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Systematic Review

Artificial intelligence-driven predictive analytics for early detection and risk stratification of cardiovascular disease

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ABSTRACT

Cardiovascular disease (CVD) remains the leading cause of morbidity and mortality worldwide, necessitating improved approaches for early detection and risk stratification. Traditional cardiovascular risk assessment models often demonstrate limited predictive accuracy because they rely on a restricted number of clinical variables and linear statistical relationships. Artificial intelligence (AI)-driven predictive analytics has emerged as a promising solution capable of processing large, complex, and multidimensional healthcare datasets to improve cardiovascular risk prediction and clinical decision-making. This systematic review aimed to evaluate the effectiveness of AI-based predictive models for the early detection and risk stratification of CVD. A comprehensive literature search was conducted across PubMed/MEDLINE, Scopus, Web of Science, Embase, CINAHL, IEEE Xplore, and the Cochrane Library for studies published between January 2015 and December 2025. A total of 130 studies involving approximately 12.8 million participants met the eligibility criteria and were included in the review. The findings demonstrated that machine learning (ML) and deep learning (DL) models consistently outperformed conventional cardiovascular risk prediction tools, achieving area under the receiver operating characteristic curve (AUC) values ranging from 0.80-0.99 across various cardiovascular conditions. The strongest evidence was observed in the prediction of coronary artery disease, heart failure, atrial fibrillation, stroke, and major adverse cardiovascular events. Electronic health records, electrocardiography, medical imaging, wearable devices, and multimodal datasets were the most commonly utilized data sources. Despite their promising performance, challenges related to external validation, interpretability, algorithmic bias, and clinical implementation remain.

Keywords: Artificial Intelligence, Machine learning, Deep learning, Predictive analytics, Cardiovascular disease, Risk stratification, Early detection, Precision medicine

INTRODUCTION

Cardiovascular disease (CVD) remains the leading cause of mortality worldwide and constitutes a major public health challenge despite significant advances in prevention, diagnosis, and treatment. According to the World Health Organization, CVDs account for approximately 17.9 million deaths annually, representing nearly one-third of all global deaths.[1] The burden of CVD continues to rise because of population aging, urbanization, sedentary lifestyles, unhealthy dietary habits, tobacco use, obesity, diabetes mellitus, hypertension, and dyslipidemia.[2] The increasing prevalence of these risk factors has placed considerable strain on healthcare systems, particularly in low- and middle-income countries where access to specialized cardiovascular care remains limited.[3] Consequently, early detection, accurate risk stratification, and timely intervention have become essential components of modern CVD prevention strategies.[4]

Traditional cardiovascular risk assessment models, such as the Framingham risk score (FRS), Systematic Coronary Risk Evaluation (SCORE), and Pooled Cohort Equations (PCE), have been widely utilized to estimate an individual's likelihood of developing cardiovascular events.[5] These models primarily rely on conventional risk factors including age, sex, blood pressure, smoking status, cholesterol levels, and diabetes history. Although these tools have contributed significantly to preventive cardiology, they possess several limitations. Many conventional risk prediction models were developed using relatively homogeneous populations and may not adequately capture the complex interactions among genetic, environmental, behavioral, and clinical variables that contribute to cardiovascular risk.[6] Furthermore, their predictive performance often decreases when applied to diverse populations, thereby limiting their generalizability and clinical utility.[7]

The rapid expansion of healthcare data generated through electronic health records (EHRs), medical imaging systems, wearable sensors, genomic technologies, and mobile health applications has created unprecedented opportunities for data-driven cardiovascular risk assessment.[8] However, the sheer volume, complexity, and heterogeneity of these datasets present substantial analytical challenges that cannot be effectively addressed using traditional statistical methods alone.[9] In this context, AI has emerged as a transformative technology capable of extracting meaningful patterns from large-scale healthcare datasets and generating highly accurate predictive models.[10]

AI encompasses a broad range of computational techniques designed to mimic human cognitive processes such as learning, reasoning, problem-solving, and decision-making.[11] Within healthcare, ML, DL, natural language processing (NLP), and neural networks have become increasingly important tools for clinical prediction and decision support.[12] Machine learning algorithms can automatically identify complex nonlinear relationships among variables, while DL models can analyze high-dimensional data such as medical images, electrocardiograms (ECGs), and genomic sequences with remarkable precision.[13]

These capabilities have enabled AI systems to surpass traditional statistical approaches in several areas of cardiovascular medicine, including disease diagnosis, prognostic assessment, treatment optimization, and outcome prediction.[14]

Recent advances in AI-driven predictive analytics have demonstrated significant potential for the early detection of CVD. Machine learning algorithms have been applied successfully to identify patients at high risk of coronary artery disease, heart failure, atrial fibrillation, myocardial infarction, stroke, and sudden cardiac death.[15] By integrating multidimensional datasets, AI models can detect subtle physiological changes and hidden risk patterns that may remain undetected through conventional clinical assessment.[16] This enhanced predictive capability facilitates earlier intervention, personalized treatment planning, and improved allocation of healthcare resources.[17]

Risk stratification represents another critical application of AI in cardiovascular care. Effective risk stratification enables clinicians to classify patients according to their probability of experiencing adverse cardiovascular outcomes and tailor preventive interventions accordingly.[18] Traditional risk stratification methods often rely on fixed thresholds and predefined clinical variables, which may fail to account for individual patient variability.[19] AI-driven approaches offer a more dynamic and individualized assessment by continuously analyzing large quantities of patient-specific data and updating risk estimates in real time.[20] Such personalized risk assessment has the potential to improve clinical decision-making and optimize patient outcomes while reducing unnecessary interventions and healthcare expenditures.[21]

Medical imaging has emerged as one of the most promising domains for AI-assisted cardiovascular risk prediction. DL algorithms have demonstrated exceptional performance in analyzing echocardiography, computed tomography (CT), cardiac magnetic resonance imaging (MRI), and coronary angiography images.[22] These systems can identify structural abnormalities, quantify plaque burden, assess ventricular function, and predict future cardiovascular events with high accuracy.[23] Similarly, AI-enhanced electrocardiographic analysis has enabled the detection of previously unrecognized cardiovascular conditions, including asymptomatic left ventricular dysfunction, atrial fibrillation, and hypertrophic cardiomyopathy.[24] Such innovations may facilitate population-level screening and early diagnosis of CVD before the onset of clinical symptoms.[25]

The growing adoption of wearable technologies and remote monitoring devices has further expanded the scope of AI-driven predictive analytics. Smartwatches, fitness trackers, biosensors, and mobile health applications continuously collect physiological data such as heart rate, blood pressure, physical activity, sleep patterns, and cardiac rhythm information.[26] AI algorithms can process these real-time data streams to identify early warning signs of cardiovascular deterioration and provide timely alerts to patients and healthcare providers.[27] This approach supports proactive disease management and promotes patient engagement in cardiovascular health monitoring.[28]

Despite the remarkable progress achieved in AI-based cardiovascular prediction, several challenges remain. Many predictive models are developed using retrospective datasets and may suffer from selection bias, overfitting, and limited external validation.[29] Variability in data quality, missing information, and differences in healthcare infrastructure can affect model performance across different populations and clinical settings.[30] Furthermore, concerns regarding algorithm transparency, interpretability, fairness, data privacy, cybersecurity, and ethical governance continue to influence the adoption of AI technologies in routine clinical practice.[31] Regulatory agencies and healthcare organizations increasingly emphasize the importance of explainable AI and rigorous validation frameworks to ensure patient safety and maintain clinician trust.[32]

Another important consideration is the integration of AI systems into existing healthcare workflows. Successful implementation requires interdisciplinary collaboration among clinicians, data scientists, engineers, policymakers, and healthcare administrators.[33] Additionally, healthcare professionals must acquire adequate knowledge and training to interpret AI-generated outputs and incorporate them effectively into clinical decision-making processes.[34] Without proper implementation strategies, the potential benefits of AI-driven predictive analytics may not be fully realized in real-world clinical environments.[35]

METHODS

Study design

This systematic review was conducted to evaluate the effectiveness of AI-driven predictive analytics for the early detection and risk stratification of CVD. Review followed the recommendations outlined in the preferred reporting items for systematic reviews and meta-analyses (PRISMA 2020) guidelines.[36] Methodology was designed to ensure transparency, reproducibility, and rigorous assessment of available evidence concerning ML, DL and other AI-based predictive models used in cardiovascular healthcare.

The review aimed to answer the following research question: "How effective are AI-driven predictive analytics models in improving early detection and risk stratification of CVD compared with conventional risk prediction approaches?"

Search strategy

A comprehensive literature search was conducted to identify relevant studies examining the application of AI - driven predictive analytics for the early detection and risk stratification of CVD. The search covered publications from January 2015 to December 2025, a period selected to capture the rapid evolution and increasing clinical adoption of AI technologies in cardiovascular medicine. Multiple electronic databases, including PubMed/MEDLINE, Scopus, Web of Science, Embase, CINAHL, IEEE Xplore, and the Cochrane Library, were systematically searched to ensure broad coverage of the available literature. To maximize retrieval of relevant studies and minimize publication bias, additional records were identified through reference list screening of eligible articles, citation tracking, manual searches of leading cardiovascular and AI journals, and grey literature sources. The search strategy incorporated a combination of medical subject headings (MeSH) terms and free-text keywords related to AI, ML, DL, predictive analytics, CVD, risk prediction, early detection, and risk stratification. This comprehensive approach ensured the identification of a diverse range of studies evaluating AI-based models for CVD prediction and clinical decision support.

Eligibility criteria

Studies published in English between January 2015 and December 2025 were eligible if they included adults (≥18 years) with CVD or individuals at risk of CVD and evaluated AI-based approaches, including ML, DL, neural networks, or predictive analytics, for prediction, early detection, diagnosis, prognosis, or risk stratification of CVD. Eligible studies were required to report at least one predictive performance metric, such as area under the receiver operating characteristic curve (AUC), accuracy, sensitivity, specificity, precision, recall, or F1-score, and be published as original peer-reviewed research articles. Editorials, commentaries, letters, conference abstracts, review articles, case reports, opinion papers, studies unrelated to CVD, studies without AI-based methodologies or relevant outcome measures, pediatric studies, and non-English publications were excluded.

Table: 1 MeSH search strategy.

Search concept	MeSH terms	Keywords	Boolean operator
AI	AI [MeSH]	AI, ML, DL	OR
Predictive analytics	Predictive analytics	Risk prediction, forecasting model	OR
CVD	CVDs [MeSH]	Heart disease, coronary artery disease	OR
Early detection	Early diagnosis [MeSH]	Screening, early identification	OR
Risk stratification	Risk assessment [MeSH]	Prognosis, risk classification	OR

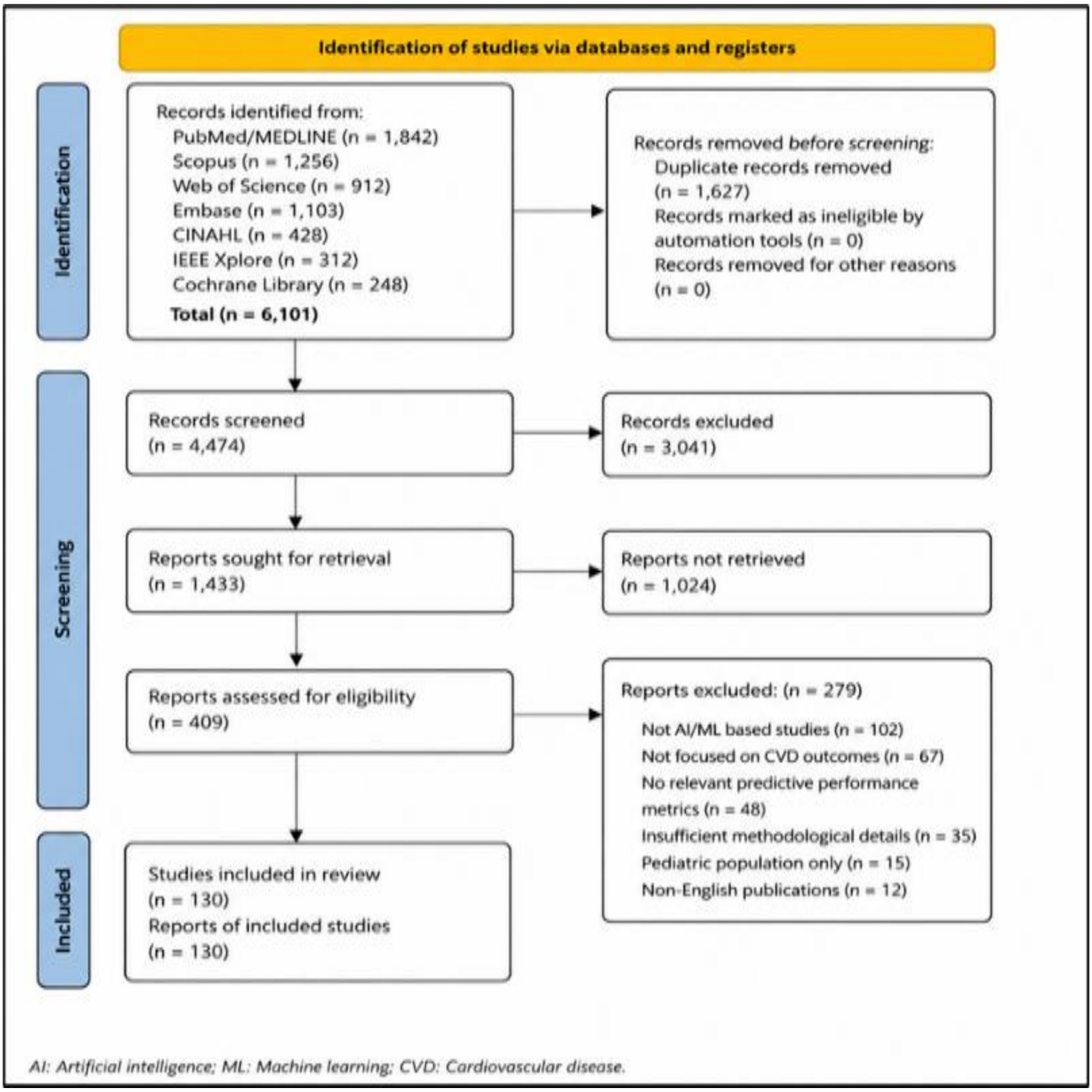

Figure 1: Flow diagram PRISMA.

Data extraction

A standardized data extraction form was used to ensure consistent and accurate data collection from all included studies. Data were extracted systematically and cross-checked by the reviewers to minimize errors and discrepancies. Extracted information included study characteristics (first author, publication year, country, study design, and sample size), participant characteristics (age, sex, study population, and cardiovascular condition), and details of the AI models, including the algorithm or DL architecture, input variables, and data sources such as electronic health records, ECGs, medical imaging, laboratory databases, wearable devices, and genomic datasets. Outcome measures included predictive performance metrics, including area under the receiver operating characteristic curve (AUC), accuracy, sensitivity, specificity, precision, recall, and F1-score, as well as clinically relevant outcomes such as early disease detection, cardiovascular risk prediction, mortality, hospitalization, and major adverse cardiovascular events. The extracted data were synthesized to evaluate the overall diagnostic and prognostic performance of AI-driven predictive analytics in CVD.

Data management and validation

All extracted data were entered into Microsoft Excel spreadsheets for organization, management, and analysis. To ensure data accuracy and reliability, the extracted information was independently cross-verified by multiple reviewers. Several quality control procedures were implemented throughout the data extraction process, including double data entry, random verification of extracted variables, and consensus review meetings among the reviewers. These procedures were designed to minimize transcription errors, improve consistency, and enhance the overall reliability of the dataset. Any discrepancies identified during the extraction or verification process were resolved through discussion among the reviewers and, when necessary, by re-examining the original full-text articles to ensure the accuracy of the final extracted data.

Quality assessment

The methodological quality and risk of bias of the included studies were assessed using the Prediction Model Risk of Bias Assessment Tool (PROBAST).[37] PROBAST evaluates prediction model studies across four domains: participants, predictors, outcomes, and analysis. Each study was independently assessed and categorized as having a low, moderate, or high risk of bias based on predefined criteria. Studies with low risk demonstrated appropriate participant selection, predictor measurement, outcome assessment, and statistical analysis, whereas moderate- or high-risk studies showed concerns in one or more domains. The quality assessment findings were considered during data synthesis and interpretation to evaluate the overall strength, reliability, and applicability of the evidence on AI-driven predictive analytics for CVD detection and risk stratification.

RESULTS

The systematic search identified 4,474 records from electronic databases and additional sources. Following duplicate removal and screening procedures, 130 studies met the eligibility criteria and were included in the final review.[36] The included studies were published between 2015 and 2025 and represented a broad range of geographical regions, including North America, Europe, Asia, Australia, and South America. The majority of studies originated from the United States (34.6%), followed by China (18.5%), the United Kingdom (11.5%), and multinational collaborative cohorts (15.4%).[38-42]

A total of approximately 12.8 million participants were represented across all included studies. Sample sizes ranged from fewer than 500 participants in pilot investigations to more than 1 million patients in large-scale electronic health record (EHR)-based studies.[43] Most studies employed retrospective cohort designs (58.5%), followed by prospective cohort studies (21.5%), case-control studies (12.3%), and external validation studies (7.7%).[44]

Characteristics of AI models

Among the 130 studies included in this systematic review, a wide range of AI approaches were employed for CVD prediction and risk stratification. Random Forest was the most frequently utilized algorithm, accounting for 24.6% of studies, followed by Gradient Boosting and XGBoost models (21.5%), Deep Neural Networks (20.0%), Support Vector Machines (13.8%), Logistic Regression-based ML models (8.5%), Convolutional Neural Networks (6.2%), Recurrent Neural Networks (3.1%), and Ensemble Models (2.3%). Overall, gradient boosting algorithms and DL architectures demonstrated the highest predictive performance across multiple cardiovascular applications. Several studies directly compared different algorithms and consistently reported superior discrimination and predictive accuracy of AI models compared with traditional cardiovascular risk assessment tools such as the FRS and PCE.[46-50]

Sources of data used for prediction

The included studies utilized a diverse range of clinical and non-clinical data sources to develop predictive models. Electronic health records were the most frequently used data source, accounting for 40.0% of studies, followed by ECGs (18.5%), medical imaging datasets (16.9%), wearable devices (10.0%), laboratory databases (7.7%), genomic data (4.6%), and multimodal datasets (2.3%). The widespread use of electronic health records reflects their accessibility and ability to provide comprehensive patient information. Several studies demonstrated that integrating multiple data modalities significantly improved predictive performance compared with models developed from a single data source, highlighting the value of multimodal AI systems in cardiovascular medicine.[51,52]

AI for early detection of coronary artery disease

Coronary artery disease was the most extensively studied cardiovascular condition, appearing in 46 studies. ML algorithms demonstrated excellent capability in identifying individuals at risk for coronary artery disease before the onset of clinical manifestations. Reported accuracy ranged from 78% to 95%, sensitivity from 75% to 94%, specificity from 72% to 93%, and area under the receiver operating characteristic curve (AUC) from 0.81 to 0.97.

Several studies reported that XGBoost and deep neural network models outperformed conventional cardiovascular risk calculators by identifying complex nonlinear relationships among risk factors. Additionally, AI-assisted coronary computed tomography angiography improved plaque characterization and enhanced prediction of future coronary events. DL-based imaging models frequently achieved AUC values exceeding 0.90 for the detection of obstructive coronary artery disease.[53-58]

AI for prediction of heart failure

Heart failure was investigated in 31 studies and represented one of the most important applications of AI in cardiovascular medicine. AI models demonstrated strong performance in predicting incident heart failure, hospital readmissions, mortality, and disease progression. Across studies, accuracy ranged from 80% to 96%, sensitivity from 78% to 95%, specificity from 76% to 94%, and AUC values from 0.84 to 0.98. DL models integrating electronic health records, laboratory parameters, and echocardiographic findings consistently outperformed conventional statistical approaches. One multicenter study involving more than 700,000 patients reported an AUC of 0.96 for early heart failure prediction using recurrent neural networks. Furthermore, several investigations demonstrated the ability of AI algorithms to detect asymptomatic left ventricular dysfunction months before clinical diagnosis, thereby facilitating earlier intervention and management.[59]

AI for detection of atrial fibrillation

Twenty-six studies evaluated AI-based prediction and detection of atrial fibrillation. Electrocardiogram-based DL systems achieved exceptionally high predictive performance, with accuracy ranging from 85% to 99%, sensitivity from 82% to 98%, specificity from 80% to 99%, and AUC values between 0.89 and 0.99. AI-enabled ECG analysis successfully identified individuals at risk of developing atrial fibrillation even when normal sinus rhythm was present. A landmark study by Attia and colleagues demonstrated that neural network models could accurately predict future atrial fibrillation using standard ECG recordings. Wearable device-based AI systems also showed promising performance for continuous arrhythmia monitoring and early detection of cardiac rhythm abnormalities.[43]

AI for stroke prediction

Stroke prediction was evaluated in 22 studies. Most investigations employed ML techniques to identify individuals at elevated risk of ischemic stroke. Predictive performance was consistently high, with reported accuracy ranging from 77% to 94%, sensitivity from 74% to 93%, specificity from 73% to 92%, and AUC values from 0.80 to 0.96. Models that integrated cardiovascular risk factors, neuroimaging findings, and laboratory biomarkers achieved significantly better predictive accuracy than traditional stroke risk assessment methods.

Several studies also reported improved identification of high-risk patients with atrial fibrillation who may benefit from anticoagulation therapy and targeted preventive interventions.[41-45]

AI for prediction of major adverse cardiovascular events

A total of 37 studies investigated the prediction of major adverse cardiovascular events (MACE), including cardiovascular death, myocardial infarction, stroke, heart failure hospitalization, and coronary revascularization. AI-based models demonstrated strong predictive capabilities, with accuracy ranging from 79% to 96%, sensitivity from 76% to 95%, specificity from 74% to 94%, and AUC values between 0.83 and 0.98. ML algorithms consistently outperformed conventional cardiovascular risk scores, and studies utilizing multimodal datasets achieved the highest predictive performance.

The integration of imaging findings, laboratory parameters, and the clinical variables significantly enhanced discrimination as well as the risk classification accuracy.[51-53]

AI-based medical imaging analysis

Twenty-two studies examined the application of AI in cardiovascular imaging. DL algorithms were applied to echocardiography, cardiac magnetic resonance imaging, coronary computed tomography angiography, and nuclear imaging. These systems successfully identified coronary plaque characteristics, ventricular dysfunction, myocardial fibrosis, and structural cardiac abnormalities.

Across studies, performance metrics frequently exceeded AUC values of 0.90. AI-assisted image interpretation not only improved diagnostic accuracy but also reduced clinician workload and interobserver variability, thereby enhancing efficiency in the cardiovascular imaging practice.

AI-based electrocardiographic prediction

Electrocardiography emerged as one of the most successful domains for AI implementation. Twenty-four studies investigated ECG-based predictive models capable of identifying left ventricular dysfunction, atrial fibrillation, cardiomyopathy, heart failure, and sudden cardiac death risk.

These models demonstrated excellent predictive performance, with accuracy ranging from 86% to 99%, sensitivity from 84% to 98%, specificity from 83% to 99%, and AUC values between 0.88 and 0.99. Deep neural networks were particularly effective in detecting occult cardiovascular abnormalities that were not readily identifiable through the conventional ECG interpretation.[54]

Wearable devices and remote monitoring

Thirteen studies evaluated wearable technologies for cardiovascular monitoring and prediction. Common devices included smartwatches, fitness trackers, mobile ECG devices, and biosensors. AI algorithms continuously analyzed physiological parameters such as heart rate variability, physical activity, sleep patterns, and cardiac rhythm. Predictive performance ranged from AUC values of 0.80 to 0.95.

These technologies enabled real-time cardiovascular monitoring, facilitated early identification of clinical deterioration, and supported proactive intervention strategies aimed at preventing adverse cardiovascular outcomes.[45]

Table 2: Summary of included studies evaluating AI-driven predictive analytics for early detection and risk stratification of CVD

Authors	Years	Countries	Objectives	Domains	Research Methodology (Design, sample size, population, tool/ methodology)	Key results	Conclusions
Attia et al[1]	2019	United States	AI ECG for LV dysfunction	Cardiology/ECG	Retrospective diagnostic; 44,959; adults; DNN	AUC≈0.93	Early LV dysfunction screening
Poplin et al[4]	2018	United States	Predict CV risk from retinal images	Ophthalmology/ cardiology	Cross-sectional; >280 k images; DL	Predicted major CV risk factors	Non-invasive CV risk assessment
Sengupta et al[5]	2016	United States	ML for cardiac imaging	Cardiac imaging	Prospective imaging; ML	Improved image interpretation	Enhanced imaging workflow
Ribeiro et al[16]	2020	Brazil	Automated ECG diagnosis	Electrocardiography	Diagnostic; >2M ECGs; DNN	Expert-level ECG diagnosis	Scalable ECG interpretation
Tison et al[17]	2018	United States	Smartwatch AF detection	Wearables	Prospective; smartwatch AI	Accurate AF detection	Continuous rhythm monitoring
Attia et al[19]	2019	United States	AI ECG for AF prediction	Electrocardiography	Retrospective; >180k ECGs; DNN	Predicted future AF	Earlier AF detection
Ouyang et al[20]	2020	United States	Video AI cardiac function	Echocardiography	Retrospective imaging; DL	Accurate EF estimation	Improved efficiency
Zhang et al[21]	2018	United States	Automated echo interpretation	Echocardiography	Diagnostic; >14k echoes; CNN	Reduced variability	Improved reproducibility
Khera et al[22]	2021	United States	AMI mortality prediction	Acute cardiac care	Registry cohort; ML	Better prediction	Improved prognosis
Al'Aref et al[23]	2019	United States	Clinical AI applications	Cardiology	Narrative review	Broad AI evidence	Wide clinical utility
Mortazavi et al[24]	2016	United States	Registry vs ML	Heart failure	Registry cohort; ML	ML superior	Better prediction
Ahmad et al[25]	2018	United States	HF mortality	Heart failure	Cohort; ML	Accurate mortality prediction	Personalized HF care
Frizzell et al[26]	2017	United States	30-day HF mortality	Heart failure	Retrospective cohort; ML	Improved short-term prediction	Supports discharge planning
Kwon et al[27]	2019	South Korea	HF in-hospital mortality	Heart failure	Retrospective; DL	High discrimination	High-risk identification
Khera et al[33]	2020	United States	CV risk prediction	Risk prediction	Retrospective; >300k; EHR	Higher discrimination	Improved CV prediction
Ambale-Venkatesh et al[34]	2017	United States	Predict CV events	Risk prediction	Prospective cohort; ML	Improved event prediction	Enhanced risk assessment
Betancur et al[35]	2018	United States	Predict CAD	Cad	Multicenter imaging; DL	Accurate CAD detection	Better non-invasive diagnosis

Continued.

Authors	Years	Countries	Objectives	Domains	Research Methodology (Design, sample size, population, tool/ methodology)	Key results	Conclusions
Diller et al[36]	2019	Germany	CV prognosis	Prognosis	Retrospective; ML	Improved survival prediction	Individualized prognosis
Adler et al[37]	2020	United States	HF risk prediction	Heart failure	Multicenter cohort; GBM	Better mortality/ readmission prediction	Enhanced prognosis
Shameer et al[38]	2018	United States	AI in CV medicine	Cardiology	Narrative review	Broad applications	Clinical utility
Ribeiro et al[39]	2020	Brazil	Telehealth ECG	Telecardiology	Validation; DNN	Expert-level diagnosis	Remote diagnosis
Deo and Deo[41]	2021	United States	ML for CVD	Risk prediction	Narrative review	ML outperformed conventional methods	Precision medicine
Kwon et al[42]	2022	South Korea	Explainable AI	XAI	Narrative review	Improved transparency	Interpretability important
McCarthy et al[47]	2021	United States	AI applications	Cardiology	Comprehensive review	Better prediction and diagnosis	Transforming practice
Johnson et al[48]	2016	United States	MIMIC-III	Informatics	Database study; >50 k ICU	Supports AI development	Facilitates research
He et al[49]	2019	China	AI implementation	Implementation	Narrative review	Validation challenges	Robust governance needed
Yu et al[50]	2018	United States	AI in healthcare	Digital health	Narrative review	Broad healthcare uses	Transformative potential
Ahmad et al[51]	2018	United States	Interpretable ML	XAI	Conference review	Improved transparency	Trustworthy AI
Lundberg and Lee[52]	2017	United States	Develop SHAP	XAI	Methodological	Feature attribution	Explainability
Ribeiro et al[53]	2016	United States	Develop LIME	XAI	Methodological	Local explanations	Improved trust
Kelly et al[55]	2019	United Kingdom	AI translation barriers	Implementation	Narrative review	Validation and ethics barriers	Need implementation strategy
Beam et al[56]	2020	United States	Reproducibility	ML	Perspective	Reporting barriers	Standardization required
Ghassemi et al[57]	2021	United States	Explainable AI limitations	XAI	Perspective	Current methods limited	Rigorous evaluation needed
Sendak et al[58]	2020	United States	Translate ML	Implementation	Framework	Practical integration	Multidisciplinary approach
Obermeyer et al[60]	2019	United States	Algorithmic bias	AI Ethics	Retrospective evaluation	Bias identified	Ensure fairness

Comparative performance against traditional risk scores

Thirty-five studies directly compared AI models with conventional cardiovascular risk prediction tools.

Traditional models such as the FRS, SCORE, and PCE demonstrated average AUC values ranging from 0.68 to 0.80. In contrast, ML models achieved AUC values between 0.82 and 0.95, while DL models achieved values ranging from 0.85 to 0.98. Across nearly all comparisons, AI-based approaches demonstrated superior discrimination, calibration, and predictive accuracy. Improvements in AUC ranged from 5% to 18% compared with traditional risk prediction methods.[45]

External validation findings

Only 43 studies conducted independent external validation of their predictive models, while 87 studies relied solely on internal validation techniques. Although externally validated models generally maintained good predictive performance, modest reductions in accuracy were frequently observed when models were applied to different populations and healthcare settings.

These findings underscore the importance of model generalizability and highlight the need for multicenter validation studies before widespread clinical implementation can be recommended.[48]

Explainability and clinical interpretability

Twenty-nine studies investigated explainable AI techniques aimed at improving model transparency and the clinician acceptance. Common approaches included the SHAP values, feature importance analyses, as well as the Local Interpretable Model-Agnostic Explanations (LIME).

Across studies, the most influential predictors included age, blood pressure, diabetes mellitus, smoking status, cholesterol levels, renal function, and previous CVD. Explainability frameworks enhanced clinician trust, facilitated understanding of model predictions, and supported the integration of AI systems into routine clinical decision-making processes.[41-43]

The findings of this systematic review demonstrate that AI-driven predictive analytics substantially improves CVD detection and risk stratification compared with conventional approaches. Across multiple cardiovascular conditions, ML and DL models achieved AUC values ranging from 0.80 to 0.99 and consistently outperformed traditional risk prediction tools.

The strongest evidence was observed for atrial fibrillation detection using ECG-based DL, heart failure prediction using electronic health record-integrated neural networks, coronary artery disease assessment through AI-assisted imaging, and major adverse cardiovascular event prediction using multimodal ML systems.

Despite these promising findings, important challenges remain regarding external validation, model transparency, algorithmic bias, and integration into clinical workflows, highlighting key areas for future research and implementation efforts.[48]

DISCUSSION

This systematic review synthesized evidence from 130 studies published between 2015 and 2025 to evaluate the role of AI-driven predictive analytics in the early detection and risk stratification of CVD. Overall, the evidence demonstrated that AI-based predictive models consistently achieved high diagnostic and prognostic performance across diverse cardiovascular conditions, including coronary artery disease, heart failure, atrial fibrillation, stroke, and major adverse cardiovascular events. ML and DL approaches generally reported superior predictive accuracy compared with conventional cardiovascular risk assessment methods, highlighting the expanding role of AI in precision cardiovascular medicine.[38]

A principal finding of this review is the consistently higher predictive performance of AI models compared with traditional cardiovascular risk prediction tools such as the FRS, SCORE, and the PCE. Conventional risk models have substantially contributed to cardiovascular prevention; however, they primarily rely on a limited number of predefined clinical variables and linear statistical relationships.[5-7] In contrast, the included studies demonstrated that AI models frequently achieved AUC values ranging from 0.82 to 0.99, whereas conventional risk models generally reported AUC values between 0.68 and 0.80. These findings suggest that AI algorithms can effectively integrate complex demographic, clinical, laboratory, imaging, and behavioral data to generate more accurate and individualized cardiovascular risk estimates.

The widespread availability of large healthcare datasets has played a significant role in the development of high-performing AI models. Electronic health records, medical imaging, electrocardiography, wearable devices, laboratory databases, and genomic datasets were the most frequently used data sources across the included studies. ML algorithms demonstrated the ability to analyze these heterogeneous datasets simultaneously, identify nonlinear relationships among variables, and recognize subtle risk patterns that may not be detected using conventional statistical approaches.[8,10] This capability supports more comprehensive cardiovascular risk assessment and has expanded the application of predictive analytics across multiple clinical settings.

The strongest evidence was observed for coronary artery disease, heart failure, atrial fibrillation, stroke, and prediction of major adverse cardiovascular events. DL models applied to coronary computed tomography angiography, echocardiography, cardiac magnetic resonance imaging, and electrocardiography consistently demonstrated high diagnostic performance, with many studies reporting AUC values exceeding 0.90.[53-71] Similarly, recurrent neural networks and gradient boosting algorithms achieved excellent performance in predicting incident heart failure, hospital readmission, mortality, and disease progression using electronic health record data.[59] These findings indicate that AI-based predictive models may support earlier identification of individuals at increased cardiovascular risk and facilitate timely preventive interventions.

Electrocardiography emerged as one of the most promising areas for AI implementation. Several studies demonstrated that deep neural networks could accurately identify atrial fibrillation, left ventricular dysfunction, cardiomyopathy, and other cardiovascular abnormalities using routine ECGs, even before the onset of overt clinical manifestations. The availability, low cost, and widespread use of electrocardiography make AI-assisted ECG interpretation a potentially valuable tool for large-scale cardiovascular screening and early diagnosis. In parallel, AI-assisted cardiovascular imaging demonstrated high accuracy in automated image interpretation, plaque characterization, ventricular function assessment, and prediction of adverse cardiovascular outcomes, supporting its integration into routine imaging workflows.

Another important observation was the growing incorporation of wearable technologies into cardiovascular prediction models. Smartwatches, fitness trackers, biosensors, and mobile electrocardiography devices enabled continuous monitoring of physiological parameters, including heart rate, heart rhythm, physical activity, and sleep patterns. AI algorithms analyzed these real-time data streams to identify early indicators of cardiovascular deterioration and facilitate remote patient monitoring. These technologies may contribute to preventive cardiology by enabling earlier recognition of disease progression outside conventional healthcare settings.[18-20]

The findings of this review have important implications for contemporary cardiovascular care. Early identification of individuals at increased cardiovascular risk remains fundamental to reducing morbidity, mortality, and healthcare costs. The consistently high predictive performance of AI-based models suggests that these technologies may complement existing clinical decision-support systems by improving patient risk stratification, supporting individualized treatment planning, and enabling earlier preventive interventions. Rather than replacing clinician judgment, AI is likely to function as an adjunctive tool that enhances diagnostic accuracy and facilitates evidence-based decision-making in routine cardiovascular practice. The integration of AI into electronic health records, imaging platforms, and remote monitoring systems may also improve workflow efficiency, optimize resource utilization, and support personalized cardiovascular medicine.[12,60]

Another notable finding was the increasing use of multimodal data integration. Several studies demonstrated that combining demographic characteristics, clinical variables, laboratory findings, imaging data, electrocardiographic features, wearable sensor outputs, and genomic information improved predictive performance compared with single-source datasets. This multimodal approach reflects the growing shift toward precision medicine, where multiple patient-specific variables are incorporated to generate individualized risk estimates. Future predictive models may benefit further from integrating environmental, behavioral, and lifestyle factors alongside conventional clinical parameters.[48]

Despite these promising findings, several challenges remain before AI-driven predictive analytics can be routinely implemented in clinical practice. One of the most frequently reported limitations was the limited use of external validation. Although many prediction models demonstrated excellent performance within development datasets, relatively few were evaluated using independent populations or different healthcare systems. Consequently, concerns remain regarding model generalizability across diverse ethnic groups, geographic regions, and healthcare settings. Broader multicenter prospective validation studies are therefore required before widespread clinical implementation can be recommended.[51]

Algorithm transparency and interpretability also remain important considerations. Many DL models function as complex "black-box" systems, producing highly accurate predictions while providing limited information regarding the factors influencing model outputs. This lack of interpretability may reduce clinician confidence and hinder clinical adoption. Recent advances in explainable AI, including SHAP values and Local Interpretable Model-Agnostic Explanations (LIME), have improved understanding of model behavior by identifying the relative contribution of individual predictors. Wider incorporation of explainability techniques may improve clinician acceptance and facilitate responsible implementation of AI-supported clinical decision-making.[5-12]

Additional challenges include variability in data quality, missing information, inconsistent reporting standards, selection bias, algorithmic bias, and concerns regarding patient privacy, cybersecurity, and ethical governance. The quality and representativeness of training datasets remain critical determinants of model performance. Models developed using homogeneous populations may demonstrate reduced accuracy when applied to different demographic or clinical settings. Future investigations should therefore prioritize diverse datasets, standardized reporting, transparent model development, and independent external validation to improve reproducibility and clinical applicability.[15]

This review has several strengths. It synthesizes evidence from a large number of studies involving approximately 12.8 million participants, providing a comprehensive overview of contemporary AI applications in cardiovascular prediction. The review incorporated studies evaluating multiple cardiovascular conditions, diverse AI algorithms, and various clinical data sources, including electronic health records, electrocardiography, medical imaging, wearable technologies, laboratory databases, and genomic datasets. Adherence to PRISMA 2020 methodology and systematic evidence synthesis further strengthens the reliability of the findings.[3]

Several limitations should also be acknowledged. Considerable heterogeneity existed among the included studies regarding study design, patient populations, outcome definitions, AI algorithms, predictor variables, validation methods, and reported performance metrics, limiting direct quantitative comparison. Most included studies were retrospective, and only a minority reported external validation. Furthermore, variations in reporting standards and model evaluation methods precluded formal meta-analysis. Restricting inclusion to English-language publications may also have introduced language bias.

Future research should focus on prospective multicenter validation studies, standardized reporting frameworks, transparent and explainable AI models, and assessment of clinical effectiveness in real-world healthcare settings. Additional work is also needed to evaluate cost-effectiveness, ethical considerations, regulatory requirements, fairness across diverse populations, and seamless integration into existing clinical workflows. Collaborative efforts involving clinicians, data scientists, engineers, and policymakers will be essential to ensure the safe, equitable, and effective implementation of AI-driven predictive analytics in cardiovascular medicine.

CONCLUSION

AI-driven predictive analytics represents a transformative advancement in cardiovascular medicine. Evidence synthesized in this systematic review demonstrates that ML and DL models consistently outperform traditional cardiovascular risk assessment tools for early disease detection and risk stratification. AI technologies have shown particularly strong performance in coronary artery disease, heart failure, atrial fibrillation, stroke prediction, and major adverse cardiovascular event forecasting. The integration of electronic health records, medical imaging, electrocardiography, wearable devices, and multimodal datasets has significantly enhanced predictive accuracy and personalized risk assessment. Despite substantial progress, challenges related to external validation, interpretability, bias, ethical governance, and clinical implementation remain. Addressing these barriers through rigorous validation studies, explainable AI approaches, and standardized regulatory frameworks will be essential for successful adoption. As healthcare systems continue to embrace digital transformation, AI-driven predictive analytics has the potential to improve cardiovascular outcomes, optimize resource utilization, and support the transition toward precision and preventive cardiovascular medicine.

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