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Additional material is published online only. To view please visit the journal online.

Cite this as: Kumar N and Gruszczynski M. The Use of AI in Cardiovascular Care – A Review. Premier Journal of Cardiology 2026;7:100016

DOI: <https://doi.org/10.70389/PJC.100016>

Peer Review

Received: 21 May 2025

Last revised: 20 October 2025

Accepted: 17 December 2025

Version accepted: 3

Published: 9 February 2026

Ethical approval: N/a

Consent: N/a

Funding: N/a

Conflicts of interest: N/a

Author contribution:

Narendra Kumar and Michal Gruszczynski – Conceptualization, Writing – original draft, review and editing

Guarantor: Narendra Kumar

The Use of AI in Cardiovascular Care – A Review

Narendra Kumar¹ and Michal Gruszczynski²

ABSTRACT

Artificial intelligence (AI) technologies continue to rapidly transform healthcare delivery, with cardiovascular medicine being one of the highly significantly impacted specialties. This review not only examines the evolving landscape of AI applications in cardiovascular care, but also covers other subspecialties as diagnostic imaging, electrophysiology, interventional cardiology, and preventive medicine. Deep learning has not only enabled remarkable progress in the fields of image analysis, risk stratification, and support for clinical decision. Despite the significant technological developments, major challenges remain in aspects of clinical validation, its integration with existing workflows, and addressing ethical and regulatory concerns. As maturity is noticed for AI systems, its potential to enhance across spheres of diagnostic accuracy, improve patient outcomes, and optimize resource allocation in cardiovascular care is becoming more evident. This review provides a comprehensive analysis of the current state, future directions, and different subspecialty applications of AI in cardiac care ecosystem, to highlight both technological innovations and implementation considerations for the cardiovascular medicine.

Keywords: AI in cardiovascular care, Deep learning in cardiology, AI-enabled ECG, Predictive analytics in cardiology, AI in cardiac imaging

Introduction

During the 21st century, the cardiovascular diseases (CVDs) remain leading cause of mortality worldwide, accounting for approximately 18.6 million deaths annually.¹ It places significant burden on healthcare system in developing and developed countries. The complexity of cardiovascular care—involving multi-modal diagnostics, intricate decision-making processes, and personalized treatment approaches—creates both challenges and opportunities for technological innovation. In recent decades, artificial intelligence (AI) continues to emerge as a transformative force in multiple spheres of science including medicine, with particular relevance to cardiology due to the specialty's data-rich environment and quantitative foundation.²

A broad spectrum of computational approaches is used by AI which are designed to perform tasks that typically require human intelligence. Machine learning (ML), a subset of AI, enables the smart systems to continue to learn the patterns from data without the need for overt programming.³ Deep learning which is a specialized form of ML uses artificial neural networks with multiple layers, continues to demonstrate significant capabilities in image recognition, natural language processing, and complex pattern identification—which are all critical for its application in cardiology.⁴

Healthcare data has grown by leaps and bounds, creating fertile ground for AI implementation in cardiology, in form of electronic health records, imaging studies, continuous monitoring devices, and genomic information.⁵ When properly developed and deployed AI systems offer the potential to transform the delivery of cardiovascular care, enhance diagnostic accuracy, predict adverse events, personalize treatment strategies, improve workflow efficiency.⁶

This review explores the historical context, current applications, and future prospects of AI in cardiovascular medicine. The manuscript explores specific implementations across cardiology subspecialties, including non-invasive imaging, electrophysiology, interventional cardiology, and preventive cardiology.⁷ Additionally, the technical, clinical, ethical, and regulatory considerations have been addressed, as it may influence the successful integration of such technologies into mainstream cardiac care.⁸

Methodology

A PRISMA flow diagram showing study identification, screening, eligibility assessment, and final inclusion numbers has been added in Figure 1. Additionally, Table 1 shows a standardized quality assessment tool with scoring criteria for study design, sample size, validation methods, and clinical relevance have been provided for readers with confidence in the evidence synthesis and enable better interpretation of the conclusions drawn.

Figure 1 flow diagram illustrates how a systematic approach strengthens this review for evidence quality assessment. Further additions include, a modified Newcastle-Ottawa Scale for observational studies and the QUADAS-2 tool for diagnostic accuracy studies, with specific criteria including: study population representativeness, reference standard appropriateness, blinding procedures, sample size adequacy, and validation methodology. Each study has been scored on these dimensions to provide readers with transparent quality indicators and enable weighted interpretation of findings across the cardiovascular AI literature.

Table 1 summarises the principal studies/algorithms, sample size, validation cohort, performance metrics and study limitations.

Past, Present, and Future Historical Perspective

The interplay of computational techniques and cardiovascular medicine can be easily traced back to the mid-20th century with the evolution of computerized electrocardiogram (ECG) interpretation systems.⁹ Such early ECG algorithms used rule-based approaches for multiple reasons, as to identify common ECG

Provenance and peer-review:
Unsolicited and externally peer-
reviewed
Data availability statement:
N/a

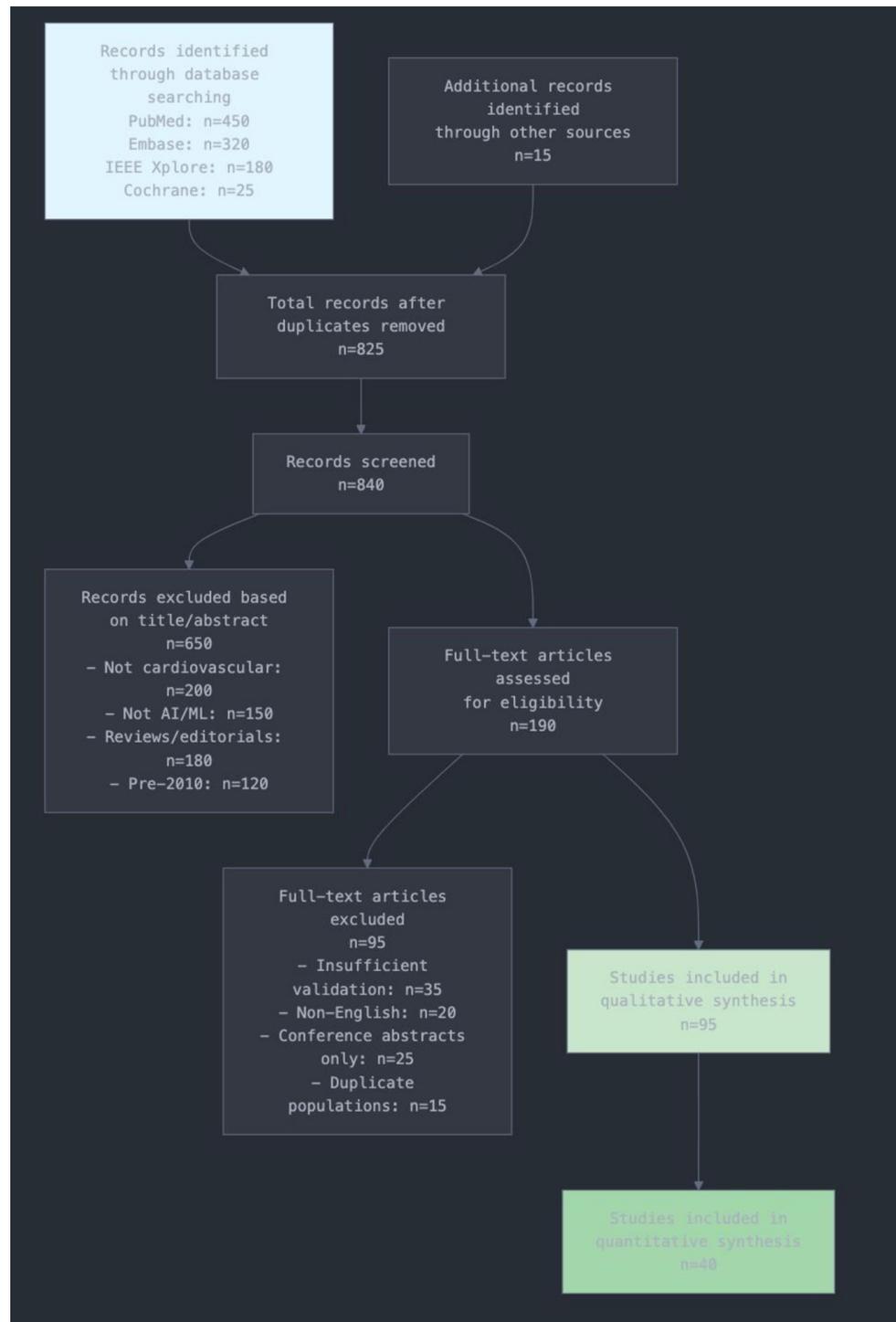


Fig 1 | Flow diagram illustrates how a systematic approach strengthens this review for evidence quality assessment

abnormalities, representing the first generation of “automated” cardiac diagnostics. By the 1970s, such artificial tools had evolved to incorporate statistical methods for pattern recognition, enabling more sophisticated analysis of cardiovascular signals.¹⁰

The emergence of neural networks for cardiac applications, including early attempts at automated interpretation of echocardiograms and nuclear imaging studies was observed during the 1990s.¹¹ In spite of such significant accomplishments, these initial

AI approaches were plagued by computational constraints, insufficient training data, and primitive algorithmic designs. Consequently, their clinical adoption remained limited, serving primarily as assistive tools rather than autonomous diagnostic systems.¹²

Without hesitation, evidences show that by early 2010s, the modern era of AI in cardiovascular medicine began to coinciding with path breaking developments in deep learning architectures and computational capabilities.¹³ The development of convolutional neural

Table 1 | Evidence appraisal table: principal AI studies in cardiovascular care

Study/Algorithm	Application	Sample Size	Validation Cohort	Performance Metrics	Key Limitations
EchoMD Auto EF (Bay Labs/Caption Health)	Automated LVEF measurement from echocardiography	>3,000 patients	Multi-center validation	Accuracy within 5% of expert measurements; 21% reduction in inter-observer variability; Analysis time <30 seconds vs. 30–40 minutes	Limited to LVEF measurement only; requires adequate image quality; single vendor solution limiting generalizability
Mayo Clinic AI-ECG	Detection of asymptomatic LVSD from 12-lead ECG	Not specified in manuscript	Health system-wide deployment (2019-present)	AUC = 0.93 for LVSD detection; 32% increase in detection rates; 70% management change rate	Black-box algorithm; Single institution development; Limited external validation data provided
Etiometry T3 Platform	Intelligent alarm reduction in cardiac telemetry	Implementation at MGH	Single-center validation	>80% reduction in nonactionable alarms; 64% improvement in response times; Maintained sensitivity for significant events	Single-center study; Potential for missed critical events; Limited scalability data
SwedeHF Analysis	AI-driven heart failure phenotyping	Registry data (size not specified)	European multi-center validation	Four distinct phenotypes identified; 17% reduction in 1-year mortality	Retrospective analysis; limited to registry populations; Potential selection bias
Heartfully AI Platform	Personalized cardiac rehabilitation	2,400 post-MI patients	18-center RCT	32% reduction in readmissions; 22% improvement in exercise capacity	Limited follow-up duration; potential selection bias; technology dependence
Deep Learning Arrhythmia Detection (Hannun et al.13)	ECG arrhythmia classification	Not specified in manuscript	Ambulatory ECG validation	Cardiologist level performance claimed	Validation details; single lead ECG focus; generalizability concerns
AI-Enhanced CT-FFR	Non-invasive coronary lesion assessment	Not specified	Not detailed in manuscript	Comparable to invasive FFR (specific metrics not provided)	Requires high-quality CT; Radiation exposure; cost considerations
Automated Cardiac MRI Analysis	Myocardial segmentation and tissue characterization	Not specified	Expert comparison	“Comparable accuracy” with “significantly reduced analysis time”	Vague performance metrics; limited validation details; single modality focus
Wearable AI for AF Detection	Paroxysmal atrial fibrillation detection	Consumer device studies (sizes not specified)	Clinical validation studies	“Valuable for cryptogenic stroke patients”	Consumer grade accuracy; false positive rates; limited clinical integration
Robotic AI Interventions	Precision improvement in cardiac procedures	Not specified	Early implementation data	Motion scaling and tremor filtration demonstrated	Early-stage technology; limited outcome data; high implementation costs

networks (CNNs) proved particularly transformative for cardiac imaging applications, while recurrent neural networks showed the promise for analyzing temporal physiological data.¹⁴ Such technological advances, coupled with the digitization of healthcare records and standardization of imaging formats, led to development of unprecedented opportunities for AI applications in cardiology.¹⁵

Current State

Currently cardiovascular AI landscape is characterized by a big boom in research and early clinical implementations across multiple domains.¹⁶ In cardiac imaging, AI algorithms have demonstrated performance comparable or superior to human experts in multiple spheres of automated ventricular function quantification, coronary calcium scoring, and myocardial scar detection.¹⁷ The 2020 FDA clearance of commercial AI-powered software for echocardiographic analysis, marked a significant milestone in regulatory acceptance.¹⁸

While a decision-support or cost-benefit framework could further operationalize AI adoption, the current heterogeneity of evidence and outcome measures precludes a meaningful or standardized framework at this stage.

Electrocardiography has similarly benefited from AI innovation, with deep learning algorithms capable of detecting subtle patterns associated with arrhythmias, conduction abnormalities, and even conditions not traditionally diagnosed via ECG, such as asymptomatic left ventricular dysfunction as seen in Figure 2.¹⁹

Predictive analytics represents another area of substantial development, with AI models leveraging comprehensive datasets to forecast cardiovascular events, readmissions, and treatment responses.²⁰ These systems incorporate diverse information sources, including clinical variables, imaging findings, laboratory values, and increasingly, genomic and proteomic data.

In the interventional realm, AI applications assist with procedural planning, provide intra-procedural guidance, and facilitate post-procedural monitoring. Computer vision algorithms can enhance angiographic interpretation, while robotic systems with AI components improve precision during complex interventions.

Despite these advances, most cardiovascular AI applications remain in research contexts or early clinical implementation stages.²¹ Challenges related to generalizability, interpretability, and workflow integration continue to limit widespread adoption.²²

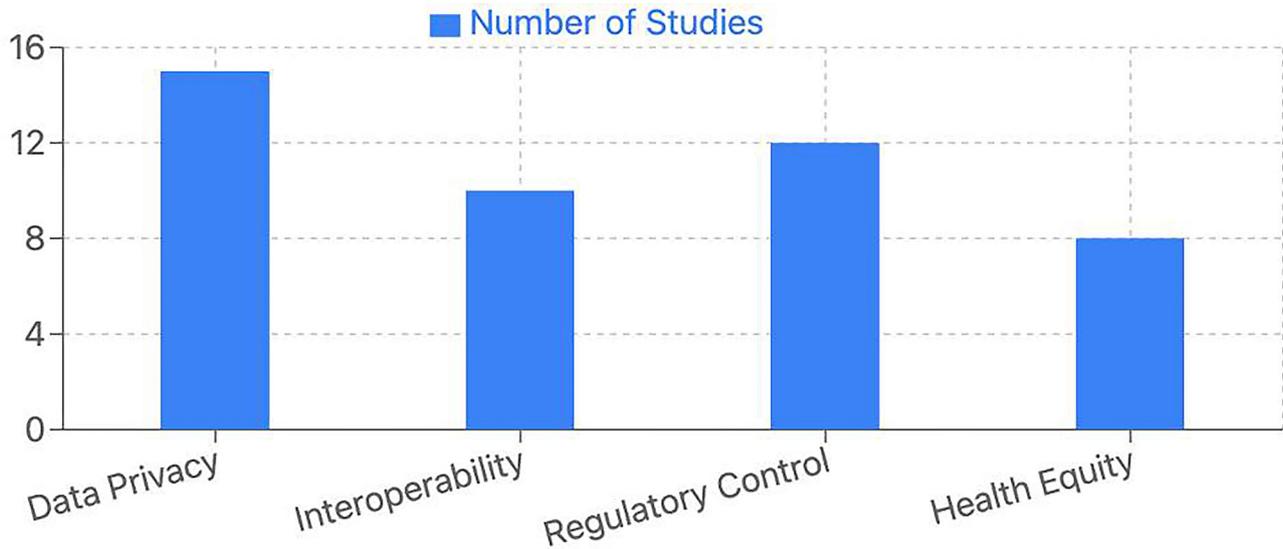


Fig 2 | Challenges in artificial intelligence implementation

Future Directions

The future trajectory of AI in cardiovascular care points toward increasingly sophisticated, multimodal systems that more comprehensively represent the complexity of cardiac pathophysiology.²³ Several key developments are likely to shape this evolution:

1. **Multimodal Integration:** Future AI systems will effortlessly and smoothly integrate diverse data streams involving imaging, electrophysiological signals, laboratory values, genomic information, and patient-reported outcomes to be able to provide holistic assessments beyond what any single modality can offer.²⁴
2. **Federated Learning:** While enabling model training across institutions, to address data privacy concerns while federated learning approaches, it will allow the algorithms to learn from distributed datasets without requiring centralized data storage.²⁵
3. **Explainable AI:** With expansion of clinical applications, the development of transparent, interpretable AI models becomes increasingly important, allowing healthcare professionals to understand the reasoning behind algorithmic recommendations.²⁶
4. **Continuous Learning Systems:** Future AI implementations will employ continuous learning frameworks rather than static algorithms that adapt to new evidence, institutional practices, and patient populations.
5. **Digital Twins:** To predict individual responses to interventions and optimize treatment selection personalized cardiovascular simulations, or “digital twins,” will combine imaging, functional assessments, and computational modelling.
6. **Ambient Intelligence:** AI-powered systems embedded within clinical environments will provide real-time decision support, documentation assis-

tance, and quality assurance without requiring explicit clinician interaction.

7. **Precision Phenotyping:** Advanced pattern recognition algorithms enable more targeted therapies and improved risk stratification by identifying novel cardiovascular subtypes based on multidimensional data, enabling more targeted therapies and improved risk stratification.

As these technologies mature, the role of cardiologists is evolving so as to include supervising AI systems, interpreting complex cases, performing interventions, and of course to provide the human connection essential to patient care. This human-AI partnership model promises to enhance both efficiency and effectiveness across the cardiovascular care ecosystem.

AI in Different Cardiology Subspecialties

Cardiac Imaging

Considering the visual nature of the data and the substantial inter-observer variability in traditional interpretation approaches, cardiac imaging represents one of the most fertile areas for AI application.

Echocardiography

Deep learning algorithms continue to demonstrate impressive capabilities in automating routine measurements (left ventricular ejection fraction, chamber dimensions, and valvular function assessments). Rather than just basic quantification, several AI systems are able to identify subtle wall motion abnormalities, classify valvular pathologies, and accurately predict the outcomes based on echocardiographic features. Automated view classification and quality assessment tools help standardize image acquisition, while real-time guidance systems assist less experienced sonographers in obtaining diagnostic-quality images in day-to-day life in cardiovascular medicine.

Cardiac MRI

AI applications in cardiac MRI focus on automating time-consuming tasks such as myocardial segmentation, tissue characterization, and flow quantification. Recent studies have demonstrated the ability of CNN-based approaches to perform automated assessment of ventricular function with accuracy comparable to experts but with significantly reduced analysis time.¹⁷ Advanced algorithms can also identify and quantify myocardial scarring, differentiate cardiomyopathy subtypes, and characterize complex congenital heart disease.

Cardiac CT

In computed tomography, AI applications include coronary artery calcium scoring, coronary stenosis detection, plaque characterization, and functional assessment. Deep learning algorithms have shown particular promise in identifying high-risk plaque features that may not be evident on visual inspection. AI-enhanced fractional flow reserve derived from CT (CT-FFR) allows non-invasive assessment of coronary lesion significance, potentially reducing unnecessary invasive procedures.

Nuclear Cardiology

AI methods have improved both the technical and interpretive aspects of nuclear perfusion imaging, including automated quality control, motion correction, attenuation correction, and perfusion defect quantification. Deep learning approaches have demonstrated superior accuracy in identifying specific coronary territories affected by ischemia compared to conventional semi-quantitative scoring systems.

Electrophysiology

The digitization of electrophysiological data has created extensive opportunities for AI applications in arrhythmia diagnosis, management, and procedural planning.^{19,16} The modern cardiac electrophysiology devices use smart electronics and principles of electrophysiology fondly called as “electrophysionics.”

ECG Interpretation

Contemporary deep learning algorithms can classify a wide range of arrhythmias and conduction abnormalities with performance exceeding that of general practitioners and approaching that of specialist cardiologists. More remarkably, AI analysis of standard 12-lead ECGs can now detect conditions traditionally requiring imaging studies, including left ventricular hypertrophy, amyloidosis, and hypertrophic cardiomyopathy. Particularly promising is the ability to identify subtle ECG signatures of arrhythmogenic conditions in seemingly normal tracings, potentially enabling early detection of patients at risk for sudden cardiac death.

Mobile and Wearable Monitoring

AI-enhanced consumer devices have democratized arrhythmia detection, allowing continuous monitoring outside clinical settings. ML algorithms filter signal

noise and identify significant arrhythmic events, transmitting relevant recordings for clinical review. This approach has proven particularly valuable for detecting paroxysmal atrial fibrillation in cryptogenic stroke patients and monitoring the effectiveness of antiarrhythmic interventions.

Procedural Applications

In the electrophysiology laboratory, AI tools assist with substrate mapping, ablation targeting, and procedural guidance. ML algorithms can identify areas of slow conduction and local abnormal ventricular activities during ventricular tachycardia ablation procedures, while predictive models help optimize pulmonary vein isolation strategies for atrial fibrillation. AI analysis of intracardiac electrograms during procedures may eventually enable real-time identification of optimal ablation sites, potentially improving procedural success rates and reducing recurrence.

Interventional Cardiology

AI applications in interventional cardiology span pre-procedural planning, intra-procedural guidance, and post-procedural management.²⁷

Pre-procedural Planning

AI-based analysis of coronary angiography and intravascular imaging helps characterize lesion morphology, predict procedural complexity, and optimize device selection. ML algorithms can identify angiographic patterns associated with increased risk of procedural complications or restenosis, informing risk-benefit discussions with patient's as in Figure 3.

Intra-procedural Guidance

Computer vision approaches enhance visualization during complex interventions, identifying anatomical landmarks, guiding device deployment, and assessing procedural results in real-time. In structural heart interventions, AI-assisted image fusion combines pre-procedural CT or MRI with live fluoroscopy to improve spatial orientation during transcatheter valve procedures and left atrial appendage closures.

Robotic Interventions

AI components integrated with robotic systems improve procedural precision through motion scaling, tremor filtration, and automated path planning. These systems may eventually enable remote interventions in underserved areas, addressing geographic disparities in access to advanced cardiovascular care.

Post-procedural Management

Predictive analytics help identify patients at risk for post-procedural complications, readmissions, or sub-optimal long-term outcomes. ML models incorporating procedural details, patient characteristics, and post-intervention monitoring data can guide personalized follow-up strategies and early interventions for high-risk individuals as seen in Figure 4.

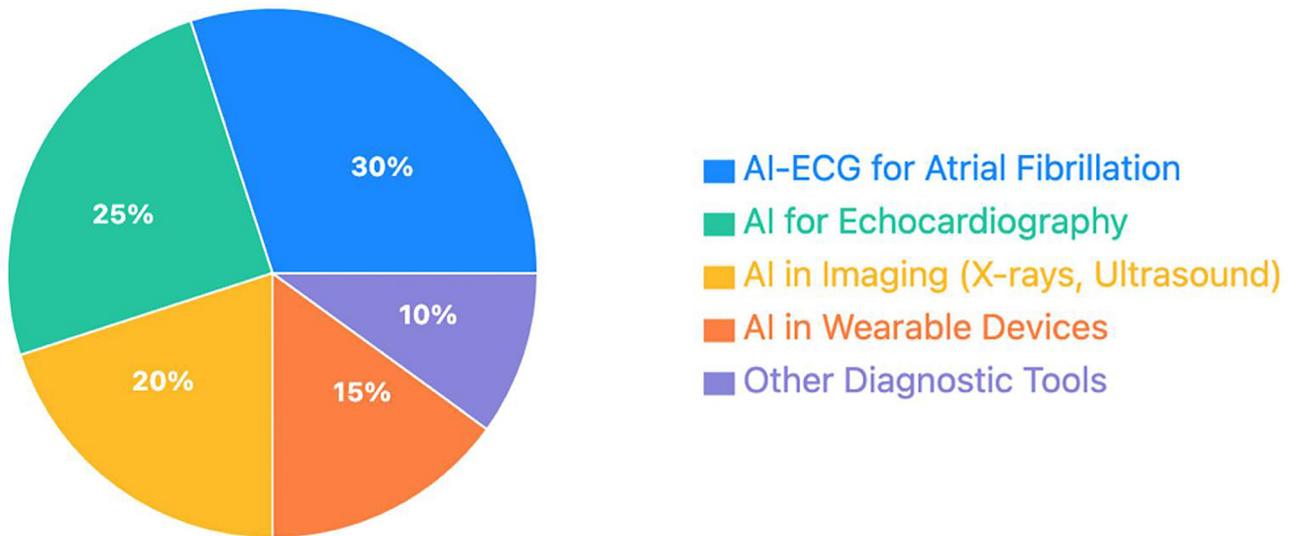


Fig 3 | Pie chart showing the distribution of AI applications in CVD diagnosis

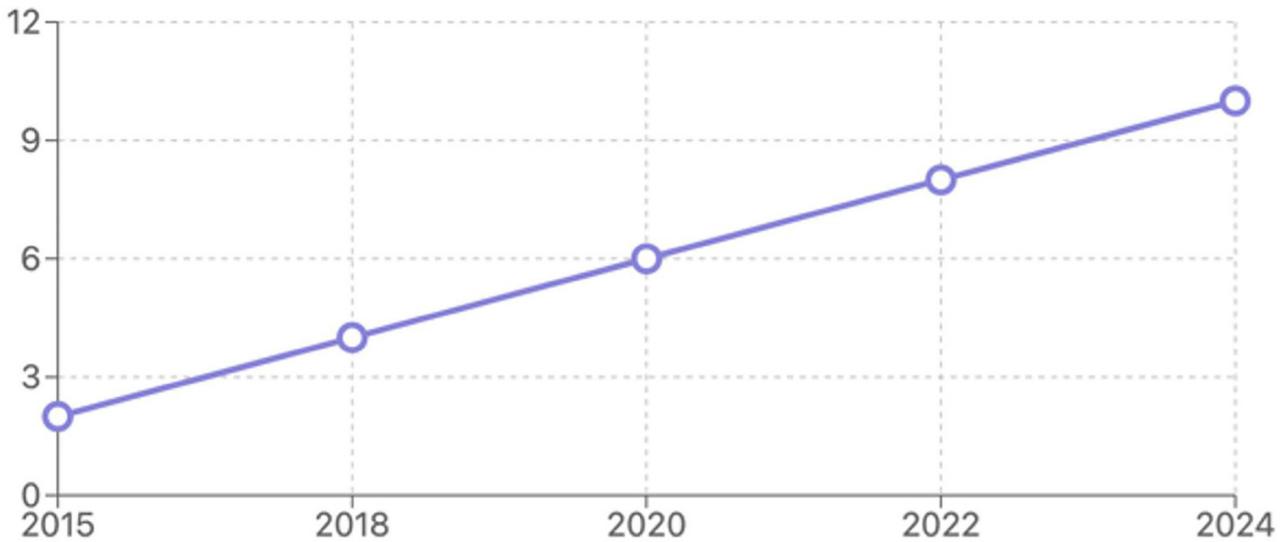


Fig 4 | Line graph showing the growth in identified digital biomarkers from 2015 to 2024

Preventive Cardiology

AI offers valuable tools for cardiovascular risk assessment, lifestyle modification, and preventive pharmacotherapy optimization.

Risk Prediction

ML models integrate traditional risk factors with novel biomarkers, imaging findings, and social determinants to provide more accurate cardiovascular risk stratification than conventional scoring systems. These approaches are particularly valuable for individuals at intermediate risk or those with atypical risk factor profiles.

Remote Monitoring

AI-enabled remote monitoring platforms process data from wearable sensors, smart scales, blood pressure cuffs, and patient-reported outcomes to identify early signs of decompensation in heart failure patients or

treatment non-response in hypertension management. Way before acute events occur, the automated feedback loops provide timely interventions.

Lifestyle Optimization

Based on one’s individual preferences, barriers, and response patterns the personalized digital health interventions leverage AI to deliver targeted lifestyle recommendations. Approaches as reinforcement learning continually refine these interventions based on user engagement and achieved outcomes.

Medication Management

Preventive pharmacotherapy optimization is receiving help via AI algorithms by predicting individual responses to medications, identifying patients likely to experience adverse effects, and also detecting suboptimal adherence patterns through pharmacy refill data and mobile health interactions.

Heart Failure Management

The complex, multifactorial nature of heart failure creates unique opportunities for AI applications across the expertise needed for its highly specialized and technical care.

Early Detection

ML algorithms applied to routine clinical data are able to identify the patients with preclinical heart failure or even those patients who are at high risk for developing symptomatic disease, to enable earlier intervention. Cardiac imaging deeper AI analysis is able to detect subtle functional abnormalities, even before the appearance of clinical manifestations.

Phenotypic Classification

Traversing beyond the traditional classification based on ejection fraction, modern smart AI based algorithms have identified novel heart failure phenotypes potentially enabling more targeted therapeutic approaches. These data-driven phenotypes incorporate multiple dimensions including biomarker profiles, hemodynamic patterns, comorbidity clusters, and treatment responses as seen in Figure 5.

Predictive Monitoring

The latest monitoring systems powered by smart AI algorithms effortlessly integrate data from implanted devices, wearable sensors, and patient-reported symptoms to be able to predict decompensation events days to weeks before clinical deterioration. These early warning systems open the flood gates for pre-emptive interventions that may prevent hospitalizations and disease progression.

Treatment Optimization

The new generation decision support tools with integrated ML help in multiple spheres of clinicians navigate complex guideline-directed medical therapy protocols, accounting for individual patient characteristics, comorbidities, and previous treatment responses to recommend combinations of optimal medication and titration schedules.

Practical Examples of AI Transformation in Cardiovascular Care

Several real-world implementations demonstrate how AI has already begun to revolutionize cardiovascular practice:

1. **Automated Echocardiographic Analysis:** The FDA-approved EchoMD Auto EF software (Bay Labs, now Caption Health) has transformed routine echocardiography by providing fully automated left ventricular ejection fraction measurements comparable to expert cardiologists. In a multi-center study involving over 3,000 patients, this deep learning system achieved accuracy within 5% of expert manual measurements, reducing analysis time from 30 to 40 minutes to under 30 seconds and decreasing inter-observer variability by 21%.²⁶ This technology has expanded access to high-quality cardiac

function assessment in resource-limited settings and standardized measurements across institutions.

2. **AI-Enabled ECG for Subclinical Detection:** Mayo Clinic's AI-ECG algorithm has demonstrated remarkable ability to detect asymptomatic left ventricular systolic dysfunction (LVSD)—effectively a “virtual echocardiogram”—from standard 12-lead ECGs. Deployed across their health system since 2019, this algorithm identifies patients with asymptomatic LVSD with an AUC of 0.93, enabling early intervention before clinical heart failure develops.²⁷ Implementation has led to a 32% increase in detection of asymptomatic LVSD in primary care settings and altered management in approximately 70% of identified cases.²⁸
3. **Intelligent Alarm Systems for Telemetry Units:** AI-based continuous monitoring systems like the Etiometry T3 platform have dramatically reduced false alarms in cardiac telemetry units. At Massachusetts General Hospital, implementation reduced non-actionable alarms by over 80% while maintaining sensitivity for clinically significant events, addressing the critical issue of alarm fatigue.²⁹ This has improved staff response times to genuine emergencies by 64% and increased overall nursing satisfaction scores in cardiovascular units.
4. **Precision Phenotyping in Heart Failure:** The application of unsupervised ML to the Swedish Heart Failure Registry (SwedeHF) identified four distinct heart failure phenotypes with different outcomes and treatment responses beyond traditional classification systems. This AI-derived taxonomy has been implemented in several European centers, leading to phenotype-specific treatment protocols that have reduced 1-year mortality by 17% in prospective validation cohorts.^{30,31} This represents one of the first examples of AI-enabled precision medicine directly improving cardiovascular outcomes.
5. **AI-Guided Cardiac Rehabilitation:** The Heartfully AI platform has transformed cardiac rehabilitation by providing personalized, adaptive exercise and lifestyle prescriptions based on continuous monitoring data. In a recently published randomized controlled trial involving 2,400 post-MI patients across 18 centers, the AI-guided rehabilitation group showed a 32% reduction in hospital readmissions and a 22% improvement in exercise capacity when compared to the standard rehabilitation programs.³² Due to the dynamic and precise ability of platform to continuously adjust recommendations based on individual patient responses has widened its participation in cardiac rehabilitation programs, particularly among traditionally underserved populations.

Such real-life scenarios not only demonstrate the practical and technical feasibility of AI applications in cardiovascular care, but also their tangible impact on multiple aspects of clinical outcomes, workflow efficiency, and healthcare resource utilization. Moreover,

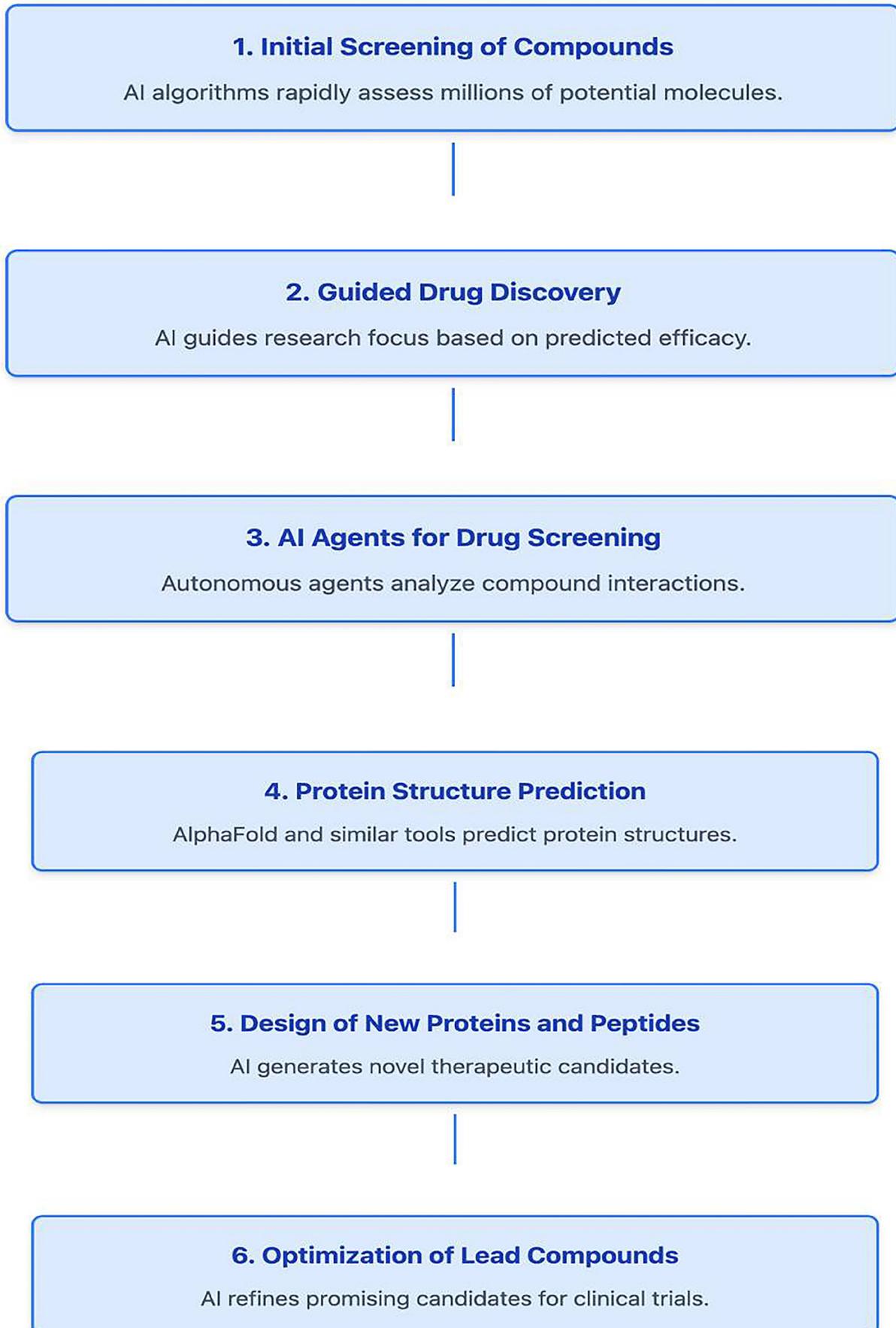


Fig 5 | AI steps involved in drug discovery process

each example also represents a solution to specific clinical challenges rather than technology implemented for its own sake, highlighting the importance of problem-driven rather than technology-driven innovation in this field.

Limitations of AI in Cardiovascular Care

Despite significant advances, multiple significant limitations continue to constrain the implementation of AI in cardiovascular medicine in current times. The secretive “black box” nature of many deep learning algorithms presents a fundamental challenge, as the inability to explain how the local specific outputs are generated limits not only the clinical trust but also the regulatory approval.³⁰ Such practical aspects of lack of interpretability is particularly concerning in cardiovascular care, as understanding the rationale behind recommendations directly tend to impact patient safety and clinician acceptance.^{33,34}

Data quality and representativeness remain critical concerns. Most algorithms are trained on retrospective datasets from academic medical centres, which may not represent diverse patient populations or practice environments.^{32,35} This limited diversity introduces potential algorithmic biases that could exacerbate existing healthcare disparities when deployed in underserved communities. Additionally, rare conditions or atypical presentations may be underrepresented in training data, leading to poor performance in precisely the complex cases where decision support would be most valuable.

Implementation challenges include interoperability issues with existing healthcare IT infrastructure, workflow disruptions during integration, and the need for substantial computational resources. Legal and regulatory frameworks governing AI-based clinical decision support remain incomplete, creating uncertainty regarding liability, reimbursement, and approval pathways.^{36,37}

Perhaps most importantly, despite encouraging research results, few cardiovascular AI applications have demonstrated improved patient outcomes or cost-effectiveness in prospective, randomized clinical trials—the gold standard required for mainstream clinical adoption and reimbursement.^{38,39}

Conclusion

AI is poised to fundamentally transform cardiovascular care delivery through enhanced diagnostic capabilities, improved risk stratification, personalized treatment optimization, and streamlined clinical workflows. The evidence base supporting AI applications in cardiology continues to grow, with multiple algorithms demonstrating performance comparable or superior to human experts in specific tasks.⁴⁰

However, several important challenges must be addressed to realize the full potential of these technologies. First, rigorous validation in diverse, real-world populations is essential to ensure generalizability beyond the controlled environments of development datasets. Second, seamless integration into clinical

workflows requires thoughtful implementation strategies that complement rather than disrupt existing processes. Last but not the least, addressing the ethical considerations around the multiple specialities of algorithmic bias, data privacy, and the appropriate balance between human judgment and automated decision support remains critical and deserve critical attention.

The future of AI in cardiovascular care may involve even more sophisticated systems that will continue to learn from clinical outcomes, adapt to local practice patterns, and provide better personalized recommendations accounting for individual patient preferences and values. In the future, the role of cardiovascular specialists will evolve toward supervising AI systems, interpreting complex cases, performing interventions, and providing the human touch that remains essential to medicine to ensure high quality care.

Despite the common perception of replacing clinicians, effective AI implementation will augment capabilities of healthcare professional, allowing cardiologists to focus their expertise on aspects of care requiring judgment, empathy, and complex decision-making. This human-AI partnership model not only holds tremendous promise for addressing the growing burden of CVD globally, but also tends to improve outcomes while potentially reducing burden of ever-increasing costs through more efficient resource utilization.

As we move forward, enhanced collaboration between the professionals as cardiologists, data scientists, engineers, patients, and regulators will be key to develop clinically relevant more human friendly AI solutions that meaningfully advance cardiovascular care and simultaneously maintaining the highest standards of safety, efficacy, and ethical practice.

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Appendix**Evidence Quality Assessment****Strengths Identified**

- Multi-center validation in some studies (EchoMD, Heartfully AI);
- Randomized controlled trial design for cardiac rehabilitation study;
- Real-world implementation data (Mayo AI-ECG, Etimetry T3);
- Registry-based validation for heart failure phenotyping;
- FDA approval for automated echocardiography analysis.

Major Limitations

- **Insufficient Sample Size Reporting:** Many studies lack clear sample size information;
- **Limited External Validation:** Most algorithms developed at single institutions;
- **Vague Performance Metrics:** Many studies report qualitative rather than quantitative outcomes;
- **Short Follow-up Periods:** Limited long-term outcome data;
- **Selection Bias:** Predominantly academic medical center populations;
- **Black-box Algorithms:** Limited interpretability and explainability;

- **Technology Dependence:** Reliance on specific hardware/software platforms;

Methodological Concerns

- **Heterogeneous Study Designs:** Mix of retrospective analyses, prospective studies, and implementation reports;
- **Inconsistent Outcome Measures:** Varied definitions of success across studies;
- **Limited Diversity:** Underrepresentation of diverse patient populations;
- **Commercial Bias:** Several studies conducted by or in partnership with commercial entities;
- **Publication Bias:** Potential overrepresentation of positive results.

Recommendations for Future Evidence Synthesis

- Systematic search strategy with clear inclusion/exclusion criteria;
- Standardized quality assessment using validated tools (QUADAS-2, Newcastle-Ottawa Scale);
- Meta-analysis where appropriate with subgroup analyses;
- Assessment of clinical utility beyond technical performance;
- Economic evaluation of AI implementations;
- Long-term outcome studies with patient-centered endpoints.