A Conceptual Multimodal Wearable Platform for Acute Myocardial Infarction Risk Estimation Using Clinical, Electrocardiographic and Echocardiographic Data

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ABSTRACT

Acute myocardial infarction (AMI) is a time-critical cardiovascular emergency in which early recognition of high-risk ischemic patterns can influence treatment decisions and access to timely reperfusion. Current assessment relies mainly on clinical evaluation, 12-lead electrocardiography (ECG), serial high-sensitivity cardiac troponin (hs-cTn) measurements, and, where indicated, cardiac imaging. While these approaches provide complementary diagnostic information, delays in obtaining and interpreting investigations, limited laboratory and specialist capacity, and difficulty recognizing subtle or initially non-diagnostic ischemic changes can delay appropriate care. These challenges are particularly relevant in pre-hospital and resource-constrained settings. This review examines clinical, technological, and engineering evidence relevant to the development of a conceptual multimodal wearable platform for early recognition and risk estimation of AMI, with emphasis on STEMI-pattern ischemia, suspected NSTEMI, and occlusion myocardial infarction (OMI). The review also develops a proposed system architecture, preliminary engineering requirements, a quality-aware approach to multimodal data fusion, and a staged pathway for development and validation. Evidence was synthesized from the supplied reference set, clinical guidelines, systematic reviews, studies of wearable ECG systems, AI-assisted ECG analysis, artificial-intelligence applications in echocardiography, and emerging transdermal biomarker technologies. Established clinical practices were considered separately from technologies that remain at an experimental or early-development stage. The reviewed evidence suggests that the proposed modalities could provide complementary information rather than replace existing diagnostic methods. Clinical variables can help establish pre-test probability, while ECG provides immediate information on cardiac electrical activity. Echocardiography can add mechanical evidence, including regional wall-motion abnormalities, whereas emerging optical and transdermal technologies may eventually provide biochemical information. Wearable ECG systems offer potential for continuous or on-demand monitoring, although differences in lead configuration, motion artifacts, signal-quality variation, and electrode placement limit their direct equivalence to standard 12-lead ECG. Portable echocardiography is more realistically suited to episodic, connected assessment than to integration into a conventional wrist-worn device. Similarly, although artificial intelligence may improve recognition of clinically relevant patterns, issues relating to generalizability, calibration, missing data, false alerts, uncertainty, and prospective clinical validation remain unresolved. Based on the current evidence, the most realistic near-term application is a modular multimodal decision-support platform that produces calibrated risk estimates and reports signal quality alongside the available physiological measurements. Such a system should complement, rather than replace, clinical assessment, standard 12-lead ECG, serial hs-cTn testing, and indicated cardiac imaging. The proposed framework therefore provides a practical foundation for prototype development, analytical performance testing, silent-mode prospective

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evaluation, external validation, and subsequent clinical outcome studies. It also avoids assuming a level of technological and clinical maturity that has not yet been demonstrated.

Keywords: Acute myocardial infarction; STEMI; NSTEMI; occlusion myocardial infarction; wearable ECG; echocardiography; cardiac troponin; multimodal artificial intelligence; clinical decision support; digital health; point-of-care diagnosis.

INTRODUCTION

Acute myocardial infarction (AMI) is a time-critical cardiovascular condition in which early recognition and appropriate treatment can substantially influence clinical outcomes. The current definition distinguishes myocardial injury from myocardial infarction: an elevated cardiac troponin concentration indicates myocardial injury, whereas the diagnosis of infarction requires evidence of acute myocardial injury together with clinical evidence of myocardial ischemia [1]. In practice, this assessment brings together the patient's symptoms and clinical history, electrocardiography (ECG), serial cardiac troponin measurements, and, where appropriate, cardiac imaging. Current acute coronary syndrome (ACS) guidelines emphasize rapid assessment, early ECG acquisition, appropriate use of high-sensitivity cardiac troponin (hs-cTn), risk stratification, and timely reperfusion or invasive management according to the clinical presentation [2]. For any technology intended to support earlier recognition of AMI, therefore, the challenge is not simply to generate another diagnostic signal, but to provide reliable information without implying that a single wearable measurement can replace established clinical assessment.

The distinction between ST-elevation myocardial infarction (STEMI) and non-ST-elevation myocardial infarction (NSTEMI) remains important because patients presenting with clear ST-elevation may require immediate reperfusion, whereas many patients without diagnostic ST-elevation undergo further assessment using serial biomarkers, clinical findings, risk stratification, and other investigations [2]. At the same time, the conventional STEMI/NSTEMI classification does not fully describe the underlying coronary pathology. Studies using the concept of occlusion myocardial infarction (OMI) have shown that acute coronary occlusion can occur without meeting conventional STEMI criteria, creating a group of patients who may be less readily identified by the traditional binary classification [3–5]. This limitation has increased interest in ECG features that may indicate coronary occlusion even when the conventional ST-elevation thresholds are not met. More recently, machine-learning models trained on ECG data have demonstrated the potential to identify OMI-related patterns that may be missed by conventional interpretation, although such approaches still require broader prospective validation before they can be incorporated into routine clinical decision-making [6].

The diagnostic challenge is therefore inherently multimodal. Symptoms, medical history, and cardiovascular risk factors contribute to the initial assessment of the likelihood of ACS, but none of these variables is sufficiently specific to establish myocardial infarction on its own. ECG provides rapid information about cardiac electrical activity and remains central to the initial assessment. However, most wearable ECG systems are designed around one or a limited number of leads and therefore do not provide the same spatial information as a conventional 12-lead ECG. Wearable cardiac-monitoring technologies can nevertheless support repeated or prolonged acquisition outside the clinical environment, which may be useful when intermittent symptoms or transient electrical abnormalities are suspected [7]. This distinction is important when considering a wearable AMI platform: a wearable ECG should initially be regarded as an additional source of information rather than as a direct substitute for a diagnostic-quality 12-lead recording.

Cardiac biomarkers provide another important component of AMI assessment. High-sensitivity cardiac troponin has become central to the detection of myocardial injury and the evaluation of suspected ACS, but interpretation generally depends on the clinical context and, in many diagnostic pathways, serial measurements rather than a single isolated result [2]. This creates an obvious limitation for a purely wearable system because laboratory-based hs-cTn testing cannot currently be assumed to be available continuously through a conventional wrist-worn device.

Echocardiography provides a different form of evidence by allowing assessment of ventricular function and regional wall-motion abnormalities. Focused and portable cardiac ultrasound has also become increasingly

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relevant in settings where conventional imaging services are difficult to access. Evidence from resource-limited settings, including sub-Saharan Africa, indicates that simplified cardiac ultrasound protocols can be implemented outside traditional specialist centres, although image acquisition and interpretation remain dependent on appropriate training and adequate imaging conditions [8,9].

Wearable and connected health technologies provide an opportunity to extend cardiovascular monitoring beyond hospitals and specialist clinics. Contemporary wearable systems can incorporate ECG, photoplethysmography (PPG), motion sensing, oxygen saturation, temperature, and other physiological measurements [7,10]. PPG is particularly attractive for wearable applications because it can be acquired continuously using relatively simple optical sensors, although its measurements are affected by factors such as motion and changes in the conditions of optical contact with the skin [10]. These signals could provide useful physiological context around an ECG recording, but they should not be treated as direct substitutes for the electrical or biochemical measurements used in established AMI diagnosis.

A multimodal approach may therefore be more realistic than attempting to build a single wearable sensor capable of independently diagnosing AMI. Continuous or on-demand wearable ECG could provide electrical information; structured clinical information could contribute to the assessment of pre-test probability; portable echocardiography could provide episodic mechanical evidence; and future non-invasive biochemical sensors could potentially add information about myocardial injury if their analytical and clinical performance is demonstrated. The combination of these modalities could also allow the system to recognize when one source of information is unavailable or of insufficient quality rather than forcing a diagnostic decision from an unreliable signal. Artificial intelligence (AI) offers another possible means of integrating these heterogeneous data streams. In particular, machine-learning approaches have shown promise in extracting clinically relevant information from ECG waveforms, including patterns associated with OMI that may not be readily recognized using conventional criteria [6]. However, promising retrospective performance does not establish clinical effectiveness. Differences between patient populations, acquisition devices, signal quality, disease prevalence, and clinical workflows can affect model performance. Issues such as calibration, missing modalities, false alerts, uncertainty estimation, and external validation therefore need to be addressed before an AI-enabled multimodal system can be considered suitable for routine clinical use. Against this background, this review does not claim that a clinically validated wearable device capable of independently diagnosing AMI is currently available. Instead, it develops a conceptual framework for a multimodal decision-support platform in which the wearable sensing unit forms one component of a broader clinical system. The review considers the separation between continuous wearable sensing and episodic clinical measurements, identifies preliminary engineering requirements, examines the potential role of AI-based multimodal fusion, and proposes a staged pathway for analytical, technical, and clinical validation. This approach is intended to keep the proposed system technically achievable while maintaining a clear distinction between established AMI diagnostic practice and technologies that are still under development.

REVIEW METHODOLOGY

This article uses a structured narrative-integrative review approach because the evidence relevant to the proposed platform comes from several different fields, including clinical cardiology, diagnostic medicine, wearable sensing, artificial intelligence (AI), echocardiography, and emerging biomarker technologies. These sources differ considerably in study design, outcome measures, and technological maturity. A quantitative meta-analysis was therefore not considered appropriate for the present objective. Instead, the review brings together findings from these areas and uses them to develop a clinically defensible and technically realistic framework for a multimodal AMI decision-support platform.

Evidence Identification Framework

The literature was organized into five main evidence domains: (i) the definition, diagnosis, and clinical management of AMI and acute coronary syndrome (ACS); (ii) wearable and limited-lead ECG acquisition and interpretation; (iii) artificial-intelligence approaches for ECG analysis and occlusion myocardial infarction (OMI) recognition; (iv) portable echocardiography and automated assessment of regional wall-motion

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abnormalities (RWMA); and (v) cardiac biomarker sensing and emerging multimodal digital-health technologies.

Priority was given to peer-reviewed journal articles, clinical guidelines, consensus documents, systematic or state-of-the-art reviews, and primary diagnostic and technology studies. The evidence was considered in relation to the intended role of each modality rather than simply according to reported diagnostic performance. This was important because the proposed platform combines technologies that are already established in clinical practice with others that remain at an early research stage. For example, 12-lead ECG and laboratory cardiac troponin testing have established clinical roles, whereas wearable ECG configurations, AI-based OMI detection, and transdermal troponin measurement require further validation before their findings can be considered clinically equivalent to conventional methods [11–16].

Eligibility and Evidence Weighting

Evidence was weighted according to its clinical maturity and relevance to the proposed system. The universal definition of myocardial infarction and contemporary ACS guidance were used as the primary sources for diagnostic terminology, clinical pathways, and safety boundaries [11,12]. Peer-reviewed reviews were used to establish the current state of wearable cardiac monitoring and related technologies [13]. Primary studies were then used where specific technical or diagnostic claims required direct supporting evidence, particularly for AI-assisted ECG interpretation, OMI recognition, echocardiographic RWMA detection, and emerging transdermal cardiac biomarker approaches [14–18].

The synthesis distinguishes four stages of technological and clinical evidence: analytical feasibility, diagnostic discrimination, clinical validation, and clinical utility. This distinction is important for the proposed platform. Demonstrating that a sensor can acquire a physiological signal does not establish that the signal is diagnostically reliable. Similarly, a machine-learning model with strong discrimination in a retrospective dataset does not by itself demonstrate clinical benefit or improved patient outcomes. Wearable cardiac monitoring has demonstrated considerable potential for long-term physiological data collection, but its appropriate clinical role depends on the intended application, signal quality, and validation in representative patient populations [13].

Emerging technologies were therefore treated conservatively. In particular, non-invasive cardiac biomarker sensing was considered a potential future component rather than an established replacement for laboratory hs-cTn testing. Transdermal cardiac troponin measurement has been proposed as a future direction, but its analytical and clinical equivalence to conventional laboratory assays has not yet been established [18]. This distinction is maintained throughout the review.

CLINICAL AND DIAGNOSTIC BASIS OF THE PROPOSED PLATFORM

Clinical Definition and Target Phenotypes

For an engineering system intended to estimate the likelihood of AMI, the target condition must be defined independently of the signals used by the model. The reference standard should therefore be based on clinical adjudication using the established diagnostic framework, including symptoms and clinical findings, serial cardiac troponin measurements, 12-lead ECG, imaging, angiographic findings when available, and relevant follow-up information [11,12]. This approach reduces the risk of circular labeling, in which an abnormal wearable measurement is used both as the predictor and as part of the definition of the outcome being predicted.

The proposed platform should consequently avoid reducing its output to a simple positive or negative diagnosis. A more appropriate output could include: (i) an estimated probability of acute myocardial ischemia or infarction; (ii) an estimated probability of a high-risk ischemic ECG pattern; (iii) an estimated probability of an OMI or other high-risk occlusive phenotype; and (iv) an explicit indeterminate or inadequate-signal state. These outputs should be interpreted as risk estimates and escalation signals rather than as independent diagnoses.

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Such an approach is consistent with the current clinical understanding of AMI, in which myocardial injury must be interpreted in the context of evidence of ischemia [11]. It also provides a safer basis for integrating heterogeneous sensor information because the system can indicate when the available evidence is insufficient rather than forcing a definitive classification.

STEMI, NSTEMI and OMI

ST-elevation myocardial infarction (STEMI) is commonly associated with acute coronary occlusion and characteristic ST-segment elevation on the ECG, although the relationship between ST elevation and coronary occlusion is not absolute [12,14]. NSTEMI, by contrast, involves acute myocardial injury in an ischemic clinical setting without a diagnostic ST-elevation pattern. Its assessment therefore depends more heavily on the combination of clinical presentation, serial cardiac troponin measurements, ECG findings, and other evidence of ischemia [11,12].

For a wearable platform, these differences have important engineering implications. Recognition of a high-risk ischemic ECG pattern is a more realistic initial target than attempting to diagnose NSTEMI independently from a wearable signal. The platform should instead estimate the likelihood of acute ischemia or myocardial injury and use an elevated estimate to prompt conventional assessment with 12-lead ECG, hs-cTn, and clinical evaluation. This is particularly important because an elevated troponin concentration can reflect myocardial injury arising from conditions other than type 1 MI, including systemic illness and other forms of cardiac stress [11].

OMI provides a useful secondary target because it focuses attention on acute coronary occlusion rather than on ST elevation alone. Research has shown that some patients with acute coronary occlusion do not satisfy conventional STEMI criteria, and this has motivated approaches that attempt to identify occlusion-related ECG patterns beyond simple ST-elevation thresholds [14,15]. Machine-learning models have subsequently demonstrated the ability to identify ECG features associated with OMI and to improve discrimination in selected study populations [16]. Nevertheless, such models should be understood as decision-support tools. A wearable platform cannot establish anatomical coronary occlusion from ECG data alone, and its output should therefore be described as a high-risk occlusion phenotype or suspected OMI, rather than as confirmation of an occluded artery.

EVIDENCE FOR INDIVIDUAL DATA MODALITIES

Clinical Variables

Clinical information remains an essential component of AMI assessment because symptoms, medical history, risk factors, and haemodynamic status influence the initial probability of ACS. Relevant information may include age, sex, diabetes, hypertension, smoking status, dyslipidaemia, established coronary artery disease, previous myocardial infarction, chronic kidney disease, family history, symptom onset, characteristics of chest discomfort, dyspnoea, diaphoresis, syncope, and vital signs. Structured risk scores such as the HEART score illustrate the value of combining clinical history, ECG findings, age, cardiovascular risk factors, and troponin measurements when assessing patients with suspected ACS [19].

For the proposed platform, these variables could be entered through a smartphone or clinical interface. Where interoperable electronic records are available, selected demographic and historical information could be retrieved automatically. Clinical information should contribute to the overall risk estimate rather than override a clearly abnormal physiological signal. Conversely, a low-risk clinical profile should not be used to suppress an otherwise concerning ECG or other objective finding.

Electrocardiographic Sensing

ECG is the most immediate electrical modality available for the assessment of suspected myocardial ischemia. Conventional 12-lead ECG provides spatial information from multiple anatomical perspectives, whereas many wearable devices use a single lead or a limited number of electrodes. Wearable cardiac-monitoring systems are

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well suited to repeated or prolonged measurements, but their configuration and acquisition conditions differ from those of diagnostic 12-lead ECG systems [13].

The ECG component of the proposed platform should therefore have a clearly defined lead configuration and intended use. A multi-electrode chest patch or flexible electrode arrangement may provide more spatial information than a conventional watch-based single-lead configuration. Other possibilities include repeated recordings from predefined body positions or computational estimation of additional lead information. However, reconstructed or inferred leads should remain research outputs until their performance has been demonstrated against simultaneously acquired clinical 12-lead ECGs. Signal quality should be assessed before diagnostic inference is attempted. The quality-control layer should be capable of identifying baseline drift, electrical interference, motion artifact, electrode detachment, signal saturation, and inadequate skin contact. This is particularly important for wearable systems because prolonged ambulatory acquisition introduces movement and electrode-position variability that are less prominent during controlled clinical ECG acquisition [13]. The available evidence supports the feasibility of wearable ECG for ambulatory cardiac monitoring, but it does not justify treating a limited-lead wearable recording as interchangeable with a standard diagnostic ECG [13]. Accordingly, a high-risk wearable alert should trigger confirmation using a conventional 12-lead ECG rather than serve as the sole basis for a diagnosis of AMI.

Echocardiography

Echocardiography contributes information that is complementary to ECG because it provides direct assessment of cardiac structure and mechanical function. Regional wall-motion abnormalities, ventricular systolic function, chamber dimensions, and other structural findings can provide additional evidence when myocardial ischemia is suspected. RWMA can be particularly informative when the abnormality corresponds to a plausible coronary distribution, although such findings must be interpreted within the clinical context [11,20].

Recent studies have demonstrated that artificial-intelligence methods can assist with automated RWMA detection from echocardiographic images. For example, deep-learning models have been evaluated for identifying regional abnormalities across coronary territories, while other studies have examined automated analysis of echocardiographic images and comparison with human readers [17,20]. These findings support the feasibility of automated image interpretation but do not eliminate the need for adequate image acquisition and clinical oversight.

The near-term architecture should therefore not assume that full echocardiography can be incorporated into a wrist-worn device. A more realistic design would connect the continuous wearable sensing unit to a handheld or portable ultrasound probe used when the risk engine or clinician determines that additional imaging is warranted. Predefined echocardiographic views could be acquired during these episodes, followed by automated image-quality assessment before any RWMA analysis is attempted. There is also an important clinical limitation. An RWMA is not, by itself, proof of a new myocardial infarction. Previous infarction, cardiomyopathy, conduction abnormalities, ventricular pacing, and other cardiac conditions can produce abnormal regional motion. The interpretation of a detected RWMA should therefore incorporate previous imaging, when available, together with the patient's current clinical and ECG findings [20].

Hs-cTn and Emerging Transdermal Sensing

High-sensitivity cardiac troponin remains a central laboratory biomarker for detecting myocardial injury and contributes substantially to the diagnosis and risk assessment of suspected ACS [11,12]. Its measurement, however, normally requires a biological sample and laboratory or point-of-care analytical equipment. This limits its direct integration into conventional wearable devices.

Transdermal or non-invasive troponin sensing is consequently of interest as a possible future component of multimodal wearable systems. Early work and technical discussions have considered whether cardiac troponins might eventually be measured through the skin, potentially providing biochemical information without venous blood sampling [18]. At present, however, this technology should be regarded as investigational rather than as an alternative to laboratory hs-cTn.

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A future transdermal sensing channel would need to demonstrate analytical sensitivity and specificity, an appropriate limit of detection, calibration stability, repeatability, inter-device consistency, and robustness to factors such as skin characteristics, tissue perfusion, temperature, hydration, motion, and environmental conditions. Most importantly, its measurements would need to be compared directly with validated laboratory hs-cTn assays in clinically relevant populations.

For these reasons, the proposed platform should treat transdermal biomarker sensing as an optional research module. Until analytical equivalence and clinical performance have been demonstrated, it should not influence clinical decision-making in the same manner as laboratory hs-cTn. This conservative approach allows the technology to be incorporated into future prototype development without overstating its current maturity.

CONCEPTUAL MULTIMODAL PLATFORM ARCHITECTURE

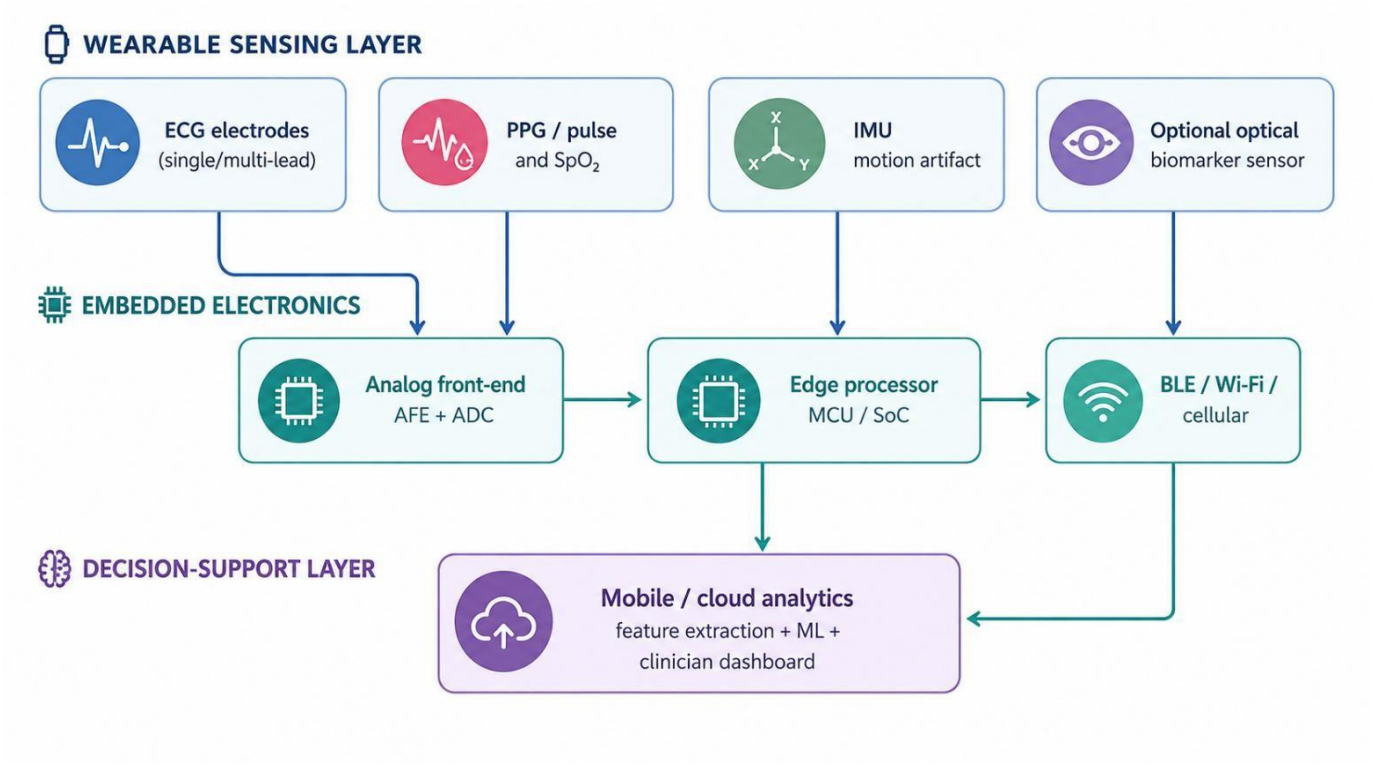

Figure 1. Proposed multimodal diagnostic architecture for early AMI risk estimation. The architecture separates continuous wearable sensing from episodic portable echocardiography and optional future biochemical sensing; all modalities enter a quality-aware decision-support engine.

PROPOSED MULTIMODAL PLATFORM ARCHITECTURE

The proposed system is conceived as a modular platform rather than as a single wearable sensor. The continuous wearable unit would primarily acquire ECG together with supporting physiological signals, such as photoplethysmography (PPG) and motion data from an inertial measurement unit (IMU). A smartphone, tablet, or dedicated gateway could serve as the communication and processing interface, allowing structured clinical information to be entered, physiological events to be time-stamped and synchronized, and relevant data to be transmitted to the decision-support layer. This type of distributed architecture is consistent with the broader development of wearable cardiovascular monitoring, where multiple sensing and communication components are combined to support continuous or intermittent physiological assessment [21,22].

Portable echocardiography would constitute a separate, connected component of the platform. Rather than attempting to incorporate ultrasound imaging into the continuously worn device, a handheld or portable ultrasound probe could be used when the initial assessment indicates that additional cardiac information is required. The resulting images could then be transferred to the decision-support engine for image-quality assessment and, where validated, automated analysis of ventricular function and regional wall motion [23,24].

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The decision-support engine would combine the available clinical and physiological information and generate a calibrated estimate of risk rather than a definitive diagnosis. Its outputs should include the estimated level of AMI-related risk, the quality or adequacy of each available signal, and an indication of the appropriate level of clinical urgency. Importantly, the system should be capable of operating with incomplete data. For example, an episode may contain a high-quality ECG but no echocardiographic examination, or an ultrasound study may be unavailable because the required probe or trained operator is not present. The architecture should therefore accommodate missing modalities without treating unavailable information as normal or artificially replacing it with unreliable estimates.

This modular arrangement also addresses an important practical issue in wearable-device engineering. Continuous monitoring requires a device that is small, comfortable, energy-efficient, and capable of acquiring physiological signals over extended periods. Echocardiography has very different hardware, power, data-processing, and operator requirements and is therefore better suited to episodic assessment than continuous wrist-based monitoring. Separating these functions allows the wearable component to remain focused on continuous surveillance while the portable ultrasound unit is introduced when additional mechanical information is justified. The platform remains integrated because the measurements are time-synchronized, transferred through a common communication pathway, and interpreted within the same decision-support workflow.

The proposed architecture should therefore be understood as an integrated multimodal clinical decision-support system, rather than as a single device that independently diagnoses AMI. This distinction is consistent with current evidence on wearable cardiac monitoring, which supports the use of wearable devices for ambulatory physiological data acquisition but also highlights the differences between wearable measurements and conventional diagnostic investigations [21]. It also provides a more realistic pathway for subsequent prototype development, because individual sensing components can be evaluated independently before their combined performance is assessed in prospective clinical studies.

WEARABLE HARDWARE AND COMMUNICATION ARCHITECTURE

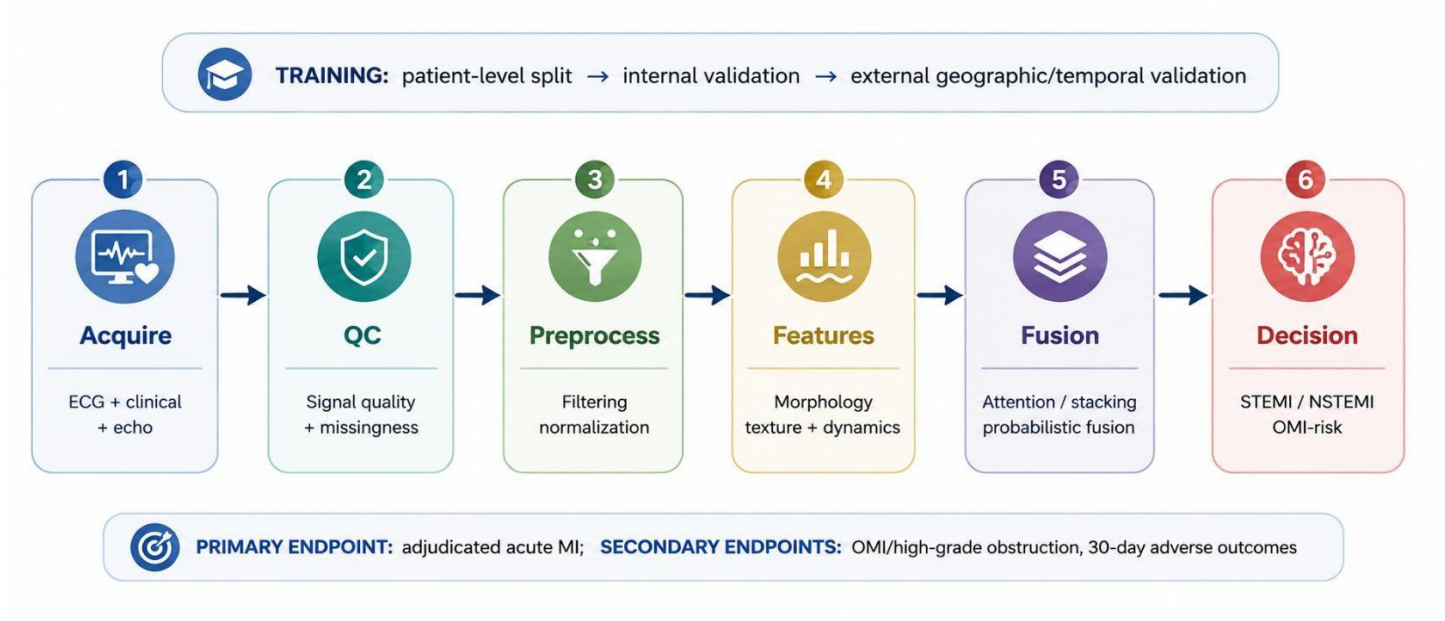

Figure 2. Proposed hardware and communication architecture of the wearable platform. The architecture separates sensing, analogue front-end processing, embedded computation, wireless communication, data security and clinical decision support.

ECG Front End

The ECG front end should be designed around medical-grade instrumentation amplification with high common-mode rejection and low input-referred noise to ensure that small cardiac signals can be captured

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reliably. The design should also incorporate appropriate input protection, lead-off detection, and controlled filtering to reduce interference without removing clinically relevant ECG features. For the initial prototype, it would be preferable to use a clearly defined 1–3 channel chest-mounted configuration rather than referring broadly to a "wearable ECG." The choice of leads and electrode locations should be specified in advance and evaluated against simultaneously recorded clinical 12-lead ECG signals during validation. This comparison will help establish the extent to which the wearable configuration can reproduce clinically relevant ECG information.

Provisional Engineering Requirements

The original article described the engineering requirements mainly in qualitative terms and did not establish specific quantitative targets for prototype development. To translate the proposed architecture into measurable engineering objectives, Table 1 presents a set of provisional requirements. These values are intended as practical starting points for system design and bench testing rather than as established clinical specifications. They should therefore be reviewed and refined as experimental results become available during prototype development, signal-quality testing, and subsequent validation.

Table 1. Provisional engineering specifications and design requirements for the proposed wearable AMI platform

Parameter	Provisional target / design requirement	Rationale
ECG channels	1–3 channels for initial prototype; chest-patch configuration preferred	Improves spatial information while retaining portability
Sampling rate	≥500 samples/s; verify against final diagnostic bandwidth	Preserves P-QRS-T morphology and supports ST analysis
ADC resolution	≥16-bit target	Supports low-amplitude ST-segment analysis
ECG bandwidth	Approximately 0.05–150 Hz, with application-specific digital filtering	Balances ST preservation and high-frequency morphology
Input protection	Medical electrical safety and defibrillation/ESD protection appropriate to intended use	Protects the patient and ECG front-end circuitry
Signal-quality index	Continuous assessment of contact, motion, baseline wander, saturation and interference	Prevents inference from corrupted data
Lead-off detection	Required	Identifies electrode detachment or poor contact
Time synchronization	Common timestamp across wearable, gateway and ultrasound	Enables temporal multimodal fusion
Wireless link	Bluetooth Low Energy to gateway; cellular fallback where appropriate	Enables low-power local communication and remote escalation
Local storage	Sufficient for raw event segments and metadata during connectivity loss	Supports offline-first operation
Battery	Target ≥12 h continuous operation for prototype; verify by load testing	Supports clinical shifts and emergency use
Latency	Local high-risk alert target ≤30 s after adequate ECG segment acquisition	Supports rapid escalation without cloud dependence
Enclosure	Lightweight, sweat-resistant and cleanable; target <100 g for wearable unit	Improves usability and prolonged wear
Operating environment	Target 10–40 °C and clinically relevant humidity range; verify experimentally	Supports field and facility deployment
Security	Encrypted storage/transmission, authentication, audit trail and model-version logging	Protects clinical data and supports traceability

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Physiological and Motion Sensors

PPG can provide useful information about pulse and peripheral perfusion, while an inertial measurement unit (IMU) can provide information about body movement and posture. These sensors should not, however, be presented as independent detectors of AMI. Their main purpose within the proposed system is to provide additional physiological context and help identify periods when the ECG signal may be affected by movement or other artifacts. For instance, when substantial motion is detected, the system could reduce the weight assigned to the corresponding ECG segment or flag it for further review. Oxygen saturation and skin temperature may also provide useful contextual information, but their additional value for AMI assessment should be established through experimental and clinical evaluation rather than assumed in advance.

Embedded Processing, Communications and Interoperability

The embedded processor should handle the basic processing tasks required for reliable operation of the wearable unit. These tasks may include signal conditioning, signal-quality assessment, event detection, data protection, and relatively simple inference algorithms. More computationally demanding multimodal models could be executed on a connected smartphone or secure server when sufficient processing capacity and network connectivity are available. An edge-first approach would allow the system to continue performing essential functions even when continuous access to cloud services is unavailable, which is particularly relevant for deployment in rural and resource-constrained settings.

The communication layer should retain the information needed to interpret and audit each recorded event. This should include timestamps, sensor identifiers, signal-quality measures, model version, prediction confidence, and relevant system logs. Interoperability should also be considered from the early stages of development, with the system designed to use appropriate standard formats for clinical data and physiological waveforms. Importantly, the platform should distinguish between different reasons for missing information. A sensor that was unavailable, a recording that was of poor quality, a device that malfunctioned, and a modality that was not clinically required represent different situations and should not simply be treated as the same type of missing data.

MULTIMODAL DATA FUSION AND ARTIFICIAL INTELLIGENCE

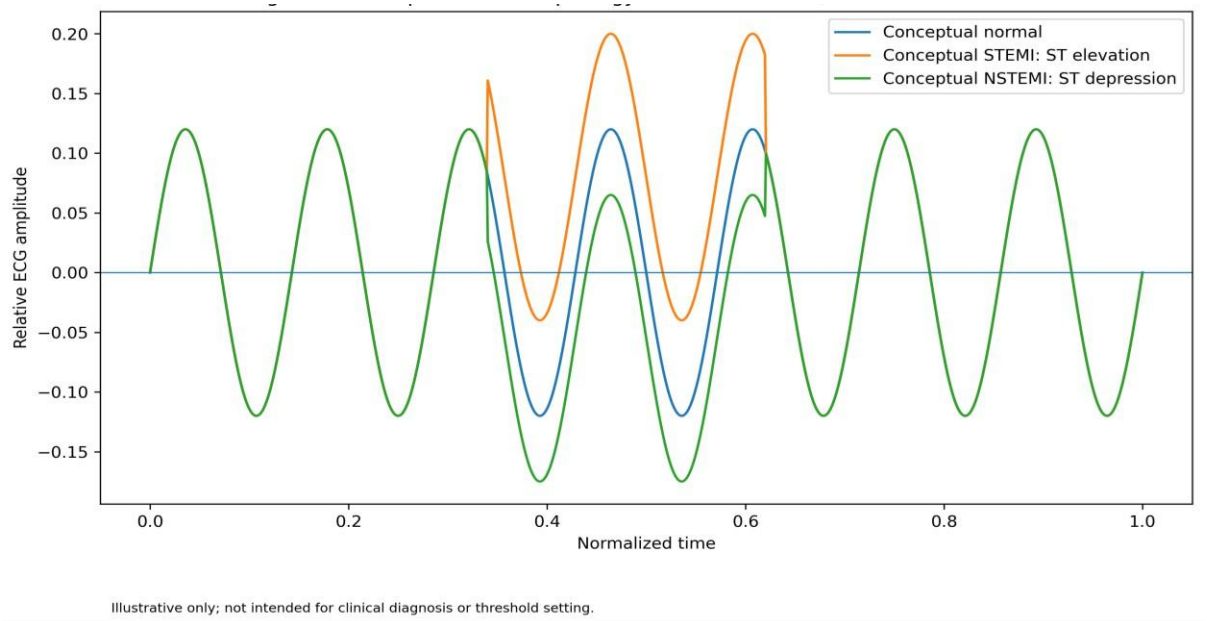

Figure 3. Proposed machine-learning and validation pipeline.

The revised framework emphasizes patient-level data separation, missing-modality handling, calibration, uncertainty estimation, external validation and prospective evaluation. The figure is retained as an original conceptual illustration and does not represent measured model performance.

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Feature Representation

The ECG component of the model may use features such as ST-segment deviation, T-wave morphology, QRS duration, QT/QTc interval, R-wave progression, cardiac rhythm, repolarization variability, and waveform representations learned directly from the ECG signal. Clinical inputs may include demographic characteristics, symptom descriptions, time of symptom onset, and established cardiovascular risk factors. From echocardiography, potentially useful features include the distribution of regional wall-motion abnormalities (RWMA), left ventricular ejection fraction (LVEF), chamber dimensions, wall thickness, ventricular volumes, and indicators of image quality [18].

For the proposed system, combining clinically recognizable features with learned representations would provide a useful balance between interpretability and predictive capability. Conventional engineered features allow clinicians and researchers to understand which physiological characteristics are contributing to a prediction, while learned representations may capture more complex relationships that are difficult to describe using predefined variables. The level of model complexity should therefore be determined from the available data and subsequent validation results, taking into account sample size, event prevalence, computational requirements, calibration, and performance on independent datasets rather than assuming that a more complex model will necessarily perform better.

Quality-Aware Fusion and Missing Modalities

The integration of information from different sensing modalities can generally be approached through early, intermediate, or late fusion. Early fusion combines normalized features from the different modalities before model training, intermediate fusion combines modality-specific representations within the model, and late fusion combines predictions generated separately by each modality. For the proposed platform, late fusion or another quality-aware approach may be particularly suitable because the system will not always have access to every modality during an assessment [17].

The model should explicitly recognize the condition of each data source. A modality may be available and of adequate quality, available but affected by poor signal quality, unavailable, or simply not required for a particular clinical situation. These conditions should not be treated as equivalent. Training the model with planned modality dropout could help it remain useful when some inputs are missing. At the time of prediction, the system should also indicate which modalities were actually used and whether missing or poor-quality information affected the confidence of the result.

Model Development and Validation

A range of algorithms could be considered during development, including logistic regression, random forests, gradient boosting, support-vector machines, multilayer perceptrons, convolutional neural networks, recurrent neural networks, transformers, and calibrated ensemble methods. The initial development stage should, however, begin with a relatively transparent model such as logistic regression or gradient boosting. This provides a useful baseline against which more complex approaches can be compared and helps determine whether additional model complexity produces a meaningful improvement in performance.

Before model training begins, the primary prediction target should be clearly defined. Possible targets include adjudicated acute myocardial infarction, high-risk STEMI-pattern ischemia, or angiographically supported occlusion myocardial infarction (OMI). Sample-size calculations should consider the expected frequency of the target event, the number of candidate predictors, and the requirement for independent validation [20]. Hyperparameter tuning should be performed using only the training data to avoid information leakage, and the final model should be fixed before it is evaluated on an external test dataset [18].

Explainability, Calibration and Uncertainty

Good discrimination alone is not sufficient for a system intended to support clinical decisions. The proposed platform should provide calibrated risk probabilities together with an indication of prediction uncertainty,

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signal quality, and the contribution of the available modalities. Methods such as saliency maps, SHAP values, and highlighted regions of ECG or echocardiographic data may help clinicians examine why a model produced a particular output. However, these methods should not automatically be interpreted as evidence of causal relationships. Their reliability, consistency, and practical value should be examined through appropriate human-factors and clinical evaluation [20].

The system should also be designed to recognize situations in which the incoming data differ substantially from those used during model development. Such differences may involve unfamiliar ECG morphologies, inadequate or unusual echocardiographic images, or patient characteristics that are poorly represented in the training population. In these situations, the system should be able to reduce its confidence or return an indeterminate result rather than produce a highly confident prediction from unfamiliar or corrupted data [18]. This type of uncertainty handling is particularly important for a multimodal clinical platform, where an apparently precise prediction may otherwise conceal limitations in the underlying measurements.

PROPOSED CLINICAL DECISION-SUPPORT ALGORITHM

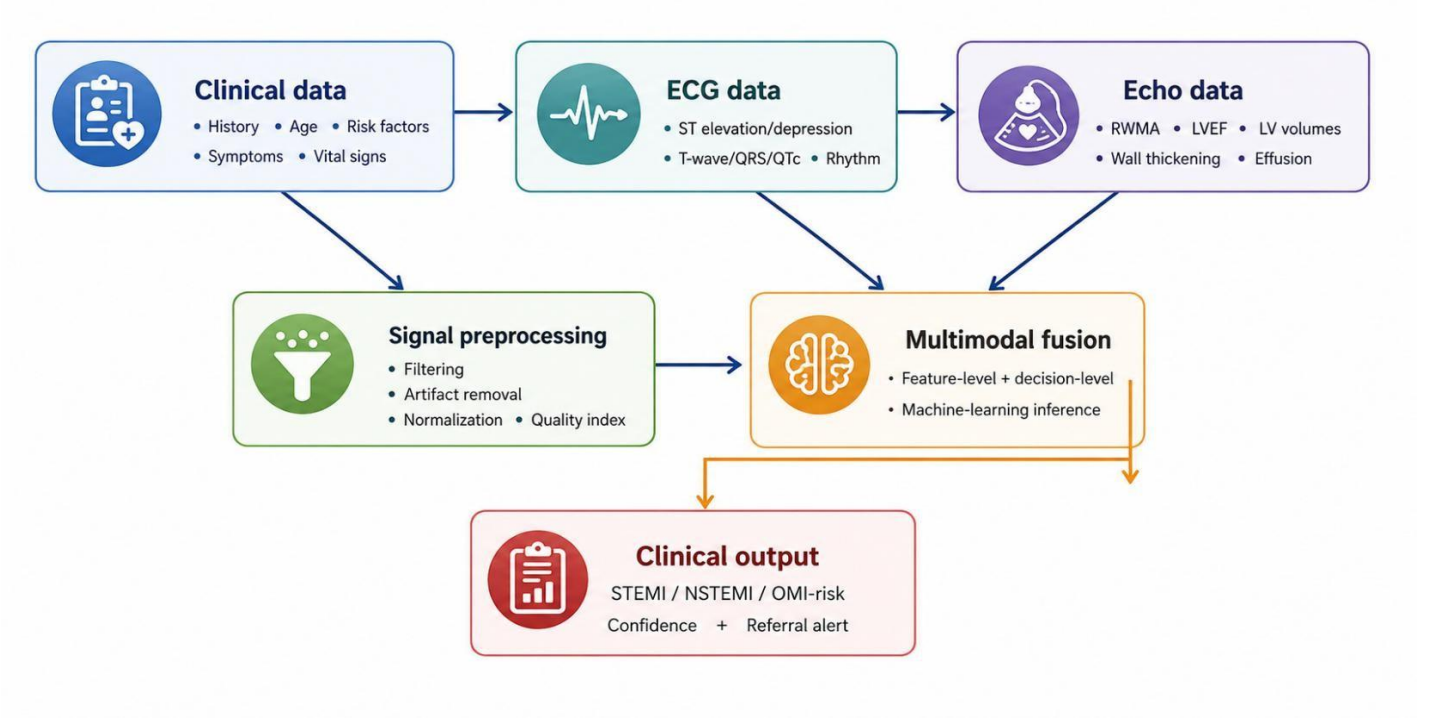

Figure 4. Conceptual ECG morphology and multimodal evidence pathway relevant to STEMI-pattern, NSTEMI-risk and OMI-risk assessment. Waveforms are schematic only and are not diagnostic examples, thresholds or definitions of NSTEMI.

The proposed platform should function as a clinical decision-support cascade rather than as a single black-box classifier. The first stage should assess the quality of the available signals and determine whether they are suitable for further analysis. The second stage should examine the ECG for immediate high-risk patterns and generate an initial estimate of STEMI or OMI risk. Structured clinical information can then be incorporated at the third stage, followed by echocardiographic findings when an adequate examination is available. The final stage should combine the available evidence and provide a calibrated risk estimate together with an indication of the appropriate level of clinical urgency. For STEMI-pattern risk, the system should be designed to favor sensitivity because failing to identify a potentially occlusive event may have serious clinical consequences. A positive high-risk alert should therefore prompt rapid acquisition of a conventional 12-lead ECG and initiation of the appropriate acute coronary syndrome pathway. The wearable system should support and accelerate clinical assessment and should never be used in a way that delays established reperfusion procedures.

In suspected NSTEMI, the platform output should be expressed as an estimated probability of acute myocardial ischemia or myocardial injury that requires confirmatory clinical assessment. Compatible symptoms,

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potentially ischemic but non-diagnostic ECG findings, a new regional wall-motion abnormality, or an increasing overall risk estimate should increase the urgency for serial high-sensitivity cardiac troponin testing and appropriate specialist assessment. A transdermal biomarker channel could potentially provide additional information in the future, but it should only contribute to clinical decision-making after its analytical performance and clinical usefulness have been adequately established.

For OMI risk, the system should be capable of identifying a high-risk occlusion phenotype even when the ECG does not show conventional ST-segment elevation. This output should be understood as a risk estimate rather than confirmation of anatomical coronary occlusion. Its practical purpose would be to prompt timely clinical review, repeat ECG assessment, biomarker testing, and consideration of early invasive evaluation in accordance with the applicable local clinical protocol.

PROPOSED MODEL OUTPUTS AND SAFETY ACTIONS

The proposed outputs are summarized in Table 2, which defines how each risk category should be interpreted and linked to an appropriate clinical response. The table also establishes safety boundaries to prevent model outputs from being misinterpreted as definitive diagnoses or as a substitute for conventional clinical assessment.

Table 2. Proposed model outputs, clinical interpretation, and safety boundaries

Output	Interpretation	Suggested action	Prohibited interpretation
High STEMI-pattern probability	High-risk ischemic ECG phenotype	Immediate conventional 12-lead ECG and emergency ACS pathway; do not delay reperfusion	Not a standalone diagnosis
High OMI-risk	Possible acute coronary occlusion despite non-diagnostic ST elevation	Urgent clinician review, serial ECG/hs-cTn, and protocol-based invasive assessment	Not proof of anatomical occlusion
Intermediate AMI probability	Conflicting, incomplete, or moderate-risk evidence	Prompt hs-cTn/serial ECG and focused echocardiography where available	Not a rule-in or rule-out result
Low estimated risk + adequate signal	Lower estimated risk under current inputs	Continue standard clinical rule-out pathway	Must not independently discharge the patient
Indeterminate / poor quality	Insufficient evidence for reliable inference	Repeat acquisition or use conventional diagnostics	Must not be interpreted as normal

CLINICAL VALIDATION FRAMEWORK

Reference Standard

Validation should be based on an independent clinical assessment performed by appropriately qualified clinicians who are blinded to the predictions generated by the wearable system. The reference standard should draw on the information normally used to establish an AMI diagnosis, including the patient's symptoms and clinical history, serial high-sensitivity cardiac troponin (hs-cTn) measurements, standard 12-lead ECG findings, imaging when clinically indicated, coronary angiography when performed, and relevant follow-up information [1]. For suspected OMI, angiographic findings can provide stronger evidence of anatomical coronary occlusion than relying on an ECG-based classification alone.

Study Population

Prospective validation studies should recruit consecutive adults presenting with suspected acute coronary syndrome rather than selecting patients who already have an obvious diagnosis of myocardial infarction. The study population should reflect the range of conditions encountered in actual clinical practice and should

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therefore include STEMI, NSTEMI, OMI, MINOCA, type 2 MI, unstable angina, non-cardiac chest pain, chronic myocardial injury, arrhythmias, heart failure, and renal disease. Including this broad spectrum is important because the platform will ultimately be used in patients whose diagnosis is uncertain, rather than in carefully selected healthy individuals or patients with clearly established MI.

Data Splitting and External Validation

Patient-level separation should be maintained throughout model development and testing so that recordings from the same patient do not appear in both datasets. After this separation has been established, temporal and geographic separation should be introduced to provide a more realistic assessment of generalizability. External validation should, where feasible, involve multiple hospitals, geographical regions, device operators, demographic groups, and different acquisition hardware. Testing the model across these settings is important because prediction models can perform differently when they are applied to populations or clinical environments that differ from those used during development [23, 24].

The final model should be evaluated on an external dataset that was not used for model development, tuning, or model selection. The model should be applied in its locked form, and its discrimination, calibration, and clinical usefulness should then be assessed in the new population [20]. This approach provides a more meaningful indication of whether the system is likely to remain reliable outside the environment in which it was developed.

Performance and Clinical Utility

Evaluation should extend beyond a single measure of discrimination. The primary performance measures should include sensitivity, specificity, positive and negative predictive values, likelihood ratios, area under the receiver operating characteristic curve (ROC-AUC), precision-recall AUC, and calibration. Point estimates should be accompanied by appropriate confidence intervals. Decision-curve analysis should also be considered to determine whether using the model at clinically relevant alert thresholds provides a meaningful net benefit compared with alternative strategies [23].

The burden created by incorrect alerts should also be measured. In practice, an apparently accurate model may still be difficult to deploy if it generates frequent false alarms, unnecessary transfers, or avoidable investigations. The validation study should therefore report false-alert rates, alert frequency, time from signal acquisition to alert, and the proportion of alerts that lead to clinically relevant actions. Performance should also be examined across clinically relevant subgroups, including sex, age, important comorbidities, skin characteristics where optical sensing is used, body habitus, geographic location, device type, and acquisition operator. Particular attention should be given to errors involving common diagnostic mimics and challenging clinical conditions, such as renal disease, heart failure, bundle-branch block, paced rhythms, and previous myocardial infarction. Reporting these subgroup results will help identify populations in which the platform may require recalibration, additional data, or more cautious interpretation [20].

Staged Prospective Validation

A staged validation pathway would provide a safer and more practical route toward clinical deployment. The initial stage should involve analytical and bench testing of ECG fidelity, resistance to motion-related artifacts, battery performance, wireless interruptions, data loss, and stability under relevant environmental conditions. This should be followed by usability testing to assess whether patients, clinicians, and technical personnel can operate the system reliably.

Once the basic system has demonstrated acceptable technical performance, the locked model should undergo prospective silent-mode evaluation. During this phase, the system would process real clinical data without displaying its predictions to treating clinicians, allowing its performance and failure modes to be assessed without influencing patient management. Only after satisfactory evidence of safety, calibration, signal quality, and generalizability should real-time predictions be introduced into clinical workflows [20, 24]. A subsequent interventional or stepped-wedge study could then examine whether the platform changes clinical workflow,

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time to assessment, resource utilization, treatment decisions, or patient outcomes. This staged approach separates technical validation from clinical impact assessment and reduces the risk of introducing an incompletely validated decision-support system directly into routine care [20–24].

Table 3. Proposed staged validation framework for the multimodal wearable AMI platform

Validation stage	Primary purpose	Key endpoints
Bench / analytical testing	Verify hardware and signal fidelity	ECG fidelity, noise, motion artifact, lead-off detection, battery life, latency, data loss, environmental robustness
Usability / human factors	Assess safe operation by intended users	Task completion, comprehension, alarm handling, training burden, usability errors
Prospective silent mode	Estimate clinical performance without influencing care	Sensitivity, specificity, calibration, subgroup performance, OOD detection, false-alert burden
Prospective interventional	Assess impact on workflow	Time-to-12-lead ECG, time-to-diagnosis, transfer time, escalation decisions
Outcome / stepped-wedge or randomized evaluation	Determine patient and system benefit	Time-to-reperfusion, infarct size where feasible, admissions, invasive procedures, adverse events, mortality

PROPOSED VALIDATION DESIGN

The clinical validation of the proposed platform should follow a structured framework that addresses population representativeness, reference-standard quality, statistical validity, external generalizability, patient safety, clinical utility, and governance. Table 4 summarizes the recommended practices required to establish reliable and clinically meaningful evidence before deployment.

Table 4. Recommended clinical validation and governance framework for the proposed multimodal wearable AMI platform

Domain	Recommended practice
Population	Consecutive suspected-ACS presentations including STEMI, NSTEMI, OMI, MINOCA, type 2 MI, non-cardiac chest pain and chronic myocardial injury
Reference standard	Independent clinical adjudication using symptoms, serial hs-cTn, 12-lead ECG, imaging and angiography where available
Data split	Patient-level split; no ECGs or images from the same patient across development and test sets
External validation	Multiple hospitals, regions, operators, device types and demographic groups
Statistical reporting	Point estimates with 95% confidence intervals; calibration and appropriate non-parametric comparisons where stochastic/model comparisons are made
Safety	False-negative analysis, false-alert burden, signal-quality failures and out-of-distribution detection
Clinical utility	Time-to-alert, time-to-diagnosis, time-to-reperfusion, transfer time, admissions, invasive procedures and patient outcomes
Governance	Consent, privacy, cybersecurity, auditability, model-version control, human factors and regulatory compliance

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PROPOSED IMPLEMENTATION STRATEGY

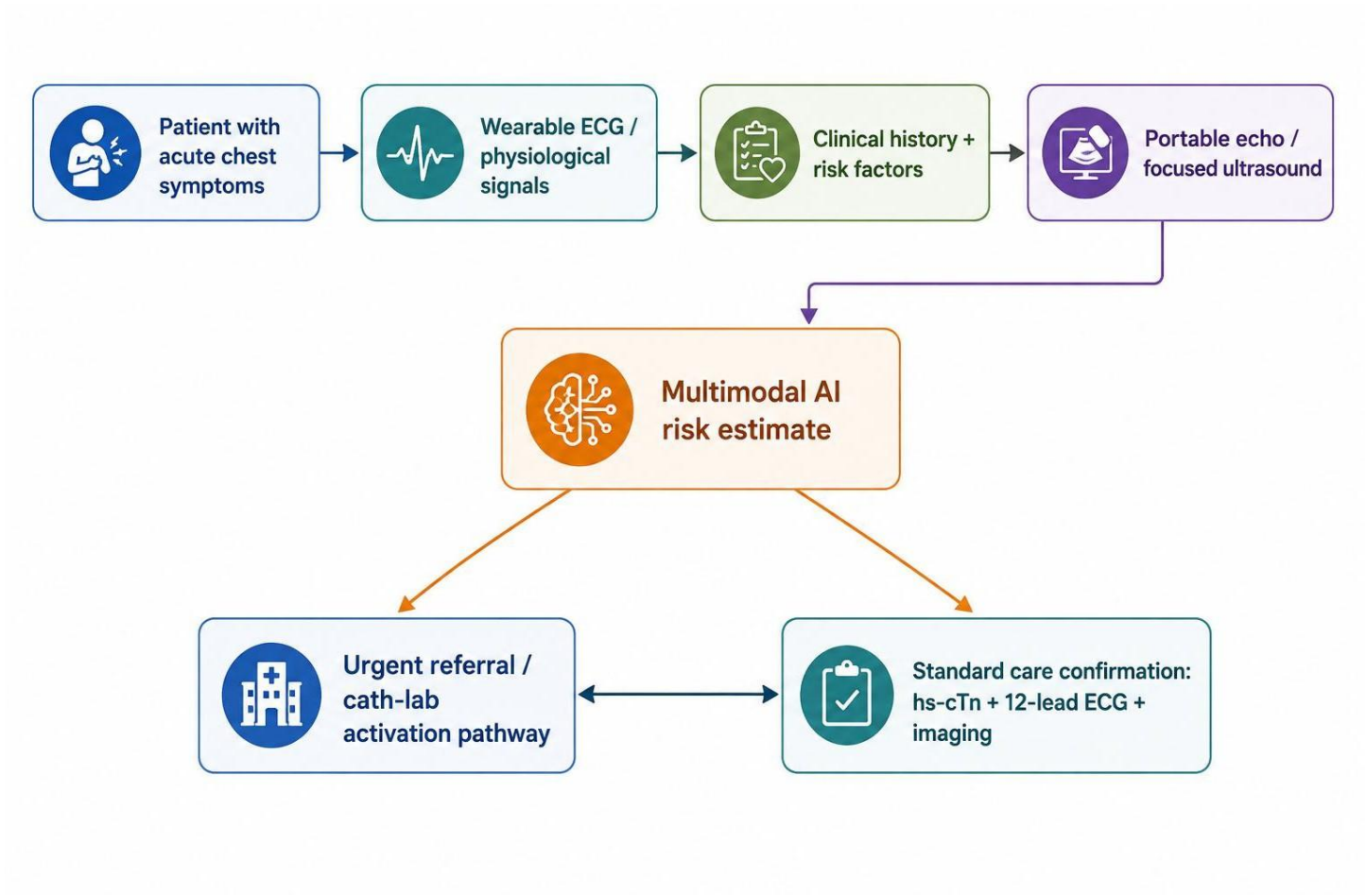

Figure 5. Proposed clinical deployment pathway and safety boundary. The platform generates an adjunctive risk estimate while standard 12-lead ECG, serial hs-cTn and clinician assessment remain confirmatory.

A staged implementation strategy would help reduce both technical and regulatory risks during development. The first phase should focus on establishing reliable ECG acquisition, dependable signal-quality assessment, secure wireless communication, protected data storage, and basic STEMI/OMI risk estimation. The second phase could then incorporate structured clinical information and a connected portable echocardiography system, including automated assessment of image quality and regional wall-motion abnormalities (RWMA). The third phase would explore optional transdermal biomarker sensing and more advanced multimodal AI models. Each phase should have clearly defined go/no-go criteria so that progression to the next stage is based on demonstrated performance rather than development timelines alone. Power consumption is likely to be one of the main practical limitations of a continuously worn system. Continuous ECG recording, wireless communication, and real-time processing can place considerable demands on the battery. To reduce this burden, basic processing tasks such as signal-quality assessment and event detection should be performed locally. The system could then transmit only clinically relevant ECG segments or suitably compressed features when appropriate, rather than continuously sending all raw data. Battery-health monitoring, safe charging mechanisms, and protection against excessive temperature should also be incorporated into the design.

Patient comfort and usability are equally important if the device is expected to be worn for extended periods. The electrodes should maintain reliable skin contact while minimizing irritation, and the device enclosure should be lightweight, durable, and easy to clean. Where a chest patch is used, the adhesive should be suitable for the intended duration of wear without causing unnecessary discomfort. The user interface should also make it immediately clear when recording has started successfully and when the signal quality is inadequate. At the same time, alerts should be carefully designed to avoid generating excessive notifications that could lead to alarm fatigue for patients or clinicians.

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DEPLOYMENT IN RESOURCE-CONSTRAINED SETTINGS

The proposed platform may be particularly useful in settings where access to advanced cardiac investigations is limited or delayed. Patients with suspected ACS in rural and underserved areas may face delays in diagnosis, referral, transfer, and reperfusion [8, 9]. A wearable ECG system that can be used in an ambulance, primary health centre, or other first-contact setting could help identify patients who require urgent attention and support earlier prioritization. Its usefulness, however, would depend on having a clear pathway for confirmatory testing, referral, and definitive treatment.

An offline-first design would therefore be appropriate for such environments. The system should be capable of performing basic signal processing and generating an initial risk estimate without relying on continuous internet connectivity. When a suitable connection becomes available, selected ECG segments, relevant clinical information, and echocardiographic clips could be transmitted to a remote specialist for further assessment. Even so, the technology cannot by itself solve problems such as limited transport, unavailable catheterization services, insufficient laboratory capacity, or lack of beds at referral hospitals. Evaluation should therefore consider the entire patient pathway rather than focusing only on the diagnostic accuracy of the device.

Deployment planning should also address the practical requirements that determine whether the system can be maintained over time. These include equipment ownership, routine maintenance, electrode replacement, cleaning, battery replacement, data and communication costs, user training, and access to technical support. The platform should also be tested under conditions that are likely to occur in the intended setting, including power interruptions, loss of network connectivity, temperature and humidity changes, and intermittent equipment availability. In many settings, a simple and dependable ECG system may ultimately provide greater clinical value than a more sophisticated platform that is difficult to operate or maintain.

HUMAN FACTORS, CYBERSECURITY, ETHICS AND REGULATION

Because the proposed platform could influence decisions about emergency cardiac care, false reassurance represents an important safety concern. A low-risk or negative output should never be used on its own to exclude AMI when the patient's symptoms, conventional ECG, cardiac biomarkers, or clinical assessment remain concerning. The user interface should therefore make a clear distinction between a high-risk STEMI-pattern ECG, suspected OMI, suspected myocardial injury or ischemia, low estimated risk with adequate signal quality, and an indeterminate result. The system should also account for practical human-factors issues such as alarm fatigue, acknowledgement of alerts, accidental dismissal, repeated notifications, failed data transmission, and uncertainty about who is responsible for responding to an alert. Each clinically relevant event should generate an auditable record containing the model version, modalities used, signal-quality status, prediction, confidence level, and subsequent clinical action. Maintaining this information would support quality assurance, troubleshooting, clinical review, and longer-term monitoring of model performance.

Cybersecurity should be incorporated from the beginning of system development rather than added after the hardware and software have been completed. Appropriate safeguards should include authentication of devices and users, encryption of stored and transmitted information, secure firmware updates, control of model versions, access logging, procedures for lost or compromised devices, and protection against unauthorized modification of physiological signals or decision thresholds. At the same time, loss of cloud connectivity should not disable the basic safety functions of the wearable system. Algorithmic bias is another important consideration. A model may inadvertently learn characteristics that are specific to a particular hospital, patient population, device, acquisition procedure, or clinical practice rather than features that are genuinely related to myocardial ischemia. Development and validation should therefore include patients from different demographic groups and acquisition environments, with subgroup performance reported explicitly. Regulatory requirements will ultimately depend on the intended use and claims made for the system. Nevertheless, risk management, software lifecycle controls, human-factors engineering, cybersecurity, and plans for post-market performance monitoring should be considered from the earliest stages of development.

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Research Gaps and Future Directions

One of the most important gaps is the limited availability of large, synchronized multimodal datasets containing wearable ECG, clinical information, echocardiographic recordings, hs-cTn measurements, and angiographic outcomes for the same patients. Access to such datasets would allow researchers to investigate multimodal models under conditions that more closely resemble real clinical practice and would reduce the limitations associated with combining data from separately collected cohorts. The spatial limitations of wearable ECG also require further investigation. Multi-lead chest patches, standardized recordings from several body positions, and validated methods for estimating additional lead information are promising approaches. However, reconstructed or inferred leads should not be used for high-stakes clinical decisions until their performance has been directly compared with conventional 12-lead ECG in appropriate patient populations.

Portable echocardiography presents a similar challenge. Reliable automated assessment of image quality should occur before an algorithm attempts to interpret cardiac structure or wall motion. The same quality-first principle should apply to ECG acquisition, particularly in ambulatory settings where movement, electrode displacement, and environmental interference can affect the recording. Transdermal biochemical sensing remains an interesting future direction, but important questions remain regarding calibration, analytical specificity, biological confounding, and equivalence with laboratory hs-cTn measurement [10–12]. Future studies should also place greater emphasis on clinical usefulness rather than diagnostic discrimination alone. Important outcomes may include time to correct diagnosis, time to transfer, time to reperfusion, frequency of false alerts, unnecessary invasive procedures, and outcomes that matter directly to patients. Post-discharge monitoring for recurrent ischemia is another possible application of wearable technology, although this would require different alert thresholds, individualized baseline measurements, and a separate validation strategy from that used for acute presentation.

DISCUSSION

The evidence reviewed supports the conceptual feasibility of an integrated multimodal platform for AMI decision support, but it does not support the claim that a single wearable device can independently diagnose STEMI and NSTEMI with the same capability as a complete hospital-based ACS pathway. The strongest evidence currently relates to individual components of the proposed system. Wearable ECG can provide useful electrical information, AI methods can identify ECG patterns that may be difficult to recognize using conventional approaches, AI can assist with echocardiographic interpretation, and emerging transdermal approaches may eventually provide additional biochemical information [10–18]. The main research opportunity is therefore to integrate these technologies while retaining an appropriate level of uncertainty around each component.

The distinction between the continuously worn sensing unit and the episodic ultrasound component is particularly important for keeping the proposed design technically realistic. Continuous ECG and physiological monitoring are relatively well suited to wearable implementation, whereas continuous diagnostic echocardiography presents much greater challenges related to acoustic coupling, probe positioning, beamforming, power consumption, data processing, and image quality. A connected portable ultrasound probe is therefore a more practical near-term option. The platform should also focus on clinically meaningful phenotypes rather than relying entirely on the traditional STEMI/NSTEMI classification. STEMI-pattern risk remains an important trigger for urgent escalation. OMI-risk provides a way of identifying patients who may have acute coronary occlusion despite not meeting conventional ST-elevation criteria. Suspected NSTEMI, on the other hand, should remain a multimodal probability estimate until appropriate biochemical and clinical evidence is available. This approach allows the engineering system to complement rather than replace the established diagnostic pathway.

Quality-aware fusion is equally important. A multimodal system that treats missing or corrupted information as if it were normal could create greater clinical risk than a simpler system that openly reports uncertainty. Signal-quality assessment, explicit missing-modality states, probability calibration, and detection of inputs that fall

outside the model's development population should therefore be treated as fundamental design requirements rather than optional additions.

External validation should also be considered from the beginning of model development. Temporal, geographic, and multicenter testing can reveal reductions in performance caused by differences in patient populations, acquisition hardware, operator practices, and local clinical workflows [18, 20]. The final model should be locked before external testing, and reported performance should include confidence intervals together with relevant subgroup analyses.

An important limitation of this review is that the proposed platform has not yet been implemented as a complete prototype or evaluated in a clinical population. The architecture and associated figures represent a conceptual synthesis of the available evidence and should not be interpreted as measured diagnostic performance. Similarly, the provisional engineering requirements presented in Table 4 are development targets rather than validated medical-device specifications. The immediate research priority is therefore to construct and test a limited-lead ECG prototype, followed by usability assessment, prospective silent-mode evaluation, external clinical validation, and, only after these stages have been satisfactorily completed, studies focused on clinical outcomes.

CONCLUSION

This review provides a conceptual and engineering framework for a multimodal wearable platform intended to support earlier recognition and risk estimation of acute myocardial ischemia and infarction. The different information sources contribute complementary aspects of the clinical picture: clinical variables help establish the initial probability of disease, ECG provides immediate electrical information, echocardiography provides mechanical evidence, and future validated biochemical sensors may eventually provide additional information about myocardial injury.

The proposed system would combine a continuously worn ECG and physiological sensing unit with synchronized clinical information, connected portable echocardiography, quality-aware multimodal machine learning, secure communication, and calibrated decision support. Rather than producing a single definitive diagnosis, the system should communicate STEMI-pattern risk, suspected AMI or ischemia, OMI or high-grade occlusion risk, and explicit signal-quality or uncertainty states. These outputs should be used to support appropriate escalation and clinical review rather than replace established diagnostic procedures.

Until prospective evidence demonstrates that such a platform can safely perform these functions, standard 12-lead ECG, serial hs-cTn testing, clinical assessment, and indicated imaging should remain the confirmatory pathway. The most appropriate next step is therefore to develop and bench-test a limited-lead ECG prototype with robust signal-quality monitoring, followed by prospective comparison with standard clinical investigations. A staged development and validation process will help determine whether the platform can genuinely shorten the time to recognition, referral, and reperfusion while keeping false alerts and diagnostic risk within acceptable limits, particularly in resource-constrained settings.

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Figure Legends

Figure 1. Proposed multimodal diagnostic architecture for early AMI risk estimation. Clinical, ECG and echocardiographic information are combined with optional physiological/biochemical sensing and a quality-aware machine-learning engine.

Figure 2. Proposed hardware and communication architecture of the wearable platform. The architecture separates sensing, analogue front-end processing, embedded computation, wireless communication, security and clinical decision support.

Figure 3. Proposed machine-learning and validation pipeline. Patient-level splitting, missing-modality handling, external validation, calibration, uncertainty estimation and prospective evaluation are emphasized.

Figure 4. Conceptual ECG morphology and multimodal evidence pathway relevant to STEMI-pattern, NSTEMI-risk and OMI-risk assessment. The waveforms are schematic only and are not clinical diagnostic examples or threshold specifications.

Figure 5. Proposed clinical deployment pathway and safety boundary. The platform generates an adjunctive risk estimate while standard 12-lead ECG, serial hs-cTn and clinician assessment remain confirmatory.

Source and Figure Note

All five figures in this article are original conceptual/illustrative figures prepared for the manuscript and are not reproduced from published figures. Their scientific content is synthesized from the cited wearable ECG, AI-ECG, AI-echocardiography, transdermal-sensing and ACS literature [1–3,10–23]. The figures are conceptual and do not constitute evidence of prototype performance or clinical validation.