

Commentary

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# Artificial intelligence in coronary plaque characterization and risk assessment: from images to impact

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**How to cite this article:** Lauretti A, Borgi M, Versaci F. Artificial intelligence in coronary plaque characterization and risk assessment: from images to impact. *Vessel Plus.* 2025;9:16. <https://dx.doi.org/10.20517/2574-1209.2025.54>

**Received:** 6 May 2025 **First Decision:** 4 Jul 2025 **Revised:** 11 Aug 2025 **Accepted:** 4 Sep 2025 **Published:** 18 Sep 2025

**Academic Editor:** Aijun Sun **Copy Editor:** Ping Zhang **Production Editor:** Ping Zhang

## Abstract

Accurate characterization of coronary atherosclerotic plaque and individualized cardiovascular risk assessment remain active challenges in clinical and interventional cardiology. In recent times, Artificial Intelligence (AI) has emerged as a powerful new tool able to support clinicians in determining diagnoses and prognoses from coronary imaging. This commentary focuses on the current applications of AI in coronary plaque imaging, particularly on coronary computed tomography angiography (CCTA), intravascular ultrasound (IVUS), and optical coherence tomography (OCT), evaluating its role in identifying high-risk plaque features and predicting future adverse cardiovascular events. We discuss limitations of conventional assessment methods, illustrating how AI algorithms can improve reproducibility, reduce operator dependence, and examine current evidence from registries and clinical studies. Furthermore, some key challenges remain to be addressed, including data quality, model generalizability, clinical integration, and regulatory concerns. We argue that AI's promise lies not in replacing clinical expertise, but in empowering coronary risk stratification and characterization. Ongoing validation and clinician-AI collaboration will be essential to ensure meaningful patient outcomes.

**Keywords:** Artificial intelligence, coronary plaque, risk stratification



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## INTRODUCTION

### The need for better risk stratification

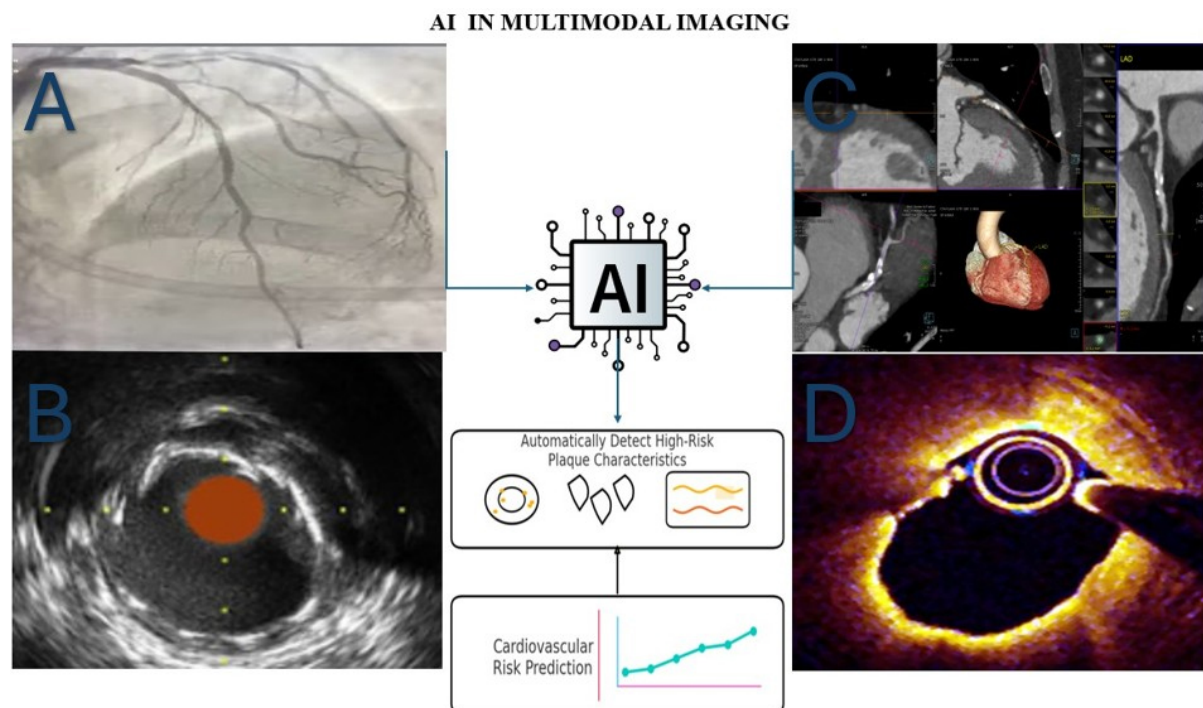
Atherosclerotic cardiovascular disease remains the leading cause of death worldwide, accounting for an estimated 17.9 million deaths each year, representing approximately 32% of all global deaths, according to the World Health Organization<sup>[1]</sup>. The capability to detect and characterize coronary plaque morphology using non-invasive methods has recently improved with the advancement of imaging techniques<sup>[2]</sup>. However, current clinical practice still heavily relies on angiographic imaging evaluation to assess the severity of coronary stenoses, although it is now considered a marker with limited precision<sup>[2]</sup>. Indeed, angiographic stenosis provides only a luminal silhouette and correlates poorly with underlying plaque vulnerability, a key driver of acute coronary events<sup>[2]</sup>. Angiographic stenosis reflects only the degree of luminal narrowing and offers limited insight into the biological characteristics of the atherosclerotic plaque, which are more directly linked to the risk of rupture and acute coronary events<sup>[2,3]</sup>. With the increasing availability of large imaging datasets and computing power, artificial intelligence (AI) offers new opportunities to extract hidden information from images and provide more specific assessments of cardiovascular risk and prognosis<sup>[2-4]</sup>.

## IMAGING TECHNIQUES AND THEIR LIMITATIONS

Coronary computed tomography angiography (CCTA) is widely used for plaque detection, while intravascular ultrasound (IVUS) and optical coherence tomography (OCT) offer high-resolution views of the vessel wall<sup>[3]</sup>. Although evidence suggests that specific plaque characteristics, such as a thin fibrous cap, large lipid core, and signs of inflammation, effectively predict future cardiovascular events, intra-coronary imaging often performs suboptimally in cath labs, limited by interobserver variability, manual analysis, and suboptimal identification of vulnerable plaque features<sup>[4,5]</sup>. There is perhaps a critical need for methods able to integrate anatomical, morphological, and potentially functional data in a consistent and scalable manner, increasing exam reproducibility and improving workflow in cath labs<sup>[6]</sup>. Coronary OCT resolves structures at roughly 10-20  $\mu\text{m}$  axially and 20-40  $\mu\text{m}$  laterally, with tissue penetration of about 1-2 mm, which helps distinguish thin fibrous caps and lipid pools with high contrast<sup>[7]</sup>. By comparison, conventional 40-MHz IVUS has lower spatial resolution (about 100-150  $\mu\text{m}$  axially and 200-250  $\mu\text{m}$  laterally) but penetrates deeper into the vessel wall. Higher-frequency (~60-MHz) IVUS improves axial resolution relative to 40-MHz systems, although OCT remains finer overall<sup>[7,8]</sup>. Reproducibility depends on what is being measured: OCT lumen measurements are generally highly reproducible, whereas fibrous-cap thickness shows only moderate agreement in routine practice [Intraclass Correlation Coefficient (ICC) ~0.52] that improves to ~0.88 with standardized methods; plaque-type classification reaches substantial agreement ( $\kappa$  ~0.71)<sup>[8]</sup>. For IVUS, volumetric analyses-including Virtual Histology Intravascular Ultrasound (VH-IVUS)-show good-to-excellent reproducibility across centers for vessel and plaque volumes (ICC ~0.83-0.99)<sup>[9]</sup>.

## AI IN CORONARY PLAQUE CHARACTERIZATION

AI algorithms have demonstrated high accuracy in automating plaque detection in CCTA, quantifying plaque burden, and distinguishing high-risk morphologies, such as low-attenuation plaque, positive remodelling, or the napkin-ring sign<sup>[10,11]</sup>. Companies such as Cleerly, HeartFlow, and others have developed tools that provide rapid, reproducible, and quantitative assessments of plaque components on CCTA<sup>[12,13]</sup>. Similarly, deep learning models have shown reliability in analyzing OCT and IVUS images for core-lipid characterization and fibrous cap thickness<sup>[14,15]</sup>. The integration of AI into coronary imaging involves multiple stages, from image acquisition to automated plaque analysis and clinical decision support. **Figure 1** illustrates a typical workflow for AI-assisted coronary plaque characterization across imaging modalities.

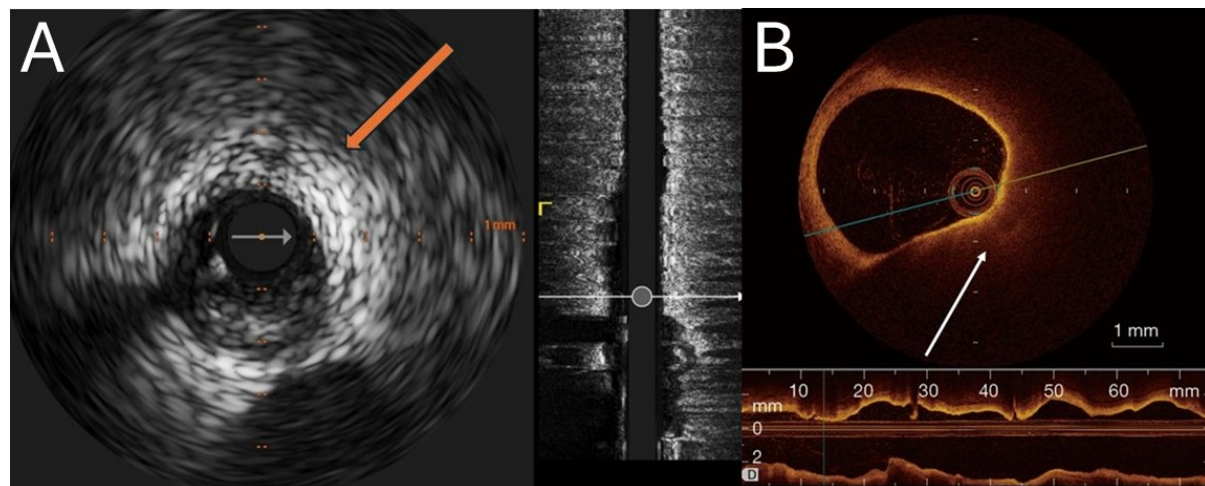


**Figure 1.** Schematic overview showing how AI integrates data from CCTA, OCT, and IVUS to identify high-risk plaque features, such as thin fibrous caps, lipid cores, and inflammation, for improved coronary risk assessment. (A) Image of coronary angiography from my clinical activity in Santa Maria Goretti Hospital, Latina; (B) Image of IVUS adapted from reference 26<sup>[26]</sup>. Licensed under CC BY 4.0 (<https://creativecommons.org/licenses/by/4.0/>). Changes: cropped and relabeled in GIMP; (C) Images of CCTA by MBq, via Wikimedia Commons, licensed under CC BY-SA 4.0 (<https://creativecommons.org/licenses/by-sa/4.0/>). Changes: cropped/relabeled/recolored<sup>[27]</sup>; (D) Image of OCT adapted from reference 28<sup>[28]</sup>. Licensed under CC BY 4.0. Changes: cropped/relabeled/recolored. AI: Artificial intelligence; CCTA: coronary computed tomography angiography; OCT: optical coherence tomography; IVUS: intravascular ultrasound; GIMP: GNU image manipulation program.

AI makes it possible to combine clinical information such as age, cholesterol levels, and symptoms with imaging findings, offering a more comprehensive assessment than traditional tools such as Coronary Artery Disease - Reporting and Data System (CAD-RADS) or Agatston scores<sup>[16]</sup>. Although the coronary artery calcium (CAC) score, most commonly calculated using the Agatston method, is a robust marker of total atherosclerotic burden and widely used for cardiovascular risk stratification, it has important limitations<sup>[17]</sup>. By design, the CAC score quantifies only macroscopic calcified plaque and fails to capture non-calcified components, which are often more vulnerable and prone to rupture<sup>[17]</sup>. Moreover, it does not differentiate between stable, densely calcified lesions and unstable plaques containing microcalcifications, low-attenuation components, or necrotic cores, features that are more directly linked to acute coronary events<sup>[17,18]</sup>. Figure 2 provides an example of high-risk lipid-rich plaques in the context of IVUS/OCT/CCTA. As highlighted in recent literature, this lack of granularity reduces its utility in assessing plaque vulnerability and limits its predictive value for cardiovascular events in certain populations<sup>[17,18]</sup>. This fusion of image-derived and clinical features represents a step forward in personalized cardiovascular risk stratification. AI tools can synthesize features from multiple imaging techniques, such as CCTA, OCT, and IVUS, to identify high-risk plaque components. Figure 1 provides an overview of this multimodal integration.

## PROGNOSTIC APPLICATIONS AND RISK PREDICTION

AI models trained on large datasets have shown reliability in predicting major adverse cardiovascular events



**Figure 2.** Representative intracoronary imaging of high-burden lipid-rich plaques. (A) Grayscale IVUS of the left circumflex artery showing an eccentric, predominantly hypoechoic plaque with marked deep ultrasound attenuation (arrow) and no bright calcific leading edge, consistent with attenuated plaque; (B) OCT from routine clinical imaging demonstrating a large, signal-poor, diffusely bordered lipid-rich plaque with long contiguous involvement on the longitudinal view. Scale bars = 1 mm. IVUS: Intravascular ultrasound; OCT: optical coherence tomography. Images were acquired during routine care at our institution and are fully de-identified.

(MACEs), sometimes outperforming decisions made by clinicians<sup>[19]</sup>. Recent findings from the CONFIRM2 Registry highlight how advances in quantitative imaging, particularly AI-derived plaque characteristics, provide a detailed and powerful tool for predicting Major Adverse Cardiovascular Events<sup>[20]</sup>. These AI-based assessments offer a more comprehensive view of coronary artery disease burden than traditional human evaluations of stenosis severity alone<sup>[20]</sup>. The Scottish Computed Tomography of the Heart (SCOT-HEART) study's semi-automatic-based sub-analyses demonstrated that plaque burden was more strongly associated with MACE than human-read stenosis assessments<sup>[21]</sup>. In a post hoc analysis involving 1,769 patients, those with low-attenuation plaque (LAP) burden exceeding 4% experienced a nearly fivefold increase in the risk of myocardial infarction (MI) compared to those with lower LAP burden [hazard ratio [HR] 4.65; 95%confidence interval [CI], 2.06-10.5;  $P < 0.001$ ]<sup>[21]</sup>. Additionally, the presence of adverse plaque features, such as positive remodeling or low-attenuation plaques, was associated with a threefold higher incidence of coronary heart disease death or nonfatal MI (HR 3.01; 95%CI, 1.61-5.63;  $P = 0.001$ ]<sup>[21]</sup>. Notably, patients exhibiting both obstructive disease and adverse plaque characteristics faced the highest event rates, with a tenfold increase in risk compared to individuals with normal coronary arteries (HR 11.50; 95%CI, 3.39-39.04;  $P < 0.001$ ]<sup>[21]</sup>. Important insights also come from the Decisions for Treating Coronary Disease are Changed in Patients Evaluated With Quantified Plaque Analysis (DECODE) study, which evaluated 100 patients who underwent CCTA<sup>[12,22]</sup>. Initially, three expert cardiologists assessed each case and formulated a management plan based on standard CCTA interpretation and clinical information. Subsequently, AI-based quantitative plaque characterization was introduced<sup>[20]</sup>. The inclusion of AI data led to a change in the initial management strategy in 66% of cases. Reclassification rates varied by risk profile: 47% in patients with a CAC score of 0, 96% in those with a CAC score  $> 400$ , and 89.5% in patients with stenoses  $\geq 50\%$ <sup>[12,22]</sup>. Although limited, emerging evidence suggests that AI-guided imaging may offer comparable performance to conventional intravascular imaging in guiding percutaneous coronary intervention (PCI)<sup>[22]</sup>. The Fully Automated Quantitative Coronary Angiography Versus Optical Coherence Tomography Guidance for Coronary Stent Implantation (FLASH) trial, a prospective, multicenter, randomized controlled study, evaluated the effectiveness of AI-based quantitative coronary angiography (AI-QCA) compared to OCT guidance during PCI<sup>[22]</sup>. Involving 400 patients, the trial demonstrated noninferiority of AI-QCA-guided PCI in achieving optimal stent expansion, with a mean post-PCI minimal stent area (MSA) of  $6.3 \pm 2.2 \text{ mm}^2$ .



in the AI-QCA group versus  $6.2 \pm 2.2 \text{ mm}^2$  in the OCT group ( $P$  for noninferiority  $< 0.001$ )<sup>[22]</sup>. At six-month follow-up, clinical outcomes, including target lesion failure and stent thrombosis, were comparable, supporting AI-QCA as a viable and practical alternative to intravascular imaging<sup>[22]</sup>. Moreover, explainable AI (XAI) methods are being developed to visualize the contribution of each variable to the prediction, which may increase clinical trust and usability<sup>[23]</sup>. A comparison between conventional imaging interpretation and AI-enhanced analysis is presented in Table 1, highlighting differences in reproducibility, integration, and prognostic value.

## CHALLENGES IN IMPLEMENTATION

### Data and model limitations

Despite recent advancements, several challenges continue to limit clinical translation<sup>[3,10,24]</sup>. Data heterogeneity across scanners, protocols, and populations constrains model robustness and large-scale applicability<sup>[3,10,24]</sup>. External validation remains limited, leaving generalizability uncertain<sup>[3,10,24]</sup>. Model opacity (“black-box” behavior) undermines clinician trust, alongside ethical concerns regarding bias, privacy, and accountability<sup>[3,10,24]</sup>. Plaque-specific issues include inconsistent feature definitions and reference standards across OCT, IVUS, and CCTA, and a paucity of prospective validation against hard MACE endpoints<sup>[3,10,24]</sup>. Addressing these gaps will require standardized multicenter datasets and outcome-anchored trials with harmonized endpoints<sup>[3,10,24]</sup>.

### Regulatory frameworks

Regulatory concerns exist regarding the appropriate clinical use, as every model must be validated and receive approval. Regulatory approval processes vary by country and the evolving nature of AI algorithms poses challenges related to recurrent regulatory revalidation.

### System integration

Furthermore, AI models, to be effective, need to be incorporated into picture archiving and communication systems (PACS) and electronic health records. Current limitations in interoperability represent barriers to the adoption of these systems<sup>[25]</sup>. To highlight the technological evolution, Table 2 lists key patents underpinning AI applications in coronary imaging modalities, spanning angiography, IVUS, and OCT.

## FUTURE DIRECTIONS

The future of artificial intelligence in plaque characterization will depend on several factors: the launch of large, multicenter prospective studies that assess real clinical outcomes; the use of federated learning to train AI models across institutions without sharing raw patient data, improving both privacy and generalizability. Current literature points toward the integration of AI models in daily practice to support clinicians, rather than replace human expertise. Progress will also be linked to the development of hybrid platforms that bring together imaging data, such as perfusion and plaque morphology, with molecular, genetic, or biomarker information to provide a more comprehensive view of disease. Another promising direction lies in the integration of imaging-derived data with clinical, laboratory, and non-invasive instrumental parameters<sup>[13]</sup>. Combining high-sensitivity biomarkers [e.g., troponin, C-Reactive Protein (CRP)], clinical features (e.g., symptom presentation, risk factor burden), and echocardiographic findings (e.g., regional wall motion abnormalities) with imaging data could enable the development of complex and multimodal AI systems<sup>[3,13]</sup>. To illustrate how hybrid platforms integrating imaging and clinical data may enhance coronary risk stratification in practice, we propose the following hypothetical clinical scenario: A 63-year-old man with hypertension and a history of elevated low-density lipoprotein (LDL) cholesterol presents with atypical chest pain. He undergoes coronary Computed Tomography (CT) angiography, which is analyzed using an advanced platform that integrates imaging findings with clinical and laboratory data. The automated report identifies high-risk plaque features, such as low-attenuation plaque and positive remodeling, and combines

**Table 1. Comparison of conventional vs. AI-based coronary plaque assessment**

Dimension	Conventional imaging	AI-enhanced analysis
Median interpretation time	Manual quantitative plaque assessment by experts: $-25.7 \pm 6.8$ min per scan <sup>[29]</sup>	Automated plaque quantification $-5.7 \pm 1.9$ s (research setting); total report time remains site-dependent <sup>[29]</sup>
Interobserver variability	ICC 0.44-0.75 (CCTA stenosis) <sup>[30]</sup>	ICC > 0.90 (Quantitative Plaque Volume by advanced CT/AI) <sup>[29]</sup>
Diagnostic performance for ischemia vs. invasive FFR (per-patient)	CCTA: Sensitivity $\sim 0.95$ , specificity $\sim 0.35$ - $0.45$ (vs. FFR). CT-FFR: sensitivity $\sim 0.85$ - $0.90$ , specificity $\sim 0.70$ - $0.80$ <sup>[31]</sup>	AI-QCT_ISCHEMIA AUC $\sim 0.85$ across CREDENCE/PACIFIC analyses; comparable to CT-FFR/PET and higher than SPECT <sup>[32,33]</sup>
Prognostic AUC for 5 years MACE	0.73-0.75 (SCOT-HEART semi-quantitative scores) <sup>[34]</sup>	0.85 (AI algorithm for CHD death) <sup>[35]</sup>
Change in management rate		66% (DECODE). Management recommendations changed after adding AI-QCPA to the standard CCTA <sup>[32]</sup>
Regulatory status	Multiple CE/FDA-cleared devices <sup>[31]</sup>	Several FDA-cleared AI tools <sup>[31]</sup>

This table compares traditional imaging interpretation with AI-enhanced methods across dimensions such as reproducibility, risk prediction, and clinical integration. AI: Artificial intelligence; ICC: intraclass correlation coefficient; CCTA: coronary computed tomography angiography; CT: computed tomography; QCT: quantitative computed tomography; AUC: area under the curve; PET: positron emission tomography; SPECT: single-photon emission computed tomography; MACE: major adverse cardiovascular event; CHD: coronary heart disease; QCPA: quantitative coronary plaque analysis; CE: conformité européenne; FDA: food and drug administration; FFR: fractional flow reserve; CREDENCE: computed tomographic evaluation of atherosclerotic determinants of myocardial ischemia; PACIFIC: prospective comparison of cardiac PET/CT, SPECT/CT perfusion imaging and CT coronary angiography with invasive coronary angiography; SCOT-HEART: Scottish computed tomography of the heart; DECODE: decisions for treating coronary disease are changed in patients evaluated with quantified plaque analysis; CT-FFR: computed tomography-derived fractional flow reserve.

**Table 2. Patents on artificial intelligence in coronary imaging modalities**

Modality	Patent number	Title	Key features	Year
Coronary angiography	US9962124B2	Automated analysis of vasculature in coronary angiograms	Machine learning for segmentation and stenosis detection in angiograms	2018
Coronary angiography	US20250114150A1	Artificial intelligence for coronary angiography	AI to analyze coronary angiography images for enhanced diagnostic accuracy	2025
Coronary IVUS	US7397935B2((based on WO2005107366A2)	Method for segmentation of IVUS image sequences	Statistical methods for detecting vessel boundaries in IVUS	2008
Coronary OCT	CN107993221A	Automatic identification of vulnerable plaques in cardiovascular OCT images	Machine learning to identify vulnerable plaque types	2018
Coronary OCT	WO2017214421A1	Automated coronary plaque characterization and risk assessment using OCT	AI for plaque characterization and risk assessment in OCT	2017
CCTA	WO2015058044A1	ML-based assessment of fractional flow reserve	Predicts FFR using machine learning on coronary CT angiograms	2015
CCTA	US11263188B2	Generation and management of an artificial intelligence (AI) model	AI model management applicable to CCTA data analysis	2022
QCA	US20240273723A1	Automated analysis of coronary angiograms	ML-based classification and estimation of stenosis severity	2024

This table summarizes key patents underlying AI applications across major coronary imaging modalities, highlighting innovations in image analysis and plaque characterization. AI: Artificial intelligence; IVUS: intravascular ultrasound; OCT: optical coherence tomography; FFR: fractional flow reserve; CT: computed tomography; CCTA: coronary computed tomography angiography; QCA: quantitative coronary angiography; ML: machine learning.

these with his risk factors, including blood pressure and lipid profile, to estimate his individualized cardiovascular risk. Although no significant stenosis is present, the overall assessment supports intensification of medical therapy with high-dose statins and lifestyle changes. The platform allows for follow-up imaging and biomarker tracking, enabling more precise monitoring over time and personalized adjustments to therapy.

**Table 3. AI systems in coronary imaging modalities - summary table**

System (Company)	Modality	First release	Core DL architecture	Performance metrics	Validation dataset
Ultreon 1.0 (Abbott) <sup>[36]</sup>	OCT	2021	Not publicly disclosed	No peer-reviewed, product-specific accuracy/AUC for the AI features	Pan-London PCI cohort study
AVVIGO+ (Boston Sci) <sup>[37]</sup>	IVUS	2023	Automated lesion assessment (ALA), architecture not disclosed	No peer-reviewed, product-specific accuracy/AUC for the AI features	Multiple studies, including a 48-patient study on its machine learning <sup>[38]</sup>
AI-QCA platform (Various) <sup>[39]</sup>	QCA	2024	Ensemble of DeepLabV3+, U-Net++, and U2-Net	Randomized FLASH trial: post-PCI MSA $6.3 \pm 2.2$ vs. $6.2 \pm 2.2$ mm <sup>2</sup> (AI-QCA vs. OCT), met noninferiority; OCT-defined endpoints comparable	FLASH RCT, 400 patients, 13 centers
HeartFlow plaque <sup>[40]</sup>	CCTA	2023	Proprietary algorithms Proprietary 3-D CNN	No peer-reviewed, product-specific accuracy/AUC for the AI features	REVEALPLAQUE study, 258 patients, prospective, multicenter
Cleerly coronary <sup>[41]</sup>	CCTA	2021	Proprietary machine learning algorithms; generates 3D model, 3-D CNN	AI-QCT AUC vs. MPI for $\geq 50\%$ stenosis 0.88 vs. 0.66; $\geq 70\%$ 0.92 vs. 0.81	CREDENCE and PACIFIC-1 studies
Siemens Alrad companion <sup>[42]</sup>	CCTA	2019	Deep learning algorithms; specific architecture not explicitly confirmed for cardiac features in provided materials	AUC 0.90, NPV 98% (CAD-RADS $\geq 4A$ ), and plaque-burden agreement ( $\kappa_w$ 0.97 for CACS; 0.79 for SIS) <sup>[43]</sup>	Multiple studies and extensive datasets, with patient counts ranging from dozens to hundreds, for each module <sup>[43]</sup>
Nanox HealthCCSng 2.0 <sup>[44]</sup>	Non-contrast CT	2024	Not explicitly stated in provided materials	No peer-reviewed, product-specific accuracy/AUC for the AI features	Multiple real-world studies, with patient cohorts from hundreds to thousands <sup>[45]</sup>

Overview of commercially available AI-based tools for coronary imaging, including their core features, availability, and estimated cost structures. DL: Deep learning; OCT: optical coherence tomography; PCI: percutaneous coronary intervention; AUC: area under the curve; AI: artificial intelligence; IVUS: intravascular ultrasound; QCA: quantitative coronary angiography; RCT: randomized controlled trial; CNN: convolutional neural network; CCTA: coronary computed tomography angiography; CAD-RADS: coronary artery disease - reporting and data system; CACS: coronary artery calcium score; SIS: segment involvement score; CT: computed tomography; MPI: myocardial perfusion imaging; NPV: negative predictive value; MSA: minimal stent area; AVVIGO: Boston Scientific trade name for their multi-modality IVUS/FFR guidance system; FLASH: fully automated quantitative coronary angiography versus optical coherence tomography guidance for coronary stent implantation; REVEALPLAQUE: a prospective, multicenter study to analyze plaque using Ccta; CREDENCE: computed tomographic evaluation of atherosclerotic determinants of myocardial ischemia.

These platforms may substantially enhance risk stratification and support personalized decision making in coronary artery disease. An overview of commercially available AI-based systems, including their imaging modality, availability, and core features, is provided in [Table 3](#).

## CONCLUSION

AI-based analysis of coronary plaque constitutes a great technological advancement with an increasing role in personalized cardiovascular care. Beyond its technical capabilities, the true value of AI in coronary imaging lies in its progressive integration into daily cardiology practice. AI tools can significantly reduce interpretation time by automating plaque quantification and risk assessment, freeing clinicians to focus on decision making and patient care. Embedding AI outputs directly into PACS or electronic health records can substantially improve communication and collaboration across the care team, supporting a shared

understanding of risk profiles. Future improvements in accuracy, reproducibility, and scalability of imaging-based risk assessment by AI models will be determinant for their integration into routine clinical practice. Nonetheless, robust validation, ethical safeguards, and clinician engagement are essential to ensure that AI complements, rather than compromises, evidence-based cardiology.

## DECLARATIONS

### Authors' contributions

conceived the idea for the commentary, performed the literature review, and wrote the first draft: Lauretti A contributed to the critical revision of the manuscript and provided additional references and insights on clinical applications: Borgi M

provided supervision, critically reviewed the manuscript for intellectual content, and approved the final version: Versaci F

All authors read and approved the final manuscript.

### Availability of data and materials

Not applicable.

### Financial support and sponsorship

None.

### Conflicts of interest

All authors declared that there are no conflicts of interest.

### Ethical approval and consent to participate

Not applicable.

### Consent for publication

Not applicable.

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