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Comprehensive Review

Artificial Intelligence in Coronary Artery Interventions: Preprocedural Planning and Procedural Assistance

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ABSTRACT

Artificial intelligence (AI) has profoundly influenced the field of cardiovascular interventions and coronary artery procedures in particular. AI has enhanced diagnostic accuracy in coronary artery disease through advanced invasive and noninvasive imaging modalities, facilitating more precise diagnosis and personalized interventional strategies. AI integration in coronary interventions has streamlined diagnostic and procedural workflows, improved procedural accuracy, increased clinician efficiency, and enhanced patient safety and outcomes. Despite its potential, AI still faces significant challenges, including concerns regarding algorithmic biases, lack of transparency in AI-driven decision making, and ethical challenges. This review explores the latest advancements of AI applications in coronary artery interventions, focusing on preprocedural planning and real-time procedural guidance. It also addresses the major limitations and obstacles that hinder the widespread clinical adoption of AI technologies in this field.

Introduction

Artificial intelligence (AI) has emerged as a promising tool in health care, offering the potential to enhance diagnostic accuracy and improve patient outcomes.[1] In cardiovascular interventions, particularly coronary artery procedures, increasing procedural complexity necessitates improved precision and efficiency. AI technologies, such as machine learning, deep learning, and predictive analytics, process vast patient data to improve risk stratification and personalized treatment strategies.[2–4] Table 1[5,6] details the definitions of relevant terms.

The introduction of robotics in the early 2000s marked the start of a technological shift in coronary interventions, which is now magnified by AI-mediated advancements in image analysis, predictive modeling, and precise procedural guidance.[2,3,7,8] Beyond enhancing procedural accuracy, AI improves safety for both operators and patients. AI algorithms can guide decisions on whether patients should undergo noninvasive tests, such as cardiac computed tomography angiography (CCTA), versus invasive coronary angiography (ICA).[9] AI-driven decision-support systems that integrate findings from noninvasive tests, such as computed tomography-derived fractional flow reserve (FFR_{CT}), can accurately determine the need for ICA, thereby guiding patient selection, reducing procedural risks and the potential complications from unnecessary interventions.[10,11] Although AI shows promise in streamlining tasks and augmenting clinical decision making, its clinical application remains in the early stages. Many AI tools, particularly those focused on procedural safety and operator well-being, require more robust evaluation in clinical trials to substantiate their impact in clinical practice.

In this review, we explore the most recent AI advancements in preprocedural planning and procedural guidance of coronary artery interventions (Figure 1). The paper highlights the complementary role of upstream and downstream AI tools across the spectrum of coronary artery disease (CAD) management. Upstream tools, such as AI-enabled stress echocardiography interpretation, chest radiograph-based cardiovascular risk assessment, and the in silico score for CAD, primarily focus on identifying individuals at increased risk of CAD. These tools provide insights into the initial stages of patient evaluation, supporting decisions regarding further investigations and management. Downstream AI tools directly influence procedural planning and execution. Notable downstream applications include AI-guided CCTA analysis for plaque characterization and stenosis detection, computational simulation platforms for

Abbreviations: 3D, 3-dimensional; AI, artificial intelligence; CABG, coronary artery bypass graft; CCTA, cardiac computed tomography angiography; CMR, cardiac magnetic resonance; FFR, fractional flow reserve; ICA, invasive coronary angiography; IVUS, intravascular ultrasound; OCT, optical coherence tomography; PCI, percutaneous coronary artery intervention.

Keywords: artificial intelligence; cardiovascular interventions; coronary artery disease; procedural planning.

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Table 1. Definitions of terms.

Term	Definition
Artificial intelligence	Computational systems capable of autonomously carrying out tasks that typically demand human intelligence. It encompasses learning (gathering and interpreting information), reasoning (applying rules to derive conclusions), and self-improvement (adjusting based on feedback).[5]
Machine learning	A branch of artificial intelligence that involves training algorithms to adjust and enhance their performance and results as they are exposed to increasing amounts of data, all without direct human intervention.[5]
Deep learning	An evolution of machine learning that relies on less structured data to learn from extensive data sets simultaneously. It is characterized by a complex artificial neural network designed to process and transmit information.[5]
Natural language processing	A subfield of artificial intelligence that focuses on the interaction between computers and human language. It enables machines to understand, interpret, generate, and respond to text or speech in a way that is meaningful and useful.[5]
Predictive analytics	A type of data processing that uses statistical techniques, machine learning algorithms, and data analysis to predict future outcomes based on historical data. It involves examining patterns and trends in data to make informed predictions about future events or behaviors.[6]
Cognitive computing	An advanced computational programming that simulates human intelligence and thought processes by integrating technologies such as artificial intelligence, machine learning, and natural language processing to enable reasoning, learning, and intelligent decision making. It facilitates dynamic, contextualized problem solving, with applications ranging from health care diagnostics to personalized decision-support systems.[6]

predicting postpercutaneous coronary artery intervention (PCI) hemodynamics, and advanced coregistration systems integrating invasive imaging modalities like intravascular ultrasound (IVUS) and optical coherence tomography (OCT) for precise stent sizing and deployment. Additionally, AI-enhanced real-time platforms, such as robotics for PCI and computational stenting simulations, provide intraprocedural support. We aim to provide a balanced overview of the benefits, current limitations, and challenges associated with integrating AI into clinical workflows, as well as future directions for research and application.

Role of AI in CAD risk prediction

Machine learning algorithms have enabled advanced tools for CAD risk prediction. For example, the in silico score for CAD, derived from electronic health records, quantifies CAD and mortality risk by analyzing clinical and demographic factors, aiding early diagnosis and preventive interventions.[12] In a multiethnic study of the prediction of CAD in asymptomatic patients, machine learning techniques, particularly the random survival forests method, outperformed traditional risk scores by incorporating multiple variables (eg, imaging, electrocardiographic data, and blood biochemistry) across a large data set.[13] The capacity of AI to analyze complex, multivariable data sets enables more accurate disease progression predictions than single-point risk scoring. Machine learning models outperform traditional logistic regression in predicting post-PCI outcomes such as in-hospital death, heart failure, and 30-day readmission.[14] AI algorithms analyzing electrocardiography and chest radiographs predicted short-term (3-year) and long-term (10-year) risks of major cardiovascular events in CAD patients.[15,16] Machine learning models have outperformed clinical scores in predicting 3-year mortality post-PCI.[17] While AI showed only modest improvements in predicting bleeding and acute kidney injury compared to traditional National Cardiovascular Data Registry (NCDR-CathPCI) risk scores,[18] AI models incorporating clinical and proteomic biomarkers accurately predicted acute kidney injury in patients undergoing ICA.[19]

Role of AI in coronary artery imaging analysis

Noninvasive anatomical imaging

Implementation of deep learning algorithms, such as convolutional neural networks, with CCTA have automated coronary artery segmentation, plaque assessment, and stenosis detection.[20,21] Integration of

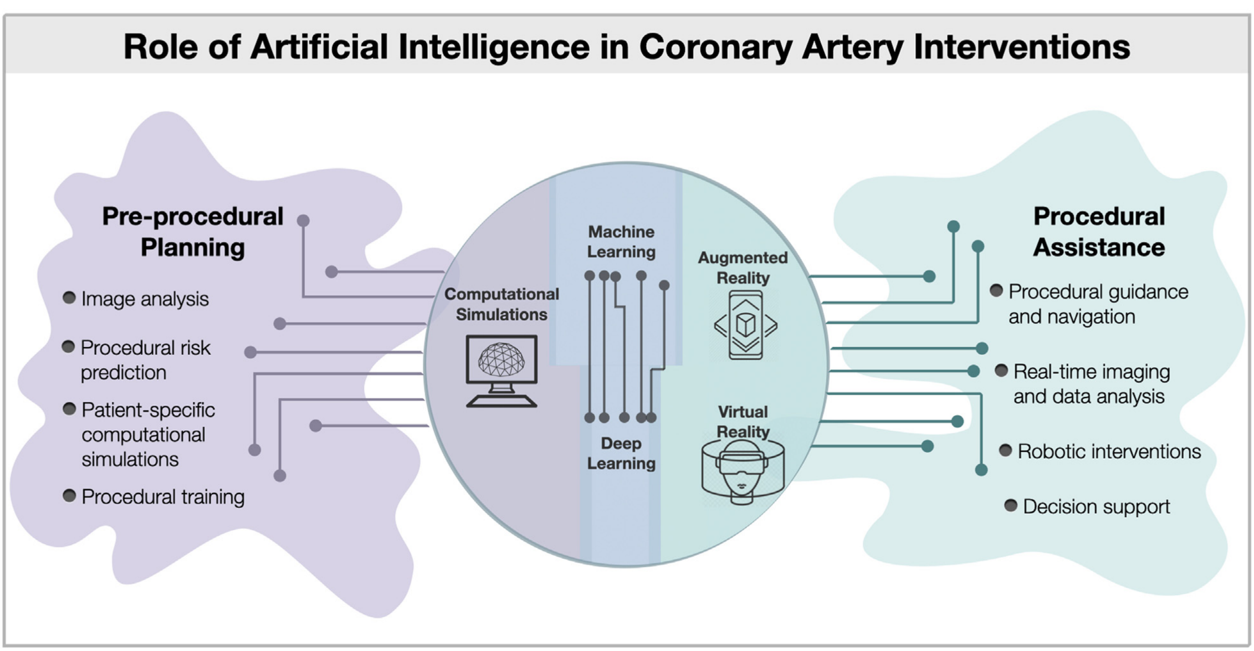


Figure 1.
Key role of artificial intelligence integrated with computational simulations and virtual/augmented reality at different stages of preprocedural planning and procedural assistance for coronary artery interventions.

CCTA with machine learning enables acute coronary syndrome prediction in high-risk plaques by analyzing anatomical, hemodynamic, and compositional features, such as luminal diameter, lesion length, FFR_{CT}, and plaque characteristics such as thin fibrous caps and lipid cores.[22] In a multicenter study, deep learning integration in CCTA analysis led to coronary plaque segmentation with differentiation between calcified and noncalcified plaque and accurate plaque volume quantification.[23] Deep learning algorithms can also stratify stenosis severity and categorize it according to the Coronary Artery Disease Reporting and Data System (CAD RADS) standards.[23] Integration of radiomics with machine learning models has augmented the ability to critically analyze complex cardiovascular imaging data and discern patterns.[24] For example, a radiomics-based model predicted chronic myocardial ischemia by analyzing the texture, shape, and intensity of cardiac structures on CCTA.[25] Radiomics and machine learning integration has also contributed to the identification of high-risk or unstable plaques, enabling precision phenotyping.[26] AI-guided CCTA analysis has significantly advanced cardiac imaging by providing rapid automated coronary segmentations,[27] improving diagnostic accuracy, and refining risk stratification through detailed plaque characterization and quantification.[28,29] As AI continues to evolve, some commercial solutions are expected to further advance the capabilities of CCTA, leading to improved patient outcomes and more efficient health care delivery. Table 2[30–36] summarizes all commercially available AI-assisted CCTA applications.

Noninvasive functional imaging

AI technologies enhance the diagnostic accuracy of stress echocardiography by automating key measurements, such as left ventricular volumes, ejection fraction, and global longitudinal strain. This automation reduces operator dependence, improves consistency, and minimizes interobserver variability, providing faster, more consistent evaluations of myocardial perfusion and ischemia.[37–39] In 1 study, machine learning models identified geometric and kinematic features from stress echocardiograms to detect severe CAD with 86.7% sensitivity and 85.7% specificity.[40] Deep learning methods, such as DeepLabV3+, have been developed to improve myocardial segmentation in contrast echocardiograms, handling complex myocardial structures effectively.[41] The PROTEUS study found that AI-guided stress echocardiography was noninferior to clinician interpretation in assessing severe CAD and guiding referrals for invasive angiography.[42]

AI algorithms, especially convolutional neural networks, automate cardiac magnetic resonance (CMR) imaging analysis, such as ventricular function assessment, myocardial perfusion, wall motion analysis, and gadolinium enhancement detection, achieving high diagnostic accuracy comparable to manual analysis.[43–45] In a multicenter study, AI-based CMR perfusion mapping provided critical prognostic information, linking lower-stress myocardial blood flow and perfusion reserve with increased risk of death and major adverse cardiovascular events.[46] AI-based CMR enhances preprocedural planning by improving the accuracy, speed, and efficiency of image reconstruction, segmentation, and ischemia detection, facilitating more precise interventions.[47]

Role of AI in PCI planning

CCTA-assisted PCI planning

FFR_{CT} utilizes patient-specific models for noninvasive simulations to predict the physiological outcomes of coronary stenting. While FFR_{CT} shows moderate correlation with post-PCI invasive FFR, it offers potential for intervention planning without requiring invasive tests.[30] The CCTA-assisted PCI approach leverages preprocedural CCTA images and FFR_{CT} analysis to assess coronary disease, allowing clinicians to simulate different stenting strategies and optimize procedural plans by predicting functional gains post-PCI with anatomical and physiological insights.[48] In the Precise Percutaneous Coronary Intervention Plan (P3) study, the accuracy and precision of the FFR_{CT} Planner in predicting post-PCI FFR were validated against invasive FFR, establishing it as a potential noninvasive tool for enhancing patient selection, optimizing stent placement, and predicting procedural outcomes for more effective PCI.[49] In a multicenter study, FFR_{CT} predicted post-PCI invasive FFR values of <0.90 and <0.80 with over 71% and 83% accuracy, respectively.[50] In the FAST FFR trial, AI-guided angiography-based virtual FFR systems demonstrated accurate hemodynamic assessment of CAD, providing a noninvasive alternative closely aligned with invasive FFR measurements, thereby streamlining decision making during interventions.[10,51] Additionally, deep learning analysis of left ventricular myocardium combined with traditional evaluation of coronary stenosis from CCTA imaging significantly improved diagnostic performance in identifying functionally significant stenosis (area under the receiver operating characteristic curve [AUC] = 0.76), especially in patients with intermediate coronary lesions.[52]

Invasive imaging-assisted PCI planning

AI enables the integration of various invasive imaging modalities, such as ICA, IVUS, OCT, and CCTA, for patient-specific computational simulation of coronaries, allowing interventionalists to predict the biomechanical and hemodynamic outcomes of stenting procedures,

Table 2. Commercially available AI-assisted CCTA applications.

Product	FDA cleared	Commercially available	Description
HeartFlow FFR_{CT} Analysis (HeartFlow)[30]	Yes	Yes	Functional assessment of coronary lesions with automated fractional flow reserve computed tomography (FFR_{CT}) assessment
Arterys Cardio AI (Arterys)[31]	Yes	Yes	Real-time cloud processing AI platform for automated segmentation and quantification of coronary artery disease burden
Zebra Medical Vision AI1 (Zebra Medical Vision)[32]	Yes	Yes	Automated identification and quantification of coronary plaques and coronary calcium scores
AI-Rad Companion Cardio (Siemens Healthineers)[33]	Yes	Yes	Software for automated segmentation and quantification of coronary arteries
Aidoc Cardiac Solutions (Aidoc)[34]	Not for coronary artery stenosis detection	Yes	Real-time triage and detection coronary artery stenosis
Cleerly Coronary (Cleerly Inc)[35]	Yes	Yes	Automated analysis of plaque characteristics and plaque burden
vascuCAP (Elucid Bioimaging)[36]	Yes	Yes	Noninvasive imaging analysis software that quantifies and classifies plaque morphology

AI, artificial intelligence; CCTA, cardiac computed tomography angiography; FDA, US Food and Drug Administration.

including assessments of stent expansion, apposition, side branch jailing, and computational fluid dynamics.[53–57] CathAI (HeartWise.AI, Montreal Heart Institute) is a fully automated pipeline for coronary angiogram analysis that accurately identifies coronary stenosis location and severity.[10] DeepCoro (HeartWise.AI, Montreal Heart Institute) uses angiographic videos to identify stenosis with even higher accuracy (AUC 0.8294 vs 0.7953), greater reliability, and closer correlation with expert assessments.[58] CathWorks FFRangio system (CathWorks) provides noninvasive, computational FFR values directly from routine ICA to guide treatment decisions, demonstrating similar clinical outcomes to wire-based FFR guidance.[59]

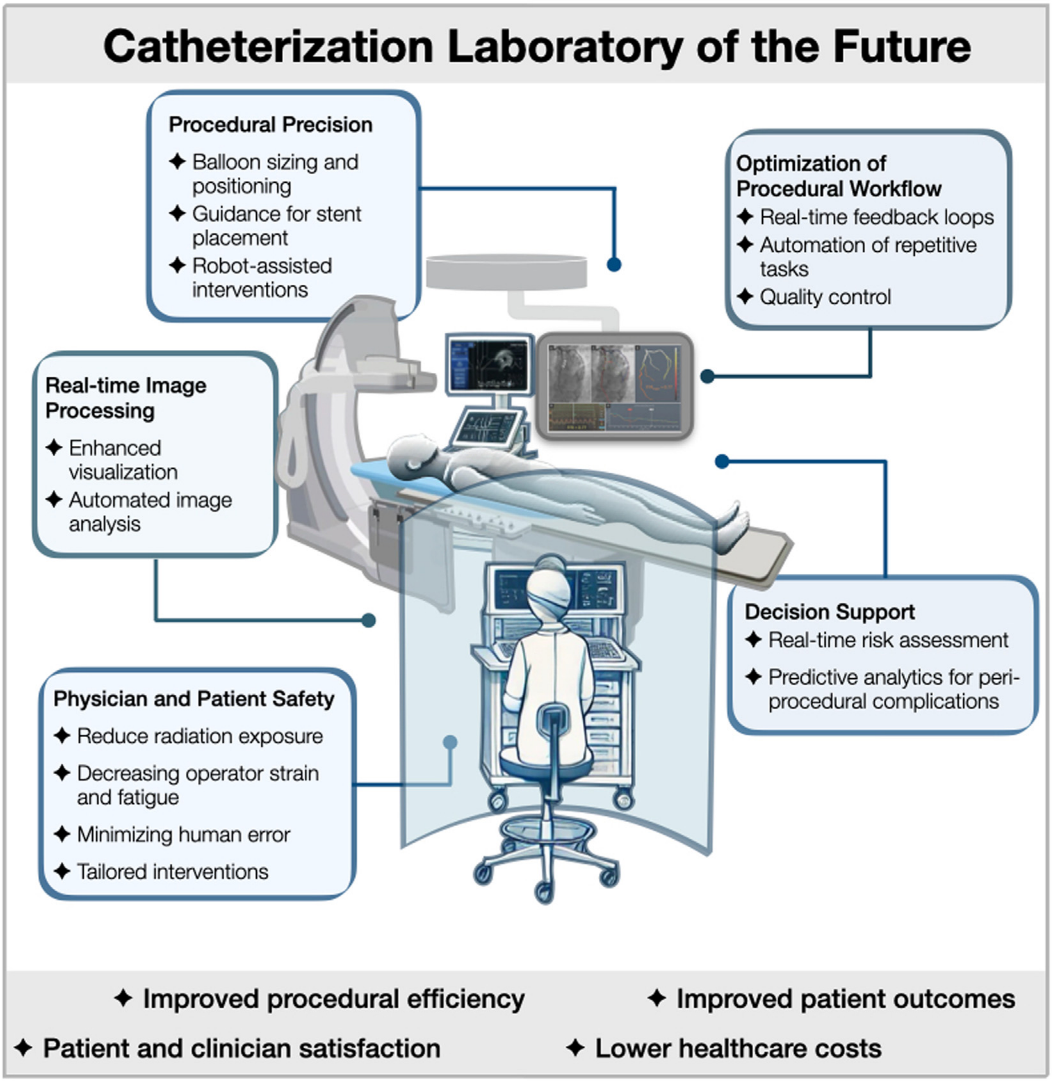
The integration of AI into intravascular imaging has led to the development of several commercial platforms that enhance procedural planning and execution, offering clinicians advanced tools for precise lesion assessment and stent optimization.[60,61] Real-time coregistration of OCT and ICA has demonstrated higher accuracy in identifying vulnerable plaques and improved PCI outcomes by reducing longitudinal geographical mismatch and edge dissections in complex lesions.[62–64] In the COMBINE OCT-FFR trial, AI-assisted OCT predicted high-risk plaques even in patients with normal FFR values, underscoring the potential of OCT in detecting lesions that traditional FFR might overlook.[65] Ultreon 2.0 (Abbott) is an AI-driven OCT platform that assists clinicians in identifying culprit lesions and characterizing plaque morphology, optimizing stent sizing, and deployment by providing real-time coregistration with angiography. This level of precision aids in correct stent deployment, minimizing complications such as stent malapposition, edge dissections, and the subsequent need for repeat interventions, thereby improving patient safety and outcomes.[66] AI-assisted IVUS imaging systems (AVVIGO+ Multi-Modality Guidance, Boston Scientific) provide real-time navigation, lesion assessment and guidance for stent sizing, selection, and placement.[67] Moreover, a morphology-based framework for coregistering CCTA and intravascular images significantly improved bifurcation alignment accuracy by addressing nonrigid distortions from irregular catheter paths. This approach facilitates precise integration of 3-dimensional (3D) coronary anatomy with high-resolution intravascular imaging, enhancing lesion assessment and facilitating large-scale studies with reduced user dependency.[55] Table 3[59,66–73] summarizes all commercially available AI-assisted intracoronary imaging software. These AI-assisted intracoronary imaging applications could change clinical practice by providing automated tools that enhance procedural precision and decision making. For example, platforms such as CathWorks FFRangio and Medis QAngio XA 3D enable real-time 3D reconstructions of coronary anatomy, allowing for detailed stenosis mapping and vessel analysis.[59,68] Tools such as Ultreon 2.0 and AVVIGO IVUS Imaging System offer automated plaque characterization, lumen segmentation, and stent guidance, reducing operator variability and improving procedural outcomes.[66,67] By integrating advanced imaging modalities with automated features, these applications could streamline workflows, improve diagnostic accuracy, and enable more personalized and effective coronary interventions (Central Illustration).

AI-driven computational simulations optimize stenting strategies for complex coronary lesions by enabling real-time 3D coronary reconstruction and post-PCI FFR prediction, providing data-driven guidance for interventionalists.[74,75] A novel computational simulation platform (Center for Digital Cardiovascular Innovations, University of Miami) integrates imaging-derived anatomical and plaque stiffness data with finite element analysis and computational fluid dynamics to enable patient-specific simulations of coronary bifurcation stenting. By modeling different stenting techniques, it provides valuable insights into the effects on local hemodynamics and aids in preprocedural planning to optimize intervention outcomes (Figure 2).[74] Computational stenting simulations using coronary anatomies from ICA accurately predicted post-PCI FFR, achieving a mean difference of just 0.01 $\pm$ 0.03 compared to invasive FFR.[76] The AI-ENCODE study from the Mayo Clinic in Rochester, Minnesota validated an AI algorithm that extracts data from ICA to predict left ventricular ejection fraction, intracardiac pressures, and cardiac index with high accuracy during interventions.[77] Patient-specific computational simulations of coronary artery bypass graft (CABG) procedures aid in surgical planning by

Table 3. Commercially available AI-assisted intracoronary imaging software.

AI-assisted applications	Imaging modality	Company	Key features
CathWorks FFR angio (CathWorks)[59]	Angiography	CathWorks	• Real-time calculation of FFR from standard coronary angiograms and detailed FFR mapping across the entire coronary vasculature, not just in the location of a specific lesion. • 3D reconstruction of coronary artery stenosis
Medis QAngio XA 3D (Medis Medical Imaging)[68]	Angiography	Medis Medical Imaging	• 3D reconstructions of coronary arteries from angiography views • Accurate detection and quantification of coronary artery stenosis • Measurement of vessel anatomy, especially bifurcation anatomy
CAAS IntraVascular (Pie Medical)[69,70]	Angiography, OCT, IVUS	Pie Medical	• Automated segmentation and 3D reconstruction of coronary artery anatomy • Real-time evaluation of stent placement and deployment • Quantitative coronary analysis of degree of stenosis and plaque burden
AVVIGO + IVUS Imaging System (Boston Scientific)[67]	IVUS	Boston Scientific	• High-resolution IVUS imaging for detailed visualization of vessel morphology • Automated measurements of lumen area and vessel dimensions • Real-time guidance for stent sizing and deployment
QIvus (Medis)[71]	IVUS	Medis	• Automated detection and segmentation of the lumen and external elastic membrane • Plaque characterization and quantification • Real-time guidance on stent sizing and deployment
IntraSight Imaging and Physiology Platform (Philips)[72]	IVUS, iFR, FFR	Philips	• High-resolution IVUS imaging with automated lumen and vessel wall segmentation • Real-time plaque and lesion characterization • Integration with iFR and FFR measurements • SyncVision coregistration with angiography for precise stent sizing and deployment
Ultreon 2.0 (Abbott)[66]	OCT	Abbott	• Automated vessel segmentation with plaque characterization • Real-time guidance on stent sizing and positioning
LUNAWAVE OCT Imaging System (Terumo)[73]	OCT	Terumo	• Automated lumen and vessel wall segmentation, plaque characterization • Provide real-time data for optimizing stent placement

3D, 3-dimensional; AI, artificial intelligence; FFR, fractional flow reserve; iFR, instantaneous wave-free ratio; IVUS, intravascular ultrasound, OCT, optical coherence tomography.



Central Illustration.
Catheterization laboratory of the future. Integration of advanced imaging with artificial intelligence-driven decision-support systems and robotic procedural assistance allows for real-time image processing, preprocedural planning, and optimization of workflow during coronary artery interventions.

identifying optimal configurations, adequate blood flow, and graft patency and improve patient outcomes.[78,79] A deep learning model accurately predicted 3D cardiovascular hemodynamics pre- and post-CABG, delivering results 600 times faster than traditional computational fluid dynamic methods with ~90% accuracy.[80]

Role of AI in real-time procedural guidance and navigation

Augmented reality (AR) systems enable interactive visualization and manipulation of patient anatomy through holographic displays. These systems provide critical information during interventions that traditionally require multiple monitors, enhancing both accuracy and efficiency. SentiAR has developed AR platforms that display holographic representations of patient anatomy, offering real-time visualization during procedures.[81] The HoloLens (Microsoft), with its advanced holographic projection capabilities, has shown significant potential in cardiovascular interventions.[82] For example, an interactive hologram was proven feasible and cost-effective for assisting ultrasound-guided femoral arterial cannulation.[83] The HoloLens 2, used with CarnaLife Holo software (Medapp), enabled real-time 3D holographic measurements of CABGs from CCTA images, achieving rapid and accurate measurements in just over 3 minutes per case, even in cases with complex anatomy.[84] In an animal study, AR was used to monitor myocardial perfusion intraoperatively by projecting infrared temperature maps directly onto the cardiac surface during open-heart surgery, providing real-time visual feedback.[85] AI-powered virtual reality simulations have been used for guiding catheter placement in complex anatomies, such as anomalous right coronary artery origin.[86] AI-driven technologies have also been integrated into real-time guidance, such as a deep learning-based Bayesian filtering approach that dynamically tracks catheter tips during PCI. This system compensates for cardiac and respiratory motion and facilitates more precise catheter manipulation and efficient navigation, leading to fewer repeat angiographic acquisitions, lower cumulative radiation doses for the interventionalist, and lower contrast exposure for the patient (Central Illustration).[87]

Robot-assisted coronary artery interventions

Since the first human robot-assisted PCI study in 2006, robotics in coronary artery interventions have rapidly evolved, aiming to improve

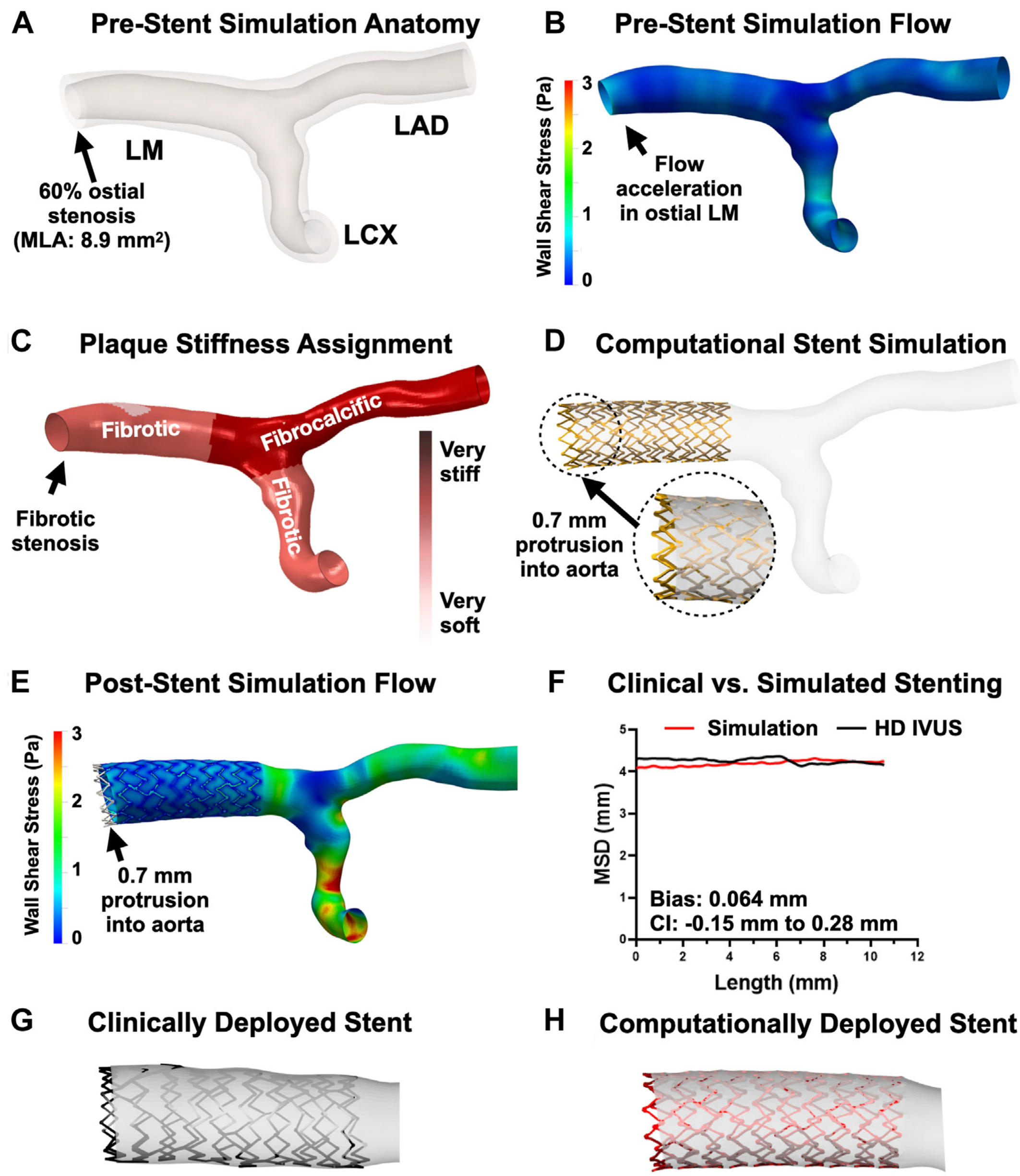


Figure 2.

Preprocedural computational planning using patient-specific coronary anatomy. Baseline anatomy (A), computational fluid dynamics showing wall shear stress and flow acceleration in the ostial left main (LM) coronary artery (B), and plaque stiffness mapping using high-definition intravascular ultrasound (HD IVUS) identifying fibrocalcific stenosis (C). Computational stent deployment from the mid-LM to the aortic ostium with 0.7-mm protrusion into the aorta (D) shows wall shear stress poststenting (E). A 3D reconstruction of the clinically deployed stent from HD IVUS compared with the computationally deployed stent (F-H) demonstrates high quantitative and qualitative agreement. 3D, 3-dimensional; LAD, left anterior descending artery; LCX, left circumflex artery; MLA, minimal lumen area. Adapted from Chatzizisis et al.[74]

procedural efficacy, accuracy, and safety.[2,8] Studies such as PRECISE and CORA-PCI have demonstrated high success rates (98.8% and 81.5%, respectively) for robot-assisted PCI.[8] Systems such as CorPath GRX (Corindus Vascular Robotics) now provide improved guide wire control, device exchange, and joystick-based catheter manipulation, reducing the need for unplanned manual intervention, particularly in complex cases.[8,88] The robotic system includes a bedside unit and an interventional cockpit, where operators control procedures with joysticks and touchscreens, significantly reducing radiation exposure and operator fatigue, thereby improving overall procedural safety for the operators and patients.[7] While robot-assisted PCI has shown better immediate outcomes—such as precise stent placement and fewer major adverse events—challenges remain in complex cases, and long-term benefits over manual PCI are still uncertain.[7,89] Limited evidence is available on long-term outcomes; 1 study found no significant benefit of robot-assisted PCI over manual PCI at 6-month and 12-month follow-ups.[88] Systems such as the da Vinci Surgical System have enabled minimally invasive procedures, such as totally endoscopic coronary artery bypass and robot-assisted minimally invasive direct CABG.[90] These techniques offer several advantages, including reduced recovery time, lower infection rates, and higher rates of graft patency, with long-term outcomes comparable to traditional methods.[91,92]

Table 4[13–17,19,23,25,40–42,46,49,50,52,58,62,65,75,77,80,88,91,93] summarizes the study characteristics and the overall level of evidence and robustness of the major studies that were mentioned.

Table 4. Critical appraisal of reported studies on application of artificial intelligence in coronary artery risk prediction, procedural planning, and interventions.

Study name	Study design	Sample Size	Study end points	Validation	Limitations	Potential methodological improvements
AI in CAD risk prediction						
Cardiovascular Event Prediction by Machine Learning: The Multi-Ethnic Study of Atherosclerosis (MESA)[13]	Prospective, observational cohort study using machine learning (random survival forests) to predict 6 cardiovascular outcomes and key predictors in a diverse, multiethnic population	6814 patients	Compare machine learning techniques for predicting cardiovascular outcomes and identifying key predictors using Cox regression and standard risk scores.	Internal validation within the MESA data set, with training and test data sets split (66.6% training, 33.3% testing).	Limited to middle-aged, cardiovascular disease-free individuals, reducing generalizability. Genetic data and genome–phenome interactions were excluded. Deep phenotyping may be constrained by cost, and variable selection needs refinement for clinical practicality and to balance prediction accuracy.	Expand validation to external, diverse populations with established cardiovascular disease. Incorporate genetic data for assessing genome–phenome interactions. Explore cost-effective strategies for deploying deep phenotyping in clinical and research settings.
Leveraging Machine Learning Techniques to Forecast Patient Prognosis After Percutaneous Coronary Intervention (PCI)[14]	Retrospective study using machine learning (random forest regression) to predict outcomes after PCI	11,709 patients with 14,349 PCI procedures	Predict in-hospital mortality, 30-d CHF readmission, and 180-d cardiovascular death. Also, identify high-risk subgroups.	Internal validation used 8-fold cross-validation to minimize overfitting, with temporal consistency tested across two 5-y subsets. Performance was compared to logistic regression models.	Single-center data with limited diversity, reliant on well-structured data sets. High in-hospital mortality performance driven by dominant predictors such as shock (3% of the cohort).	Expand to multicenter data sets for validation, include diverse populations, develop interpretable AI, and integrate real-time updates with EHRs for practical use.
Identification and Risk Stratification of Coronary Disease by AI-Enabled ECG (ECG-AI Study)[15]	Retrospective observational study	Model development included 7,116,209 patients, with validation cohorts of 98,684 (CAC), 19,363 (obstructive CAD), and 58,519 (LV akinesis), totaling 72,278 for event prediction.	Develop AI-ECG models to detect CAC $\geq$300, obstructive CAD, and LV akinesis Assess 3-, 5-, and 10-y risk prediction for acute coronary events and mortality and evaluate their additive value to traditional risk scoring.	Validation performed on external subsets within Mayo Clinic's diverse health care system, including unseen ECGs for testing.	Retrospective design with inherent biases, limited diversity, and underrepresentation of younger populations. Neural networks lack transparency, and baseline risk tied to clinical decision making (eg, ECGs obtained for suspected risk), potentially inflating observed event rates.	Expand data sets for diversity, conduct prospective studies, include younger cohorts for primary prevention, and develop interpretable AI for clinical decision making.
Deep Learning to Estimate Cardiovascular Risk from Chest Radiographs (CXR CVD-Risk Study)[16]	Retrospective risk prediction study	Development cohort: 40,718 individuals with 147,801 CXRs External validation: 11,001 outpatients (8869 unknown ASCVD risk, 2132 known ASCVD risk)	Develop a deep learning model using chest radiographs to estimate 10-y MACE risk. Compare its performance to ASCVD risk scores in cohorts with unknown and known ASCVD risk.	External validation conducted in outpatients treated at 2 hospitals (Massachusetts General Hospital and Brigham and Women's Hospital) using real-world clinical data from the Mass General Brigham health care system.	Retrospective design with potential biases, limited generalizability due to a predominantly white population, high-risk cohort, and ICD-based phenotyping with low specificity. Neural networks lack interpretability, and the focus is on ages 50-75, which excludes younger patients.	Conduct prospective trials, expand validation to diverse populations, enhance model interpretability. Explore cost-effective integration of CXR CVD-risk into routine EHRs for opportunistic screening.
Prediction of 3-year all-cause and cardiovascular cause mortality in a prospective PCI registry: Machine learning model outperforms conventional clinical risk scores[17]	Prospective registry	2242	All-cause mortality and cardiovascular mortality.	Internal validation using train-test split (70%-30%) with hyperparameter optimization. Comparison to validated clinical scores.	Single-center study on eastern European cohort. Moderate recall for multinomial classification. Lack of external validation.	External validation across diverse populations. Inclusion of additional data sets for multinomial classification to improve recall. Integration into EHR systems.
A clinical, proteomics, and AI-driven model to predict AKI in patients undergoing coronary angiography[19]	Prospective cohort study	889	Procedural AKI defined.	Internal validation with Monte Carlo cross-validation (400 iterations, 80:20 split) with performance measured by AUC, sensitivity, and specificity.	Single-center, predominantly Caucasian cohort with no external validation, exclusion of contrast dye volume, and a retrospective design.	Validate externally in diverse populations, include contrast volume and nephroprotective strategies, and test prospectively in real-world settings.

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Table 4 (*continued*)

Study name	Study design	Sample Size	Study end points	Validation	Limitations	Potential methodological improvements
AI in coronary artery imaging analysis						
Deep Learning-Enabled Coronary CT Angiography for Plaque and Stenosis Quantification and Cardiac Risk Prediction[23]	Retrospective data collection and prospective evaluation	1611 patients across cohorts: 921 in the training set (5045 lesions) and 690 in the test set (1901 lesions)	Evaluate DL CCTA-based plaque quantification and stenosis severity against experts and invasive standards and assess its prognostic value for predicting MI.	Compared with expert cardiologists, IVUS, and invasive coronary angiography, with external validation in the SCOT-HEART trial cohort.[93]	Retrospective design limits causality, with smaller IVUS validation samples, reliance on preprocessed centerlines, exclusion of poor-quality scans, and no lesion-specific prognosis.	Expand to diverse populations, integrate automated centerline extraction, and enhance model tolerance for varying image quality.
Predicting Chronic Myocardial Ischemia Using CCTA-Based Radiomics Machine Learning Nomogram[25]	Retrospective study	203 patients (154 for training and testing, 49 for external validation)	Predicting myocardial ischemia using a nomogram.	Internal validation with 10-fold cross-validation. External validation cohort (n = 49).	Single-center retrospective study with a small, nondiverse sample, subjective SPECT-MPI reference, and no prospective testing.	Expand sample size, conduct multicenter prospective studies, explore diverse populations and biomarkers, and enhance automated segmentation.
Automated Echocardiographic Detection of Severe Coronary Artery Disease Using Artificial Intelligence[40]	Prospective multicenter study using an AI ensemble model trained on stress echocardiography features to identify severe CAD and validated independently	578 patients for training, 154 patients for validation	Primary: Detect severe CAD on invasive coronary angiography. Secondary: Enhance interreader agreement, sensitivity, and diagnostic confidence with AI.	Independent validation in a retrospective US cohort, evaluated by sensitivity, specificity, and AUC.	Limited by small sample sizes and potential bias from adjudication-based disease classification instead of quantitative stenosis measures.	Expand data sets, use quantitative ICA measures, include diverse populations, and develop stress-specific models with severity stratification.
Semantic Segmentation Method for Myocardial Contrast Echocardiogram[41]	Randomized crossover reader study	100 patients, 9000 images, 7:3 split between training and testing	Segmentation accuracy was high, as demonstrated by strong Dice similarity coefficients and Intersection over Union metrics across 3 standard apical chamber views.	Against manual annotations of myocardial regions by an experienced echocardiographer, using Dice coefficient and Intersection over Union metrics.	Small data set, reliance on operator-dependent color mapping, and lack of testing on original contrast echocardiography frames impact robustness.	Expand the data set with original contrast frames, validate on diverse populations, and balance model accuracy with computational efficiency for clinical use.
PROTEUS Study[42]	Randomized multicenter noninferiority study comparing standard decision making with AI-augmented decision making	2341 patients	Primary: Appropriate coronary angiogram referral at 6 mo post stress echocardiogram. Secondary: Superiority of AI in predicting severe CVD, decision accuracy, diagnostic confidence, reduced interclinician variability, follow-up testing impact, patient symptoms and health status, and economic and quality-of-life outcomes.	Stress echocardiography findings validated against coronary angiography results; clinician responses and patient outcomes corroborated through adjudication.	Limited diversity affects generalizability, clinician self-reports introduce bias, and impact of AI on workflow efficiency remains unclear.	Expand to include more diverse demographics. Minimize self-report bias with objective measures. Assess AI integration's real-world impact on workflow.
Prognostic Significance of Quantitative Myocardial Perfusion Using Artificial Intelligence[46]	Two-center study evaluating AI-based myocardial perfusion mapping for automated stress blood flow and perfusion reserve measurement	1049 patients	Assessing the prognostic value of stress perfusion mapping and blood flow for mortality and cardiovascular events, with AI enabling automated clinical application.	Outcomes adjudicated by blinded experts and adjusted for confounders using multivariable modeling.	Observational design limits causality assessment, with potential unmeasured confounding, low event rate bias, and perfusion assessed for all-cause mortality rather than cardiovascular-specific mortality.	Conduct randomized trials to confirm findings, include cause-specific mortality, assess diverse populations, and improve algorithm robustness.

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Table 4 (continued)

Study name	Study design	Sample Size	Study end points	Validation	Limitations	Potential methodological improvements
AI in PCI planning						
Rationale and Design of the Precise PCI Plan (P3) Study[49]	Prospective, multicenter, international study	127 patients	Primary: Agreement between post-PCI FFR predicted by FFR_{CT}, planner, and invasive FFR. Secondary: Compare noninvasive and invasive FFR pullbacks, lesion gradients, post-PCI OCT luminal dimensions, and SAQ-7 scores.	Internal. Bland–Altman method for agreement. Statistical powering for FFR_{CT} vs invasive FFR comparison.	Surrogate end point (post-PCI FFR), small sample size, nonprospective FFR_{CT} Planner use, unassessed outcomes, and reliance on advanced imaging not reflective of routine practice.	Expand the study size to evaluate clinical outcomes and integrate FFR_{CT} Planner into prospective decision-making workflows.
Clinical Validation of a Virtual Planner for Coronary Interventions (FFR_{CT} Planner)[50]	Prospective, multicenter, investigator-initiated study	120 patients and 123 vessels	Primary: Agreement between FFR_{CT} Planner-predicted and invasive post-PCI FFR. Secondary: Agreement in luminal dimensions (minimal stent area) with OCT and FFR pullback curve consistency.	Internal validation using Bland–Altman analysis (mean difference and SD) and OCT agreement metrics.	Lack of clinical outcomes validation, exclusion of complex lesions, reliance on OCT and FFR pullbacks, single-vendor dependency, and underrepresentation of female patients.	Conduct randomized trials to assess clinical benefits, include diverse lesions and imaging modalities, and evaluate outcomes in less-optimized PCI settings.
Deep Learning Analysis of Left Ventricular Myocardium in CT Angiographic Intermediate Stenosis[52]	Retrospective, single-center observational study	126 patients	Primary: Diagnostic accuracy of DL-enhanced CCTA for functionally significant stenosis. Secondary: Improved sensitivity and specificity over degree of stenosis evaluation alone.	Fifty 10-fold cross-validation repetitions comparing AUC values for stenosis-only and combined methods.	Retrospective single-center study with selection bias, limited functional method comparisons, single-vendor reliance, and low DL model interpretability.	Conduct prospective, multicenter studies, include quantitative stenosis measures, compare DL with functional assessments such as FFR_{CT}, and expand data sets for balance.
Evaluation of stenoses using AI video models applied to coronary angiography[58]	Retrospective, multicenter, observational study	82,418 coronary angiography videos from 80,857 patients	Primary: Diagnostic performance (stenosis severity classification and regression). Secondary: Comparison with expert cardiologists and existing CathAI pipeline.	Cross-validation on data set A (75% training, 10% validation, 15% test), external validation on data set D (5904 videos, QCA labels), and interobserver comparisons on data set B (1926 videos, 1628 patients).	Exclusion of side branches and CABG cases, retrospective design, variability in training ground truth, high computational demands, and few cases with complex stenoses.	Conduct multicenter randomized trials; expand data sets to include side branches, CABG, and complex cases; optimize computational efficiency and integrate hybrid diagnostic modalities.
The OPTICO-integration study[62]	Prospective observational study	50 patients, 58 coronary lesions	Primary: Impact of OCT-ACR on PCI decisions, including stent selection and strategy. Secondary: PCI optimization after postprocedural OCT and ACR.	Internal validation comparing ACR to standalone OCT in decision making, focusing on lesion complexity and device optimization changes.	Small single-center study focused on short-term outcomes, with no follow-up for clinical impact; postprocedural ACR showed limited added benefit.	Conduct larger multicenter studies with long-term follow-up to assess outcomes and include broader lesion types such as chronic total occlusions and diffuse disease.
The COMBINE OCT-FFR trial[65]	Prospective, double-blind, observational	550 patients from 14 sites in 7 countries, with 483 included for final analysis	Primary: Composite of cardiac death, target vessel MI, target lesion revascularization, or unstable angina at 18 mo. Secondary: Individual events such as target vessel MI and unstable angina.	Blinded OCT analysis with independent event adjudication and internal validation of thin cap fibroatheroma classification in diabetic patients with stable CAD or ACS.	Non-randomized study using OCT, limited in assessing plaque burden and detecting rare outcomes, with no follow-up beyond 18 mo, focused on diabetic patients with intermediate lesions.	Conduct larger randomized trials comparing imaging- and ischemia-guided strategies, incorporate IVUS for plaque assessment, extend follow-up for clinical events, and perform stratified analyses for stable angina versus ACS.

(*continued on next page*)

Table 4 ***(continued)***

Study name	Study design	Sample Size	Study end points	Validation	Limitations	Potential methodological improvements
AI and cloud-based platform for fully automated PCI guidance from coronary angiography-study protocol[75]	Single-center, observational, pilot study	Retrospective Phase**:** 190 ACS patients, 3000 angiograms, 270 pre-PCI FFR, and 100 post-PCI FFR measurements Prospective Phase: 50 ACS patients requiring PCI to validate AI models and cloud platform.	Primary: Develop AI for coronary assessment, post-PCI FFR, and optimal PCI strategy. Secondary: Assess cloud platform for real-time, standardized PCI decision making.	Prospective validation in a pilot clinical study to compare AI-derived PCI strategies with clinician-derived decisions and invasive measurements.	Monocentric design and retrospective biases limit generalizability; small prospective sample; real-time functionality unvalidated.	Conduct multicenter studies with larger prospective samples, diverse populations, randomized comparisons to traditional strategies, and extended follow-up for long-term outcomes. Large-scale validation needed for clinical and cost-efficiency impact.
AI for Extracting Non-Coronary Data from Angiography: The AI-ENCODE Study[77]	Retrospective study with proof-of-concept validation	Retrospective study: 20,000 angiograms (2016-2021) compared to echocardiograms for LVEF, LV diastolic dysfunction, and RV function, and right heart catheterization for cardiac index.	Primary: Develop AI to extract LVEF, LV diastolic dysfunction, RV dysfunction, and cardiac index from coronary angiograms. Secondary: Improve accuracy by integrating additional data (eg, ECG, hemodynamics).	AI model performances showed LVEF and LVDD prediction: AUC of 0.87, RV function: AUC of 0.78, and cardiac index: AUC of 0.74. Proof-of-concept inclusion of ECG and invasive hemodynamic data further improved prediction accuracy.	Retrospective design, no external validation, variability in angiographic quality, single-institution data set limits generalizability, and challenges in real-time catheterization laboratory application.	Conduct multicenter prospective validation, real-time catheterization laboratory trials, test robustness with diverse data sets, and validate with extended follow-up for clinical outcomes.
Prediction of 3D cardiovascular hemodynamics before and after coronary artery bypass surgery via deep learning[80]	Retrospective study with DL-based validation	110 coronary CT angiography models expanded to 1100 through geometric parameter modifications.	Primary: Use DL to predict 3D velocity and pressure fields pre- and post-CABG. Secondary: Validate predicted hemodynamics (FFR and graft flow) against CFD and clinical metrics.	AI model results were compared to CFD simulations for 3D hemodynamics.	Limited clinical data set, biased synthetic data, no personalized boundary conditions, no invasive FFR comparison, higher errors in aortic vortex regions, and untested generalization to other pathologies.	Validate prospectively with larger data sets and real boundary conditions, include invasive FFR and diverse pathologies, and enhance vortex region accuracy with improved training and models.
Robot-assisted coronary artery interventions						
Complex robotic compared to manual coronary interventions: 6- and 12-month outcomes[88]	Observational, retrospective cohort study	Robotic-PCI Group: 103 patients Manual-PCI Group: 210 patients	Primary MACE at 6 and 12 mo.	Retrospective comparison between robotic PCI and manual PCI groups.	Retrospective single-center study with a small robotic PCI sample, potential selection bias, unaccounted operator experience, and no randomization or blinding.	Conduct randomized multicenter trials, include operator experience data, and evaluate quality of life and cost-effectiveness.
In-Hospital Mortality and Morbidity After Robotic Coronary Artery Surgery[91]	Retrospective national database analysis	Total 484,128 patients (Robotic: 2582 and Conventional: 481,546)	Primary: In-hospital mortality Secondary: Cardiovascular complications, stroke, transfusion, LOS, cost	Outcomes compared between robotic and conventional CABG using propensity score-matched cohorts	Limited long-term data, no robotic technique distinction, patient selection bias, and low annual robotic case volume (<6 per institution).	Conduct prospective studies comparing robotic and conventional CABG, include long-term outcomes, and expand robotic data sets for broader generalizability.

3D, 3-dimensional; ACR, angiography coregistration; ACS, acute coronary syndrome; AI, artificial intelligence; AKI, acute kidney injury; ASCVD, atherosclerotic cardiovascular disease; AUC, area under the receiver operating characteristic curve; CABG, coronary artery bypass graft; CAC, coronary artery calcium; CAD, coronary artery disease; CCTA, coronary computed tomography angiography; CHF, congestive heart failure; CVD, cardiovascular disease; CXR, chest x-ray; DL, deep learning; ECG, electrocardiogram; EHR, electronic health record; FFR_{CT}, computed tomography-derived fractional flow reserve; ICA, invasive coronary angiography; ICD, *International Classification of Diseases*; IVUS, intravascular ultrasound; LV, left ventricle; LVDD, left ventricular diastolic dysfunction; LVEF, left ventricular ejection fraction; MACE, major adverse cardiac event; MI, myocardial infarction; OCT, optical coherence tomography; PCI, percutaneous coronary intervention; QCA, quantitative coronary angiography; RV, right ventricle; SAQ-7, Seattle Angina Questionnaire-7 items; SPECT-MPI, single photon emission computed tomography myocardial perfusion imaging.

Role of AI in training of procedural skills

The success of PCI is closely tied to the operator's experience, with high-volume PCI operators demonstrating significantly lower risks of in-hospital mortality compared to their low- and intermediate-volume counterparts.[94] AR and virtual reality, combined with AI, have introduced new possibilities for training interventionalists and refining procedural skills (Figure 1). Given the steep learning curve in coronary interventions, AI-assisted simulations offer a patient-specific, safe, and reproducible platform for practicing complex scenarios. The CATHI (Catheter Instruction System) is one such technology designed to train interventionalists in catheter-based procedures such as PCI. By incorporating virtual reality and computational simulations, CATHI provides a highly realistic training environment with haptic feedback, high-fidelity graphics, and patient-specific scenarios, allowing practitioners to refine skills and practice complex interventions in a risk-free setting.[95,96] The VIST virtual reality simulator (Mentice AB) enables interventionalists to perform simulated coronary procedures, effectively differentiating skill levels through performance metrics and providing feedback to enhance proficiency and skill acquisition.[97] Several commercially available virtual reality simulators, including VIST (Mentice AB), Simantha (Medical Simulation Corporation), and ANGIO Mentor system (Simbionix) provide comprehensive platforms for practicing a wide range of endovascular procedures that include realistic simulations of complex anatomical variations and pathologies.[98,99] When integrated with AI-driven analytics, these tools can adapt training programs to individual users, offering performance feedback that helps accelerate skill development and proficiency. For example, VCSim3, a real-time virtual reality simulation software, uses the VSP haptic device (Vascular Simulation Platform, Mentice AB) to replicate the physical behavior of catheters and guide wires. This creates a realistic and dynamic training environment, helping health care trainees effectively practice procedural techniques.[100] By integrating AI and computational simulations using virtual reality and AR, the Center for Digital Cardiovascular Innovations (University of Miami) can generate digital twins of individual patients' coronary anatomy. These tools allow medical students, residents, and early-career clinicians to visualize coronary conditions, practice procedures virtually, and develop a deeper understanding of complex coronary interventions, ultimately improving clinical skills and decision making.[101]

Limitations

Data integrity

AI algorithms are advancing rapidly, enabling the processing of large volumes of raw data quickly. However, the accuracy of these models relies on data quality. Poor-quality or biased data can lead to inaccurate predictions and reduced reliability, particularly across diverse populations.[102,103] Additionally, biases related to race, ethnicity, sex, and comorbid conditions often present in unbalanced data sets used to train AI models, resulting in reduced performance, accuracy, and generalizability, particularly across diverse populations and varying disease conditions.[104] Standardizing data and validation methods remains challenging, as inconsistencies in protocols can impact performance. Limited quality data also affects AI accuracy, as seen in AI-assisted coronary angiography, which may underestimate stenoses.[105] In a single-center retrospective study, AI-driven CABG risk prediction models overestimated mortality rates in intermediate-risk patients, highlighting the limitations of these technologies when not carefully validated.[106] Therefore, despite the potential of AI, human oversight is essential, especially in complex cases, as AI models, often functioning as "black boxes," lack transparency, which slows clinical adoption and knowledge development.

Ethical challenges and regulatory considerations

AI systems in cardiovascular medicine rely on large patient data sets, creating challenges for data security, especially with cloud storage vulnerable to cyber threats.[107] The complexity of AI also raises concerns about consent, as patients and clinicians may not fully understand data usage.[107] Additionally, AI often operates as a closed system, limiting transparency in decision making, which can affect clinician trust.[103] Accountability is another issue, as it is unclear who holds responsibility—the clinician, AI developer, or institution—if harm arises from an AI-driven decision, complicating the use of AI in critical interventions such as coronary procedures. Regulatory bodies such as the US Food and Drug Administration[108] and federal government[109] have issued guidelines for AI deployment in medicine, but more clarity is needed. There is a need for more robust regulation, transparent AI systems, and safeguarding patient rights to ensure that the integration of AI into coronary interventions is both safe and beneficial.

Operational integration and clinical utility

Despite the potential of AI in coronary artery interventions, its widespread adoption in clinical practice remains limited due to factors such as high costs, the absence of standardized protocols, and the need for specialized computational resources. Although many AI models show potential in research, they lack validation in large clinical trials, limiting their real-world application. AI has advanced coronary imaging, but challenges such as high-resolution image acquisition, particularly in complex cases, remain. Complex AI algorithms often require significant processing time, limiting real-time use in urgent settings. Furthermore, AI models may lack context sensitivity, leading to varying recommendations for similar cases, complicating decision making. Robotic PCI and CABG interventions show promise but are still in early adoption stages and struggle with anatomical complexities and intraprocedural complications. However, integrating machine learning, real-time computational modeling, and advanced image analysis may address these limitations, enhancing automation, precision, and decision making in future applications.[110]

Future perspectives

The accumulation of trials in this review underscores the transformative potential of AI in cardiovascular medicine while also highlighting key directions for future research and implementation. Many studies demonstrate promising improvements in diagnostic accuracy, risk prediction, procedural planning, and outcome assessment, yet recurring limitations emphasize the need for robust validation studies and broader applicability. Specifically, most studies are constrained by single-center designs, retrospective analyses, and limited population diversity, underscoring the importance of external, multicenter validation across heterogeneous cohorts. Moreover, while retrospective findings are encouraging, prospective trials are critical to confirm the real-world clinical utility of AI-guided models. The integration of AI into routine practice will also depend on developing interpretable models, fostering clinician trust and transparency. Seamless integration into electronic health records and existing workflows is essential to ensure scalability and real-time decision making. Finally, future research must prioritize comprehensive outcome assessment, including long-term clinical outcomes, cost-effectiveness, and patient-reported measures, to fully capture the value of AI-driven approaches. Addressing these gaps will enable the transition of AI from experimental innovation to a cornerstone of evidence-based cardiovascular care, optimizing outcomes while enhancing efficiency and accessibility.

Conclusion

The integration of AI in coronary artery interventions has significantly advanced preprocedural planning, intraoperative guidance, and postprocedural evaluations. The ability of AI to enhance risk stratification, streamline complex imaging analyses, and support real-time clinical decision making highlights its potential to improve patient outcomes and enhance procedural efficacy. Beyond increased precision, AI has introduced innovative avenues for real-time procedural guidance and serves as a valuable educational tool in training clinicians in interventional techniques. However, challenges such as algorithmic transparency, ethical and regulatory concerns, and substantial costs remain substantial barriers to broader implementation. Addressing these challenges through ongoing research, refined regulatory standards, and interdisciplinary collaboration will be essential to fully harness the transformative potential of AI in cardiovascular care and facilitate its seamless integration into routine clinical practice.

Declaration of competing interest

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Ethics statement

This manuscript adheres to ethical research and publication practices. No primary data collection involving human or animal subjects was conducted as part of this review. Hence, an ethical approval was not required.

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