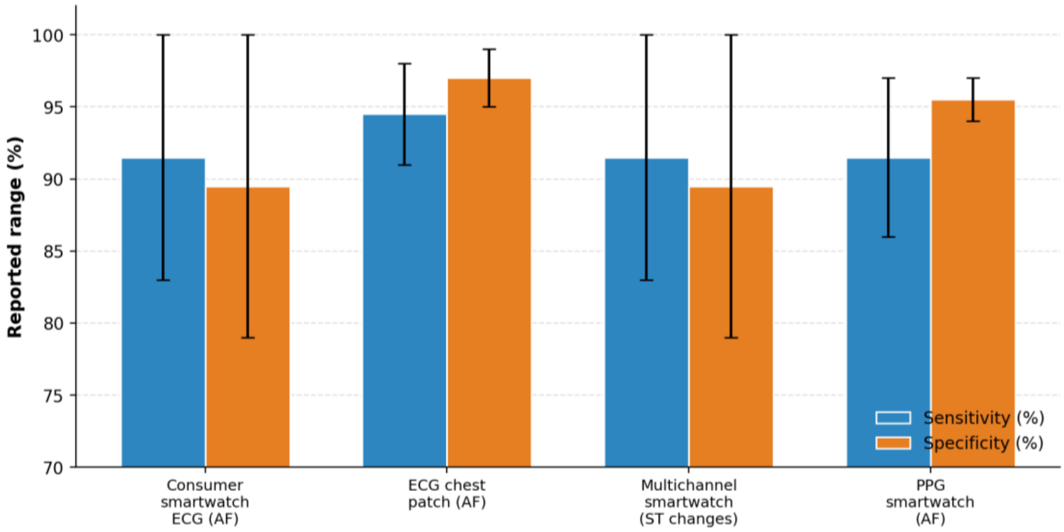

Figure 2. Reported diagnostic accuracy ranges of wearable ECG devices for arrhythmia and ischaemic ECG-change detection, compiled from systematic reviews and validation studies cited in this review (Iqhrammullah et al., 2025; Isenegger et al., 2024; Pepplinkhuizen et al., 2022; Wouters et al., 2025).

Artificial Intelligence and Deep Learning for Ecg-Based Myocardial Infarction Detection

A substantial and rapidly growing body of literature has applied deep-learning architectures to ECG-based detection and localization of myocardial infarction. Early convolutional neural network (CNN) models trained on the PTB diagnostic ECG database achieved average accuracies above 93% for MI beat classification, with performance improving further once denoising preprocessing was applied (Acharya et al., 2017). Subsequent architectures incorporating real-time multilead processing (Liu et al., 2018), multiscale and attention-based ResNet variants (Cao et al., 2022), vectorcardiogram-derived multichannel CNNs (Karhade et al., 2021), and hybrid Gabor-transform CNN models (Jahmunah et al., 2021) have progressively improved both detection and anatomical localization accuracy, with several architectures reporting areas under the receiver-operating-characteristic curve exceeding 0.97 in internal validation.

A comprehensive literature review covering 59 major deep-learning studies published over a five-year period found that CNN and ResNet architectures were the most frequently applied and generally the best-performing model families for MI detection and localization from ECG, with maximum reported accuracies across studies consistently exceeding 97%, albeit predominantly on curated, single-centre datasets (Xiong et al., 2022). Larger-scale validation has increasingly moved toward multi-centre, real-world data: a deep neural network trained and externally validated on more than 145,000 ECGs from three Swedish hospitals combined convolutional and recurrent layers with an attention mechanism to distinguish STEMI, NSTEMI, and non-AMI controls, demonstrating that performance generalized reasonably well across hospitals while highlighting the sensitivity of model performance to differences in local case-mix and ECG acquisition equipment (Hilgendorf et al., 2025). A separate multicentre study evaluated an AI-ECG algorithm specifically for ruling out acute myocardial infarction in the emergency department, reporting diagnostic performance that could meaningfully reduce reliance on serial troponin testing when combined with a single presentation ECG (Lee et al., 2025).

Foundational automatic ECG interpretation networks trained on very large annotated datasets — such as the Brazilian 12-lead DNN validated on over two million ECGs (Ribeiro et al., 2020) and AI-ECG models for detecting left ventricular systolic dysfunction (Attia et al., 2019; Kashou et al., 2021) — illustrate that deep-learning ECG interpretation now extends beyond rhythm classification to structural and functional cardiac abnormalities relevant to AMI complications. Publicly available benchmark datasets such as PTB-XL (Wagner et al., 2020) have been central to enabling reproducible comparison across these architectures, while risk-stratification models such as AI-enabled ECG scores for coronary disease (Awasthi et al., 2023) and end-to-end

CNNs applied directly to 12-lead ECG images without manual preprocessing (Uchiyama et al., 2025) reflect a broader trend toward deployment-ready, minimally-pre-processed pipelines suited to point-of-care and wearable contexts. Foundational preprocessing and detection techniques that underpin many of these pipelines — including the classical Pan–Tompkins QRS-detection algorithm (Pan & Tompkins, 1985) and deep-learning-based complex detection methods (Zhong et al., 2018) — remain integral building blocks even in contemporary end-to-end architectures. Table 2 summarizes representative deep-learning studies for ECG-based MI detection.

Table 2. Representative Deep-Learning Studies for ECG-Based Myocardial Infarction Detection

Study	Architecture	Data source	Reported performance
Acharya et al., 2017	CNN (11-layer)	PTB diagnostic ECG database	93.5–95.2% accuracy (with/without denoising)
Liu et al., 2018	Real-time multilead CNN	PTB database	High MI detection accuracy across leads
Karhade et al., 2021	Multichannel multiscale two-stage CNN	Vectorcardiogram signals	High detection and localization accuracy
Cao et al., 2022	Multi-scale ResNet with attention	Public ECG datasets	Improved MI localization over baseline CNN
Ribeiro et al., 2020	Deep neural network	> 2 million 12-lead ECGs (Brazil)	Specialist-level automatic diagnosis
Hilgendorf et al., 2025	Conv-BiLSTM-Attention	145,656 ECGs, 3 Swedish hospitals	Robust cross-hospital generalization for STEMI/NSTEMI/control
Lee et al., 2025 (ROMIAE)	AI-ECG rule-out model	Multicentre emergency department cohort	High negative predictive value for AMI rule-out

Artificial-Intelligence-Assisted Point-of-Care Echocardiography

Point-of-care ultrasound (POCUS) devices, some no larger than a smartphone, have substantially broadened access to bedside cardiac imaging, but image acquisition and interpretation by non-expert operators remain a bottleneck (Shittu & Quaye, 2025). AI-assisted guidance systems now provide real-time feedback on probe positioning and image quality, while automated measurement algorithms calculate left ventricular ejection fraction (LVEF) and other functional parameters without requiring sonographer expertise (Sengupta et al., 2025). In the Point-of-care AI-enhanced Novice Echocardiography for Screening Heart Failure (PANES-HF) study, novice operators with only two weeks of training used AI-guided handheld echocardiography to detect reduced LVEF with an area under the curve of 0.88, outperforming natriuretic-peptide-based screening thresholds and demonstrating good agreement with expert-performed comprehensive echocardiography (Huang et al., 2024).

A prospective single-arm study of AI-enhanced focused cardiac ultrasound performed by non-cardiologist physicians across 660 patients found that AI-guided assessment of ventricular function, valvular disease, pericardial effusion, and inferior vena cava size altered clinical management in a substantial proportion of cases, including detection of previously undocumented diagnoses (Campbell et al., 2025). Fully automated AI analysis of handheld echocardiography images in patients with suspected heart failure has similarly shown diagnostic accuracy approaching that of comprehensive echocardiography interpreted by cardiologists (Campbell et al., 2025). Collectively, this evidence indicates that AI-assisted handheld echocardiography could, in principle, extend focused structural and functional cardiac assessment — including identification of regional wall-motion abnormalities relevant to AMI — into pre-hospital and low-resource settings where trained sonographers are unavailable, although prospective evaluation specifically in the context of acute STEMI/NSTEMI differentiation remains limited in the current literature.

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Point-of-Care High-Sensitivity Troponin Testing

High-sensitivity cardiac troponin assays have transformed rule-in and rule-out pathways for AMI in the emergency department, but historically required centralized laboratory platforms with turnaround times that can meaningfully delay disposition decisions (Lee et al., 2019; Hammerer-Lercher et al., 2013). Point-of-care (POC) high-sensitivity troponin platforms have narrowed this gap considerably. A multicentre evaluation of a POC high-sensitivity troponin I assay against best-validated central-laboratory assays in patients with suspected MI reported an area under the curve of 0.95, statistically comparable to central-laboratory testing, while enabling result availability in under ten minutes (Koechlin et al., 2024; Clerico et al., 2024). Similarly, a study specifically evaluating POC high-sensitivity troponin for excluding NSTEMI in the emergency department found consistently high discriminative accuracy (area under the curve greater than 0.90) with substantially reduced turnaround time relative to core-laboratory testing (Zalama-Sánchez et al., 2024).

Earlier comparative work confirmed that POC troponin assays could achieve diagnostic performance approaching that of central-laboratory high-sensitivity assays under routine emergency-department conditions, although some earlier-generation POC platforms did not meet formal high-sensitivity analytical criteria (Wilke et al., 2017). More recent evaluation in the pre-hospital ambulance environment demonstrated that a novel POC high-sensitivity troponin assay could support early triage decisions before hospital arrival (Gilman et al., 2026), a capability directly relevant to wearable and portable multimodal diagnostic concepts. A recent narrative synthesis concluded that coupling POC troponin testing with biosensor technology and structured triage algorithms represents one of the most promising near-term pathways to reducing diagnostic delay in acute coronary syndrome care (Goldberg et al., 2024).

Multimodal Data Fusion and Integrated Wearable Diagnostic Frameworks

Individually, wearable ECG, AI-assisted echocardiography, and point-of-care troponin testing each address specific limitations of conventional single-modality diagnosis, but the diagnostic literature increasingly emphasizes that multimodal integration — combining clinical, electrocardiographic, imaging, and biomarker data within a single algorithmic framework — yields superior diagnostic performance compared with any single modality applied alone (Hilgendorf et al., 2025). This principle is well established in the broader AI-in-medicine literature, where multimodal fusion models that combine structured clinical variables with signal or image data consistently outperform unimodal counterparts on discrimination and calibration metrics, reflecting the complementary and only partially overlapping information captured by each data stream.

Despite this conceptual rationale, the peer-reviewed literature identified for this review contains comparatively few studies that fuse clinical symptomatology, wearable ECG signals, and echocardiographic imaging within a single integrated STEMI/NSTEMI classification pipeline; most published work addresses ECG-only detection (Xiong et al., 2022; Ribeiro et al., 2020), echocardiography-only functional assessment (Huang et al., 2024; Campbell et al., 2025), or troponin-only rule-out algorithms (Koechlin et al., 2024) in isolation. The Conv-BiLSTM-Attention model validated across three Swedish hospitals represents one of the more advanced examples of multimodal fusion currently reported, combining raw 12-lead ECG waveforms with demographic covariates to distinguish STEMI, NSTEMI, and non-AMI presentations, though it does not yet incorporate echocardiographic or point-of-care biomarker inputs (Hilgendorf et al., 2025).

Figure 3 presents a conceptual framework, synthesized from the technologies reviewed above, for an integrated wearable multimodal system capable of acquiring clinical, ECG, and echocardiographic data streams, preprocessing and fusing these within a deep-learning classifier, and producing a STEMI, NSTEMI, or non-AMI classification to support triage and referral decisions at the point of first contact.

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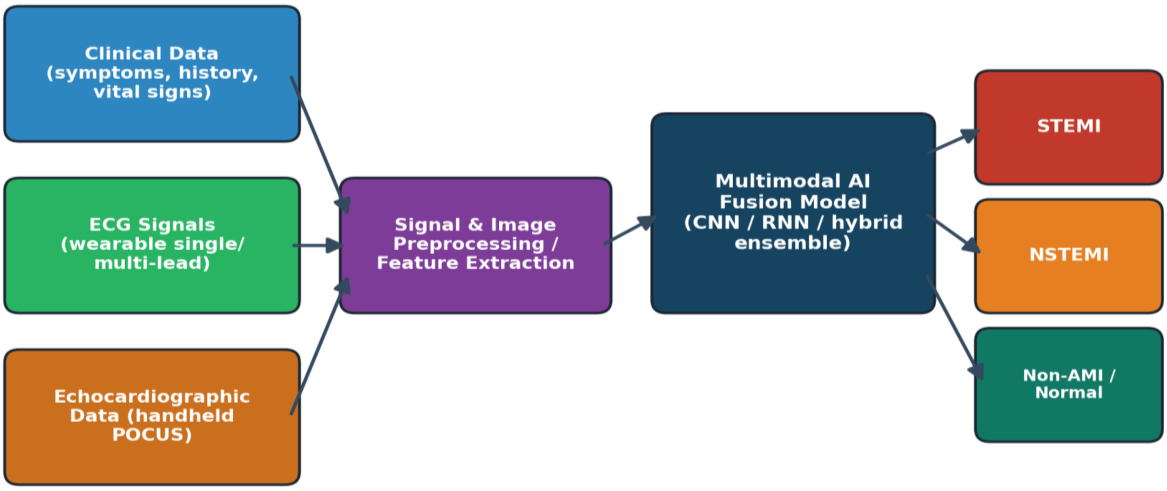

Figure 3. Proposed conceptual framework for a wearable, multimodal, AI-enabled diagnostic system for early detection and classification of acute myocardial infarction, synthesized from the reviewed literature on wearable ECG, AI-assisted point-of-care echocardiography, and deep-learning fusion architectures.

Underlying this fusion concept is a standard signal- and image-processing pipeline common to most reviewed AI-ECG systems: raw signal acquisition, denoising and normalization, feature extraction, deep-learning classification, and generation of a diagnostic output or alert (Figure 4). Classical preprocessing techniques, including QRS-complex detection (Pan & Tompkins, 1985) and, more recently, deep-learning-based waveform segmentation (Zhong et al., 2018), continue to underpin even the most modern end-to-end architectures reviewed in Section 6.

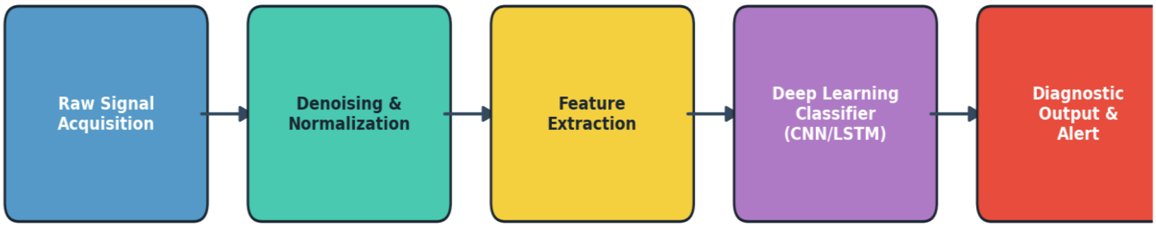

Figure 4. Typical artificial-intelligence processing pipeline underlying wearable ECG-based myocardial infarction detection systems reviewed in this article.

Table 3: Summary of reported diagnostic performance across the five technology domains reviewed in Sections 5–9.

Domain	**Representative technology**	**Reported diagnostic performance**	**Key sources**
Wearable ECG (rhythm)	Single-lead smartwatch ECG	Sensitivity 83–100%; specificity 79–100% (AF)	Iqhrammullah et al., 2025; Perez et al., 2019
Wearable ECG (ischaemia)	Multichannel smartwatch reconstruction	High agreement with 12-lead ECG for ST changes (supervised settings)	Iqhrammullah et al., 2025
AI-ECG (MI detection)	CNN / ResNet / attention models	AUC generally > 0.90; accuracy frequently > 95%	Acharya et al., 2017; Xiong et al., 2022; Hilgendorf et al., 2025
POC high-sensitivity troponin	Whole-blood POC hs-cTnI assays	AUC 0.93–0.95, comparable to central laboratory	Koechlin et al., 2024; Zalama-Sánchez et al., 2024

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AI-assisted handheld echocardiography	Novice-operator handheld POCUS + AI	AUC 0.88 for reduced LVEF detection	Huang et al., 2024; Campbell et al., 2025

Applications and Evidence Gaps in Low- and Middle-Income Settings

The health-system rationale for an integrated wearable multimodal AMI-detection device is arguably strongest in low- and middle-income countries, where the shortage of cardiologists, sonographers, and central-laboratory infrastructure most directly translates into diagnostic delay and preventable mortality (Bloomfield et al., 2013; Keates et al., 2017; Minja et al., 2022). Nonetheless, the majority of wearable ECG validation studies, AI-ECG training datasets, and AI-assisted echocardiography trials reviewed above were conducted in North American, European, or East Asian populations and healthcare settings, raising legitimate questions about algorithmic generalizability to African populations, disease-prevalence profiles, and equipment-resource contexts (Mocumbi, 2012).

In Uganda specifically, the epidemiological transition toward non-communicable disease is well documented at the population risk-factor level, but hospital-based data specifically characterizing STEMI and NSTEMI presentations, treatment pathways, and diagnostic delay remain comparatively sparse relative to the volume of literature available from high-income settings. This evidence gap reinforces the case for context-specific validation of any wearable multimodal diagnostic device prior to clinical deployment, including recalibration of AI models on locally representative ECG and echocardiographic data, and prospective evaluation of diagnostic accuracy, workflow integration, and cost-effectiveness within Ugandan emergency and referral-hospital settings.

Explainability, Trust, and Clinical Adoption of AI Diagnostic Systems

Diagnostic accuracy alone does not guarantee clinical adoption of AI-based decision-support tools. A systematic review of clinician trust in AI-based clinical decision-support systems identified explainability, transparency, and human-centred design as consistent determinants of whether healthcare workers are willing to act on algorithmic recommendations (Abbas et al., 2025). A broader narrative synthesis similarly found that while explainable AI (XAI) methods can improve clinician confidence and appropriate reliance, poorly designed explanations risk fostering overreliance or confusion, indicating that the objective of XAI in clinical settings should be calibrated rather than maximal trust (Mohammadi, 2026). Reviews focused specifically on medical image analysis have reached comparable conclusions, noting that the opacity of deep-learning models remains a central barrier to adoption in settings — such as emergency cardiac triage — where decisions carry immediate medico-legal and clinical consequences (Muhammad & Bendechache, 2024).

Factors identified across this literature as influencing clinician trust in medical AI include explainability, interpretability, usability, provenance of training data, and structured education about model capabilities and limitations (Tucci, 2022). For a wearable multimodal AMI-detection system intended for use by non-specialist clinicians, nurses, or emergency responders in resource-constrained settings, these findings suggest that model outputs should be accompanied by interpretable visual or textual justification — for example, highlighting the ECG leads or echocardiographic regions driving a STEMI classification — rather than presenting a bare probability score.

Ethical, Regulatory, and Data-Privacy Considerations

Deployment of a wearable, AI-enabled diagnostic device for a time-critical, life-threatening condition raises regulatory and ethical considerations distinct from those applicable to lower-acuity wearable health applications. Regulatory clearance pathways for AI-based diagnostic algorithms — whether functioning as software as a medical device or embedded within a combined hardware-software product — require prospective validation of sensitivity and specificity against a recognized reference standard, together with post-market surveillance to detect performance drift across populations and hardware revisions (Koechlin et al., 2024). Continuous physiological monitoring and cloud-connected Internet-of-Things architectures, of the type reviewed for wearable cardiac biosensors (Lee et al., 2018; Bhaltadak et al., 2024), also raise data-security and privacy obligations, particularly where personally identifiable health data are transmitted over mobile networks in settings with variable connectivity and cybersecurity infrastructure. Any wearable AMI-detection system intended for deployment in Uganda or comparable settings would need to align with applicable national data-protection frameworks and international medical-device regulatory guidance, alongside context-specific consideration of consent, affordability, and equitable access.

Wearable Biosensors, Flexible Electronics, and Connectivity Architectures

Advances in flexible and stretchable materials science have enabled cardiac biosensors that conform to the skin surface, permitting long-term ambulatory monitoring with a form factor unattainable with rigid conventional electrodes. Early flexible, disposable cardiac sensors demonstrated that ultrathin, lightweight ECG patches could achieve signal quality suitable for ambulatory rhythm monitoring while remaining low-cost enough for single-use deployment (Lee et al., 2018). More recent reviews of wearable technologies in cardiovascular medicine describe the convergence of sensor miniaturization, on-device signal processing, and cloud connectivity into integrated Internet-of-Things (IoT) health-monitoring platforms capable of transmitting continuous physiological data to remote clinical review (Bhaltadak et al., 2024; Gaoudam et al., 2025).

For a device intended to integrate clinical, ECG, and echocardiographic inputs, connectivity architecture is a non-trivial design consideration: physiological streams must be acquired, locally preprocessed to reduce transmission bandwidth and preserve battery life, and either processed on-device (edge computing) or transmitted to a cloud-based inference engine, with each approach carrying distinct trade-offs in latency, power consumption, connectivity dependence, and data-privacy exposure relevant to deployment in areas with unreliable network coverage. Advances in low-power biosignal sensor materials (Kim et al., 2024) and IoT-connected biosensor platforms (Bhaltadak et al., 2024) suggest that on-device edge inference, with intermittent cloud synchronization for model updates and clinical audit, may be the more pragmatic architecture for pre-hospital and rural deployment contexts.

Synthesis: Toward an Integrated Wearable Multimodal Diagnostic Pathway

Synthesizing the evidence reviewed in Sections 5–9, three observations emerge. First, each individual technology domain — wearable ECG, AI-assisted echocardiography, and point-of-care troponin testing — has reached a level of diagnostic maturity that would plausibly support integration into a combined device, with reported accuracy metrics for each modality summarized in Table 3. Second, the strongest existing evidence for AI-based STEMI/NSTEMI classification remains ECG-centric, and while multimodal fusion is conceptually well supported, published systems that combine clinical, electrocardiographic, and echocardiographic streams into a single classifier remain limited, representing the principal technical gap for a device of the kind proposed in this review. Third, evidence specifically generated in, or validated for, low- and middle-income health-system contexts — including Uganda — is markedly under-represented relative to the scale of unmet clinical need in these settings, underscoring both the opportunity and the validation burden associated with developing such a device for deployment in sub-Saharan Africa.

Limitations of the Current Evidence Base

Several limitations of the underlying literature should be considered when interpreting the synthesis presented in this review. Many of the wearable ECG and AI-assisted echocardiography studies cited were conducted under supervised, single-centre, or tertiary-hospital conditions that may not generalize to unsupervised or pre-hospital use by non-specialist operators. Deep-learning ECG models are frequently trained and internally validated on the same limited set of public benchmark datasets (for example, the PTB and PTB-XL databases), raising the possibility of optimistic performance estimates that may not replicate on independent, demographically distinct populations. Point-of-care troponin and AI-echocardiography studies, while increasingly multicentre, remain concentrated in high-income health systems with different case-mix, comorbidity prevalence, and equipment standards than typical LMIC emergency and referral facilities. Finally, because this is a narrative rather than a systematic review, formal risk-of-bias appraisal and meta-analytic pooling were not undertaken, and the reported accuracy ranges should be interpreted as indicative of the current evidence landscape rather than as pooled effect estimates.

Future Directions

Building on the gaps identified above, four priorities appear central to advancing an integrated wearable multimodal AMI-detection system. First, prospective multicentre studies are needed that explicitly fuse clinical, wearable-ECG, and AI-assisted echocardiographic data within a single classification pipeline and report standard diagnostic accuracy metrics against the Fourth Universal Definition of Myocardial Infarction as reference standard (Thygesen et al., 2018). Second, algorithm development and validation should deliberately include populations from sub-Saharan Africa and other under-represented LMIC settings, both to establish generalizability and to identify any population-specific recalibration requirements. Third, human-factors research is required to determine how model outputs — including explainable-AI visualizations — should be presented to non-specialist clinicians, nurses, and emergency responders operating such a device under time pressure (Abbas et al., 2025; Mohammadi, 2026). Fourth, health-economic and implementation-science evaluation will be necessary to establish the cost-effectiveness, workflow feasibility, and regulatory pathway for deployment of such a device within resource-constrained emergency and pre-hospital cardiac-care systems.

CONCLUSION

Acute myocardial infarction continues to impose a substantial and, in low-resource settings, disproportionate global health burden, and rapid differentiation of STEMI from NSTEMI remains central to reducing preventable morbidity and mortality. The literature reviewed here demonstrates that wearable electrocardiography, deep-learning ECG interpretation, AI-assisted point-of-care echocardiography, and point-of-care high-sensitivity troponin testing have each individually matured to a point of credible diagnostic performance. The principal unmet opportunity lies in the multimodal fusion of these data streams into a single, low-cost, wearable diagnostic pathway validated for use by non-specialist operators in emergency, pre-hospital, and low-resource settings such as those in Uganda. Realizing this opportunity will require not only further engineering and algorithmic development, but also context-specific clinical validation, attention to explainability and clinician trust, and careful navigation of the regulatory and data-privacy considerations attached to AI-enabled diagnosis of a life-threatening, time-critical condition.

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