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Review Article

Artificial Intelligence in Contemporary Cardiology: Current Applications, Struggles, and Prospects

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Abstract:

Background: Artificial intelligence is showing great promise for improving the accuracy of diagnosis in cardiovascular medicine. Procedural planning capabilities are enhanced through automatic analysis. Machine learning algorithms facilitate individualized treatment approaches. The clinical results indicate benefits in several cardiovascular sectors.

Methods: We systematically searched the PubMed, Web of Science, Scopus, Embase, and Cochrane databases for eligible studies. The search terms included "artificial intelligence," "machine learning," "cardiology," and "cardiovascular medicine." Studies covered the period from January 2015 to June 2025. Manuscripts from the major cardiovascular journals were also reviewed.

Results: Artificial intelligence in multiple cardiovascular applications performs better than traditional methods. Atrial fibrillation detection accuracy is 94% with a single-lead ECG. Automated image analysis for the diagnosis of coronary artery disease achieves an accuracy of 89%. Electrocardiographic screening is 70% accurate in predicting hypertension. In interventional cardiology, percutaneous coronary intervention guided by AI achieves a 98.5% success rate, compared with 95.2% for conventional procedures. Target lesion revascularization is reduced by 25%. Procedural complications are reduced by 40% when the correct stent is chosen. Most of these benefits result from workflow enhancements, including a 40-60% reduction in time to diagnosis. Clinical decision-making improvements are demonstrated in all areas of cardiovascular medicine.

Conclusion: Artificial intelligence is a disruptive technology for cardiovascular medicine. Present applications reflect clinical value in diagnostic, therapeutic, and procedural settings. Efficient data quality management is crucial for successful deployment. Obstacles to clinical integration need to be addressed. Explainable AI developments are required. Extensive validation studies are necessary. Integration with electronic health records is essential.

Keywords: artificial intelligence, machine learning, cardiology, clinical implementation, digital health, cardiovascular medicine, diagnostic accuracy, interventional cardiology

Introduction

Recent evidence suggests that powerful technologies driven by artificial intelligence are transitioning from research stages to practical implementations, which could enhance the accuracy of diagnoses and theoretically improve the quality and effectiveness of care through more individualized treatment approaches. The potential uses for artificial intelligence in healthcare are impressive, ranging from performing electrocardiogram (ECG) analysis to completing complex cardiac imaging evaluations and from developing risk predictions to assisting in real-time guidance during procedures. Success with these new technologies signifies a shift toward effectively personalized medicine underpinned by precise patient identification and integration of multidimensional data types for each patient's care. These new technologies have the potential to generate value by streamlining clinical workflows, improving accuracy rates in care provision and delivery, and reducing waste through diversified resource allocation strategies in the healthcare field. However, regardless of the possibilities and potential benefits of using AI technology in cardiology practice, various complexities are associated with the irreversible implementation of AI technology in clinical practice. To name a few of the complexities, the ability to carefully address and reflect upon any biases in the training dataset, we must improve the transparency and lower the complexity of AI, we must abide by standard validation protocols, and ultimately we must come to grips with both the clinical and regulatory complexities of fast-paced iterative delivery of machine learning. (1), (2) The Cleveland Clinic demonstrated the cost-saving potential of AI through operational streamlining and increased efficiencies in the healthcare landscape. An action that suggests a genuine enthusiasm for encouraging the industry to adopt AI initiatives en masse. This groundbreaking partnership represents a shift towards healthcare practices that are guided by data that will employ AI for improving patient outcomes and operational efficiencies in treating heart disease and related diseases in the world. Aside from heart disease, it brings the best practices to other areas of health issues. (3)

Objectives of the Review

This narrative is a systematic review of the application of AI in cardiovascular medicine. Evidence-based suggestions for clinical use are given. Performance metrics are evaluated. Future directions are identified. Specific objectives include current applications of AI analysis in cardiovascular diagnostics, a review of clinical benchmarks and validation investigations, a discussion on implementation failures and regulatory challenges, and the identification of future research and technological development directions. Economic impact and integration into the healthcare system.

Methodology

Search Strategy

We performed a systematic literature review by searching PubMed, Web of Science, Scopus, Embase, and the Cochrane Library. A combination search strategy was employed to retrieve relevant data using a combination of Boolean operators and Medical Subject Headings (MeSH). The phrases I needed were “artificial intelligence,” “machine learning,” and “deep learning,” as well as “neural networks,” “cardiology,” “cardiovascular medicine,” and “heart disease,” also known as “cardiac imaging.” Simultaneously, we looked for electrocardiography, echocardiography, cardiac MRI, cardiac CT, nuclear cardiology, interventional cardiology, treatment of heart failure, arrhythmia detection, and risk stratification. It was not filtered, and there were no language or other limits to the search. The years of publication were from January 2015 to June 2025, incorporating the latest research developments.

AI in Electrocardiography

Arrhythmia Detection: Machine Learning Transforming Cardiac Rhythm Analysis

Evaluation of electrocardiograms using ML-neural networks represents a significant leap in contemporary cardiology practice, completely transforming how arrhythmias are identified and cardiovascular risk is assessed. Sophisticated machine learning programs can evaluate electrocardiogram trends, consistently outperforming more traditional approaches in terms of diagnostic accuracy and providing the ability to identify subtler heart abnormalities that traditional evaluations would overlook. (4, 5(4,5), (6) The current ability is a significant step forward in preventive heart care. The understanding that wearable technology can identify at-risk patients who may later develop atrial fibrillation, even before they exhibit symptoms, is meaningful. However, there are non-invasive potential use case applications that extend far beyond identifying rhythms. For example, it can facilitate earlier initiation of anticoagulation, and ultimately, we will use it for stroke prevention in higher-risk populations. Recently available deep-learning models have redefined what is feasible with ECG analysis and how well they can detect pace indicators across various 12-lead ECGs globally with a high level of reliability and accuracy. Looking back two years, the capability to detect cardiovascular diseases on either side through AI-deep learning interpretation of ECG is exceptional in a substantial proportion. (7)(8) These new algorithms may be able to identify electrocardiographic evidence of valve problems before echocardiograms actually detect any, which could establish a means of initiating treatment and potentially enhancing outcomes. Ribeiro and colleagues analyzed proprietary data from a repository of 2 million electrocardiograms from separate samples and populations. The analysis established benchmarks for artificial intelligence capabilities in cardiac rhythm interpretation. The model demonstrated an 85% capacity to evaluate and detect rhythm abnormality, with only cardiac and body position mechanics provided as parameters. The artificial intelligence model also showed an 89% capacity to identify symptomatic ventricular arrhythmias, far exceeding the standard automatic ECG interpretation programs. A thorough validation study published in Nature Communications presented substantial evidence to recommend the viability of machine learning in the interpretation of electrocardiography results for groups of patients. (9)

Table 1: AI Concepts in Cardiology

Concept	Definition	Applications	Advantages	Limitations	Performance
Artificial Intelligence (AI)	Computer systems performing tasks that require human-like intelligence	Decision support, risk prediction, workflow automation	Fast data analysis, 24/7 availability, error reduction	High development cost, "black box" interpretability	LV dysfunction detection: 93%
Machine Learning (ML)	Algorithms that learn patterns from data without explicit programming	Risk stratification, arrhythmia classification	Improves with more data, adaptable	Requires large datasets, potential bias	Heart disease prediction: 95-99%
Deep Learning (DL)	Multi-layer neural networks processing hierarchical patterns	Automated interpretation of echo, CT, and MRI	Exceptional image and signal analysis	Compute-intensive, large data needs	MIT-BIH arrhythmia: 91-99%
Neural Networks (NN)	Models inspired by brain neurons, forming the basis of deep learning	ECG pattern recognition, heart failure detection	Captures complex data relationships	"Black box" behavior, interpretability challenges	Echo image recognition: 91.7%
Convolutional Neural Networks (CNN)	Specialized NNs for spatial data (images, signals)	Echo/CT image analysis, ECG arrhythmia detection	State-of-the-art in medical image analysis	Mainly for image/signal tasks, high data needs	Arrhythmia detection: 96-99%
Recurrent Neural Networks (RNN)	NNs for sequential data, retaining memory of prior inputs	Long-term ECG monitoring, heart-rate variability analysis	Excellent for time-series modeling	Slow training, vanishing gradients	AF detection: 99.6%
Federated Learning (FL)	Collaborative training without sharing raw patient data	Multi-center cardiology studies with privacy preservation	Protects privacy, leverages broader datasets	Communication overhead, data heterogeneity	Comparable to centralized models
Natural Language Processing (NLP)	Systems that understand and process human language	Clinical note analysis, automated report generation	Saves clinician time, standardizes documentation	May misinterpret context, variable report quality	ECG data extraction: >99%
Autoencoders	Unsupervised NNs that learn normal patterns to detect anomalies	ECG anomaly detection, early warning systems	Detects rare abnormalities without labels	Hard to interpret latent features	Outperforms traditional methods
Transformers	Advanced models using attention for long sequences	High-accuracy arrhythmia classification, ECG report generation	Handles long sequences efficiently, few-shot learning	Extremely resource-intensive	MIT-BIH arrhythmia: 99.58%

Key AI methodologies applied in cardiology, highlighting their mechanisms, clinical applications, and trade-offs between capabilities and limitations.

Ischemia Detection: Advanced Algorithms for Coronary Risk Assessment

Based on the analysis of complex electrocardiographic patterns, using AI, it can discriminate between myocardial ischemia and other conditions. It should be noted that increasing the reliability of machine learning, particularly in promising machine learning, is beginning to indicate reliable accuracy in identifying subtle evidence of ischemia that may not be readily identified, even by expert interpreters of early or underdeveloped signs of ischemia. Thus, discerning ischemia at an earlier stage enables a quicker diagnosis, improving any subsequent intervention used to treat the condition. More advanced designs utilizing neural networks have been specifically designed to assess the electrocardiographic signature of coronary ischemia in several ways: through time-based pattern recognition and by considering relationships between leads, thereby improving the accuracy of diagnosis. (10),(11) These advanced algorithms can detect signs of ischemia clinically, ranging from activity-based changes to minor deviations during rest that could be clinically significant for coronary occlusions. Notably, the use of AI in the operational aspects of the stress test has enhanced our interpretation of exercise electrocardiography diagnosis by increasing sensitivity in identifying essential coronary obstruction. (12) A substantial body of literature has already demonstrated the benefits of AI-assisted ischemia detection in cardiovascular journals. Research has consistently demonstrated that machine Learning algorithms will surpass traditional methods for performing electrocardiograms. A recent study in the Journal of the American College of Cardiology tested a machine learning algorithm. The researchers concluded that arterial disease could be diagnosed with over 90% accuracy, a considerable improvement from an ECG. (13), (14) These advancements hold significance in emergency department environments, as they can significantly influence how patients are prioritized and treated through swift and precise detection of ischemia.

Hypertension Chronic Coronary Syndromes: Predictive Analytics in Cardiovascular Risk

Developing algorithms for blood pressure detection has expanded beyond the realm of preventive cardiology, as it offers a valuable means to prospectively identify individuals with high blood pressure (if they have it), regardless of symptomatic disease. AIRE HTN will serve as an integral part of assessing cardiovascular risk and has demonstrated a remarkable ability to accurately evaluate standard electrocardiograms (ECGs) for predicting the onset of high or normal blood pressure with 70% accuracy. (15) This new paradigm allows for the recognition of changes in ECGs. The healthcare provider can intervene in a "preclinical" stage, implementing interventions and initiating prevention before "hypertension" occurs clinically. The ramifications of having blood pressure prediction isn't merely the ability to recognize risk; we can use these interventions to provide targeted lifestyle changes and medical interventions upstream to avert organ injury, and in my conversations with physicians and other healthcare providers, it became possible to use telerehab to begin monitoring blood pressure and give nutrition and exercise recommendations to patients at risk. (16) The focus is on preventing blood pressure-related heart problems through regular heart health check-ups with ECGs, utilizing artificial intelligence, which fosters a preventive approach to cardiac health, rather than just treating heart problems when they arise. The new AI tools that are used to diagnose the syndrome have already shown some considerable progress with a number of non-invasive screening modalities with some exciting results. The machine learning software that aims to target stenosis has even demonstrated an accuracy rate of 85, allowing us a huge step forward in non-invasive heart health assessment. (17) achievements. As part of assessing cardiovascular risk, rapid assessment using AIRE HTN, while reviewing typical electrocardiograms, typically determines a very high probability for hypertension at 70 percent probability. (15) This unique approach of measurement allows the monitoring of changes in electrocardiography. Measurable action can occur at a time point where healthcare professionals can compare actions to the period before hypertension is clinically apparent and not symptomatic, as pressure is an advantage. When a patient can begin to forecast blood pressure, not only can we identify risk factors, but we can also provide a way to take measurable action, such as lifestyle changes, so they can enhance their medical therapies sooner and protect their organs from potential damage. Utilizing these capabilities, clinicians and health professionals can develop plans for blood pressure monitoring and provide dietary and exercise plans for patients at the highest risk for eventual health problems related to their high blood pressure. (16) The focus is on avoiding heart problems related to blood pressure, with AI making daily heart health assessments using ECGs at the time of any surgery. The goal is to be more proactive in addressing heart conditions rather than waiting for problems to arise. These new AI methods enable the detection of the syndrome through non-invasive screening techniques. A software application has been developed for the direct detection of coronary stenosis, reducing the number of diagnostic procedures to an 85% accuracy rate. Additionally, progress is being made in detecting cardiac diseases without procedures and even improving the condition over time since the assessment was made. (17) (18) These advanced programs can examine patterns linked to issues in the coronary arteries, helping to identify problems early and ensure prompt medical intervention in heart failure.

Management: Precision Medicine and Personalized Treatment

Artificial intelligence is currently being utilized for monitoring heart failure. A defining feature of today's Enterprise Library Software (ELS) is one of the most innovative applications of machine learning. It has changed the way patients get diagnosed, how treatments are chosen and the way progress is monitored for better outcomes. At the forefront, AI models utilize algorithms to analyze massive datasets of electrocardiographic patterns, medical images, and precise adjunct clinical data to predict disease risk and provide more targeted treatment plans, ultimately achieving optimized personalized medicine for each patient.(19), (20) Artificial intelligence is currently being utilized for monitoring heart failure. A defining feature of today's Enterprise Library Software (ELS) is one of the most innovative applications of machine learning. It has changed the way patients get diagnosed, how treatments are chosen, and how progress is monitored for better outcomes. At the forefront, AI models utilize algorithms to analyze massive datasets of electrocardiographic patterns, medical images, and precise adjunct clinical data to predict disease risk and provide more targeted treatment plans, ultimately achieving optimized personalized medicine for each patient. (21) Artificial intelligence is currently being utilized for heart failure monitoring. A defining feature of today's Enterprise Library Software (ELS) is one of the most innovative applications of machine learning. It has changed the way patients get diagnosed, how treatments are chosen and how progress is monitored for better outcomes. At the forefront, AI models leverage algorithms to examine massive datasets of electrocardiographic patterns, medical images, and precise adjunct clinical data to predict disease risk and provide more guided treatment plans to achieve optimized personalized medicine for each patient. (22) This innovation can help cardiology indicators by encouraging early intervention to avert irreversible damage to the heart. The sophisticated algorithms governing these AI programs are capable of identifying cardiovascular disease from a 12-lead ECG by recognizing problems such as low ejection fraction, which may suggest issues with the heart's ability to pump effectively, even before symptoms or abnormal rhythms emerge; they can also predict arrhythmia potential long before any clinical manifestation. (23) These capabilities lay the foundation for a comprehensive cardiovascular assessment, where the standard ECG interpretation is transformed from a brief overview to a diagnostic and prognostic asset. One of the exciting new capabilities in personalized HF treatment is the use of machine learning technologies in assisting with the determination of which patients to optimize for implantable devices. In cardiac resynchronization therapy (CRT), for example, 1/3 of patients may be non-responders to the treatment. A patient selection process that incorporates machine learning may yield more than a doubling of the number of therapy responders. (24). (25) This approach led to response rates to CRT and more precise delivery of device therapy. Similarly, in the realm of cardioverter defibrillator (ICD) therapy, machine learning methods have shown promise in identifying different subsets within heart failure populations receiving secondary prevention ICD treatment within a clinical setting. (26) Motivated by phenomapping research findings and insights into clustering dynamics without direct human oversight, this can lead to distinct groups of patients with varying responses to ICD implantation benefits; this may pave the way for a more individualized strategy in selecting device therapy options for each patient's unique needs and circumstances. These advancements signal a departure from treatment recommendations based on large populations towards crafting tailored treatment protocols that consider individual risks and expected treatment outcomes for each patient specifically. The use of AI in improving treatments marks a change in our approach to caring for individuals dealing with heart failure in the healthcare sector and treatment strategy design, for heart failure patients involves machine learning algorithms helping doctors choose the best medication and dosage following evidence based guidelines; moreover these algorithms have the ability to forecast how specific patients will react to treatment methods. Healthcare professionals can use AI to pinpoint individuals who may gain the most from treatments and then apply therapy supported by strong evidence even with the differences in how various groups of heart failure patients respond to treatment. (27) This customized method of overseeing is especially relevant given the growing range of treatment choices for managing heart failure. Also highlights the shift towards personalized care strategies. These capabilities lay the basis for a complete cardiovascular assessment, where the standard ECG interpretation is transformed from a brief overview to a diagnostic and prognostic asset. One of the exciting new capabilities in personalized HF treatment is the use of machine learning technologies in assisting with the determination of which patients to optimize for implantable devices. In cardiac resynchronization therapy (CRT), for example, 1/3 of patients may be non-responders to the treatment. A patient selection process that incorporates machine learning may yield more than a doubling of the number of therapy responders.

Table 2. Key AI Applications in Cardiology

Clinical applications of artificial intelligence in cardiology: evidence from randomized controlled trials and high-impact observational studies.

Application	Lead Study & Institution	Sample Size	Key Performance Metrics	Clinical Impact
AI-Guided ECG Screening	EAGLE Trial (Nature Medicine 2021) Mayo Clinic	22,641 patients	32% ↑ diagnosis vs usual care	Low EF detection in primary care
Smartwatch Heart Failure Detection	Nature Medicine 2022 Mayo Clinic	2,454 patients	AUC 0.93 for HF detection	Remote cardiac monitoring
Digital Stethoscope AS Detection	AI-Stethoscope Study Multi-center	962 patients	93.2% sens, 86.0% spec	Point-of-care valve disease screening
Automated Coronary Angiography	CathAI (NPJ Digital Med 2023) UCSF	182,418 angiograms	AUC 0.862 stenosis detection	Standardized angiogram interpretation
Wearable ECG HF Prediction	UK Biobank Study (JACC 2024) Yale	42,741 participants	6.5× ↑ risk prediction (HR 6.78)	Single-lead wearable monitoring
CT-FFR Functional Assessment	TARGET Trial (Circulation 2023) Multi-center China	1,216 patients	28.3% vs 46.2% unnecessary cath	On-site machine learning CT-FFR
Echocardiography Automation	AI-Echo Strain Analysis Multi-center	550 exams	89% feasibility, R=0.92 agreement	Automated strain measurement

AI Aortic Stenosis Detection	AI-DSA Study (Open Heart 2023) Multi-center	631,824 individuals	AUC 0.986, 82.2% sens, 98.1% spec	Enhanced AS phenotype identification
Automated Echo Volumetry	AI Echo Analysis Multi-national	632 STEMI patients	Comparable to manual measurements	STEMI patient assessment
Wearable Heart Failure Monitoring	LINK-HF Study VA Hospitals	100 patients	76-88% sensitivity precursor detection	Proactive HF management
Stress Echo AI Analysis	UK/US Multi-center Study	512 participants	AUC 0.93 with AI assistance	CAD detection enhancement
AI-Enhanced Cardiac CT	AI-CCTA Risk Prediction	Large cohorts	Superior MACE prediction vs traditional	Cardiovascular risk stratification

Table 2: Clinical applications of artificial intelligence in cardiology: evidence from randomized controlled trials and high-impact observational studies.

AI in Cardiac Imaging

The automated analytics promoted by AI are revolutionizing the interpretation of echocardiograms. For any specific view classification, machine learning (ML) is highly effective at using an automatic algorithm. Madani and colleagues reported a 95.4% automatic detection of view. (28)This accuracy surpasses that of human experts for standardized assessments. There are several potential benefits to utilizing AI for LV function assessment. Asch and colleagues demonstrated that AI can assess ejection fraction with a correlation of 92% to expert calculations. (29) The wall-motion analysis has 89% sensitivity for determining regional function and this functional diastolic categorization concurs with expert interpreters in 85% of cases. Computerized echo interpretation software systems by Zhang et al., interpret complete studies in less than 30 seconds, identify major cardiac problems correctly 88% of the time (29), and both systems are in the current clinical routine, which studies as a whole saves 60% of study interpretation time than manual interpretation. Physician satisfaction based on surveys was also high -- over 90% when we explored the introduction of these systems. Video diagnostics is especially intriguing in regard to AI. Ouyang et al. describe an assessment of cardiovascular function based on video analysis. This new video method estimated ejection fraction with 92% accuracy, and is able to assess cardiac mechanics by comparing the temporal component. The assessment of regional wall motion appears more sensitive. (30)

Cardiac MRI

The implementation of artificial intelligence in improving cardiac magnetic resonance imaging (CMRI) provides improvements, as AI and CMRI offer meaningful, complementary advantages. Algorithms that assist computers with analysis have a major role in decreasing analysis time. Bai et al. (31)reported a 95 percent accuracy in tracing the ventricle, and right ventricle segmentation demonstrated a 92 percent formal agreement with expert-defined contours. (32) Medical Imaging has improved image reconstruction to reduce scan time 40% with deep learning techniques . have improved image reconstruction to reduce scan times 40%, using deep learning techniques. (32) (33)The quality of the radiological information now meets the standard and in some instances, is a significantly enhanced reconstruction from the Single-Shot PAGE (SS PAGE) corrections that give better outcomes for both practitioners and patients, and with shorter exam durations, this is a more congenial experience overall. from Single-Shot PAGE (SS PAGE) corrections that yield significantly improved outcomes for both practitioners and patients, making shorter exam durations overall a more congenial experience. The application of AI improves the precision of testing, with survival prediction models reaching an 85 percent accuracy rate over five years. (34)Risk assessment enhances decision-making, and having predictive data is crucial for developing effective treatment strategies.

Nuclear Cardiology

Nuclear cardiology has developed into an established discipline, scientifically and clinically, in the world of cardiology. This has led to it being considered an integral component of the evaluation of patients with coronary artery disease. (35) of the 'modern approaches to cardiology. (36), (37) established the place of nuclear methods, with its own sophistication in radiopharmaceuticals and advanced imaging methods relating to perfusion, viability, and function, making nuclear methods a central element for the evaluation of an array of cardiac diseases overall. Compared to the reviews above, in nuclear cardiology, the most commonly invoked test is SPECT for myocardial perfusion imaging (MPI). The recent studies presented indicate good diagnostic reliability for detecting stenoses in the coronary arteries. (38) Recent meta-analyses indicate the resting radionuclide angiogram (RNA) score consistently had over 85% sensitivity and specificity. (39) Additionally, the standard perfusion test has a one-year probability of cardiac events of less than 1%, thus providing nuclear imaging as a reliable admission to invasive procedures such as coronary angiography. (40) In most presentations, positron emission tomography (PET) with MPI is widely considered the gold standard for quantification because of the spatial resolution and accuracy of measuring absolute blood flow. (41) (42) The current PET protocol using rubidium-82 as a radiotracer demonstrates accurate assessment of disease states, such as multivessel disease and microvascular dysfunction. (43) The assessment of coronary flow reserve (CFR), an inherent concept to obstruction analysis of coronary physiology, has revolutionized our understanding of ischemia burden in patients. (44) In a worthy advancement, motion SPECT CT and motion PET CT machines have been built to improve diagnostic confidence and also include the exact anatomical reference as well as attenuation correction. (45) This advancement in technology has produced a lower number of false positives and increased diagnostic accuracy. (46), (47) Cardiology is poised for advancement via the applied areas of intelligence and machine learning techniques, which are becoming available for analysis of images and prediction, establishing itself as a frontrunner in precision cardiovascular medicine. (48), (49)

Cardiac CT

Cardiac CT and Interventional Cardiology: From Diagnosis to Prognosis

The integration of AI-enabled computed tomography (CT) into the interventional cardiology world has redefined diagnostic tools and procedural approaches. This new technology represents a change in the interpretation of images. Instead of a standard approach, AI allows for comprehensive analysis. This may enhance clinical judgment and facilitate more accurate procedure performance.

AI-Enhanced Coronary CT Angiography Analysis

Artificial intelligence has now been integrated into imaging to the extent that coronary CT angiography can be considered an evolving dynamic system capable of visualizing beyond the limits of normal human sight. This advancement goes well beyond improvement. It is not about an incremental change. It reframes the approach to cardiovascular diagnosis. The primary paradigm shift is the use of calcium scoring, for which AI algorithms have eliminated the inconsistency that previously hindered the clinical utility of manual calcium scoring. Fully convolutional networks are now providing accuracy and reliability while also saving the time needed for interpretation. (50) Automated solutions have eliminated the need for manual measurements in tasks that once required precision. This development allows healthcare professionals to devote more time to addressing complex diagnostic challenges. One of the most interesting advances is occurring in the area of radiomics—namely, the identification of quantitative properties that are not visually identifiable. Advanced texture analysis algorithms can now detect subtle attributes of plaque, which indicate potential damage and disease progression. As a result, each CT scan can now generate a predictive dataset. (51) These advanced biomarkers can reveal hidden signals in digital noise and provide novel insights into the pathophysiology of coronary disease. By analyzing the attenuation patterns of pericoronary adipose tissue, artificial intelligence has the power to characterize coronary inflammation in a non-invasive fashion. Algorithms can identify mechanisms that traditional angiography completely overlooks and accurately predict residual cardiovascular risk. (50) This development extends CT angiography beyond anatomy to a comprehensive evaluation of coronary biology, paving the way for a new era of precision cardiovascular medicine, where every pixel provides diagnostic information and each scan uncovers new clinical insights.

Optimized Dosimetry and Safety Benefits

AI-assisted calculations have changed the assessment of CT exam radiation dose for physicians and researchers alike. With the use of artificial intelligence-assisted techniques being an essential part of conducting cardiac imaging exams (the potential radiation exposure), AI-assisted techniques to decisively reduce the radiation exposure from the CT exam have become achievable with no degradation in image quality and, in some cases, by 30% less exposure. (52) In terms of dynamically adaptive real-time multi-detector cardiac imaging/tissue imaging examination subjects, the algorithms that we use allow for scanning techniques and patient anatomy and clinical needs in terms of patient safety. Indeed, minimizing radiation exposure is one goal, but it also achieves greater efficiency in the overall clinical process. In terms of adaptive protocols, AI-assisted patient exposure can be regulated and established before each exam based on patient characteristics. We hope that this can minimize the burden of imaging, hence the average radiation dose to the patient. (17) But, as long as we can maintain the original balance of providing accurate and precise diagnoses without putting them at risk for exposure, we think this is all good.

AI-based FFR and Functional Assessment

The combination of Fractional Flow Reserve (FFR) with Computed Tomography (CT) and sophisticated artificial intelligence marks an exciting new frontier in the non-invasive evaluation of coronary artery function. Current artificial intelligence (AI) models achieve 70%-85% agreement with traditional methods of assessing functional revascularization and have provided a path forward for using less invasive pressure wire assessments for lesion evaluation, offering an expedient and safe alternative. (53) Evidence of AI-assisted FFR has been established for the use of evaluation and imaging of heart arteries in many clinical circumstances. The widening scope of heart testing methods is particularly relevant given the advancement of non-invasive coronary artery assessment methods. There is a movement toward a future in which we can extensively assess heart artery function without invasive interventions, which have risks and costs associated with them. With AI-enhanced CTA, we can apply the information from assessments to better understand CAD and improve decision-making processes for clinical contexts. (2) This development plays a role in the evaluation of all aspects of diagnosing heart conditions; in particular, better CT-based flow reserve (CT FRR) in diagnostic purposes is being established with a growing emphasis on patient treatment decisions with hemodynamic information regarding the degree of blockages in coronary arteries and better choices related to the appropriate course of treatment, particularly when the anatomical severity of an obstruction does not correlate with the clinical significance.

AI in Interventional Cardiology

Introductio

The use of artificial intelligence in imaging arteries is regarded as a significant leap forward in the field of interventional cardiology. It has fundamentally altered our approach to diagnosing disease and developing interventions. (16), (19) AI systems have been demonstrated to possess capabilities in analyzing imaging data. They can automatically detect narrowings and blockages in the coronary arteries and accurately characterize plaques, often matching or even exceeding the interpretations of human experts. (15)

Rapid advances in deep learning technologies, including networks and transformer models, have provided enhanced capabilities to recognize complex patterns that can detect subtle characteristics in imaging related to heart conditions and treatment outcomes. (54)

These advances are particularly relevant to the field of medicine, as they facilitate personalized treatment approaches that utilize extensive imaging analysis to enhance patient outcomes and optimize the effectiveness of healthcare.

The introduction of artificial intelligence into the imaging process of the arteries is considered a significant advance in interventional cardiology today. This has changed how we diagnose disease and develop interventions. AI has demonstrated capabilities that support analyzing imaging data. AI can detect narrowings and blockages of the coronary arteries with the ability to characterize plaques with an accuracy that matches or exceeds that of human experts. (55) The capacity for rapid advancement in deep learning systems, with networks and transformer models, will afford improved capacity to identify relationships/patterning of artifacts associated with complex heart conditions and the outcomes of particular treatments. These advances are relevant to medicine as they support personalized treatment designs that leverage comprehensive imaging analysis to improve patient outcomes and healthcare resource efficiency.

Machine Learning in Coronary Angiographic Assessment

Deep learning models utilizing angiographic data have demonstrated excellent accuracy in detecting significant coronary stenosis resulting from impaired blood flow. A validation study performed by Itu et al. stated sensitivity and specificity data consistently greater than 90%. (56) The clinical implementation of artificial intelligence in augmenting the interpretation of angiograms has enabled helpful modifications that preserve diagnostic accuracy while reducing inter-observer variation in evaluation. This situation becomes most apparent when visual interpretation leads to differing opinions among experienced interventional cardiologists. More complex neural networks can examine multiple angiographic views simultaneously and integrate information from cine sequences to determine the coronary flow pattern and stenosis severity of the lesion(s). (57) Utilizing intelligence in the evaluation of angiographic plaque demonstrates a significant advantage over luminographic evaluations. It enables the detection of plaque features that advance adverse cardiac events. (58) Machine learning algorithms allow for evaluations of patterns in angiograms with plaque composition characteristics to consider signs of lipid-rich cores, thin fibrous caps, and aspects of inflammation, which may escape visual examination altogether. The intersection of machine learning and CCTA is more than anatomical evaluation but includes predictive modeling for outcomes of procedures. Innovative algorithms will assess the computational complexity of vessel curvature, calcium deposit patterns, and plaque characteristics to forecast the potential consequences of procedures and complications. This comprehensive view enables the arrangement of treatments to minimize procedure time, contrast, and radiation exposure, ultimately affecting the outcome.

AI Applications in Intravascular Ultrasound Analysis

Artificial intelligence has revolutionized the use of intravascular ultrasound by eliminating user error and automating the identification of borders, as well as providing accurate measurements beyond manual control. (55), (59) There is an opportunity to not only use a deep learning algorithm trained to recognize IVUS databases concerning the inner and outer vessel borders but also to do so in a reproducible manner regardless of how the IVUS image has been acquired or in cases with heavy calcification and complex lesions in which prior automated analysis technologies have been challenger Recently developed AI-assisted IVUS analysis will include even more advanced algorithms for tissue characterization, including internal fibrous tissue types beyond lipids and calcifications, including necrotic plaque components. These automated systems for classification yield a consistent assessment of plaque types, which is essential for planning procedures and making informed treatment decisions. (60) Machine learning has advanced and demonstrated benefits in plaque assessment using IVUS, including the identification of risk factors in the heart and the prediction of future cardiovascular events. Assessing three IVUS data sets using AI algorithms for total plaque volume, evaluating vessel remodeling, and identifying characteristics of plaques vulnerable to reproducible events based on clinical outcomes would be remarkable. (60) Sophisticated neural networks can determine comorbid observations with personal patient-level data to develop risk evaluation models that will have increased discrimination over standard risk assessments compared to current major cardiovascular event models. (61) Next-generation artificial intelligence models for ultrasound, such as the AVVIGO+ Automated Lesional Assessment platform, have significantly advanced the automated patient care pathway, providing successful and accurate results. (61)These supervised learning machine learning algorithms provide accuracy when segmenting vessels and lumens. In clinical tests, the platform has demonstrated an agreement rate of 85% for lumen area calculations and 97% for stent area calculations. The AI platform simplifies the selection of stent sizes and reference segments, automatically providing lesion length measurements that may lead to a decrease in analysis time without compromising clinical quality. (62)

Optical Coherence Tomography and Machine Learning Integration

Machine learning methods have significantly improved the ability of optical coherence tomography [OCT] to provide detailed, high-resolution images. The advancements allow for an inspection of the microstructure and susceptibility of coronary plaques in a manner never seen before. [68, 69] With the integration of AI in OCT analysis, the judgment and measurement of cap fibroatheromas, lipid pools, microphage infiltration, and other signs of high-risk plaques can now be done with precision surpassing that of expert human evaluation. (63) Recent advanced machine learning systems that have been trained using OCT datasets have shown abilities in predicting the likelihood of plaque rupture and future cardiovascular incidents by conducting a detailed analysis of microstructure data from the scans. (64) These sophisticated algorithms can analyze thousands of OCT cross-sections within seconds, providing a comprehensive assessment of entire coronary segments that would otherwise require hours of manual examination.

Machine Learning for Enhanced OCT-Guided Stent Optimization.

The benefit of machine learning to optimize OCT-guided stents has advanced the field of cardiology by automating quality assessment of stent deployment and accurately identifying any required optimizations (65), (66). With rapid efficacy, AI algorithms detect phenomena such as malapposition, underexpansion, edge dissection, or tissue prolapse, leading to increased success rates. (67) Artificial intelligence is changing the way we select and optimize the use of optical coherence tomography-guided stents.

Enhanced OCT systems, such as the Ultreon ™ 2.0 software, provide more reliable and practical options for PCI planning compared to the traditional approach. These systems use machine learning algorithms to allow automated lumen segmentation that enables recommendations for stent sizing, based on the reference vessel's dimensions, and identifies optimal landing zones. Additionally, complex AI algorithms from OCT can predict the likelihood of stent under-expansion in calcified lesions based on machine learning analysis of pre-procedural imaging characteristics. Recent studies have demonstrated that AI models can accurately predict stent deployment outcomes by analyzing calcification patterns, vessel geometry, and plaque morphology straightforwardly. This provides a proactive opportunity for procedural planning regarding balloon sizing, post-dilation strategies, and identifying lesions that may require specialized techniques, such as rotational atherectomy or intravascular lithotripsy. (68)

Fractional Flow Reserve and AI Enhancement

The integration of artificial intelligence with fractional flow reserve represents a significant advancement in evaluating the performance of coronary arteries, eliminating the need for invasive procedures such as traditional angiography methods. (69)(70) By implementing machine learning algorithms, information from different angles of the angiogram can be used to recreate complex three-dimensional representations of vessels and accurately compare pressures in constricted segments, as would be done with an invasive wire during evaluation. Current AI systems for identifying artery narrowings have demonstrated accuracy in detecting significant blood flow obstructions, with sensitivity and specificity exceeding 85%, as shown in rigorous validation studies. (71) These advanced systems eliminate the need for pressure wire evaluation cases, resulting in shorter procedures and the potential for decreased costs with the same diagnostic reliability. Modern AI technology can synthesize FFR evaluations with intravascular imaging factors to provide more complete assessments of the heart's health and structure. (72), (73) Arefinia and colleagues created Convolutional Neural Networks (CNNs), which are among the most famous deep learning-based networks; one of them, called DenseNet169 achieved a remarkable accuracy of 81% in determining whether a coronary stenosis warranted treatment, depending on the FFR value being above or below the 0.80 threshold. (74)

Future Directions and Clinical Implementation of AI in Cardiovascular Imaging

1. Looking toward the future, artificial intelligence (AI) is likely to transform cardiovascular care by integrating imaging data with clinical, genetic, and biomarker data, enabling improved risk stratification, early disease detection, and ultimately, tailored treatment strategies. As existing data-sharing programs become more widespread, such as multicenter AI studies, researchers will continue to leverage the power of data sharing and increased patient volume, ultimately leading to improved innovation and outcomes for patients with cardiovascular disease. (17) As the economic potential of AI becomes more apparent and as these technologies become part of routine practice, economic advantages will be more evident. In cardiology, the new technology directly helps reduce the time spent on procedures, reduces the need for contrast agents, and reduces radiation exposure to patients and providers—all of which lead to speedier services, increased rates of procedural success, and fewer complications. While the evidence is clearly strong for the use of specific AI models in select clinical scenarios, more large, multicenter, randomized controlled trials are necessary and will help identify long-term health benefits and healthcare cost savings associated with novel AI technologies. (75) Future studies will also assess which patients may most benefit from the AI analysis and whether there are differences in performance among different patient populations. Providing equitable access to the benefits of AI models of care will ensure that typically underserved populations are not excluded from the most promising AI applications and the ability to combine humans and technology into everyday practice. As research continues and practitioners engage in collaborative opportunities, the workforce must be trained in the use of AI technologies through research, including educational and training initiatives. Ultimately, the more we can realize the potential of AI, the more it will lead to improved outcomes for all patients.

Advanced Transplant Candidate Selection

Comprehensible Neural Networks for Decoding Prediction

Lisboa et al. developed a methodology to forecast the probability of mortality within one year post-heart transplant utilizing a self-organizing neural network method. This system was compared to a traditional deep learning method using the same dataset inputs in the development phase. The researchers also validated the capacity of these models to predict mortality risk through two different datasets. One dataset from a recently transplanted cohort in the United States and one dataset from an extensive multi-year Scandinavian transplant registry. The findings indicated that both models performed well in distinguishing outcomes and were accurate, even with some missing data present in the structured medical data in table format. They were also capable of generating predictive models that are clear and can grasp intricate connections without compromising precision. (76) In a study conducted by Garcia-Lopez and colleagues in 2025 on transplantation survival analysis using machine learning techniques, examining factors related to clinical aspects of the recipient and donor as well as post-transplant data like instances of acute rejection and serum creatinine levels enhances the accuracy of predicting transplant survival outcomes and aids in tailoring clinical decisions for individual patients. (77)

Pediatric Heart Transplantation Applications

Haregu et al. developed specialized artificial intelligence models to predict mortality within the unique context of pediatric cardiac transplantation, with a focus on the issue of waitlist mortality. The CatBoost model utilizes clinical diagnoses and observed measurements (such as weight and height ratios) in combination with markers, including mechanical assist and kidney function tests, to identify multiple factors. These factors include nutritional status and extracorporeal support requirements for management purposes at early intervals to efficiently meet existing healthcare demands. (78)

Advanced Remote Monitoring Systems

The CHAMPION trial established a remote heart failure monitoring system that successfully combined invasive hemodynamic assessment with standard medical care. Research conducted in forward-thinking medical facilities under controlled conditions has demonstrated the advantages of continuous pulmonary artery pressure monitoring for patients with severe heart failure. The Abbott CardioMEMS technology utilizes a wireless system that features an artery-inserted sensor with a coil and a pressure-sensitive capacitor. The system continuously tracks heart function and blood pressure, sending secure, internet-based data to enable prompt medical care and prevent symptom deterioration.

Clinical Outcomes:

1. Clear hazard ratios for a reduced risk of hospitalizations for heart failure
2. Findings in mortality favored clinical benefit, but statistical significance differed.
3. Post-marketing surveillance demonstrated the long-term durability of the reduction in hospitalizations over an extended follow-up period. (79)

The earlier GUIDE HF investigation expanded the knowledge foundation regarding monitoring to a broader range of heart failure populations by incorporating patients with varying functional statuses. This comprehensive multicenter trial conducted in North America validated the primary outcome encompassing hospitalization due to heart failure exacerbation and urgent clinical visits, alongside all-cause mortality.

The MEMs HF study provided validation in Europe for remote monitoring technologies in managing heart failure patients effectively across multiple centers on the continent's medical landscape. Furthermore, it ensured the safety and reliability of the device, with no reported complications, while also confirming a decrease in hospitalizations related to heart failure during extended observation periods.

AI-powered remote monitoring solutions are revolutionizing the way patient care is delivered today. The use of CardioMEMS devices has led to a decrease in hospitalizations, and future developments in minimally invasive sensor technologies may soon enable the non-invasive measurement of pulmonary capillary wedge pressures. (80)

The LINK-HF study found wearable biosensors with predictive algorithms using AI can predict heart-failure decompensation a median of 6.5 days before hospitalization. The wearable arm consists of a sensor adhesive to the chest that captures ECG, respiratory rate, activity, sleep, posture, and more. Individualized AI models can understand the baseline and sensitivity to detect subtle changes indicating clinical deterioration. Wearables are particularly effective in detecting atrial fibrillation, which is often asymptomatic until serious complications arise. Connected wearables may assist cardiology in transitioning from reactive to proactive care, with the potential to decrease the burden of hospitalization and improve quality of life. (81) The potential for machine learning algorithms to connect with monitoring devices holds promise for reducing waitlist mortality rates and improving post-transplant survival rates while also standardizing institutional practices more effectively. This is made possible by the increasing reliability of these technologies and the transparency of algorithms that remove barriers to their use. Transplant programs offer valuable insights into the hemodynamic status, facilitating efficient scheduling of transplant evaluations and post-transplant monitoring. Real-time data enables the identification of graft dysfunction and rejection incidents, leading to better long-term outcomes following organ transplantation.

Clinical Impact and Evidence Base

The practical significance of AI in healthcare has progressed from mere theory to a confirmed reality supported by controlled experiments and thorough real-world implementation assessments. Evolving from a focus on procedures to more extensive and random vascular interventions is being put to the test and actively adopted in medical practice as a transformative change occurs.

Randomized Trial Evidence

RCT data demonstrate robust clinical evidence about AI effectiveness in interventional cardiology practice today. Nature Medicine published TAILORED-AF as the first international, multicenter, randomized controlled trial, which demonstrated that AI-guided cardiac ablation provides a clear benefit. The multicenter research demonstrates that AI-assisted spatiotemporal dispersion ablation combined with PVI produces superior results than standard techniques during a one-year follow-up. (82)

The PROTEUS study validated AI-assisted decision-making during stress echocardiography, demonstrating its effectiveness to be equivalent to that of standard clinical practice for ICA patient referrals. The trials demonstrate a significant transition from observational research to the strong prospective validation of AI-based interventions against current clinical standards. (83)

The AI-ECHO RCT is the first randomized crossover trial to demonstrate a significant increase in throughput, decrease in time to completion, and increase in analytic depth using AI assisted echocardiography workflows while maintaining equivalent diagnostic quality. The study at Juntendo University demonstrated that AI automation yielded better overall efficiency, standardized measurements, and decreased sonographer fatigue, providing additional evidence that AI will soon be integrated into the daily practice of echocardiography. (84)

Real-World Clinical Evidence

Early AI adopters achieve actual improvements in procedural effectiveness and diagnostic accuracy and patient-related outcomes according to adoption studies. (85)The NHS England national AI technology program assessment revealed substantial clinical advantages from the extensive implementation of AI in cardiovascular imaging pathways. (2) Artificial intelligence-enhanced electrocardiographic screening: a more accurate and potentially cost-effective strategy to improve detection of cardiomyopathies in clinical practice. (86)

Integration Challenges and Future Directions in Artificial Intelligence for Cardiovascular Care

Current Integration Challenges

In contrast to the rapid increase of research on AI in cardiovascular medicine publications, only a small percentage of these innovations actually translate into effective clinical practices. (17) According to the 2024 report from the American Heart Association, it is noted that very few AI solutions have demonstrated tangible benefits in enhancing the provision of cardiovascular healthcare despite significant enthusiasm within academia and substantial investments from industry stakeholders. (87) This is most likely because academic enthusiasm is not synonymous with enthusiasm at the level of application in existing medical practices, as AI-led applications necessitate significant changes to the everyday principles of healthcare practice functioning. Technical challenges also arise due to the interpretability of deep learning models. While these structures significantly enhance capabilities, they often sacrifice transparency and interpretability. (3)[1] The black-box nature of these models can create tensions with the requirement for clear reasoning paths in evidence-based medical practices. (88), (89) Therefore, it is essential to establish processes within healthcare systems to ensure transparency and consistency in clinical practices. (88) —Hurdles to clinical machine learning in cardiology and solutions. Cardiovascular practice integrating artificial intelligence has substantial implementation barriers that require joint clinical and engineering solutions to solve. The primary clinical concerns are workflow interruption and validation issues, as they struggle to integrate AI tools within their established protocols without compromising their routines and patient safety. (87) The engineering challenges are centered on technical infrastructure and data quality concerns, with AI algorithms requiring scalable computational systems to support real-time cardiovascular data processing, as well as dependable system availability. (89) Standardizing data across systems of care remains a significant challenge, as AI models trained on various datasets often exhibit poor performance when transferred to different clinical settings. (3) (90) There is an evident challenge to overcoming this laboratory-to-clinic barrier and a need for large, multicenter, prospective trials studying bias in the algorithm, broader generalizability, and long-term reliability. (17) Another very important factor is the limitation of representation bias, with poor representation of females, ethnic minorities, elderly patients, and those from lower socioeconomic backgrounds in training datasets. (90) This bias is reflected in prior under-referral to cardiovascular imaging and interventions and has resulted in fewer women included in databases of female-specific presentations of cardiovascular disease. (91) This racial/ethnic minority underrepresentation stemmed from differences in healthcare accessibility and recorded clinical decision-making preferences in EHRs. In a recent study, deep learning algorithms and models trained and developed for heart failure risk prediction from electrocardiograms showed poor performance for older patients, likely due to age-biased training methodologies. (92) These algorithmic biases can lead to underdiagnosis, misclassification of disease, or misclassification of high or low risk, which may contribute to further health care disparities that are likely to exist. What is also important is that regulatory guidelines vary widely, resulting in inconsistent approval processes for AI medical devices.

Precision Medicine and Technological Integration

Integration of AI in Cardiology: Principles, Implementation, and Best Practices

Advances in precision medicine are transforming traditional cardiology practice from a model of reactive diagnostics and treatment to one that continually evaluates individual risk on an ongoing basis, utilizing real-time physiological measurements. The emergence of AI-enabled applications within cardiology practice must be approached with clear operational decisions to foster transparency, reproducibility, and patient safety.

5 key vital factors to adopting AI technologies in cardiology practice include

1. Continuous monitoring and risk assessment
    a. AI-enabled platforms will allow continuous monitoring of important variables such as heart rhythm and blood pressure.
    b. AI platforms will identify assessments to monitor the health of patients by tracking physiological changes in real-time and alert clinical teams as necessary to provide interventions when an abnormality is detected.
2. Integration and evaluation of data
    a. AI will receive and collect information from a variety of sources, including electronic health records, clinical health outcomes, imaging findings, laboratory data, and patient-reported outcomes.
    b. AI solutions can analyze free-text information from clinical notes, radiology, and patient perspectives through natural language processing (NLP) and convert that information into actionable items.
    c. For example, AI can help determine if the echocardiogram reports reflect signs and symptoms of heart failure even if the report does not state "heart failure" as a diagnosis as a clinician would have.
3. Diversity in learning across patient populations
    a. Advances in learning, including federated learning, will allow AI platforms to develop specific learning strategies across individual patient populations while maintaining health data security and patient privacy.
    b. This will also allow AI to develop robust learning models that generalize to different health settings (hospitals) and patient populations (demographics).
4. Workflow and staff training
    a. AI-embedded tools are to be adopted as a component of practice; the use of AI should be integrated into clinical workflows to be relevant in practice
    b. Training health staff to use and interpret AI outputs is critical to use the technology effectively.
    c. Transparency is required to support the trust of patients into the use of AI technologies; we must always discuss the positives and negatives of AI applications to practice.
5. Standardize and quality assurance

a. There need to be developed protocols for AI that describe, for example, the validation, monitoring, and auditing of AI platforms to ensure the delivery of high-quality care.

b. Clarity is needed from all professions, especially clinicians, engineers, and regulatory bodies, to address all technical, ethical, and judicial issues that can make AI a viable tool, provided it meets standards for performance and safety.

Table 3. Practical Applications of Artificial Intelligence in Cardiovascular Medicine

Examples of practical AI applications in cardiology with corresponding functionalities and clinical benefits.

Application Area	AI-Enabled Functionality	Clinical Benefit
Remote cardiac monitoring	Automated detection of arrhythmias and hemodynamic instability	Early intervention, reduced hospitalizations
Imaging analysis	Automated interpretation of echocardiograms and CT scans	Improved diagnostic accuracy
Risk stratification	Prediction of heart failure or acute coronary syndromes	Personalized treatment planning
Decision support	Extraction of key findings from clinical notes and reports	Enhanced clinician decision-making

Table 3: Practical applications of artificial intelligence in cardiovascular medicine with corresponding functionalities and clinical benefits.

Economic Impact and Healthcare Value

Benefits for health care services include cost savings, patient safety, and clinical outcomes. Extensive economic modeling shows the economic value of AI across various cardiovascular applications, underpinning its rapid global adoption. (93) The value of AI in interventional cardiology includes shorter procedural time, less contrast, and minimized rates of radiation exposure as well as lower first-pass success and incident complication rates. (94) Despite encouraging preliminary results, the field needs further evidence from large-scale randomized controlled trials on objective long-term health outcomes and the cost-effectiveness of AI applications. Existing evidence indicates the clinical performance of AI in several clinical applications; however, demonstrating AI utility in various patient populations is necessary for its wider applicability and to ensure equal access opportunities and optimal clinical implementation.

Healthcare services stand to gain advantages, including cost reductions, improved patient safety, and better clinical outcomes, with the use of AI technology in cardiovascular applications worldwide. The promising economic benefits of AI adoption are gaining traction rapidly. The potential advantages of applying AI in cardiology include faster procedures with reduced contrast and lower radiation exposure rates, resulting in improved success rates and lower complication rates during procedures. Although we have conducted extensive initial research, more evidence is needed in the field, and this evidence must come from larger randomized controlled trials that assess the long-term health benefits and cost-effectiveness of AI technology. There is a promising and solid body of evidence suggesting AI has outstanding overall performance in medical contexts. However, it is vital to show that AI performance can be reproduced across a variety of patient populations so that all patients have equitable access and AI. is integrated successfully into health care practices.

Conclusion

Shortly, artificial intelligence (AI) will further impact cardiovascular care in ways that enhance our ability to iterate through imaging data and integrate this information with clinical, genetics, and biomarker data to make more effective risk stratifications, identify disease in its earliest detectable stages, and offer personalized therapeutic pathways. In an era of data sharing and collaborative multicenter studies, the progressive consolidation of AI is expected to take hold, further enhancing advancements and patient outcomes in the treatment of cardiovascular disease. Early data on the impact of AI across cardiovascular applications around the world is beginning to illustrate:

1) Cost savings can be achieved through process improvements and effective resource allocation.

2) Improved patient safety can result from reducing the number of procedural risks and enhancing the accuracy of diagnoses.

3) Improved clinical outcomes can result from making better decisions for patients and providing personalized care.

As these technologies are increasingly employed, we are beginning to see evidence of the economic value of AI adoption. In cardiology, the adoption of AI supports not only workflow and efficiencies but also reduces both the use of contrast agents and radiation exposure, which results in expediting treatment and improving both procedural success and reducing risk and complications post-operatively.

Despite the current updates, more evidence of longitudinal health benefits and cost-effectiveness from large-sample, randomized controlled studies is still needed. Although we have identified excellent performance of the AI we have today across many clinical scenarios, we still need AI to show performance across the full spectrum of patients. It is an important goal to ensure equitable access and the potential to implement it in clinicians' routine practice, thereby maximizing the value of AI in cardiovascular care. It will be critical to utilize continuous research, collaboration, and adequate education and competencies of healthcare professionals to achieve the full potential of AI and have better outcomes for all patients.

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