

## ARTIFICIAL INTELLIGENCE IN RISK STRATIFICATION OF ACUTE CORONARY SYNDROME: A COMPARATIVE REVIEW WITH TRADITIONAL CLINICAL RISK SCORES

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### ABSTRACT

Acute Coronary Syndrome (ACS) demands early and effective risk stratification to guide rapid clinical decisions in emergency settings. Given the limitations of traditional scores in capturing complex non-linear biological interactions, this study aimed to review the discriminatory and predictive performance of Artificial Intelligence (AI) models, such as Machine Learning and Deep Learning, compared to conventional tools (GRACE, TIMI, and HEART) in predicting Major Adverse Cardiovascular Events (MACE). For this purpose, an integrative literature review was conducted based on the PRISMA 2020 protocol, selecting nine original articles published in PubMed between 2021 and 2026. The results consistently demonstrate that AI algorithms outperform the accuracy of current clinical scores, achieving Areas Under the ROC Curve (AUROC) of up to 0.94. This prognostic refinement is rooted in the autonomous extraction of subtle morphological variables from raw electrocardiograms — drastically reducing false positives in the cath lab — and the synergistic integration of molecular and inflammatory biomarkers. Explainable tools such as SHAP validate mathematical findings by aligning them with medical guidelines. In conclusion, AI represents a disruptive advancement in ACS risk stratification. However, definitive bedside translation still depends on overcoming methodological challenges, requiring external validations with real-time live data streams to establish a safe and personalized clinical practice.

**Keywords:** Machine learning, Cardiology, Artificial intelligence, Risk assessment, Acute coronary syndrome.

### INTRODUCTION

Acute Coronary Syndrome (ACS) remains one of the leading causes of cardiovascular morbidity and mortality worldwide, requiring rapid and accurate clinical decision-making in the emergency setting.<sup>1</sup> Successful treatment of ACS critically depends on early and effective risk stratification. This triage is essential to distinguish patients at high anatomical and clinical risk, who benefit

from immediate invasive interventions, from those at low to moderate risk, who may be managed conservatively or undergo subsequent outpatient investigation.<sup>2</sup>

Historically, risk stratification has been based on the integration of clinical parameters, electrocardiographic findings, and biomarkers of myocardial injury and has been operationalized through structured and widely validated scores, such as GRACE, TIMI, and HEART.<sup>3</sup> However, the transition toward precision medicine has highlighted important limitations of these conventional tools. Because they are predominantly based on linear regression statistical models, traditional scores have difficulty capturing complex and nonlinear interactions among multiple biological variables.<sup>4</sup> Consequently, they tend to underestimate risk in specific population subgroups and fail to integrate continuous temporal dynamics, such as the rigorous kinetics of high-sensitivity troponin and subtle morphological variations in the raw electrocardiogram (ECG) signal.<sup>2,5</sup>

In this context, Artificial Intelligence (AI), driven by Machine Learning (ML) and Deep Learning (DL) algorithms, is becoming established as a disruptive strategy for cardiology practice. Unlike traditional methods, AI models have the intrinsic ability to process vast volumes of data (Big Data) simultaneously, identifying previously imperceptible multidimensional phenotypic patterns.<sup>4,6</sup> Recent evidence demonstrates that machine learning algorithms consistently outperform current clinical scores in predictive and discriminatory accuracy for Major Adverse Cardiovascular Events (MACE).<sup>4,6</sup> By processing data ranging from sociodemographic characteristics and electronic health records to the autonomous extraction of ECG data, AI enables highly individualized prognostic prediction, optimizing resource allocation and mitigating preventable adverse outcomes.<sup>1,5</sup>

Therefore, the present study aims to synthesize contemporary scientific evidence regarding the performance of Artificial Intelligence models in risk stratification and outcome prediction in patients with Acute Coronary Syndrome, directly comparing them with conventional clinical scores. Additionally, it seeks to discuss the feasibility, methodological limitations, and perspectives for the safe translation and integration of these technologies into decision-making in real-world clinical settings.

## OBJECTIVES

This study aims to review contemporary scientific evidence regarding the discriminatory and predictive performance of Artificial Intelligence models (Machine Learning and Deep Learning) integrated with traditional clinical scores (GRACE, TIMI, and HEART) for risk stratification and the prediction of Major Adverse Cardiovascular Events (MACE) in patients with Acute Coronary Syndrome.

## METHODS

This is an integrative literature review, adapted to the recommendations of the PRISMA 2020 protocol.<sup>16</sup> The search was conducted in the PubMed/MEDLINE database using controlled descriptors (MeSH). Free original articles published between 2021 and 2026 were included. The selection process resulted in 9 studies for the final analysis.

### 2.1 Guiding Question

The guiding question was developed using the PICO strategy (Population, Interest, Context/Outcome), defined as: "How can Artificial Intelligence be applied to risk stratification in individuals with Acute Coronary Syndrome in clinical practice to optimize prognosis and personalize the care of critically ill patients based on multiple records?"

## 2.2 Inclusion and Exclusion Criteria

The inclusion criteria were: original articles from the PubMed database, available in full text free of charge ("free full text"), with no language restrictions, published between 2021 and 2026, involving human samples, and addressing the research question. Regarding content, studies evaluating the use of AI applied to different data sources were included, including automated ECG analysis and chest pain stratification; studies integrating classical and modern biomarkers with machine learning to estimate cardiovascular risk; studies evaluating the reliability of multiple predictive models; and studies focused on the development and multicenter validation of new AI-based scores. The exclusion criteria were: articles not available in full text free of charge, studies that did not report clear performance metrics, and studies focused on chronic diseases without correlation with or inclusion of the acute event.

## 2.3 Information Sources and Search Strategy

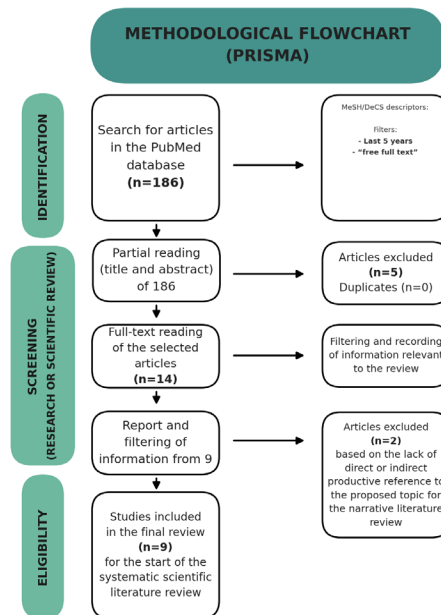
The search was conducted in the PubMed/MEDLINE database using a combination of controlled descriptors (MeSH) and free-text terms to maximize search sensitivity. The search string used was: (("Acute Coronary Syndrome"[Mesh] OR "Myocardial Infarction"[Mesh]) AND ("Artificial Intelligence"[Mesh] OR "Machine Learning"[Mesh] OR "Gradient Boosting"[tw]) AND ("Risk Assessment"[Mesh] OR "Prognosis"[Mesh] OR "Risk Stratification"[tw])). In addition, filters were applied for time (last five years), human samples, and without language restrictions.

## 2.4 Study Selection Process (Following PRISMA)

The selection was conducted in two phases: screening and eligibility. In this process, of the 186 results obtained, titles and abstracts were analyzed to exclude studies irrelevant to the research objective, and 14 were selected for more in-depth review. Thus, during the eligibility stage, the 14 preselected articles were read in full to confirm the inclusion criteria, and 9 studies were ultimately selected for the integrative literature review. The search and selection process was documented in the PRISMA 2020 flow diagram (Figure 1).

## 2.5 Data Extraction and Analysis

For data extraction, a data collection instrument developed by the authors was used, containing the following information: authors, year, country, objective, methodological design, and main results. The analysis was performed descriptively, categorizing the studies thematically to synthesize the knowledge produced on the topic.



**Figure 1:** Flow Diagram of the Study Identification, Screening, and Inclusion Process.  
**Source:** Prepared by the author (2026).

## RESULTS AND DISCUSSIONS

### 1. Discriminatory Performance and Predictive Accuracy of AI Compared With Traditional Scores

The data synthesized in this integrative review consistently demonstrate that the incorporation of models based on Artificial Intelligence (AI), using Machine Learning (ML) and Deep Learning (DL) algorithms, significantly outperforms the discriminatory accuracy of conventional clinical scores, such as HEART, GRACE, QRisk3, and the Framingham Heart Risk Score (FHRS), in predicting Major Adverse Cardiovascular Events (MACE) and mortality.

In the setting of emergency chest pain triage and ST-Segment Elevation Myocardial Infarction (STEMI), the use of automated models for electrocardiographic analysis demonstrated a disruptive operational impact. In multicenter registry data, the AI-based ECG model outperformed standard triage by achieving a sensitivity of 92% compared with only 71% for the conventional method, in addition to increasing specificity from 29% to 81%.<sup>7</sup> This substantial improvement in discriminatory performance, reflected by an Area Under the ROC Curve (AUROC) of 0.94, was accompanied by a marked reduction in false-positive rates in the cardiac catheterization laboratory (from 41.8% to 7.9%), remaining robust even in complex subgroups such as patients with bundle branch blocks and atrial fibrillation.<sup>7</sup>

This ability to extract complex nonlinear morphological patterns directly from the raw 12-lead ECG signal was also validated for the prediction of all-cause mortality. The Extra Survival Trees algorithm, based exclusively on electrocardiographic data, outperformed the HEART score by reducing the rate of undetected adverse events by more than 90%, demonstrating a Negative Predictive Value (NPV) of 93.4% and sensitivity of 85.9%.<sup>8</sup>

The superiority of AI also extends to models incorporating heterogeneous clinical data and long-term prediction scores. In large-scale cohorts of Indian and Dutch populations, the multilayer neural risk score AICVD outperformed FHRS and QRisk3 in predicting acute coronary events over 10 years, achieving an AUROC of up to 0.92 and an overall accuracy of 80.15%, compared with traditional epidemiological performance ranging from 51% to 59%.<sup>9</sup> In the short-term predictive spectrum (7 days) for major cardiovascular outcomes in the emergency setting, the automated DPI-AI classifier outperformed models based solely on structured demographic data and biological positivity (AUROC of 0.82 and 0.79), demonstrating the robustness of integrating deep numerical ECG representations with admission biomarkers.<sup>10</sup>

Complementing the perspective of extended follow-up, analysis of the large multicenter COREA-AMI registry, which evaluated 10,172 patients undergoing percutaneous coronary intervention (PCI), revealed that the Random Forest (RF) model showed consistently superior predictive performance compared with four other ML techniques and traditional logistic regression in estimating MACE at 1 and 5 years.<sup>11</sup> At the 5-year time horizon—when the cumulative incidence of composite outcomes (cardiac death, myocardial infarction, or stroke) reached 30.5% of the sample—the RF model achieved an AUC of 0.822, accuracy of 0.804, and an F1-score of 0.870.<sup>11</sup>

The relevance of the F1-score in this setting reinforces the need for more robust metrics in real-world and imbalanced datasets, where the prevalence of non-events significantly exceeds that of macrovascular events, protecting the analysis against statistical distortions commonly associated with the isolated assessment of overall accuracy or AUC.<sup>11,12</sup>

## 2. Prognostic Optimization: Integration of ECG Signals and Inflammatory Biomarkers

The findings indicate that the prognostic success of AI in Acute Coronary Syndrome (ACS) lies in its intrinsic ability to process multimodal datasets and identify variables that usually go unnoticed by the human eye or by linear statistical models.<sup>12</sup> Historically, risk stratification has neglected subtle kinetics or synergistic interactions among new pathophysiological markers due to the limitations of classical logistic regression models.<sup>13</sup> However, the understanding of the molecular complexity of myocardial infarction—which involves myocardial stress, necrosis, and remodeling—has found in artificial intelligence algorithms the ideal tool to enable strategies based on multiple biomarkers.<sup>13</sup>

A clear example of this evolution is the optimization of the traditional GRACE score through machine learning. The combination of the Random Forest classifier with contemporary inflammatory biomarkers increased the sensitivity of the GRACE score from 75% to 83%, while maintaining high levels of specificity in predicting death or reinfarction at six months.<sup>14</sup> Therefore, the integration of computational intelligence and precision biology offers a concrete pathway for personalizing care for critically ill patients, refining the identification of individuals at high anatomical risk who were previously incorrectly categorized by conventional screening methods.

## 3. Methodological Challenges: Feasibility, Interpretability, and Clinical Translation

Despite the promising statistical results, the effective translation of these technological tools into daily bedside medical practice faces important methodological and conceptual barriers. A critical gap identified in the current literature concerns heterogeneity in model development, characterized by the absence of adequate control groups, the persistence of small, homogeneous, or single-center datasets, and the scarcity of real-time validations using live data streams in the emergency setting.<sup>12</sup> Dependence on static or simulated datasets restricts the generalizability of algorithms and may lead to distorted

performance metrics when they are applied to new populations or different ethnic contexts.<sup>11,12</sup>

Furthermore, the common failure to report comprehensive metrics concurrently weakens evaluation in medical settings where the clinical costs of a false negative or false positive may be potentially fatal.<sup>12</sup> Similarly, selection biases inherent in observational registry studies and the latent risk of data leakage during complex data imputation steps require strict methodological caution to avoid overestimating the models' actual predictive capacity.<sup>11</sup>

Another major obstacle lies in the "black-box" nature of deep neural networks, which limits the acceptance of algorithms due to the lack of transparency regarding how risk predictions were structured. Because clinical decisions have a direct impact on patient morbidity and mortality, AI-based decision support intrinsically depends on the performance-trust relationship.<sup>15</sup> To mitigate this limitation, innovative agnostic approaches have proposed quantifying reliability through dimensions of robustness, confidence interval stability, and, fundamentally, interpretability—comparing the ranking of feature importance generated by the model with established clinical evidence.<sup>15</sup>

In this regard, the incorporation of innovative explanatory tools, such as Shapley Additive Explanations (SHAP) analysis, emerges as a transformative element for clinical validation. The application of SHAP values to robust models made it possible to decode the weight of individual long-term prognostic variables, isolating confounding factors arising from acute in-hospital complications that mimic predictive causes.<sup>11</sup> Through this methodology, non-modifiable parameters such as age, renal function, and left ventricular ejection fraction (LVEF) were determined to have the greatest predictive power for long-term post-infarction outcomes, even surpassing purely procedural variables such as the anatomical length of the implanted stent.<sup>11</sup>

In parallel, SHAP distinguished the crucial protective impact of modifiable interventions related to secondary prevention at hospital discharge, mapping the protective role of dual antiplatelet therapy (DAPT), statins, and renin-angiotensin-aldosterone system inhibitors.<sup>11</sup> This direct alignment between the mathematical findings of explainable algorithms and the Class I recommendations established by international cardiology guidelines not only legitimizes the practical utility of the machine learning model but also fosters the confidence required for its integrated clinical adoption.<sup>11</sup>

Additionally, the use of interpretable rule-based schemes demonstrated that it is possible to achieve an acceptable balance between predictive accuracy and diagnostic transparency, obtaining a sensitivity of 76.3% and specificity of 77.8% in predicting MACE in a manner that is completely clear to the attending physician.<sup>14</sup> Finally, it should be emphasized that satisfactory average model performance does not eliminate the need for automated individual assessments; estimating the degree of uncertainty of each point prediction emerges as an essential line of research for consolidating the safe, ethical, and effective integration of artificial intelligence into routine emergency cardiology practice.<sup>15</sup>

## CONCLUSION

This integrative review demonstrates that Artificial Intelligence, through Machine Learning and Deep Learning models, represents a disruptive and statistically superior advance in the risk stratification of patients with Acute Coronary Syndrome when compared with traditional clinical scores, such as GRACE, TIMI, and HEART. By processing complex nonlinear interactions in multimodal databases, these algorithms overcome the limitations of classical linear statistical methodologies, optimizing the predictive accuracy of Major Adverse Cardiovascular Events (MACE) and mortality both in the short-term emergency setting and during extended follow-up of up to five years.

The findings demonstrate that the prognostic refinement provided by AI is consolidated along two main fronts: the autonomous extraction of subtle morphological variables from the raw 12-lead electrocardiogram signal—drastically reducing false-positive rates in the cardiac catheterization laboratory and identifying atypical presentations—and the synergistic integration of new molecular and inflammatory biomarkers with patients' baseline clinical parameters.

However, the definitive and safe translation of these computational tools into bedside cardiology practice still depends on overcoming important methodological challenges. The future clinical applicability of AI in emergency cardiology requires real-time external validation using live data streams, mitigation of biases in imbalanced observational registries, and, fundamentally, the widespread adoption of explainable intelligence methods, such as SHAP analysis. The ability to decode the “black box” of algorithms, aligning their mathematical predictions with evidence-based medical guidelines, is the essential pillar for building the professional trust required to transform the predictive potential of Artificial Intelligence into a safe, personalized, and efficient clinical reality.

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Received: 24/08/26. Accepted: 27/08/26. Published in: 05/10/2026.