



Comprehensive Review

Harnessing Artificial Intelligence for Innovation in Interventional Cardiovascular Care



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ABSTRACT

Artificial intelligence (AI) serves as a powerful tool that can revolutionize how personalized, patient-focused care is provided within interventional cardiology. Specifically, AI can augment clinical care across the spectrum for acute coronary syndrome, coronary artery disease, and valvular heart disease, with applications in coronary and structural heart interventions. This has been enabled by the potential of AI to harness various types of health data. We review how AI-driven technologies can advance diagnosis, preprocedural planning, intraprocedural guidance, and prognostication in interventional cardiology. AI automates clinical tasks, increases efficiency, improves reliability and accuracy, and individualizes clinical care, establishing its potential to transform care. Furthermore, AI-enabled, community-based screening programs are yet to be implemented to leverage the full potential of AI to improve patient outcomes. However, to transform clinical practice, AI tools require robust and transparent development processes, consistent performance across various settings and populations, positive impact on clinical and care quality outcomes, and seamless integration into clinical workflows. Once these are established, AI can reshape interventional cardiology, improving precision, efficiency, and patient outcomes.

Introduction

Artificial intelligence (AI) is a powerful tool with the potential to transform the delivery of personalized, patient-centered care in interventional cardiology.^{1–3} Specifically, AI can augment clinical care across the spectrum for acute coronary syndrome (ACS), coronary artery disease (CAD), and valvular heart disease (VHD). In addition to leveraging diagnostic modalities to identify cardiovascular disease (CVD), AI tools have provided significant benefits for planning and conducting percutaneous coronary interventions (PCI) and structural heart interventions, such as transcatheter aortic and mitral valve replacement. AI-driven innovations are also personalizing prognostication, including postprocedural outcomes and disease progression. Collectively, these advancements promise to redefine the current paradigm in interventional cardiology care delivery.

The term AI encapsulates a wide range of computational methods that can infer relevant information from large data sets, often uncovering insights that would be imperceptible to humans. These include machine learning techniques that are effective at capturing complex, nonlinear

patterns in structured data but are generally limited to structured data readily measured in health care settings. In contrast, deep learning algorithms—utilizing neural networks—can identify intricate patterns in more complex data streams, such as electrocardiography (ECG) and cardiac imaging. Thus, AI has the potential to harness various health data streams to enhance interventional cardiovascular care.

Herein, we survey the potential role of AI in interventional cardiology, discussing advances in the diagnosis of ACS, CAD, and VHD. We also review how AI can transform preprocedural planning, intraprocedural guidance, and prognostication for coronary and structural heart interventions (Central Illustration). Finally, we discuss future areas for innovation and the challenges in developing and integrating AI tools in interventional cardiology care.

Diagnosis

By leveraging existing diagnostic modalities, AI plays a crucial role in improving diagnostic accuracy in health care settings (Figure 1). First, AI-

Abbreviations: DCR, dynamic coronary roadmap; FFR, fractional flow reserve; OCT, optical coherence tomography; OMI, obstructive myocardial infarction; RoR, rotate on retract; VHD, valvular heart disease; VR, virtual reality.

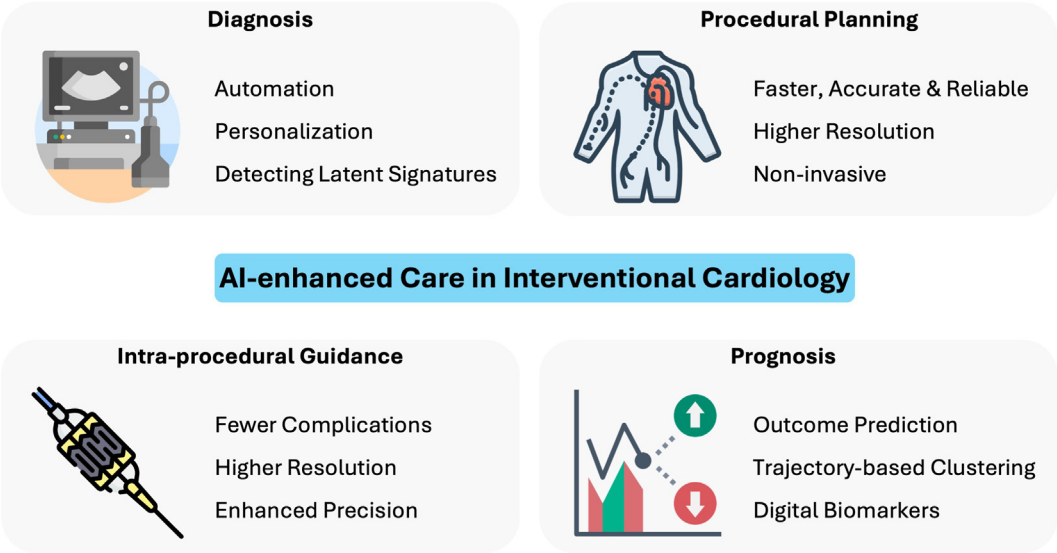
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Central Illustration.
The role of artificial intelligence in interventional cardiology. AI, artificial intelligence.

enabled tools can infer latent signatures from a wide range of diagnostic modalities, eg, chest X-ray (CXR), ECG, and transthoracic echocardiography (TTE). Second, AI can facilitate clinical workflow by automating diagnoses through the rapid and accurate interpretation of data. Third, AI can provide a more personalized sequential diagnostic workup.

Acute coronary syndrome

In the emergency room, ACS raises the clinical challenge of accurate triage between patients who require emergent coronary angiography, those who can undergo urgent angiography, and those suitable for noninvasive testing. Currently, this clinician-led decision is informed by a combination of clinical assessments, ECG findings, and levels of high-

sensitivity cardiac troponin, which helps classify patients into 1 of 3 categories: ST-elevation myocardial infarction, non-ST-elevation myocardial infarction, or unstable angina. Within this scope, emerging AI tools can be integrated with the existing diagnostic schema for ACS to personalize diagnosis and infer latent signals that are currently underutilized.

Troponin. Classification of ACS currently relies on either a single elevated troponin value or the delta between serial values over time in the appropriate clinical context. However, troponin levels are known to be influenced by patient demographics such as age and sex.⁴ Emerging AI-based approaches can enhance the evaluation of chest pain in the emergency department by integrating baseline characteristics to personalize the diagnostic use of troponin levels.⁵ The

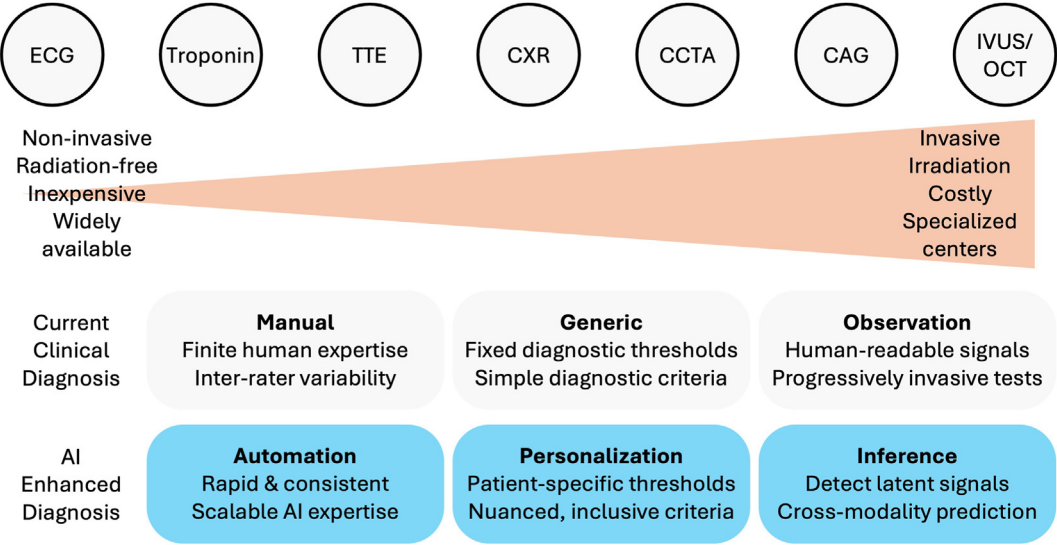


Figure 1.
AI-enabled precision diagnosis. AI, artificial intelligence; CAG, coronary angiography; CCTA, coronary computed tomography angiography; CXR, chest X-ray; ECG, electrocardiography; IVUS, intravascular ultrasound; OCT, optical coherence tomography; TTE, transthoracic echocardiography.

myocardial-ischemic-injury-index score uses a gradient-boosting algorithm to integrate patient age and sex with 2 serial troponin measurements to assess the likelihood of myocardial infarction (MI).⁶ In an external cohort of >20,000 patients, the myocardial-ischemic-injury-index score demonstrated excellent discrimination for identifying MI, with an area under the receiver operating characteristic curve (AUROC) of 0.95. It was also significantly associated with MI-specific and all-cause mortality at 1 year.⁷ However, the requirement for 2 troponin measurements in all patients to estimate MI probability may limit implementation. Moreover, troponin levels are also influenced by comorbidities such as renal function, and its interpretation is informed by the presence of cardiac symptoms and risk factors.⁸ The subsequent development of the Collaboration for the Diagnosis and Evaluation of Acute Coronary Syndrome (CoDE-ACS) system integrates these additional features with a single troponin value and has demonstrated superior performance to current guideline-recommended pathways with an AUROC of 0.95 in a cohort of >10,000 patients.⁹

Electrocardiography. The ECG is a vital tool for ACS diagnosis and management, with current decision making around emergent revascularization relying on the presence or absence of ST-segment elevation. The emerging obstructive myocardial infarction (OMI) paradigm offers a more nuanced framework for identifying acute coronary occlusion in patients who may require urgent revascularization. However, interpreting OMI ECG patterns, such as the presence of de Winter T-waves, Wellens waves, the Aslanger pattern, and the South African pattern, among others, can be challenging for nonexpert readers, potentially leading to missed or delayed diagnoses.¹⁰ In this context, the ability of AI algorithms to interpret ECG accurately and reliably enables a refined method to automate the identification of signals that may be challenging for human readers to detect. Recent studies suggest that AI models can infer latent signals to identify patients at risk of OMI earlier in their clinical presentation, providing a more comprehensive evaluation of patients with suspected ACS and potentially prompting timely intervention.^{11,12}

An OMI risk score model was developed using features extracted from prehospital ECG for patients presenting to the emergency department with chest pain to develop a random forest model predicting the likelihood of an acute culprit lesion on coronary angiography.¹² The OMI risk model displayed a validation AUROC of 0.87 in an external validation data set of >3000 patients, outperforming the emergency department clinicians who had an AUROC of 0.80.¹² Notably, the model could integrate ECG patterns of OMI that cannot be easily appreciated by experts, including subtle T-wave changes (such as prolongation of the $T_{\text{peak}}-T_{\text{end}}$ interval), and high-dimensional assessment of increased ventricular repolarization dispersion (such as the ratio between the principal components of the ST-T waveforms or the cosine angle between R-to-T).¹²

Coronary artery disease

The diagnosis of CAD requires an evaluation of whether coronary artery stenosis is present and, if so, quantifying the stenosis severity and the subsequent functional ischemia to assess whether it is actionable. The current diagnostic schema includes distinguishing between those who can be managed with noninvasive testing (imaging or stress tests) and those who need further invasive procedures (coronary angiography). The manual evaluation of coronary investigations is often labor-intensive, requires expertise, and is prone to interobserver variability. The integration of AI could provide automated evaluations as rapidly available, standardized outputs. Furthermore, AI tools also enable personalized assessment of coronary pathology, utilizing hidden signatures present in imaging modalities, providing clinicians with richer information and potentially reducing the need for invasive procedures.

Coronary computed tomography angiography. Coronary computed tomography angiography (CCTA) is a crucial modality for noninvasive anatomical assessment of CAD. The current diagnostic pathway involves manual quantification of calcified plaque burden within the coronary arteries as coronary artery calcium (CAC) scores, with higher CAC scores prompting referral for invasive coronary angiography. With manual CAC scoring being labor-intensive and prone to interobserver variability, AI algorithms can automate the CAC scoring process, providing faster and more consistent CAC assessments than manual methods.¹³ AI algorithms can use CCTA images to perform inference, providing an extra layer of information that may modulate decision-making about the need for invasive testing. This includes detecting latent signals, such as markers of vascular inflammation, which can be used to identify high-risk plaques that are more prone to rupture, even in cases in which stenosis may not be severe.¹⁴ Cross-modality inference is also possible, such as quantification of coronary atherosclerotic burden at comparable accuracy to intracoronary imaging.¹⁵ Moreover, fractional flow reserve (FFR) values—typically obtained via pressure wire measurements during angiography—can also be noninvasively inferred from CCTA images, identifying the functional impact of CAD on coronary blood flow.¹⁴

Coronary angiography. Coronary angiography is the gold-standard diagnostic modality for CAD. The manual interpretation of coronary angiography requires expertise and is subject to variability. AI algorithms have been developed to automate critical aspects of angiographic assessment. For example, a deep learning model accurately segmented the major coronary arteries from angiographic images (with an F1 score >0.8 for 94% of images) and also quantified stenosis severity.¹⁶ AI algorithms can also infer functional information directly from angiographic images, which may reduce the need for further invasive procedures such as pressure wire measurements. Quantitative flow reserve and FFR can be inferred by AI-driven models that analyze the flow dynamics within the coronary arteries and can predict the physiological significance of coronary stenoses, helping to identify which lesions are likely to cause ischemia and require revascularization.¹⁷

Intracoronary imaging. Intravascular ultrasound (IVUS) is used for the high-resolution assessment of coronary artery plaques, including identifying the extent of calcification and detecting vulnerable plaques that may be at risk of rupture. AI algorithms can automate the interpretation of IVUS data, reducing the reliance on manual expertise while enhancing the consistency and accuracy of plaque assessments.¹⁸ AI-based IVUS analysis can detect and quantify coronary calcifications, segment the coronary artery layers, and identify high-risk plaques. Vulnerable plaques, characterized by thin fibrous caps and large lipid cores, are associated with a higher risk of rupture and subsequent acute coronary events. AI models can specifically identify these high-risk plaques, enhancing the clinical utility of IVUS for more reliable risk stratification.^{19,20}

Intravascular optical coherence tomography (OCT) is another imaging modality characterizing coronary plaques at even greater resolution than IVUS. OCT images depict plaque morphology of fibrous caps and lipid cores, helping to estimate plaque stability and predict the likelihood of causing future coronary events. As with IVUS, the interpretation of OCT images is typically performed manually. AI algorithms have been developed to automate key tasks in OCT evaluation, including lumen segmentation, quantification of plaque morphology, and identification of fibroatheromas.^{21–25} AI analysis of OCT images can infer blood flow dynamics to enhance personalized risk stratification.²⁶

Valvular heart disease

The diagnosis of VHD currently requires an assessment of valve pressure gradients and velocities measured by TTE performed by a

trained operator, necessitating access to advanced equipment and expertise. AI tools can enhance VHD diagnosis using modalities with greater accessibility—CXR and ECG—and also streamline VHD diagnosis using TTE.

Chest X-ray. Recent studies have demonstrated that plain CXR can be effectively used to diagnose aortic stenosis (AS) and mitral regurgitation (MR) when augmented by AI analysis. Deep learning models developed on CXR images could detect AS with an AUROC of 0.83 and MR with an AUROC of 0.80.^{27,28} Moreover, by integrating information across the entire image, AI models can identify subtle radiographic signs of valvular pathology that may be challenging to detect, even by expert human readers. For example, while clinicians evaluate AS from a CXR by examining for calcification in the aortic region, saliency maps for the deep learning AS model showed hot spots in the aortic valve region and also in the left ventricle and left atrium, suggesting the model considered both aortic valve calcification and signs of elevated pressures in the left cardiac system.²⁷ These models may be useful for opportunistic screening for VHD in CXR repositories in health systems.

Electrocardiography. AI algorithms have been developed to detect VHD from different formats of ECG, including 12-lead and portable single-lead ECG. AI-enhanced interpretation of ECG, as a ubiquitous modality, can substantially improve VHD diagnosis, particularly where the ECG signatures are not recognizable by humans.^{29–33} Recently, a 12-lead AI-ECG algorithm, PRESENT-SHD, and a portable-adapted, single-lead AI-ECG model, ADAPT-HEART, have been developed and externally validated using data from 150,000 patients.^{34,35} These models can detect various structural heart diseases, including moderate or severe AS, with an AUROC of 0.8 from 12-lead ECG images and portable single-lead ECG, respectively.^{34,35} Further studies have demonstrated that AI-ECG algorithms offer sensitivity and specificity comparable to echocardiography.^{31,32} Therefore, AI enables leveraging ubiquitous ECG for the large-scale identification of individuals with clinically actionable VHD in various settings.

Transthoracic echocardiography. Diagnostic evaluation for VHD requires a trained cardiac sonographer to capture several high-quality views of the heart and an expert cardiologist to evaluate the results, representing a resource-intensive process. The integration of AI can enhance this workflow by automating the reporting of TTE results, which may help address the problem of interobserver variability and

improve the reproducibility of measurements.^{36,37} AI algorithms that can detect AS and MR and quantify their severity from a single echocardiographic view, even without color Doppler, have been developed and achieved near-perfect accuracy.^{38–40} In a multicenter study, an AI algorithm was developed using >17,500 TTE videos to detect severe AS from a parasternal long-axis view without color Doppler—an easy-to-obtain view. The model demonstrated an AUROC of 0.98 and performed consistently across 3 temporally and geographically distinct external validation data sets.³⁹ Together, these AI-enabled capabilities reduce the reliance on the availability of human expertise to interpret TTE scans, potentially accelerating the diagnostic pathway. Lastly, AI models are capable of inferring findings from one imaging modality to another. Cross-modality inference, predicting cardiac magnetic resonance imaging (CMR)-derived parameters or CAC scores from echocardiograms, was demonstrated to achieve good comparability offering a more integrated diagnostic workflow that could streamline clinical decision making and reduce the need for multiple imaging studies.^{41,42}

Preprocedural planning

The preprocedural planning of structural heart interventions, including transcatheter aortic valve replacement (TAVR) and transcatheter edge-to-edge repair (TEER), involves accurate measurements using cardiac imaging. Similarly, successful coronary revascularization requires accurate preprocedural identification of coronary plaque characteristics and coronary vasculature anatomy. However, such assessments are time-consuming and subject to interobserver variability. AI tools have been developed to streamline preprocedural planning, minimize human resources efforts, and ensure accuracy (Figure 2).

Coronary interventions

Accurate planning and assessment of coronary revascularization rely on high-resolution visualization of coronary plaques and lumina through OCT using infrared light.⁴³ OCT provides beneficial information on the plaque characteristics, as well as a detailed anatomical map of the coronary vasculature, including the location of vascular bifurcations and side branches, helping to inform preprocedural planning such as stent

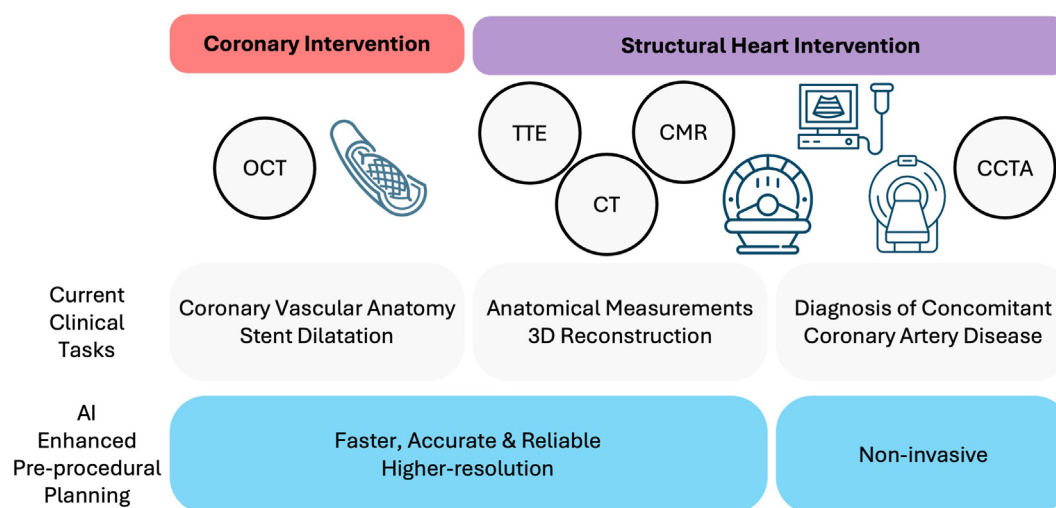


Figure 2.

Integrating AI into preprocedural planning. 3D, three-dimensional; AI, artificial intelligence; CCTA, coronary computed tomography angiography; CMR, cardiac magnetic resonance imaging; CT, computed tomography; OCT, optical coherence tomography; TTE, transthoracic echocardiography.

placement.⁴⁴⁻⁴⁶ After PCI, stent expansion, apposition, and healing can be inferred from OCT.⁴⁷⁻⁴⁹ However, OCT interpretation is time-consuming and requires expert readers with potential interobserver variability, significantly curtailing its incremental clinical value.^{50,51} In OCT images, locating stent struts to measure the protrusion distance and neointimal thickness is essential to assess stent expansion and apposition, respectively, both bearing critical post-procedural implications such as in-stent restenosis, stent fracture, and stent thrombosis.⁵²⁻⁵⁶ AI tools have been developed to accurately detect stent struts from OCT images in as fast as 59 ms per image with a sensitivity and specificity as high as 94%, depending on the case mix.^{51,57-63} This was consistent across cases undergoing as well as those with previous stent implantation. However, the performance was modestly lower for struts with thick tissue coverage >0.3 mm.^{50,51,58,59} AI-automated measurements of the stent and luminal areas had correlation coefficients of 0.96 to 0.99. In addition to substantially reducing the time required for analyzing OCT images, AI reduced interobserver variability by 30%.^{50,51,58,60}

In addition to detecting stent underexpansion and malapposition, OCT provides additional information beyond clinical characteristics to predict these outcomes before stent deployment.^{64,65} This holds substantial clinical significance as the physician can identify coronary lesions at risk for stent underexpansion and malapposition and might decide to conduct lesion preparation interventions such as atherectomy before stent deployment.⁶⁴ Conventional machine learning algorithms, including regression, support vector machines, and gradient boosting algorithms, have been used to predict stent underexpansion and malapposition from clinical characteristics as well as OCT features, including plaque calcification length and lipid arc.^{64,65} These algorithms had a discrimination of 0.85 for predicting stent underexpansion, defined as a stent expansion index $\leq 80\%$, and a discrimination of 0.82 for predicting stent malapposition, defined as the lack of contact of at least one stent strut with the vessel wall.^{64,65}

Virtual reality (VR)-based preprocedural planning is emerging as a powerful tool for complex cases involving anomalous coronary anatomy or chronic total occlusion of coronary vessels. A recent case report demonstrated the efficacy of a novel VR-guiding catheter simulation system that uses 3-dimensional reconstructions from ECG-synchronized cardiac computed tomography (CT) imaging to optimize catheter selection and navigation. By simulating catheter type, size, and positioning in a virtual environment, this tool enables precise preprocedural planning while eliminating the need for additional radiation or contrast exposure. Furthermore, in cases involving anomalous origins of the right coronary artery, VR-guided planning has been shown to reduce catheter selection time, improve procedural efficiency, and overcome the challenges posed by complex anatomy.⁶⁶

Structural heart interventions

TAVR planning and device selection are based on anatomical measurements such as aortic annulus diameter and aortic angle, locating anatomical landmarks, and 3-dimensional visualization of anatomical structures using different cardiac imaging modalities. AI tools enhance preprocedural measurements using echocardiography, CT scan, and CMR, with more accurate measurements from 3-dimensional reconstructions vs 2-dimensional measurements.^{67,68} AI-enhanced measurements demonstrated significant and strong correlations with manual annotations by senior observers, with a correlation coefficient >0.91, mean error <2 mm, and no clinically relevant bias for anatomical measurements.⁶⁹⁻⁷⁶ Notably, in a large study from 20 centers in China, the intraclass correlation coefficient values for the AI model were 0.998.⁶⁹ For device selection, the agreement between AI and the expert was 0.86 to 0.89, similar to the agreement between 2

experts. The expert-level accuracy of AI-automated measurements was achieved without the need for any human inputs, as well as with more reliable measurements in a shorter timeframe.^{70,77}

To visualize anatomical valve structures using CT in a 3-dimensional space, traditional reconstruction methods use filtered back projection, whereas newer iterative reconstruction methods leverage physical modeling with complex math.⁷⁸ Although iterative reconstruction methods can improve image quality and reduce radiation exposure, they are computationally expensive. To address this challenge, deep learning has been leveraged to provide images with higher contrast-to-noise and signal-to-noise ratios while generating them 6 times faster than iterative reconstruction methods.^{68,79,80} Therefore, deep learning represents a novel approach that enables high-quality images to visualize anatomical valve structures in 3-dimensional space using fewer computational resources in a shorter duration of time.

The shared pathophysiological pathways between AS and CAD often lead to the co-occurrence of these conditions, with two-thirds of patients undergoing TAVR having comorbid CAD.⁸¹ Before aortic valve replacement, candidates should undergo CAD evaluation to receive PCI and TAVR or coronary artery bypass grafting and surgical aortic valve replacement during the same procedure. This preprocedural assessment is conducted using CCTA, which can be facilitated using AI-automated interpretation with an accuracy comparable with expert readers.⁸² Although CCTA is highly sensitive with a high negative predictive value, enabling the effective exclusion of CAD, it lacks specificity, resulting in a high false positive rate. To further refine the false positive cases, lesion-specific FFR from invasive coronary angiography is needed to detect coronary lesions causing functional ischemia.⁸³ However, the US Food and Drug Administration (FDA) has approved an AI algorithm that noninvasively measures FFR on CCTA with the potential to improve the specificity of CCTA-enabled detection of CAD.⁸⁴⁻⁸⁶ AI-enhanced FFR assessment in TAVR candidates with coronary lesions on CCTA has shown to have a sensitivity and negative predictive value >95% with a specificity of 52% to 87% and a positive predictive value of 40% to 88%, reducing the burden of pre-TAVR invasive coronary angiography.⁸⁷⁻⁹⁰

A recent proof-of-concept and validation study introduced a multi-user, multidevice mixed reality application for collaborative cardiac interventional planning.⁹¹ This system allows for precise 3-dimensional visualization of patient-specific anatomy using data derived from CT imaging. The mixed reality application facilitated enhanced spatial understanding, improved procedural collaboration, and provided clinicians with tools to virtually manipulate anatomical structures and perform device simulations preoperatively. Notably, clinical validation confirmed that VR-derived measurements were comparable to traditional CT-derived measurements, underscoring the system's reliability and potential to optimize procedural planning.⁹¹

Intraprocedural guidance

In addition to preprocedural planning, AI can advance cardiovascular interventions by providing real-time inputs during the procedure. In particular, enhanced visualization during the procedure can improve the precision and reduce adverse events (Figure 3).

Coronary interventions

Intraprocedural guidance during PCI has been enabled by innovative technologies, such as dynamic coronary roadmap (DCR), with improved procedural outcomes. DCR dynamically overlays the coronary arteries on fluoroscopic PCI images in real time while compensating for



Figure 3.

AI-enhanced intraprocedural guidance for cardiovascular interventions. AI, artificial intelligence; AKI, acute kidney injury; CT, computed tomography; TEE, transesophageal echocardiography. Patrick J. Lynch, medical illustrator, CC BY 2.5, via Wikimedia Commons.

cardiac and respiratory-induced motions. Therefore, DCR allows for enhanced real-time visualizations during PCI and potentially diminishes fluoroscopy time and contrast volume.⁹² Multiple studies, including randomized clinical trials and retrospective analyses, have demonstrated that DCR use during PCI significantly lowers contrast medium volume and fluoroscopy time without compromising clinical success rates, regardless of the operator's experience level.^{93–95} These beneficial effects have also been observed in patients with chronic kidney disease at risk for contrast-induced acute kidney injury (AKI).⁹⁶ In a propensity score-matched retrospective study on patients with chronic kidney disease receiving PCI, those with DCR-enhanced PCI received less contrast (92 mL vs 116 mL) and incurred fewer contrast-induced AKI (0.9% vs 6.2%) compared with patients undergoing PCI without DCR, while the success rate was comparable (99.1% vs 98.2%).⁹⁶ Additionally, integrating preprocedural CT scans with live fluoroscopy has proven feasible and offers valuable insights into chronic total occlusion PCI, enhancing visualization without increasing procedural risks.⁹⁷

Structural heart interventions

Intraprocedural transesophageal echocardiography (TEE) plays a key role in real-time guidance of structural heart interventions such as TAVR and TEER.⁹⁸ Although TEE uses safe ultrasound waves and feasibly provides critical hemodynamic and anatomical information during the procedure, the quality of TEE images is inferior compared with CT, providing suboptimal procedural guidance.⁹⁹ However, using intraprocedural CT for real-time guidance is limited due to radiation exposure. To improve the real-time guidance using TTE without imposing the radiation exposure of CT, mathematical methods have been suggested to fuse 2-dimensional TEE images with preprocedural cardiac CT images to produce a 3-dimensional image using temporal and spatial registration.^{100–104} This method can serve as a real-time guidance tool, which potentially leads to

more successful interventions and improves procedural outcomes.¹⁰⁰ Although AI has not been leveraged in this domain, it has the potential to improve the efficiency and accuracy of such processes.⁸⁰ Notably, the implications of such guidance tools in terms of short- and long-term patient outcomes should be defined before wide clinical adoption.

Prognosis

AI has enabled the prediction of short- and long-term outcomes for cardiovascular interventions, which allows for personalized periprocedural risk stratification to tailor procedural conduction or to plan a postprocedural follow-up (Figure 4). Additionally, the predictions can be improved by including both postprocedural and preprocedural data. The prognostic and predictive value of diagnostic modalities such as cardiac imaging are being increasingly recognized and incorporated into risk prediction models.

Coronary interventions

In-hospital mortality following PCI can be predicted from structured clinical variables using machine learning models with an AUROC of 0.90 to 0.96.^{105–112} Furthermore, short-term mortality can also be predicted at modestly lower performances with an AUROC of 0.86 to 0.93 for 30-day mortality^{112–115} and 0.82 to 0.87 for 1-year mortality.^{116–118} In addition to mortality, machine learning models predicted adverse in-hospital outcomes, such as bleeding (AUROC: 0.70–0.89),^{108–111,119,120} AKI (AUROC: 0.75–0.89),^{108–111,121,122} and stroke (AUROC: 0.70–0.75).^{108–110} Machine learning models provided a modest improvement in predicting in-hospital mortality, AKI, and bleeding over the NCDR-CathPCI risk scores (AUROC: 0.96 vs 0.95 for mortality, 0.84 vs. 0.82 for AKI, and 0.79 vs. 0.76 for bleeding) in a

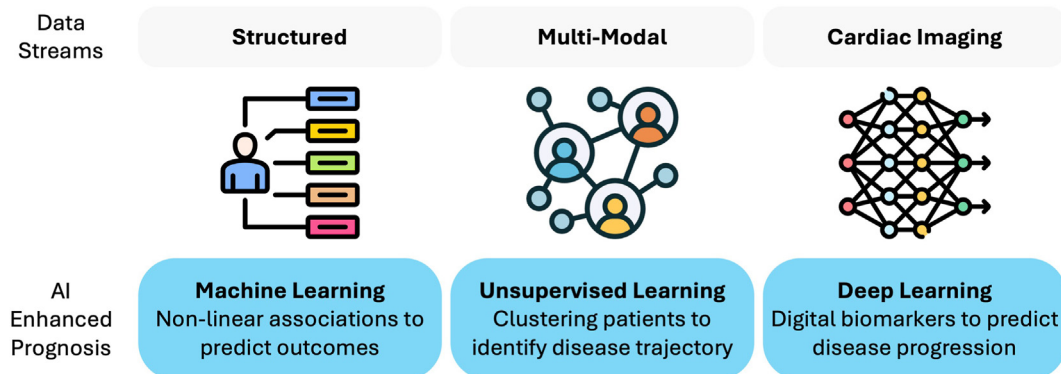


Figure 4.

AI tools to improve prognostication in interventional cardiology. AI, artificial intelligence.

registry from Japan.¹¹¹ Moreover, postdischarge outcomes, including 30-day heart failure hospitalization (AUROC: 0.90),¹¹² and 1-year target vessel revascularization (AUROC: 0.72) have been predicted.^{117,118} These models may allow for personalized risk stratification before PCI and potentially lead to enhanced outcomes.

Structural heart interventions

Machine learning models showed good discrimination in predicting in-hospital (AUROC: 0.92), 30-day (AUROC: 0.75), and 1-year mortality (AUROC: 0.72–0.8) after TAVR using structured clinical variables.^{123–126} Considering TAVR outcomes other than mortality, machine learning models predicted the need for post-TAVR permanent pacemaker implantation (AUROC: 0.81),^{127–129} and 6-month infective endocarditis (AUROC: 0.75) using structured data.¹³⁰ Furthermore, deep learning algorithms have been used to predict paravalvular leak (AUROC: 0.86),¹³¹ 2-year mortality (AUROC: 0.70),¹³² 30-day cerebrovascular events (AUROC: 0.79),¹³³ and new-onset atrial fibrillation (AUROC: 0.74) after TAVR using cardiac CT images in addition to structured data,¹³⁴ showing the incremental value of cardiac images over readily available clinical variables.

Similar efforts have been made for TEER, albeit to a lesser extent than TAVR. Using structured data, machine learning models predicted in-hospital (AUROC: 0.83)^{135,136} and 1-year mortality (AUROC: 0.79)¹³⁷ as well as 30-day readmission (AUROC: 0.72) after TEER.¹³⁸ Of note, the MITRALITY score consistently predicted 1-year mortality following TEER (AUROC: 0.78) in an external validation cohort and also demonstrated improved performance over existing risk scores.¹³⁹

Advanced prognostication

Unsupervised and semisupervised AI represents a novel approach to predicting procedural outcomes by identifying phenotypic differences across patient clusters using their preprocedural data. This approach has been adopted for TAVR,^{140–142} TEER,¹⁴³ and PCI,¹⁴⁴ using machine learning models. The observed differences in survival outcomes between patient clusters based on echocardiogram and clinical variables enable risk stratification and prediction of the disease trajectory. However, identifying human-invisible signatures of worse outcomes from more complex data streams, such as cardiac imaging, can lead to more precise prognostication strategies.¹⁴⁵ Recently, a multimodal video-based AI biomarker, DASSi (Digital AS Severity index), for AS progression has been developed and externally validated. Derived from TTE or CMR videos, higher DASSi was associated with faster AS progression, as determined by increased peak aortic valve velocity and a higher risk of aortic valve replacement.⁴⁰

Future directions

Cardiovascular disease screening

AI is set to revolutionize CVD screening by enhancing modalities available at the point of care, such as phonocardiography, ECG, and point-of-care ultrasound. Early detection of CVD improves clinical outcomes through prompt treatment, but traditional screening methods are resource-intensive and require skilled professionals for interpretation. AI-driven interpretations can overcome these limitations by automating data analysis, making screening programs more accessible and scalable, especially in resource-constrained settings. For instance, AI-driven interpretations of phonocardiography can classify heart murmurs with near-perfect accuracy and detect VHD effectively.^{146–153} Similarly, AI algorithms applied to ECG data—including images of 12-lead ECG and portable single-lead ECG—enabled scalable screening for VHD and

other structural heart diseases in the community.^{33–35,154,155} Furthermore, integrating AI with point-of-care ultrasound automated the detection of structural heart conditions, such as severe AS, even when images are acquired by minimally trained operators.^{39,156–158} These developments demonstrate the feasibility of screening approaches for early detection of VHD, such as severe AS, whose timely treatment with transcatheter interventions, especially in asymptomatic stages, improves patient outcomes.^{159–161} However, such approaches are yet to be widely implemented for CVD screening.

From bytes to bedside

Bridging the gap from bytes to bedside to bring transformative AI technology to patients involves overcoming several challenges. The development and integration of AI tools into clinical workflows require careful consideration of key aspects, as outlined in reporting checklists.^{162–166} Notable examples include TRIPOD-AI, STARD-AI, and MI-CLAIM, which focus on ensuring the robust development of AI tools.^{162–164} Additionally, checklists such as DECIDE-AI and CONSORT-AI provide guidance for the implementation of AI tools in real-world settings.^{165,166} These reporting checklists serve as an auxiliary tool to help clinicians assess the robustness and feasibility of AI technologies. In this section, we review essential concepts in AI tool development and implementation, including external validity, fairness, additional benefits over the standard of care, and effective integration into clinical workflows.^{162–169} We also highlight the infrastructure investments required for AI implementation.

The development of AI algorithms marks the first step, which should be followed by evaluating its external validity across disparate settings to ensure the algorithm can generalize well. This is essential because high-performing models may not retain their original performance in external data sources due to overfitting to the development data.^{170,171} Nevertheless, the external validity of AI models has not always been reported, particularly for some proprietary algorithms for which the model development process remains obscure. Model development using a diverse population representing a broad range of sociodemographic and clinical subgroups can improve the model's generalizability.^{1,172} While data privacy concerns can cause hurdles in validating models using external data, advancements in the field of information technology, such as the sharing of a docker container, enable end-to-end model deployment in external data without the need for sharing the underlying model or original data set.¹⁷³

The fairness of AI algorithms—exhibiting consistent performance across age, sex, racial, and ethnic subgroups—should be established before their clinical adoption. This ensures the deployment of AI algorithms will not lead to or exacerbate health disparities. This is essential because some AI algorithms may perform worse in older adults or minoritized populations.¹⁷⁴ Although model development in large and diverse populations improves the model's fairness, specific measures, such as age-/sex-matching during training, should be adopted.¹⁷⁵ Model training using age-/sex-matched cases and controls enforces learning specific biological features of the target, independent of age and sex. However, the biological effects of age and sex can then be incorporated into an ensemble model. This approach has been shown to generalize well across various settings for AI-ECG models.^{34,35}

AI algorithms should be adopted in clinical practice only if they demonstrate clear advantages over the standard of care. This requires a head-to-head comparison of AI tools with the current clinical care in terms of clinical benefit, clinical workload, and cost. It should be noted that the advantage of AI over existing tools needs to be established in external data sources as well as in the development population, because the advantage of the AI algorithm might arise from its overfitting to the development population rather than from a true added value. Moreover, automation bias should be considered and minimized,

as clinicians may trust assistive AI tools more than their clinical judgment, which can lead to worse clinical performance compared with standard care in the absence of the AI tool.¹⁷⁶

The successful integration of AI algorithms into clinical workflow hinges on their interoperability across health systems. The more technologically the algorithms are, the more effectively they can be incorporated into clinical workflow.¹ For example, ECG images can be used more readily than ECG signals with smaller infrastructural investments. Therefore, given the comparable performance of image- vs signal-based AI-ECG models, image models have an advantage in transforming care.^{177,178} Furthermore, AI tools should improve care without increasing the already exhausting clinical workload. To this end, online platforms that allow for the deployment of AI algorithms with real-time clinically meaningful outputs are needed.¹⁷⁹

Generating streamlined, real-time AI outputs to enhance patient care often requires significant infrastructural investments, including sufficient computational power and secure data storage solutions.^{1–3} While these investments require extensive planning and financial resources upfront, they support the scalability of AI-driven initiatives in the long term.^{180,181} Furthermore, the emergence of cloud computing services has enabled organizations to access high-performance computational resources on demand, reducing upfront costs and eliminating the need for extensive on-site infrastructure.¹⁸⁰

Contemporary AI applications in interventional cardiology

Recently, AI has transitioned from theoretical promise to practical application in interventional cardiology, enhancing diagnostic accuracy and procedural efficiency. Among the AI-enabled medical devices in the cardiovascular domain that have met the FDA premarket requirements,¹⁸² the FFRangio System and FEops HEARTguide have established use cases in interventional cardiology. CathWorks FFRangio is a software tool that analyzes angiography images to calculate FFRangio, a mathematically derived value based on simulated blood flow from 3-dimensional coronary models, supporting the functional evaluation of CAD.^{183,184} Similarly, FEops HEARTguide is a simulation software designed to assist in procedural planning for transcatheter left atrial appendage occlusion device implantation. It provides patient-specific predictions of implant frame deformation, helping clinicians determine the optimal device size and placement.¹⁸⁵

Another significant AI application in interventional cardiology is the CorPath GRX System, developed by Corindus Vascular Robotics. This robotic platform is designed to improve precision during PCI. In 2018, the FDA granted 510(k) clearance for the system's "Rotate on Retract" (RoR) feature, marking the first automated robotic movement in the technIQ Series. The RoR software enhances procedural efficiency by automatically rotating the guide wire upon joystick retraction, allowing operators to navigate to targeted lesions more effectively. Preclinical data demonstrated a significant reduction in wiring time among experienced physicians using the RoR feature compared with conventional methods.¹⁸⁶ In 2020, the platform also received FDA 510(k) clearance for a new feature that provides enhanced accuracy of movements for advanced PCI.¹⁸⁷

Conclusion

In summary, we demonstrated how AI-driven technologies can advance diagnosis, preprocedural planning, intraprocedural guidance, and prognostication in interventional cardiology (Central Illustration). AI can automate clinical operations, increase efficiency while ensuring accuracy, improve reliability, and individualize clinical care, establishing its potential to revolutionize interventional cardiology care. However, AI-enabled, community-based screening programs are yet to be implemented to harness the full potential of AI to improve patient

outcomes. For AI tools to move the needle in clinical practice, robust and transparent development processes, consistent performance across various settings and populations, improvements in clinical and care quality outcomes benchmarked against the current standard of care, and seamless integration into clinical workflows are required. With these efforts, AI can reshape interventional cardiology, improving precision, efficiency, and patient outcomes.

Declaration of competing interest

Rohan Khera is an Associate Editor of JAMA. He receives research support, through Yale, from Bristol-Myers Squibb, Novo Nordisk, BridgeBio, and the Blavatnik Family Foundation. He is a coinventor of US Pending Patent Applications WO2023230345A1, US20220336048A1, 63/346,610, 63/484,426, 63/508,315, 63/580,137, 63/606,203, 63/619,241, 63/562,335, and 18/813,882. He is a cofounder of Evidence2Health, a precision health platform to improve evidence-based cardiovascular care, and an academic cofounder of Ensign-AI, Inc, an AI-ECG analytics company. Arya Aminorroaya, Dhruva Biswas, and Aline Pedrosa reported no financial interests.

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Ethics statement and patient consent

This review article adheres to all relevant ethical guidelines. As it is based on a synthesis of previously published literature, it does not involve human participants, patient data, or new clinical interventions requiring ethical approval or patient consent.

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