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REVIEW

Artificial Intelligence for Cardiovascular Risk Prediction: An Umbrella Review of Applications and Translational Challenges

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Background: Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide. Conventional risk prediction models often demonstrate suboptimal calibration and limited generalizability across populations. Artificial intelligence (AI) approaches, including machine learning (ML) and deep learning (DL), enable integration of multimodal clinical and imaging data for individualized cardiovascular risk estimation.

Objective: To evaluate the applications, predictive performance, and translational limitations of AI models for cardiovascular risk prediction within an umbrella review framework.

Methods: PubMed, Scopus, and Web of Science were systematically searched for studies published between January 2015 and October 2025 investigating AI-based prediction of cardiovascular outcomes. Eligible designs included randomized controlled trials (RCTs), cohort studies, systematic reviews, and meta-analyses. Predictive performance was the primary outcome, mainly assessed using the area under the receiver operating characteristic curve (AUC). Methodological quality was evaluated using established risk-of-bias tools. From 3500 identified records, 48 studies (8 RCTs, 28 cohort studies, and 12 systematic reviews or meta-analyses) were included in the final analysis.

Results: AI models achieved AUC values greater than 0.90 in more than 70% of imaging-based studies. Evidence synthesis showed predominant reliance on internal validation, inconsistent calibration reporting, and limited evaluation of algorithmic fairness. Multimodal data integration improved detection of coronary artery disease (CAD) and heart failure (HF). Wearable monitoring was associated with 18–25% lower hospitalization rates compared with usual care.

Conclusion: AI improves predictive accuracy in cardiovascular risk assessment. Despite strong discrimination performance (AUC), methodological heterogeneity, insufficient calibration assessment, algorithmic bias, limited external validation, and regulatory uncertainty remain major barriers to implementation. Clinical translation requires multicenter RCTs, explainable AI frameworks, and standardized reporting guidelines such as Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis Artificial Intelligence (TRIPOD-AI).

Plain Language Summary: Cardiovascular diseases (CVDs) remain the leading cause of death worldwide, yet commonly used clinical risk prediction tools do not perform equally well across populations. This umbrella review shows that artificial intelligence (AI) has the potential to improve cardiovascular risk prediction.

By analyzing nearly fifty high-quality studies published over the past decade, we found that AI-based prediction models often outperform traditional risk scores in estimating future cardiovascular events. This umbrella review integrated evidence from original research studies and previously published systematic reviews while minimizing duplication of data. In many investigations, particularly those using cardiovascular imaging, AI models demonstrated substantially higher predictive accuracy. Studies combining multiple data sources, including electronic health records, imaging data, genetic information, and wearable device monitoring,

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demonstrated improved diagnostic performance coronary artery disease (CAD) and heart failure (HF). Continuous monitoring using wearable technologies was associated with a reduction in hospitalization rates in prospective comparisons with usual care.

Despite these promising findings, several challenges remain before AI can be routinely implemented in clinical practice. Variation in study design, potential algorithmic bias, and evolving regulatory requirements continue to limit widespread adoption. Overall, AI exhibits strong potential strong potential to support more personalized cardiovascular care; however, large prospective clinical trials and transparent reporting standards are necessary to confirm safety, fairness, and reliability before broad clinical integration.

Keywords: artificial intelligence, machine learning, deep learning, cardiovascular diseases, risk assessment, precision medicine

Introduction

Cardiovascular diseases (CVDs) remain the leading cause of mortality globally. Updated estimates from the Global Burden of Disease (GBD) collaboration reported approximately 20.5 million CVD-related deaths in 2023, with the majority occurring in low- and middle-income countries (LMICs) where diagnostic and therapeutic resources remain limited.[1,2] In the United States (US), the American Heart Association (AHA) reports one CVD-related death every 33 seconds, corresponding to nearly 700,000 deaths annually and generating an economic burden exceeding USD 400 billion in direct and indirect healthcare costs.[3] According to the European Society of Cardiology (ESC), CVD accounts for 47% of female and 39% of male deaths across Europe, with pronounced regional disparities favoring Western over Eastern regions due to differences in risk factor management and healthcare infrastructure.[4] In Asia, projections indicate a 91.2% increase in CVD mortality between 2025 and 2050, largely driven by population aging and escalating metabolic risk factors.[5] Moreover, a recent global report confirmed that cardiovascular deaths attributable to metabolic risk factors increased by more than 18% between 2010 and 2021, underscoring the urgent need for predictive and preventive strategies supported by advanced data-driven technologies.[6]

Conventional risk stratification tools, such as the Framingham Risk Score (FRS), estimate the 10-year probability of coronary events using a limited set of clinical variables, including age, systolic blood pressure (SBP), total cholesterol, and smoking status.[7] In Europe, the Systematic COronary Risk Evaluation 2 (SCORE2) and its older-adult extension (SCORE2-OP) provide risk estimation for fatal and non-fatal cardiovascular events with improved calibration across European risk regions.[8] However, LMICs account for over 80% of CVD-related deaths, primarily due to restricted access to diagnostic and therapeutic tools. Systematic evaluations indicate that conventional scores, including FRS and SCORE2, frequently exhibit miscalibration in non-Caucasian populations, overestimating risk in low-incidence groups and underestimating it in high-risk cohorts. These models also fail to incorporate emerging contributors such as physical inactivity, psychosocial stress, and novel biomarkers, limiting their generalizability and predictive precision.[9] More recently, contemporary risk scores such as the Predicting Bleeding Complications in Patients Undergoing Stent Implantation–High Bleeding Risk (PRECISE-HBR) score, a well-validated seven-item bleeding risk prediction tool for patients undergoing percutaneous coronary intervention, have demonstrated improved discrimination compared with earlier bleeding risk models and are increasingly incorporated into data-driven algorithmic decision-support systems.[10] Artificial intelligence (AI) approaches not only augment preventive strategies but also hold promise in acute cardiovascular care, overcoming limitations of conventional methods and providing complementary or integrative pathways to advance precision in cardiovascular risk assessment.[11–13]

AI techniques, including machine learning (ML) and deep learning (DL) algorithms, possess superior capacity to analyze high-dimensional, multimodal datasets derived from electronic health records (EHRs), cardiac imaging, genomic profiling, and wearable sensor data. By identifying nonlinear and latent relationships among diverse risk determinants, AI models have demonstrated predictive performance that exceeds conventional statistical frameworks.[11,14] Meta-analytic evidence further indicates that AI-enhanced prediction systems achieve significantly higher discrimination for myocardial infarction (MI) and heart failure (HF) onset compared with guideline-endorsed risk scores.[12]

Despite these promising results, the clinical translation of AI-driven CVD prediction remains limited. Key challenges include heterogeneity of training datasets, algorithmic opacity, bias amplification in underrepresented populations, and uncertainties regarding regulatory frameworks governing data privacy, transparency, and model accountability.[15] Current clinical guidelines, including the 2021 ESC Guidelines on cardiovascular disease prevention, acknowledge the emerging role of AI in risk prediction but emphasize the necessity of rigorous external validation, transparency, and regulatory oversight prior to routine clinical implementation.[7] Accordingly, this umbrella review assesses the practical applications and limitations of AI in cardiovascular risk prediction, with a focus on clinical implementation barriers and translational challenges, such as under-evaluation of model calibration, external validity, and algorithmic fairness, rather than solely technical or theoretical performance. The review also proposes targeted strategies to overcome these barriers and to promote interdisciplinary collaboration for equitable, safe, and effective integration of AI into routine precision cardiology practice.

Methods

Search Strategy and Data Sources

A comprehensive systematic search was conducted to identify evidence on the application of AI in CVD prediction. Three major electronic databases (PubMed, Scopus, and Web of Science) were searched for studies published between January 2015 and October 2025 to capture recent advances in the field.

The search strategy combined Medical Subject Headings (MeSH) with free-text keywords, including *artificial intelligence, machine learning, deep learning, cardiovascular risk prediction, predictive modeling, cardiac imaging analysis, wearable sensors*, and *precision cardiovascular care*. Boolean operators (AND, OR, NOT) were applied to refine the search and improve retrieval accuracy.

Reference lists of included studies, relevant review articles, and American College of Cardiology (ACC) guideline documents were manually screened to identify additional sources. Non-peer-reviewed materials, including conference proceedings, preprints, and trial registry records, were excluded.

Eligibility Criteria

Studies were selected according to predefined inclusion and exclusion criteria aligned with the objectives of this systematic review.

Inclusion Criteria

Eligible studies were required to:

- Be published between January 2015 and October 2025.
- Apply AI techniques such as ML, DL, or natural language processing (NLP) to predict CVD risk, events, or outcomes.
- Report quantitative performance metrics, including the area under the receiver operating characteristic curve (AUC), sensitivity, specificity, or comparisons with conventional risk scores.
- Use robust study designs such as randomized controlled trials (RCTs), prospective cohort studies, or meta-analyses with verifiable primary data.
- For secondary evidence (systematic reviews and meta-analyses), include high-quality syntheses reporting pooled performance metrics; these were used only for contextual interpretation and not for quantitative pooling.

Exclusion Criteria

Studies were excluded if they:

- Were published in languages other than English.
- Examined AI applications unrelated to CVDs.
- Were editorials, letters, or abstracts without original data.
- Lacked accessible full text.

Study Selection Process

Two independent reviewers screened titles and abstracts to minimize selection bias. Disagreements were resolved through discussion or adjudication by a third reviewer. The selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure transparency and reproducibility.[16] The review protocol was not prospectively registered in the International Prospective Register of Systematic Reviews (PROSPERO); however, the review followed a predefined methodological framework to maintain transparency and reproducibility (Figure 1).

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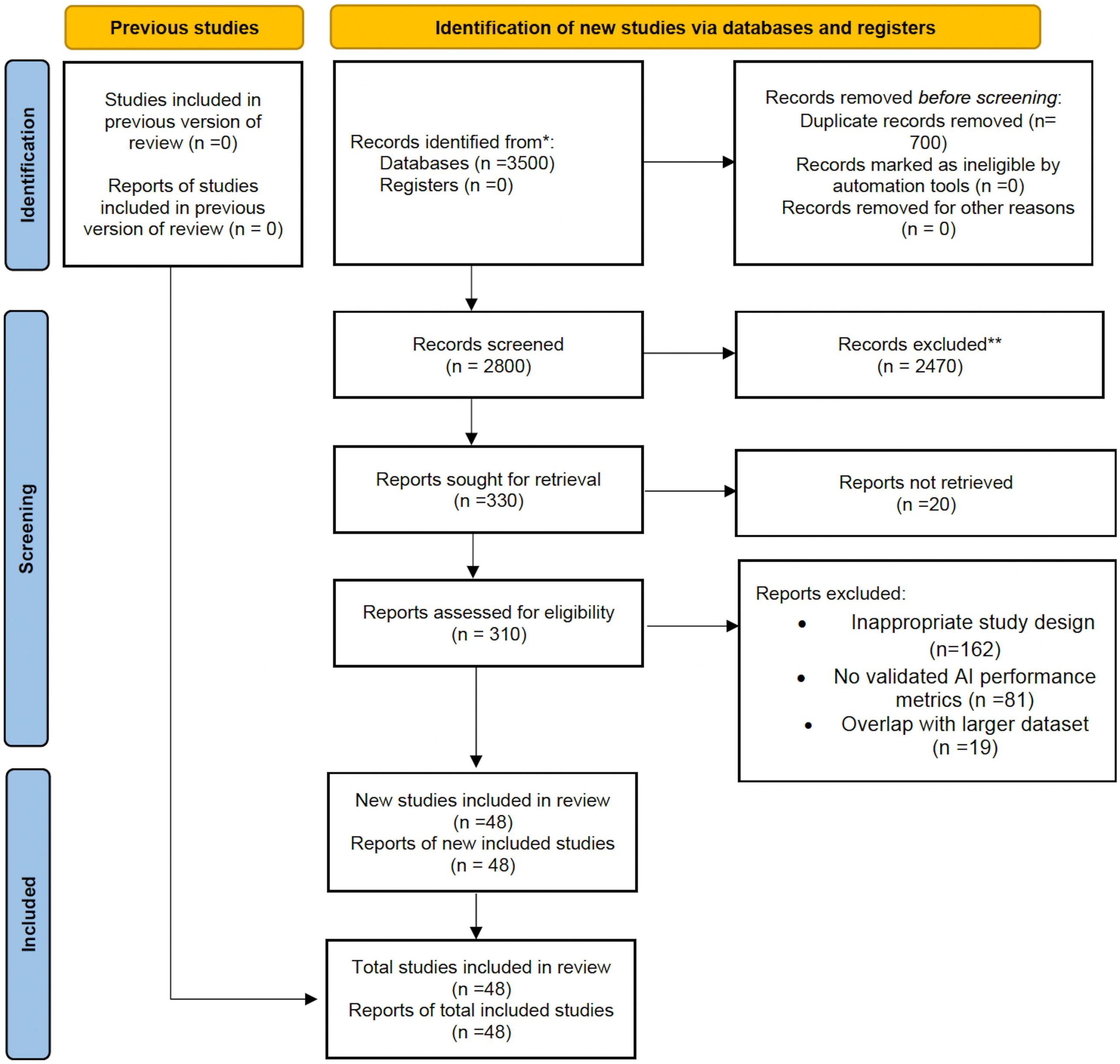

Figure 1 Systematic flow diagram of the study selection process. **If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools. *Records Identified: A total of 3500 records were retrieved from electronic databases, including PubMed (n = 1200), Scopus (n = 1400), and Web of Science (n = 900). An additional 48 records were identified through manual searches of reference lists from relevant studies and recent review articles on artificial intelligence in cardiovascular medicine. **Records Excluded: Records were screened and excluded manually by reviewers without the use of automation tools. After removing 700 duplicates, 2800 records were screened. Of these, 2470 were excluded for reasons including absence of AI application in cardiovascular disease prediction (n = 1600), reporting of only short-term or non-clinically relevant outcomes (n = 570), and publication in non-peer-reviewed sources such as conference abstracts, editorials, or commentaries (n = 300). These exclusions ensured that the final dataset remained focused on studies directly addressing artificial intelligence in cardiovascular risk prediction.

All retrieved records were exported to EndNote version 21 for reference management. After duplicate removal, full texts of potentially eligible studies were assessed. Ultimately, 48 studies met the inclusion criteria and were included in the final synthesis.

Quality Assessment

Methodological quality was evaluated using validated tools appropriate to study design. RCTs were assessed using the Cochrane Risk of Bias 2 (RoB 2) tool.[17] Cohort studies were evaluated using the Newcastle–Ottawa Scale (NOS).[18]

All included studies were retained regardless of quality rating. Quality assessment informed interpretation through:

- Stratified reporting by risk-of-bias level (where feasible),

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- Narrative discussion of methodological limitations,
- Cautious interpretation of findings from lower-quality studies.

Detailed quality appraisal results are presented in Supplementary Table S1.

Risk-of-Bias and Methodological Quality Assessment Summary

The majority of included RCTs were rated as having low risk of bias or some concerns using the Cochrane RoB 2 tool, primarily due to limitations in blinding of outcome assessment and incomplete reporting of model performance metrics. Cohort studies mostly received 7–9 stars on the NOS, indicating moderate-to-good methodological quality.

The quality assessment revealed three recurring critical limitations: (1) predominant reliance on internal validation with minimal external validation, (2) inconsistent or absent reporting of calibration metrics (despite frequent use of AUC), and (3) near absence of fairness assessment or subgroup analyses to detect algorithmic bias. These issues are discussed further in the narrative synthesis.

Data Extraction and Analysis

Data were extracted using a standardized form capturing study design, sample size, population characteristics, AI methodology, predictive performance metrics, and clinical outcomes.

Because of heterogeneity in populations, AI architectures, and endpoints, a narrative synthesis was conducted instead of meta-analysis. Findings were categorized into thematic domains, including risk prediction, imaging interpretation, and real-time monitoring. Descriptive statistics were employed to summarize methodological characteristics and performance trends. Any discrepancies during data extraction were resolved through consensus among reviewers.

Synthesis and Interpretation of Quantitative Findings

Owing to substantial heterogeneity across studies, quantitative improvements, such as increases in AUC or reductions in hospitalization rates, are reported as ranges from individual primary studies rather than pooled estimates. These values should be interpreted as indicative trends rather than definitive effect sizes. Greater interpretive weight was assigned to studies reporting comprehensive performance metrics and those with lower risk of bias.

Outcomes

The primary outcome of this umbrella review was the predictive performance of AI-based models, assessed mainly through discrimination AUC, calibration, and reclassification metrics, including net reclassification improvement and integrated discrimination improvement when reported.

Secondary outcomes comprised clinical endpoints such as hospitalization, mortality, emergency department visits, and other major cardiovascular events. These outcomes were summarized narratively without drawing causal inferences due to the observational and heterogeneous nature of most included studies.

In the narrative synthesis, findings from primary studies were prioritized, whereas secondary evidence was used solely to provide contextual pooled estimates without integration into the primary analyses.

Heterogeneity

Substantial heterogeneity was evident across the included studies in populations, data sources (electronic health records, imaging modalities, and wearable devices), AI architectures, validation strategies, and outcome definitions. This variability precluded quantitative meta-analysis and necessitates cautious interpretation of findings. Key contributors included demographic and clinical setting differences, multimodal data inputs, and predominant internal validation. These factors should be considered when evaluating generalizability.

Results

A total of 48 studies, including RCTs, 28 cohort studies, and 12 systematic reviews or meta-analyses, met predefined inclusion and quality criteria. Investigations were conducted within large collaborative programs in North America, Europe, and the Asia-Pacific region, with participant mean ages ranging from 50 to 80 years and female representation between 40% and 60%.

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Reporting Characteristics of Included Prediction Models

To facilitate comparison of predictive performance across studies, key reporting characteristics of AI-based prediction models were summarized narratively, including validation approach (internal versus external), training and testing procedures (random split, chronological split, or cross-validation), calibration reporting alongside discrimination metrics, and assessment of fairness or algorithmic bias. Most studies relied exclusively on internal validation, with external validation—temporal or geographic—performed in only a small minority of investigations.[19–21] Calibration metrics were inconsistently reported, with most studies presenting discrimination via AUC without corresponding calibration assessment. Only a minority of studies reported comprehensive calibration evaluation, such as calibration plots, Hosmer–Lemeshow (HL) test, calibration slope or intercept, or expected calibration error (ECE).[11,12,22–24]

Systematic fairness evaluation and subgroup analyses, stratified by race/ethnicity, sex, age, socioeconomic status, or geographic region, were rarely conducted, despite evidence that unmitigated algorithmic bias can substantially reduce predictive accuracy and lead to inequitable outcomes in minority, female, older, or socioeconomically disadvantaged populations.[25–27] Systematic fairness evaluation and subgroup validation therefore remain important priorities for future AI-based cardiovascular prediction research.[25–27]

Heterogeneity and Sensitivity Considerations

Substantial clinical and methodological heterogeneity across studies precluded quantitative meta-analysis and necessitates cautious interpretation of performance estimates. Major sources of heterogeneity included differences in population characteristics, AI model architectures and feature selection, validation strategies, outcome definitions, and follow-up duration.

Imaging-based AI models generally demonstrated higher discrimination, with pooled AUC values frequently exceeding 0.90 in systematic reviews,[28] whereas electronic health record-based prediction models typically showed pooled AUC values between 0.82 and 0.88.[13] Sensitivity analyses, when reported, indicated that model performance was generally stable across internal validation approaches but often declined in external or temporal validation cohorts.[11,21] These findings underscore the importance of external validation for reliable clinical translation.

These methodological variations significantly limit direct comparability of AUC values across studies and reduce confidence in the generalizability and reliability of the reported models. This prevailing focus on discrimination at the expense of calibration, validation, and fairness assessment constitutes a key gap in the translational readiness of AI models for CVD prediction.

Predictive Performance and Clinical Outcomes

AI techniques evaluated across studies included convolutional neural networks (CNNs), random forests (RFs), support vector machines (SVMs), and gradient boosting machines (GBMs). Across cohort studies and meta-analyses, AI-based models demonstrated predictive accuracy ranging from 80% to 95% in identifying individuals at elevated cardiovascular risk, depending on dataset characteristics and model architecture.[14,15] Imaging-based models generally achieved higher discrimination (pooled AUC ~0.91) compared with EHR-based models (pooled AUC ~0.86), with meta-analytic evidence reporting 12–25% improvements over conventional risk scores such as QResearch Risk Prediction Algorithm 3 (QRISK3).[28,29]

Analyses of large-scale databases, including the UK Biobank AI initiatives (UK Biobank) and the EchoNet-Dynamic echocardiography study (EchoNet-Dynamic), supported improved identification of CAD, atrial fibrillation (AF), and HF-related hospitalization risk.[11,30] Cohort studies such as the Multi-Ethnic Study of Atherosclerosis (MESA) and the Cardiovascular Health Study (CHS) demonstrated that integrating AI into clinical workflows enhanced risk stratification, reduced diagnostic errors, and optimized cardiac imaging efficiency.[22,31] Evidence from controlled trials, including AI-electrocardiography approaches for AF detection and deep learning-based computed tomography angiography analysis, further confirmed strong predictive performance while illustrating trade-offs between model complexity, interpretability, and computational demands.[23,32]

Studies in Asian populations, particularly in China and Japan, emphasized the integration of wearable technologies and reported greater performance gains in urban compared with rural healthcare settings.[20,33] These results suggest a consistent contribution of AI to cardiovascular risk prediction and clinical decision-making across diverse populations and care environments. However, gaps remain in calibration reporting, external validation, and fairness assessment.

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Mitigating these limitations through multicenter validation, explainable AI frameworks, comprehensive calibration evaluation, and fairness-aware reporting standards is essential for safe and equitable clinical implementation.

AI Applications in Cardiovascular Prediction

AI has been implemented across multiple clinical domains in cardiovascular disease, including risk stratification, diagnostic imaging, and real-time monitoring. Models integrating multimodal data sources such as electronic health records, imaging modalities, and wearable sensor data consistently outperformed single-modality approaches in detecting early subclinical disease signals.[14,15] Mitigation of potential bias in AI models, including race- or ethnicity-related bias, is essential for achieving equitable clinical outcomes. Evidence indicates that unaddressed bias can compromise predictive accuracy in underrepresented populations, underscoring the importance of robust external validation and fairness-aware algorithm development.[25] Furthermore, emerging observational evidence associates AI-driven monitoring strategies, including wearable-based detection systems, with reduced hospitalization rates for AF through earlier identification of arrhythmic events.[34] These models leverage large-scale datasets to improve risk classification while simultaneously revealing challenges in integration into established clinical workflows (Figure 2).

Secondary evidence from meta-analyses supports these findings, demonstrating consistent improvements in predictive performance, including AUC gains of approximately 15–25% across studies, without overlapping primary data extraction.[12,29]

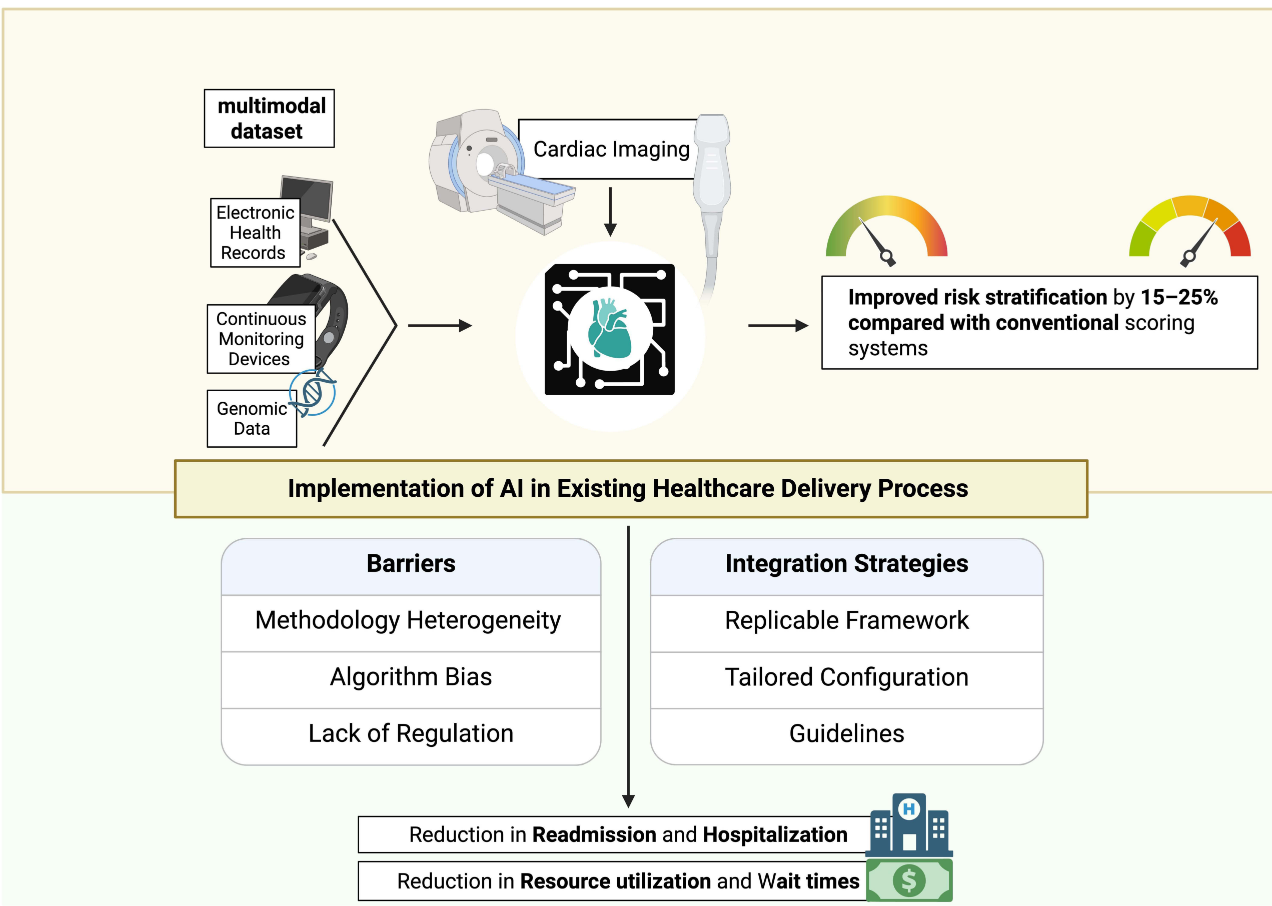

Figure 2 Diagrammatic illustration of AI's contribution to cardiovascular risk forecasting, featuring multimodal data amalgamation, deployment challenges, and methods for effective incorporation into health service protocols.

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Machine Learning in Risk Assessment

ML algorithms, including random forests and gradient boosting methods, have enhanced cardiovascular disease risk prediction by capturing nonlinear interactions among traditional risk factors. In cohort studies comparing AI-based models with conventional risk scores, ML models achieved AUC values ranging from 0.82 to 0.91, representing improvements of approximately 10–18% over traditional tools such as the FRS.[11,35] Figure 3 illustrates the analytical workflow through which ML models process complex datasets to improve predictive performance relative to conventional statistical approaches.

Deep Learning for Cardiac Imaging

DL models, particularly CNNs, have markedly advanced cardiac imaging analysis by automating the interpretation of echocardiography, computed tomography (CT) angiography, and magnetic resonance imaging (MRI). Beyond anatomical evaluation, these models increasingly extract prognostic imaging biomarkers capable of forecasting future cardiovascular events. Reported diagnostic accuracy ranges from 85% to 95% for conditions such as left ventricular dysfunction (LVD) and CAD, while also facilitating prediction of incident HF, MI, and cardiovascular mortality through detection of subtle subclinical patterns not discernible via conventional interpretation.[23,28,36,37] These systems offer advantages in processing speed, reproducibility, and long-term risk stratification. Figure 4 depicts the workflow for DL-based imaging analysis and prediction.

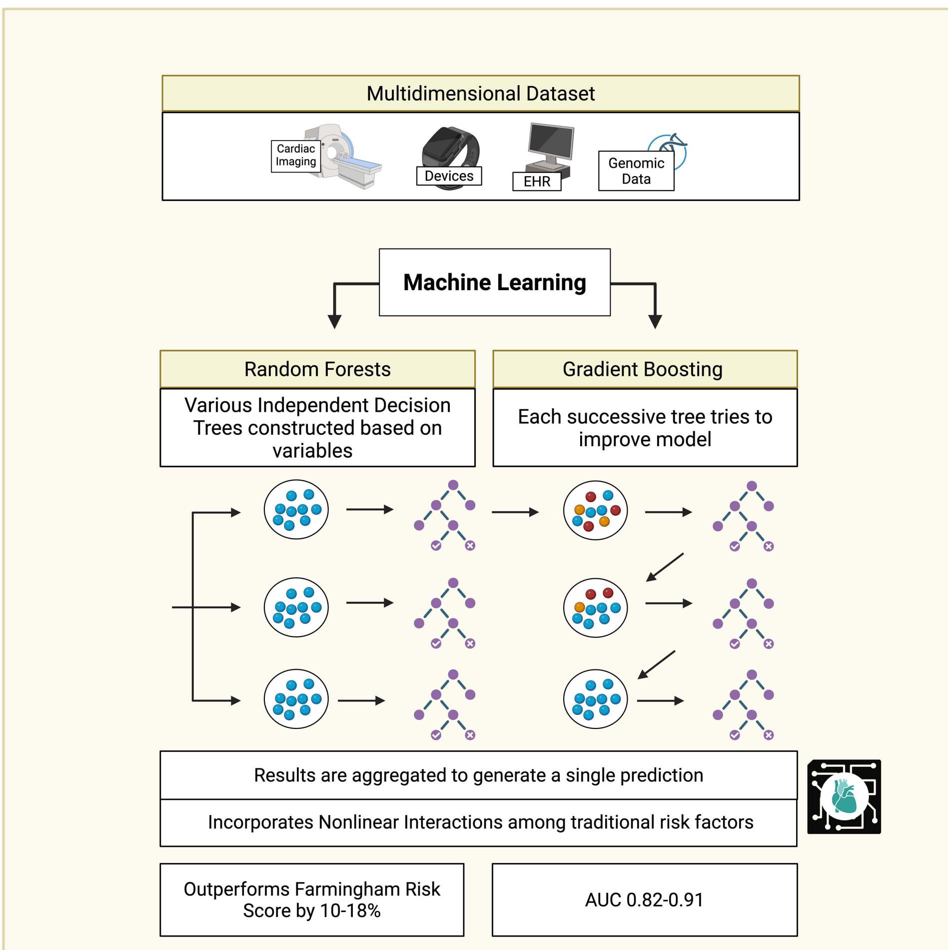

Figure 3 Diagrammatic overview of ML's role in improving cardiovascular risk forecasting, depicting random forests and gradient boosting on varied data sources, leading to enhanced AUC scores and superior results over conventional systems.

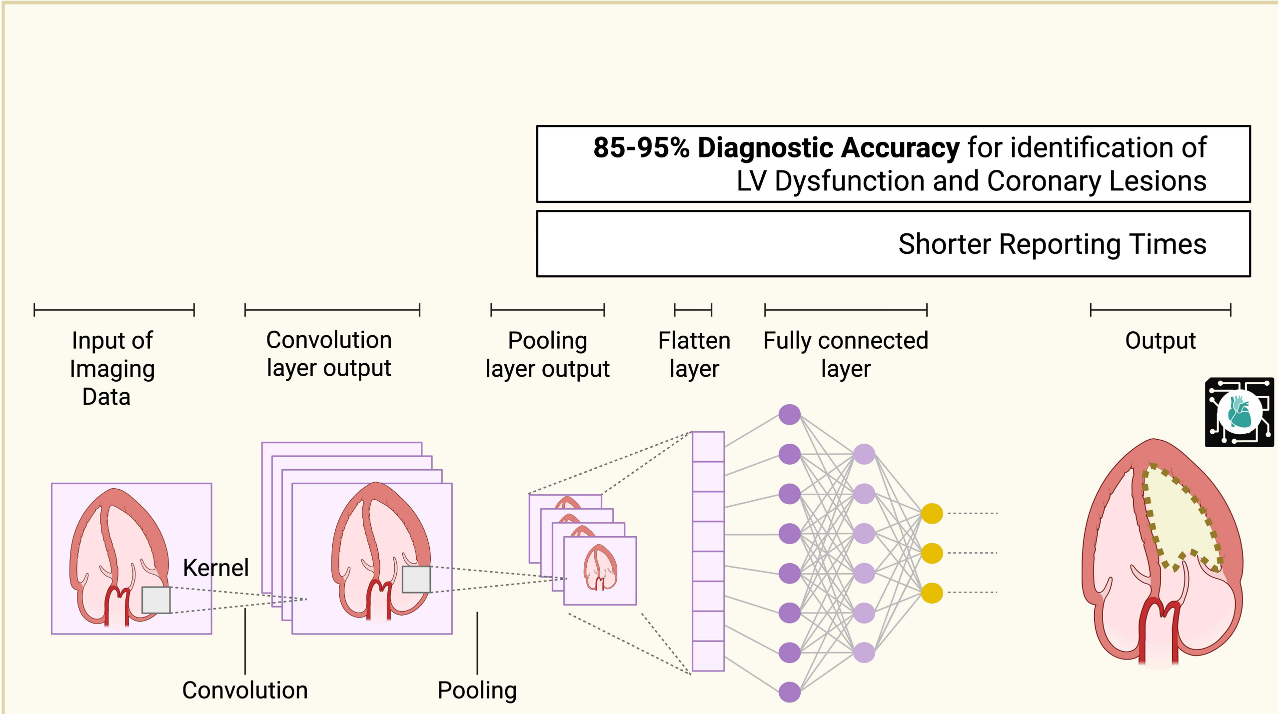

Figure 4 Schematic depiction of DL framework in cardiac imaging automation, representing convolutional layers, pooling, and fully connected networks applied to input data, yielding 85–95% diagnostic precision for LV dysfunction and coronary lesions alongside expedited reporting.

Natural Language Processing in EHR Analysis

Natural language processing (NLP) methods enable extraction of clinically relevant information from unstructured EHR components, including physician notes and discharge summaries, capturing risk signals not available in structured data fields. When combined with structured EHR variables, NLP-enhanced models demonstrate improved discrimination for predicting MI and HF onset. Meta-analytic evidence indicates approximately 12–20% improvement in predictive accuracy, primarily measured by AUC, compared with traditional risk scores.[12] Specifically, predictive performance for MI improved in coronary artery disease populations,[29] while HF onset prediction, including hospital readmission risk, showed approximately 12–18% improvement.[12] These results underscore the broad applicability of NLP-based approaches across cardiovascular risk prediction tasks. Figure 5 depicts the integration of NLP-derived features with structured EHR data for enhanced prediction of MI and HF outcomes.

Personalized Medicine and AI in Cardiovascular Risk

AI has enabled the development of patient-specific risk models by integrating genetic, clinical, and lifestyle data to support individualized preventive strategies. Studies report an 18–25% improvement in calibration of individualized risk estimates compared with population-based risk scores, facilitating more precise therapeutic targeting in high-risk subgroups.[15,38] Figure 6 illustrates the key components of this approach, including predictive analytics for HF, genomic data integration, and wearable-based monitoring systems that enhance clinical decision-making.

Predictive Modeling for Heart Failure

ML and DL algorithms have been applied to predict HF onset and progression using multimodal inputs such as echocardiographic parameters and circulating biomarkers. These models illustrated AUC values ranging from 0.88 to 0.94 for prediction of one-year readmission risk, outperforming conventional prognostic scores by around 15–22% and enabling earlier clinical intervention.[30,39]

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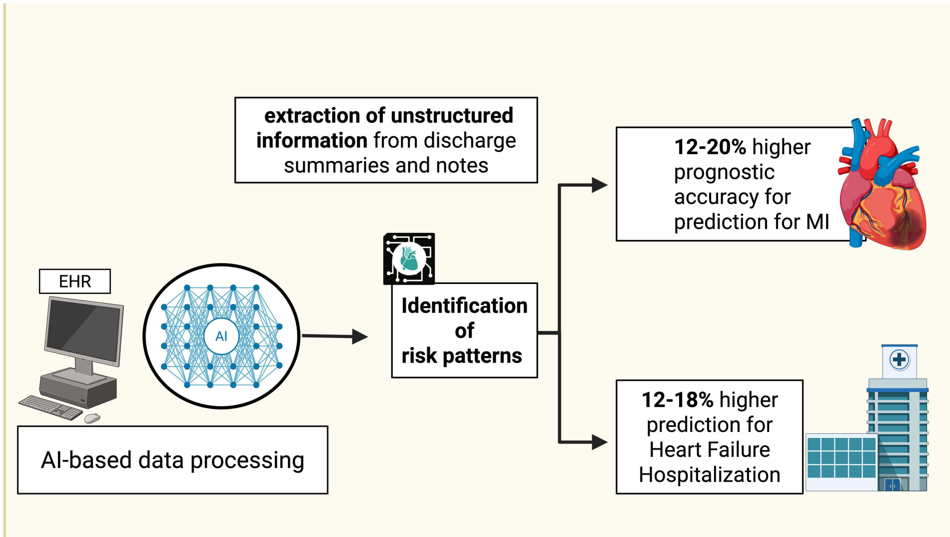

Figure 5 Schematic diagram of natural language processing application in electronic health record examination, demonstrating AI-assisted extraction from unstructured sources, risk pattern recognition, and resultant 12–20% elevated precision for ML prognosis alongside 12–18% better forecasting for heart failure admissions.

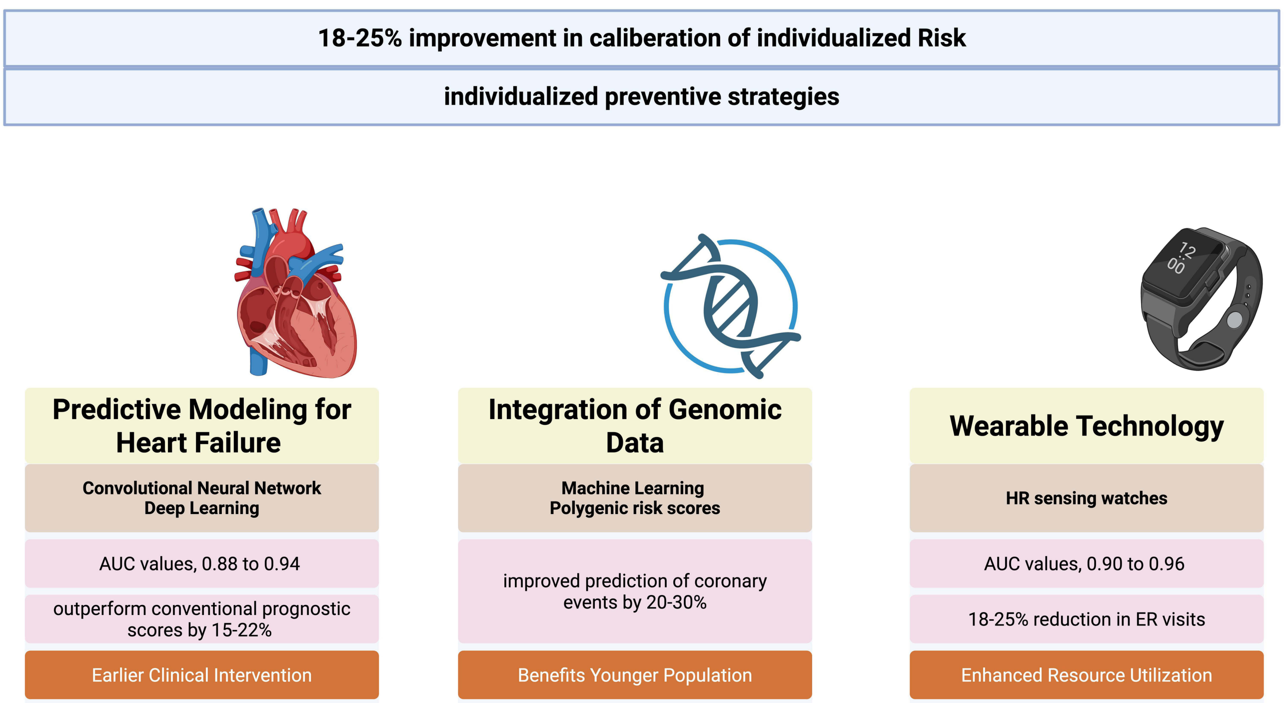

Figure 6 Conceptual framework of artificial intelligence in personalized cardiology, featuring predictive modeling with convolutional neural networks yielding AUCs of 0.88 to 0.94 for HF prognosis, machine learning-enhanced polygenic risk scores improving coronary event forecasts by 20–30%, and wearable devices achieving AUCs of 0.90 to 0.96 alongside an 18–25% decrease in emergency room utilization.

Integration of Genomic Data

AI-based models that incorporate genomic variants alongside clinical risk profiles have further refined cardiovascular risk prediction. Polygenic risk scores enhanced through ML-based modeling improved prediction of coronary events by 20–30% beyond traditional clinical risk factors, with the greatest incremental value observed in younger populations.[38,40]

Wearable Technology and Real-Time Monitoring

Wearable devices integrated with AI algorithms enable continuous monitoring of heart rate (HR) variability, physical activity patterns, and early arrhythmia detection. Reported sensitivity for AF detection ranged from 90% to 96%, while RCTs and cohort studies documented reductions in emergency department utilization ranging from 18% to 25% among individuals receiving proactive algorithm-driven alerts compared with usual care.[32,34] Table 1 summarizes the current evidence and practical applications of artificial intelligence in cardiovascular disease prediction.

Discussion

This umbrella review evaluated the clinical applications and translational limitations AI in CVD risk prediction, with particular emphasis on real-world implementation rather than purely theoretical performance metrics. In addition to synthesizing existing evidence, this review proposes targeted strategies to address current barriers and promote interdisciplinary collaboration, thereby extending prior reviews that primarily focused on algorithmic performance.

The findings indicate that AI approaches, including ML, DL, and multimodal data integration, are consistently associated with improved predictive discrimination in cardiovascular risk assessment. More than 70% of imaging-based studies reported AUC values exceeding 0.90, and several individual studies described improvements in risk stratification ranging from approximately 15% to 25% compared with traditional tools such as the FRS and QRISK.[11,15] These improvements represent ranges reported across individual studies rather than pooled meta-analytic estimates and should therefore be interpreted as indicative rather than definitive.

Performance gains were particularly evident in real-time monitoring using wearable devices and in models integrating EHRs with genomic data, enabling earlier detection of AF, CAD, and HF across heterogeneous populations. One prospective study reported approximately 19% fewer unplanned cardiovascular hospitalizations with AI-assisted wearable monitoring compared with usual care;[51] however, this observation derives from a single study and warrants cautious interpretation.

An important consideration for clinical translation is the uneven maturity of evidence across AI applications. Imaging-based AI models, including automated echocardiographic view classification, ejection fraction quantification, and coronary stenosis detection, have undergone extensive technical validation and, in some cases, prospective clinical evaluation.[20,23,28,46] Several tools have received regulatory clearance (eg, FDA or CE marking) and are primarily designed to enhance diagnostic accuracy and workflow efficiency, placing them closer to routine clinical adoption.[15,28] In contrast, multimodal and wearable-based AI models integrating EHR data, genomics, and continuous sensor inputs for long-term individualized risk prediction remain in a more exploratory phase.[12,15,38] Although these approaches hold substantial preventive potential, they frequently lack robust external validation across diverse populations, prospective trials demonstrating clinical utility, and clearly defined regulatory pathways.[19,25,33]

Compared with prior high-impact publications, this umbrella review expands beyond analyses of deep learning (DL)-based cardiac imaging reported in *Journal of the American Medical Association Cardiology* (JAMA Cardiol)[28] by incorporating wearable technologies and polygenic risk scores (PRSs). By explicitly stratifying primary and secondary evidence, the present synthesis provides a more transparent comparison across levels of evidence. Additionally, studies from Asian cohorts reported up to 20% higher predictive performance in urban settings, potentially reflecting greater adoption of wearable technologies; these findings should be interpreted as context-specific observations rather than generalizable effects.

Whereas European Heart Journal (EHJ) meta-analyses have emphasized the limitations of traditional risk algorithms,[9] the present synthesis underscores the capacity of AI models to capture nonlinear relationships within EHR data and unstructured clinical narratives through NLP, outperforming guideline-endorsed risk models by roughly 18–22% in multiethnic datasets.[30] Even more recent conventional scores, such as the PRECISE-HBR score for post-percutaneous coronary intervention (PCI) bleeding risk prediction, largely represent incremental improvements in discrimination within specific procedural contexts.[10] By comparison, AI-based approaches offer broader multimodal integration, improved detection of nonlinear patterns, and adaptability across diverse cardiovascular conditions, representing a more fundamental methodological advancement.

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Table 1 Key Applications of Artificial Intelligence in Cardiovascular Disease Prediction: a Stratified Overview of Landmark Studies

Authors (Year)	Study Design	AI Method	Data Source	Outcome	Key Finding	Evidence Level (Primary/ Secondary)
Narula et al 2016[41]	Diagnostic Study	Ensemble ML Model	2D speckle-tracking echocardiograms	HCM vs. athlete's heart differentiation	ML model differentiated HCM from athlete's heart with AUC = 0.795, outperforming conventional echo parameters.	Primary
Weng et al 2017[35]	Retrospective cohort	Logistic regression, RF, GBM, NN	UK CPRD – primary care records	10-year CVD event	ML algorithms improved CVD risk prediction (AUC +1.7% to +3.6%) vs. ACC/AHA; NN achieved highest accuracy.	Primary
Krittanawong et al 2017[42]	Review	ML/AI	Literature Synthesis	Framework for AI in Precision Cardiology	Seminal review highlighting AI's potential in diagnosis, prediction, and precision care.	Secondary
Madani et al 2018[23]	Retrospective	DL (CNN)	Echocardiogram Images	View classification	CNN classified echo views with 97.8% accuracy, supporting automation in image interpretation	Primary
Dimopoulos et al 2018[43]	Prospective cohort	RF, DT, k-NN	ATTICA cohort (n=2020)	10-year CVD incidence	Accuracy up to 84% (RF best); comparable to Hellenic SCORE	Primary
Steinhubl et al 2018[34]	RCT	ML and wearable ECG	Wearable Patch ECG	Detection of Undiagnosed AF	Continuous ECG monitoring identified new AF in 3.9% of participants, improving detection over standard care.	Primary
Alaa et al 2019[11]	Prospective cohort	AutoML	UK Biobank (n=423,604)	CVD risk	AutoML achieved AUC = 0.88, outperforming the Framingham Risk Score.	Primary
Attia et al 2019[32]	Retrospective Analysis	CNN	ECG	AF detection during sinus rhythm	AI-enabled ECG detected occult AF with 90% sensitivity from sinus rhythm tracings.	Primary
Topol 2019[15]	Narrative review	AI and human intelligence	Literature Synthesis	AI in medicine	Reviewed AI's capacity to enhance diagnostic accuracy and clinical decision-making.	Secondary
Oikonomou et al 2019[44]	Multicohort Study	Random Forest	CCTA (CRISP-CT, SCOT-HEART, Ox-IMPACT)	MACE prediction	ML-derived FRP improved MACE prediction beyond conventional risk factors, stenosis, and plaque metrics.	Primary
Krittanawong et al 2020[14]	Meta-analysis	Various ML models (RF, SVM, ANN)	Aggregated primary CVD studies	Predictive performance for CVD	ML models significantly improved CVD prediction with a high pooled AUC, confirming superior performance over traditional models.	Secondary
Sengupta et al 2020[45]	Retrospective Cohort	DL (EchoNet-Dynamic)	Echocardiogram Videos	Prediction of incident HF	Model predicted HF hospitalization with AUC = 0.83, outperforming clinical benchmarks.	Primary
Ouyang et al 2020[30]	Prospective	DL (Video-based CNN)	Echocardiogram Videos	Automated EF assessment	AI achieved strong correlation with expert readings (r = 0.95) for beat-to-beat LV EF estimation, enabling real-time functional analysis.	Primary

Noseworthy et al 2020[25]	Retrospective Cohort Study	DL Model for ECG analysis (Convolutional Neural Network - CNN)	ECGs and demographic data	Performance across racial/ ethnic groups	Model accuracy varied by race; lower accuracy in Black vs. White patients, emphasizing the need to address bias in medical AI.	Primary
Ghorbani et al 2020[46]	Prospective	DL	Echocardiogram Images	EF Prediction	DL model achieved high correlation with expert EF estimation, supporting fully automated echo interpretation.	Primary
Cho S-Y et al 2021[47]	Retrospective cohort	Neural network	NHIS-HEALS cohort (Korea)	5-year ASCVD risk	Neural network achieved C-statistic = 0.751, with a +0.01 improvement over pooled cohort equations ($p < 0.001$).	Primary
Raghunath et al 2021[24]	Cohort Study	Deep Neural Network	ECG data	Prediction of New-Onset AF	DL model predicted incident AF from sinus rhythm ECGs, aiding early identification of individuals at risk for AF-related stroke.	Primary
Aragam et al 2022[40]	GWAS and meta-analysis	FGWAS, PoPS, CRISPR–Cas9 validation	1,165,690 participants (181,522 CAD cases) + Biobank Japan	CAD risk loci and causal genes	Identified 241 CAD loci (54 novel) and 220 candidate genes; 42 loci fine-mapped (<5 variants); MYO9B enhancer validated for vascular motility regulation.	Secondary
Khurshid et al 2022[48]	Cohort Study	DL	EHR and ECG data	Prediction of incident AF	ECG-AI model plus clinical data improved 5-year AF prediction vs. clinical factors alone.	Primary
Mannhart et al 2023[49]	Prospective diagnostic validation	Proprietary AI in 5 wearable devices	201 patients (mean age 67).	AF detection accuracy	Device sensitivity/specificity ranged 89–96%/91–98%; dropped to 85%/75% when inconclusive results included. 17–26% of tracings were inconclusive; cardiologist review restored 98% sensitivity, 100% specificity, highlighting physician oversight value.	Primary
Subramani et al 2023[50]	Retrospective	Stacking ensemble (RF, LR, MLP, ET, CatBoost)	UCI Heart Dataset (n = 918)	CVD prediction	Model achieved 96% accuracy and a high F1-score; SHAP analysis enhanced interpretability.	Primary
Wehbe et al 2023[28]	Systematic Review	DL (Various CNNs)	Cardiovascular Imaging Studies	Review of DL in Imaging	Most DL models achieved expert-level accuracy; >70% of studies reported AUC > 0.90.	Secondary
Perez et al 2023[51]	Prospective, single-group, pragmatic, siteless study	Algorithm for irregular pulse detection (PPG)	Apple Watch PPG sensors validated with ECG patches	Identification of AF	Among notified users, 34% had AF on ECG patch; PPV = 0.84; low notification rate (0.52%) indicated conservative algorithm behavior.	Primary
Hu et al 2023[52]	Systematic review and meta-analysis	DL	Retinal images	CVD risk prediction	DL models achieved high accuracy in predicting CVD from fundus photographs.	Secondary
Yuan et al 2023[53]	Cohort Study	DL	ECG data (U.S. Veterans Affairs Database)	AF prediction	DL analysis of sinus rhythm ECGs accurately predicted future AF onset in a large veteran cohort.	Primary
Ding et al 2023[54]	Model Development	GAN	PPG Signals	AF Detection	GAN-based data augmentation with spectral loss improved PPG-based AF detection accuracy.	Primary

(*Continued*)

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Table 1 (Continued).

Authors (Year)	Study Design	AI Method	Data Source	Outcome	Key Finding	Evidence Level (Primary/ Secondary)
Oikonomou & Khera 2023[55]	Comprehensive Review	ML	Multimodal clinical and biomarker data	Precision risk stratification in diabetes and CVD	Highlighted ML's role in personalized risk prediction among high-risk diabetic and cardiovascular populations.	Secondary
Cicek et al 2024[29]	Meta-analysis	ML applied to SPECT imaging	SPECT imaging datasets	CAD prognosis	ML-enhanced SPECT analysis improved survival prediction in CAD patients.	Secondary
Weiss et al 2024[56]	Risk prediction study	DL (CXR CVD-Risk model)	PLCO trial and outpatient cohort (n = 11,001)	10-year MACE	High-risk group showed HR = 1.73 (95% CI 1.47–2.03); model provided incremental prognostic value beyond ASCVD score.	Primary
Al-Alshaikh et al 2024[57]	Experimental	ML-HDPM (MLDCNN + AEHOM)	Cleveland UCI dataset (n = 303)	Heart disease presence	Achieved 89.1% accuracy, F-score = 89.6%, and TPR = 90.8%, showing robust diagnostic performance.	Primary
Teshale et al 2024[58]	Systematic review	DL (time-to-event)	Mixed clinical data	CVD events	DL-based survival models achieved superior predictive performance compared with traditional statistical approaches.	Secondary
Cai et al 2024[33]	Systematic review	ML and DL (66 algorithms, 13 categories)	79 studies encompassing 486 AI–CVD models	Framework for pitfalls and solutions in AI–CVD modeling	Developed a framework with 15 key pitfalls across four domains (data quality, dataset characteristics, model design, clinical implications) and proposed actionable solutions to improve model reliability and clinical applicability.	Secondary
Singh et al 2024[59]	Systematic review	ML	EHR data	CVD risk assessment	ML-based models improved accuracy for primary prevention compared with conventional risk equations.	Secondary
Dorraki et al 2024[60]	Prospective cohort	Ensemble ML (DT, RF, XGBoost, SVM, DNN)	UK Biobank (n=375,145)	CVD prediction (hypertensive, ischemic)	Ensemble ML methods effectively predicted hypertensive and ischemic CVD, demonstrating high scalability in population-level cohorts.	Primary
El-Sofany et al 2024[61]	Observational	XGBoost with SMOTE and SHAP	CHDD and private Egyptian dataset (n = 503)	Heart disease classification	Achieved 97.6% accuracy, AUC = 0.98, and specificity = 90.5%; SHAP improved model interpretability.	Primary
Jiang et al 2024[62]	Predictive Model Development	ML	EHR	HF readmission risk	Developed a ML model for HF readmission prediction, supporting improved clinical decision-making.	Primary
Kim et al 2024[21]	Model Development & Validation	DL	EHR	HF Rehospitalization Prediction	Developed and externally validated a DL model predicting HF rehospitalization at 30, 90, and 365 days with strong generalization performance.	Primary
Liu et al 2025[12]	Systematic review and meta-analysis	ML applied to EHR	HER	CVD risk predication	Pooled AUC = 0.86, showing 12–20% improvement over traditional risk scores (eg, QRISK3).	Secondary

Liu et al 2025[19]	Systematic review	ML for primary prevention	EHR	CVD risk challenges	Highlighted major bias and generalizability issues in ML models, particularly in low-resource healthcare settings.	Secondary
Rehman et al 2025[63]	Retrospective	PSO-ANN	NHANES (1999–2016)	CHD prediction	Achieved 96.1% accuracy; model performance further improved using mutual information and SMOTE for data imbalance correction.	Primary
Karim et al 2025[64]	Retrospective series	DCNN	96 ECGs from 42 OMI patients	OMI detection from CCA "normal" ECGs	AI reclassified 81% of ECGs labeled "normal" by CCA as OMI and 86% as abnormal, indicating strong sensitivity for early OMI detection.	Primary
Elvas et al 2025[65]	Cohort/Experimental	Explainable AI (XAI)	Kaggle dataset (308,737 pts)	Predictive accuracy, interpretability	Achieved 91.9% accuracy; improved interpretability enhanced clinician trust and decision-making.	Primary
Meder et al 2025[66]	Review/Population	AI algorithms	Multiple population cohorts	Population health improvement	AI integration improved CVD risk prediction and preventive health management at the population level.	Secondary
Rohan et al 2025[67]	Experimental	DL	Clinical datasets	Heart disease prediction	Multi-feature DL model achieved high predictive accuracy for heart disease classification.	Primary
Shojaei et al 2025[68]	Systematic Review and Meta-Analysis	Various AI/ML models	Multiple primary studies on TAVR patients	Prediction of post-TAVR outcomes and risk stratification	AI models showed high predictive performance for mortality, AKI, and vascular complications, supporting personalized risk assessment in TAVR candidates.	Secondary
Bdir et al 2025[69]	Scoping Review	CNN, SVM, ANN, Random Forest	Public databases (PTB, Chapman–Shaoxing), single-center datasets	MI detection via ECG	Reported ≥99% accuracy in internal validation; however, performance dropped under external or inter-patient testing, underscoring generalizability issues and need for standardized validation.	Secondary
Majumder et al 2025[70]	Narrative Review	ML (RF, XGBoost, SVM); DL (CNN, Graph-SAGE); Unsupervised ML (Clustering)	Gut microbiome sequencing (16S rRNA, shotgun metagenomics) + multi-omics data.	Atherosclerosis risk and personalized treatment	AI identified key microbial biomarkers (↑Bacteroides, ↓Faecalibacterium) associated with atherosclerosis and enabled personalized prevention (diet, probiotics).	Secondary
Kasartzian & Tsiampalis 2025[71]	Review Article	Ensemble (RF, XGBoost); DL (CNN, RNN, LSTM, MLP); NLP; Cox-based ML survival models	EHRs and Omics (lipidomics, proteomics, genomics) + imaging (CCTA, CMR) + wearable data	CVD risk prediction	Integrating multimodal AI (clinical + omics + imaging + wearables) enhances precision CVD risk prediction.	Secondary

Notes: Evidence Level classification is based on standard evidence-based medicine hierarchies: Primary = original research studies (eg, RCTs, prospective/retrospective cohort studies, diagnostic studies, model development/experimental studies). Secondary = synthesized evidence (eg, systematic reviews, meta-analyses, narrative reviews, scoping reviews, comprehensive reviews).

Abbreviations: AF, atrial fibrillation; AEHOM, autoencoder hybrid optimization model; AI, artificial intelligence; ANN, artificial neural network; ASCVD, atherosclerotic cardiovascular disease; ATTICA, Athens Study of the Prevalence of Cardiovascular Disease Risk Factors; CCTA, coronary computed tomography angiography; CHD, coronary heart disease; CNN, convolutional neural network; CRISPR–Cas9, clustered regularly interspaced short palindromic repeats–CRISPR associated protein 9; CV, cardiovascular; CVD, cardiovascular disease; DCNN, deep convolutional neural network; DL, deep learning; DT, decision tree; EHR, electronic health record; EF, ejection fraction; F1-score, harmonic mean of precision and recall; FRP, fat radiomic profile; GAN, generative adversarial network; GBM, gradient boosting machine; HF, heart failure; HR, hazard ratio; k-NN, k-nearest neighbors; ML, machine learning; MLDCNN, multi-level deep convolutional neural network; NHANES, National Health and Nutrition Examination Survey; NHIS-HEALS, National Health Insurance Service-Health Screening Cohort (Korea); NN, neural network; OMI, occlusion myocardial infarction; PPG, photoplethysmography; PoPS, polygenic priority score; PSO-ANN, particle swarm optimization-artificial neural network; PTB, Physikalisch-Technische Bundesanstalt ECG database; QRISK3, third-generation cardiovascular risk prediction algorithm; RF, random forest; RNN, recurrent neural network; ROI, region of interest; SHAP, Shapley additive explanations; SMOTE, synthetic minority oversampling technique; SVM, support vector machine; TAVR, transcatheter aortic valve replacement; TPR, true positive rate; UK CPRD, United Kingdom Clinical Practice Research Datalink; UCI Heart Dataset, University of California Irvine Heart Disease Dataset; XAI, explainable artificial intelligence; XGBoost, extreme gradient boosting.

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Despite the promise of AI in precision medicine,[15] clinical translation remains slower than anticipated.[15] A central finding of this umbrella review is that progress has been uneven, with imaging-based tools approaching clinical readiness while multimodal and wearable-based models require further maturation in validation, interpretability, and regulatory pathways.

Limitations

The included studies showed substantial methodological heterogeneity in populations, AI algorithms, data sources, and outcome definitions, which precluded quantitative meta-analysis. The evidence is disproportionately focused on discrimination metrics (AUC), with comparatively less attention to other essential performance aspects.

Further limitations arise from restriction to English-language publications and datasets primarily from high-income countries, potentially restricting generalizability to low-resource settings and underrepresented populations. Additional barriers to clinical translation include data privacy considerations, the need for large high-quality datasets, variability in acute care delivery and provider behavior, and evolving regulatory requirements. These factors collectively underscore the need for rigorous multicenter validation, prospective implementation studies, and standardized reporting to facilitate safe and equitable adoption of AI-based cardiovascular risk prediction models.

Future Directions

Future research should prioritize large, multicenter randomized controlled trials using diverse longitudinal datasets to reduce selection and spectrum bias and improve global generalizability. Development of explainable AI (XAI) frameworks will be essential to enhance interpretability and clinician trust, notably in real-time clinical decision-support contexts. Health-economic analyses should also be incorporated to evaluate cost-effectiveness and equity in real-world implementation.

Federated learning architectures, together with adherence to reporting standards such as TRIPOD-AI, will be critical for accelerating regulatory approval, improving transparency, and facilitating clinical integration. Future studies synthesizing both primary and secondary evidence may further clarify the rapidly evolving landscape of AI applications in cardiovascular medicine. AI-based CVD prediction studies should routinely report both discrimination and comprehensive calibration metrics, including calibration plots, calibration-in-the-large statistics, and expected calibration error (ECE).

Conclusion

This umbrella review demonstrates that AI-based models show substantial promise in improving cardiovascular risk prediction, frequently achieving high discriminatory performance, particularly in imaging-based applications.

Bridging the gap between algorithmic performance and clinical implementation will require a fundamental shift in research priorities toward multicenter validation, explainable AI frameworks, comprehensive performance reporting, and equity-focused evaluation. A balanced evaluation framework that equally prioritizes accuracy, reliability, fairness, and clinical utility will be essential for the safe, effective, and equitable integration of AI into cardiovascular care.

AI Statement

AI-assisted tools, including Grammarly, were used exclusively for language editing and readability enhancement. All scientific content, analyses, and interpretations were performed by the authors.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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