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AI Applications in Aortic and Peripheral Artery Disease: Risk Prediction, Imaging, Procedural Support, and Longitudinal Surveillance

REVIEW

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ABSTRACT

Aortic disease and lower-extremity peripheral artery disease (PAD) generate substantial morbidity, mortality, and longitudinal imaging burden. Artificial intelligence (AI) is increasingly studied for vascular risk prediction, image analysis, procedural support, and surveillance, but the maturity of these applications is heterogeneous. This review evaluates recent AI applications in aortic disease and PAD, emphasizing the distinction between algorithmic performance, external validation, demonstrated workflow impact, and proven patient benefit. Automated image segmentation and opportunistic abdominal aortic aneurysm (AAA) detection have the most mature evidence base, including retrospective external validation and, for AI-assisted AAA case finding, nonrandomized evidence of improved downstream evaluation and follow-up. Conversely, while machine-learning models for vascular risk prediction and disease progression often report high retrospective accuracy, their clinical readiness remains strictly investigational.

Across most aortic and PAD applications, there is a persistent lack of independent external validation, decision-curve analysis, and prospective testing against standard care. Image-fusion guidance has clinical evidence for reducing procedural resource use, but this evidence should not be conflated with autonomous AI or robotic navigation. Cardiovascular digital twins remain largely mechanistic, computational, or early-development frameworks. AI can augment vascular imaging and risk assessment, but high retrospective accuracy is not equivalent to clinical utility. Current guideline thresholds for repair, revascularization, and surveillance should not be altered on the basis of investigational radiomics or prediction models. Translation requires multicenter external validation, prospective workflow evaluation, calibration and net-benefit assessment, transparent reporting, and trials demonstrating improved patient outcomes.

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INTRODUCTION

Aortic disease and lower-extremity peripheral artery disease (PAD) span a wide spectrum, from asymptomatic aneurysm or claudication to acute aortic syndromes and chronic limb-threatening ischemia (CLTI). Contemporary guidelines provide evidence-based thresholds for diagnosis, intervention, and surveillance, yet important clinical challenges persist. These include substantial risk variation within anatomic categories, labor-intensive imaging interpretation, and vulnerability to missed or delayed follow-up.[1-3]

Artificial intelligence (AI), including machine learning (ML), deep learning, radiomics, and multimodal models, can extract nonlinear patterns from imaging, physiology, and electronic health record (EHR) data.[4,5] These capabilities have produced impressive technical results; however, a substantial gap remains between retrospective model performance and prospective clinical utility. This distinction is especially consequential when an algorithm could influence whether a patient undergoes repair, revascularization, or additional imaging.

This review therefore focuses on clinical maturity rather than novelty alone. We examine recent evidence across aortic risk prediction, PAD and CLTI, automated vascular imaging, procedural support, longitudinal surveillance, and digital twins (Figure 1). Throughout, we distinguish three evidence states: (1) demonstrated clinical or workflow evidence, in which a tool has been evaluated after deployment in actual care; (2) model-validation evidence, in which performance has been tested retrospectively or externally without demonstrating improved outcomes; and (3) conceptual or early-development applications. This framework is intended to prevent high algorithmic accuracy from being interpreted as established clinical benefit.

LITERATURE APPROACH

For this update, we performed a targeted search of PubMed and publisher databases through August 31, 2026, using combinations of "artificial intelligence," "machine learning," "deep learning," "radiomics," "aortic aneurysm," "aortic dissection," "peripheral artery disease," "chronic limb-threatening ischemia," "revascularization," "surveillance," "image fusion," "robotics," and "digital twin." We prioritized contemporary guidelines, systematic reviews, meta-analyses, multicenter studies, external validations, and studies published from 2024 through 2026 while retaining earlier references when necessary to establish clinical standards. Because this is a narrative rather than systematic review, the search was designed to capture clinically relevant translational evidence rather than generate a pooled effect estimate. Evidence appraisal was divided into two main categories: methodological rigor was assessed through cohort size, validation design, and calibration, while clinical utility was judged by prospective testing, clinical comparators, and demonstrated workflow impact.

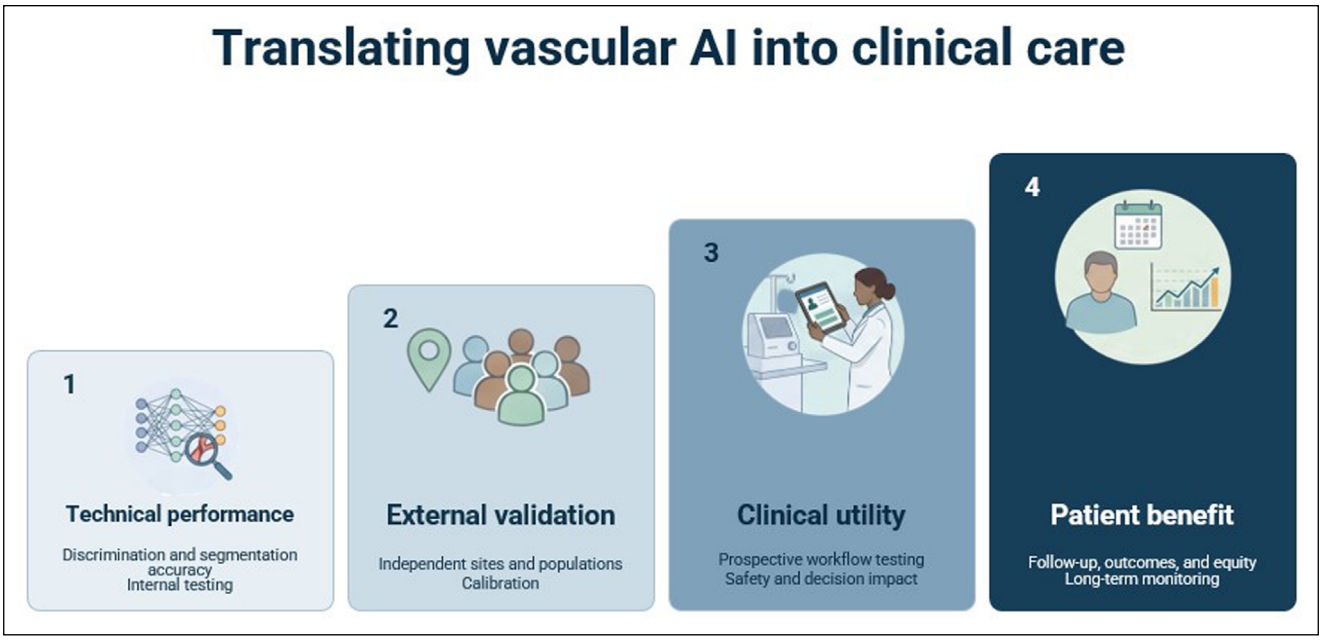


Figure 1 Conceptual roadmap of artificial intelligence in vascular disease. The diagram summarizes the progression from model development and imaging analysis toward longitudinal surveillance and adaptive decision support. Rightward elements represent increasing translational aspiration rather than established clinical utility; external multicenter validation and prospective workflow or clinical trials are required before high-stakes implementation.

INTERPRETING AI EVIDENCE: ALGORITHMIC PERFORMANCE VERSUS CLINICAL UTILITY

The central translational question is not whether an AI model can produce a high area under the receiver operating characteristic curve (AUROC) but whether it adds reliable information beyond current care and improves patient decision-making. At minimum, evaluation should address sample size and event counts; separation of training and testing data; independent external validation across institutions, scanners, and populations; calibration; comparison with established clinical models or guideline pathways; and prospective testing. Decision-curve analysis or another measure of net clinical benefit is particularly important when false-positive and false-negative predictions carry asymmetric harms.

Terminology also matters. A random train-test split from the same registry is internal validation, even when the registry contains many hospitals. A model tested at a second institution provides stronger evidence of transportability but remains retrospective unless deployed prospectively. Likewise, prospective collection of data does not by itself establish prospective clinical utility if model predictions do not influence care and outcomes are not compared with usual practice.

Accordingly, no radiomics, ML prediction, or digital-twin study reviewed here provides sufficient evidence to supersede contemporary guideline thresholds for AAA repair, acute aortic syndrome management, PAD revascularization, or postprocedural surveillance.[1-3] AI should be viewed as an adjunct to, rather than a replacement for, guideline-directed clinical judgment except where a specific tool has separately established regulatory and local implementation requirements.

AI FOR AORTIC RISK PREDICTION

ACUTE AORTIC DISSECTION

ML models have been developed to predict early mortality, acute kidney injury, and other complications after acute aortic dissection. A 2026 systematic review and meta-analysis by Mao et al. synthesized 40 studies and reported pooled C-statistics of approximately 0.89 for early mortality, 0.85 for long-term mortality, and 0.83 for acute kidney injury.[6] These results indicate strong retrospective discrimination, but the methodological appraisal is more clinically important: all included studies were judged to have high or unclear risk of bias, external validation was uncommon, and calibration and clinical-utility analyses were inconsistently reported.[6] Thus, these models are best interpreted as investigational risk-stratification tools. They do not establish that ML-guided triage improves survival or that a model should determine operative versus medical management.

AAA RUPTURE AND GROWTH

Diameter remains the cornerstone of AAA management because intervention thresholds are supported by clinical outcomes data. The 2022 American College of Cardiology (ACC)/American Heart Association (AHA) guideline recommends repair of unruptured AAA at a maximal diameter of at least 5.5 cm in men or 5.0 cm in women, with symptoms, rapid growth, and morphology contributing to individualized decisions.[1] Radiomics may eventually complement diameter by quantifying vessel-wall, thrombus, and perivascular tissue characteristics. In a 2026 multicenter retrospective study, Feng et al. reported that perivascular adipose-tissue radiomic features discriminated ruptured from stable AAA, with an external-validation AUROC of 0.77.[7] Although external testing strengthens the result, the modest sample of rupture events and retrospective case-control design limit inference about prospective rupture prediction.

Similarly, Alblas et al. evaluated geometric deep learning for local AAA growth prediction using serial computed tomography (CT) surfaces.[8] The approach demonstrated promising geometric accuracy, predicting future AAA size within 1.18 mm, but the external validation cohort was severely restricted, utilizing only 25 CT angiograms across seven patients. These studies support biological and technical feasibility, not a change in treatment threshold. A hypothetical future system might combine diameter, growth rate, radiomics, and patient-level risk to refine shared decision-making, but current evidence does not justify elective repair of a 4.8-cm AAA solely for an adverse radiomic signature, nor deferring repair of a 5.6-cm AAA because a model predicts stability; these applications remain strictly investigational.

AI IN PERIPHERAL ARTERY DISEASE AND CLTI

DETECTION AND DIAGNOSTIC PHENOTYPING

PAD is an important domain for AI because ankle-brachial index (ABI) testing is underused and disease is frequently diagnosed late.[3,4] The 2026 AHA science advisory on AI in PAD identified opportunities across screening, diagnosis, risk prediction, imaging, revascularization, and longitudinal care while emphasizing validation, fairness, interpretability, and implementation science.[4]

Digital biomarkers illustrate both the promise and limitations. Ramsis et al. developed a photoplethysmography (PPG)-based model using 5,237 lower extremities from 2,362 unique patients, reporting an AUROC of 0.83 for PPG alone and approximately 0.85 when clinical variables were added.[9] The study correctly links AI to an accessible physiologic signal, but it was retrospective, used ABI as the reference standard, and was conducted within a single health system. It therefore supports further validation rather than replacement of ABI-based diagnosis. A 2025 systematic review and meta-analysis of 24 PAD diagnostic-model studies reported a pooled AUROC of 0.79, but most studies carried high risk of bias and substantial heterogeneity.[10] A 2026 multicenter clinical-radiologic study combining clinical variables and CT-derived features reported an external-validation AUROC of 0.828 with calibration assessment, but it was retrospective and relatively small.[11] Therefore, combining CT and clinical features remains an investigational tool rather than a near-term replacement for standard physiologic testing.

AMPUTATION-FREE SURVIVAL AND REVASCULARIZATION OUTCOMES

In 2,366 symptomatic PAD patients undergoing revascularization, Goffart et al. compared nonlinear survival approaches with conventional time-to-event modeling for amputation-free survival.[12] While these models modestly improved prediction errors, the lack of independent external validation means they cannot yet determine whether or when an individual patient should undergo bypass or endovascular intervention.

Larger registries have demonstrated that ML can identify postoperative risk patterns at scale. Li et al. trained models using 235,677 lower-extremity endovascular procedures from the Society for Vascular Surgery Vascular Quality Initiative, reporting an AUROC of 0.94 for 1-year major adverse limb events or death, outperforming logistic regression.[13] A separate analysis of 21,886 patients undergoing lower-extremity endovascular revascularization in the American College of Surgeons National Surgical Quality Improvement Program also reported strong internal discrimination (AUROC 0.93) for 30-day major adverse limb events or death.[14] These sample sizes improve statistical precision and geographic diversity, but random splits within a common registry remain internal validation. Prospective testing is still required to determine whether surfacing these predictions changes therapy, follow-up, or outcomes.

CLTI AND WOUND HEALING

AI has particular potential in CLTI, where tissue loss, infection, perfusion, and wound trajectory interact. Inoue et al. developed a model for wound healing after revascularization in a multicenter retrospective cohort of 772 patients and tested it in a held-out cohort.[15] The random-forest model achieved an AUROC of 1.00 in training, 0.72 in internal validation, and 0.78 in the test cohort; a test-cohort false-positive rate of 0.70 illustrates why discrimination alone is insufficient.[15] Existing frameworks such as Wifi and GLASS therefore remain essential comparators rather than features to be displaced. A 2025 systematic review of ML for wound healing and limb salvage found only five eligible studies with substantial heterogeneity, infrequent external validation, and insufficient evidence of practical clinical impact.[16]

Prospective data collection is beginning to appear. Ghandour et al. prospectively enrolled 308 PAD patients undergoing revascularization and applied ML to serial thromboelastography with platelet mapping to predict postoperative thrombosis.[17] The best combined model reported an AUROC of 0.76, but it was developed and tested within the same cohort and did not prospectively randomize or alter care. This distinction reinforces the broader theme that a prospective dataset is not equivalent to a prospective AI intervention trial.

SURVEILLANCE AFTER LOWER-EXTREMITY REVASCULARIZATION

Current 2024 ACC/AHA PAD guidance recommends longitudinal clinical assessment after revascularization, with ABI and arterial duplex ultrasound when new signs or symptoms occur; surveillance at approximately 1 to 3 months, 6 months, 12 months, and then annually is reasonable in selected patients after infrainguinal vein bypass or endovascular therapy.[3] AI may eventually identify patients who need more or less intensive follow-up, but no reviewed model has validated individualized surveillance intervals against these guideline pathways or shown that an AI-directed schedule reduces limb events, cost, or testing burden.

AI-ENABLED VASCULAR IMAGING

AORTIC SEGMENTATION AND DIAGNOSIS

Computer vision is among the more technically mature areas of vascular AI because anatomic labels provide clear targets and output can be reviewed by a clinician before use. A 2026 systematic review and meta-analysis of deep-learning models for aortic dissection included 48 studies.[18] Reported mean Dice coefficients were approximately 0.89 for the false lumen, 0.91 for the true lumen, and 0.92 for the entire aorta, while diagnostic models demonstrated high sensitivity and specificity. Nevertheless, segmentation studies frequently lacked the variance estimates needed for formal weighted pooling, and multicenter external

validation remained uneven. A 2024 systematic review and meta-analysis of 17 deep-learning studies for aortic aneurysm CT segmentation and detection similarly reported pooled sensitivity of 0.96, specificity of 0.97, and a mean Dice coefficient of 0.94 while showing that dataset size and geographic setting were associated with performance.[19] Technical accuracy therefore supports workflow assistance, not autonomous diagnosis.

OPPORTUNISTIC AAA DETECTION

AI can also analyze CT obtained for unrelated indications and flag possible AAA for radiologist review. Chen et al. evaluated a commercial algorithm retrospectively on emergency CT examinations and reported a 7.4% incremental detection rate among AAAs not identified by the original radiology interpretation.[20] More importantly, Kostiuk et al. evaluated an AI-assisted AAA identification protocol within a real clinical workflow and compared follow-up with an historical cohort.[21] Patients identified through the AI-supported pathway were more likely to receive initial vascular evaluation, long-term follow-up, and scheduled monitoring. This represents evidence of workflow impact rather than simply algorithmic accuracy. However, the study was nonrandomized and focused on process measures, not rupture, mortality, or cost-effectiveness. Figure 2 illustrates this care-loop use case. The near-term value of opportunistic AI is therefore best framed as case finding and follow-up reliability while guideline-based treatment decisions remain unchanged.

PROCEDURAL SUPPORT: IMAGE FUSION, ROBOTICS, AND INTRAOPERATIVE AI

Image fusion, robotics, and intraoperative AI should be separated because they are often discussed together despite different evidence bases. Preoperative CTA-to-fluoroscopy image fusion is an established navigation technology and does not necessarily require AI. A 2025 systematic review and meta-analysis of 13 studies involving 1,498 patients found that image-fusion guidance for aorto-iliac endovascular procedures was associated with reductions in procedure time, fluoroscopy time, contrast use, and radiation dose, although study heterogeneity and nonrandomized designs limited certainty regarding clinical outcomes.[22] A 2026 observational endovascular aneurysm repair study similarly reported procedural resource advantages with image fusion.[23] These data support image-fusion technology, not the stronger claim that autonomous AI navigation has been proven to reduce complications.

Robotic endovascular systems are also progressing, but a 2025 review described heterogeneous platforms, limited clinical series, costs, integration barriers, and autonomy that is still in early development.[24] Accordingly, active intraoperative AI, such as real-time AI registration, autonomous wire or catheter navigation, and predictive equipment selection, remains largely speculative and should be described as investigational or conceptual unless supported by device-specific clinical studies. Ambient operating-room computer vision may quantify

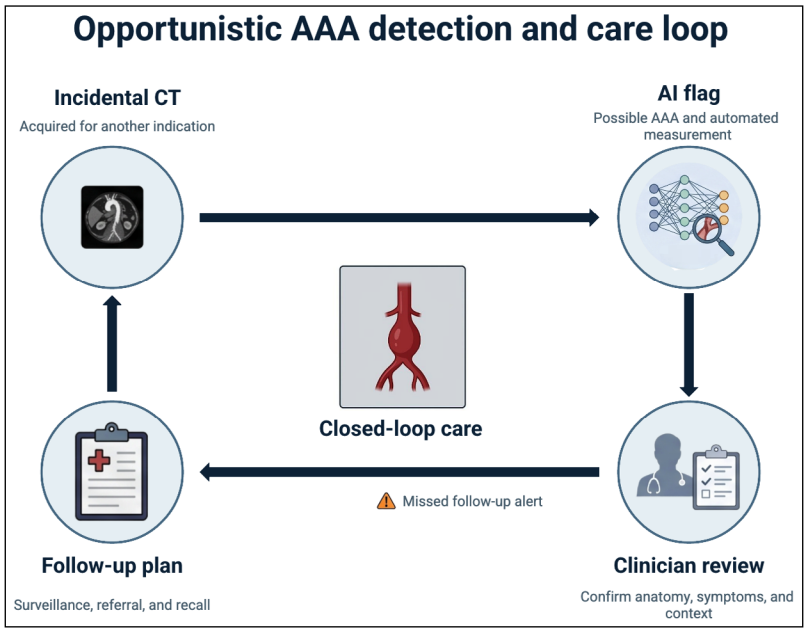


Figure 2 Artificial intelligence (AI)-assisted opportunistic abdominal aortic aneurysm (AAA) detection and care-loop workflow. A background algorithm can flag possible AAA on computed tomography (CT) obtained for another indication, prompting radiologist or vascular-team review and appropriate guideline-based follow-up. This figure depicts a workflow use case rather than autonomous treatment selection; the strongest current clinical evidence is improvement in evaluation and follow-up process measures, not rupture or mortality outcomes.

workflow phases or utilization in other surgical specialties, but current vascular evidence is insufficient to claim that such systems reliably anticipate endovascular equipment needs or improve patient outcomes. The appropriate near-term role for any intraoperative AI is strictly assistive: improving visualization, reducing repetitive manual tasks, and presenting information to the proceduralist while preserving direct human control.

AI FOR LONGITUDINAL SURVEILLANCE

AI for longitudinal vascular surveillance is attractive because disease trajectories are inherently serial. In AAA, geometric models can estimate future surface change, while radiomics and clinical variables may help model growth or post-EVAR sac behavior.[8] In chronic aortic dissection, serial segmentation could quantify true- and false-lumen remodeling more consistently than manual measurements. In PAD, EHR trajectories, ABI or duplex measurements, wound images, activity, and PPG could theoretically be combined to predict deterioration or reintervention.

At present, however, these are predominantly model-development objectives. The available evidence does not justify replacing guideline-specified imaging intervals, reducing surveillance because a model predicts stability, or performing preemptive reintervention solely because an algorithm predicts future failure.[1-3] A more defensible translational sequence would be retrospective development, geographically and temporally independent validation, prospective silent deployment to evaluate calibration and drift, then an impact study comparing AI-assisted surveillance with current care. The strongest current AI contribution to surveillance may be operational rather than predictive: identifying missed aneurysms, closing referral loops, and improving adherence to already recommended follow-up, as demonstrated by the nonrandomized AAA workflow study described above.[21]

DIGITAL TWINS: A FUTURE EXTENSION, NOT CURRENT STANDARD OF CARE

A cardiovascular digital twin is a patient-specific computational representation that can be updated with clinical, imaging, physiologic, or mechanistic data. While speculative, digital twins could eventually simulate hemodynamics, device configurations, disease progression, or treatment response. Thangaraj et al. outlined this theoretical opportunity in cardiovascular care, particularly as generative and multimodal AI expand the range of data that can be integrated.[25]

Clinical maturity remains exceedingly low, with most applications remaining entirely conceptual. A 2026 systematic review of 42 original digital-twin studies in precision cardiology found a fragmented evidence base with substantial variability in modeling, data infrastructure, reporting, and implementation readiness.[26] A 2025 meta-review of 25 reviews similarly concluded that healthcare digital twins remain early-stage, with persistent problems in standardization, scalability, interoperability, and clinical validation.[27] Furthermore, fundamental barriers in institutional data stewardship and secure data-sharing frameworks continue to limit the construction of high-fidelity digital twins for precision medicine.[28] A 2026 patient-specific aortic digital-twin framework integrates computational hemodynamics and biologic concepts but should be viewed as a translational framework rather than evidence that digital twins improve endovascular strategy in prospective care.[29]

For vascular disease, the clinically meaningful end point is not visual plausibility of a simulation but whether a twin predicts an outcome accurately across external populations and changes a decision in a way that improves net benefit. Until such evidence exists, phrases such as “optimizes procedural decisions” or “selects the best device” overstate the literature. Digital twins are better characterized as a research platform for hypothesis generation, virtual experimentation, and potential future decision support rather than a mature clinical tool.

INTEGRATED CARE PATHWAYS: ACUTE INTERVENTIONS AND SYSTEM-LEVEL TRIAGE

While much of the vascular AI literature evaluates tools in isolation, a potential future direction is an integrated clinical pathway spanning diagnosis, procedural intervention, and longitudinal follow-up. In an idealized AI-augmented workflow, algorithms may assist with vascular image analysis and case finding, while clinicians retain responsibility for diagnostic and treatment decisions, as illustrated in Figure 3.[5]

Following preoperative evaluation and planning, the pathway transitions into an active intervention arm within the procedural suite. For complex endovascular procedures, image-fusion technology can register preoperative 3-dimensional CT information with live fluoroscopy and has been associated with reductions in procedure time, fluoroscopy exposure, contrast use, and radiation dose.[22,23] Emerging robotic endovascular platforms may provide additional navigational assistance, but autonomous navigation and AI-directed device deployment remain investigational.[24]

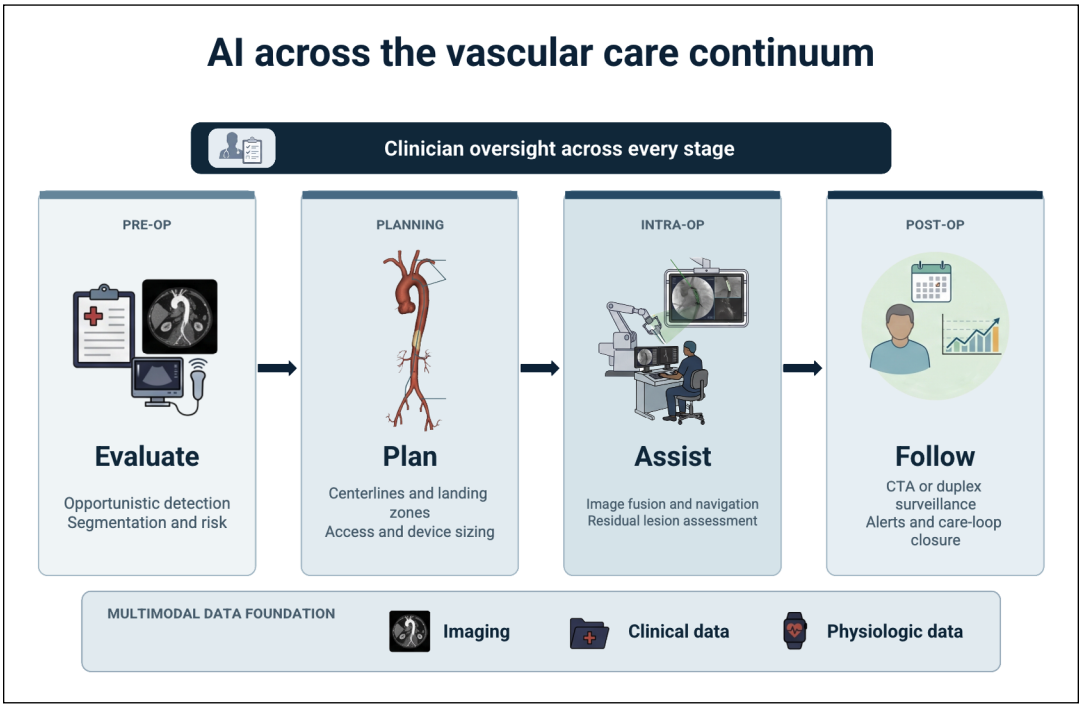


Figure 3 End-to-end technology integration in vascular care. An idealized care pathway illustrating potential artificial intelligence (AI)-assisted and image-guided support across the patient journey. The central image represents a native, unoperated abdominal aortic aneurysm (AAA) to illustrate baseline risk evaluation. The workflow progresses from AI-assisted image analysis and clinician review, to an active intervention arm incorporating clinically evaluated image-fusion guidance and investigational robotic assistance, to longitudinal surveillance emphasizing case finding, referral coordination, and follow-up.[22-24] The pathway is conceptual and does not imply that AI currently determines intervention or surveillance decisions.

In the longitudinal phase, AI-supported workflows may help address gaps in vascular follow-up. Rather than autonomously selecting treatment, the strongest current evidence supports AI-assisted case finding and care-loop closure. In a deployed AAA pathway, AI-supported identification was associated with improved downstream vascular evaluation, long-term follow-up, and scheduled monitoring compared with historical care.[21] However, prospective studies are still needed to determine whether such integrated pathways reduce complications, improve patient outcomes, or decrease resource utilization compared with standard care.

DISCUSSION: TRANSLATING VASCULAR AI TO BEDSIDE PRACTICE

The vascular AI literature now spans a wide maturity spectrum (Table 1). Automated segmentation has a comparatively strong technical evidence base but limited prospective outcomes evidence. Opportunistic AAA detection has progressed further by demonstrating improved care-process measures after clinical implementation, although randomized or patient-outcome data are still lacking.[21] Aortic and PAD risk models, including large registry models, frequently achieve strong internal discrimination (Figure 4) but have not yet shown that their predictions improve outcomes when presented to clinicians. Radiomics and personalized surveillance are even earlier, and digital twins or autonomous endovascular robotics remain largely translational.

Five evaluation priorities emerge. First, development cohorts must be large enough relative to the number of outcomes and model parameters, with transparent handling of missing data and class imbalance. Second, independent external validation should precede claims of generalizability; internal splits from a multicenter registry are not equivalent. Third, calibration should be reported alongside discrimination because a model can rank risk accurately while systematically over- or underestimating absolute risk. Fourth, models should be compared with established clinical standards, including guideline thresholds, Wifi or GLASS where applicable, and conventional statistical models. Fifth, prospective studies should measure clinical utility, including whether AI changes decisions, reduces missed follow-up, improves limb salvage or survival, reduces unnecessary testing, or improves workflow without introducing inequity or automation bias.

Implementation also requires attention to data drift, scanner and protocol variation, health-system

workflows, cybersecurity, regulatory status, and fairness across populations. Explainability tools can help clinicians interrogate model behavior, but feature attribution is not proof of causality or safety. Human factors are equally important: a technically accurate alert that arrives outside the normal picture archiving and communication system or EHR workflow can fail, while a modestly complex tool embedded at the right point in care may provide meaningful operational benefit.

The most productive near-term strategy is therefore selective augmentation. AI can assist with segmentation, case finding, measurement, and structured risk estimation while clinicians retain responsibility for diagnosis and treatment. Higher-stakes applications, altering repair thresholds, choosing revascularization strategies, reducing surveillance, autonomous navigation, or digital-twin-guided intervention require a substantially higher evidentiary bar.

APPLICATION	REPRESENTATIVE EVIDENCE	CRITICAL APPRAISAL	CURRENT MATURITY
Acute aortic dissection prediction	Mao et al.: 40-study systematic review/meta-analysis; pooled early-mortality C-statistic ≈ 0.89[6]	All studies high/unclear PROBAST risk; external validation uncommon; calibration and decision-curve analyses inconsistent; no prospective impact trial	Investigational prognostication; not a basis for operative vs medical triage
AAA radiomics/growth prediction	Feng et al.: multicenter PVAT radiomics, external AUROC 0.77.[7] Alblas et al.: geometric growth prediction with small external cohort[8]	External testing exists, but rupture events and growth cohorts remain small; retrospective; no prospective decision-threshold trial	Investigational hypothesis-generating; should not alter guideline repair thresholds or surveillance
Aortic segmentation/diagnosis	Zhao et al.: 48 studies; mean Dice ≈ 0.89-0.92 across aortic-dissection targets.[18] Wang et al.: 17 AAA CT studies; pooled sensitivity 96%, specificity 97%, Dice 94%[19]	Strong technical performance; multicenter transportability uneven; limited prospective outcome evidence	Technically mature assistive imaging; human review remains necessary
Opportunistic AAA detection and follow-up	Chen et al.: retrospective commercial-algorithm evaluation.[20] Kostiuk et al.: deployed AI-supported pathway with improved evaluation and follow-up vs historical care[21]	Real-world workflow evidence but nonrandomized and focused on process outcomes rather than rupture, mortality, or cost	Most clinically mature use case in this review; supports case finding and care-loop closure
PAD detection/phenotyping	Ramsis et al.: PPG model, 2,362 patients, AUROC 0.83-0.85.[9] Hou et al.: multicenter CT-clinical model, external AUROC 0.828[11]	Retrospective; reference standards and populations vary; prospective workflow testing and broader external validation needed	Promising diagnostic adjunct; ABI and guideline pathways remain standard
PAD outcomes after revascularization	Goffart et al.: n = 2,366 survival models.[12] Li et al.: VQI n = 235,677 and NSQIP n = 21,886 with strong internal discrimination[13,14]	Large samples but mainly internal splits/cross-validation; independent external validation and prospective utility absent	Investigational risk stratification; not established for selecting intervention or timing
CLTI wound healing/limb outcomes	Inoue et al.: multicenter retrospective n = 772; test AUROC 0.78, FPR 0.70.[15] Systematic review found only five heterogeneous studies[16]	Marked train-test performance drop; false positives clinically important; comparison with WIfI/GLASS and external prospective validation needed	Investigational; established limb-staging frameworks remain essential
Image fusion and endovascular robotics	Image-fusion meta-analysis: 13 studies, 1,498 patients; lower procedure/fluoroscopy time, contrast, and radiation.[22] Robotics review describes limited clinical series and emerging autonomy[24]	Image fusion has clinical procedural evidence but is not synonymous with AI. Autonomous navigation lacks comparable outcome evidence	Image fusion: clinically evaluated technology. AI/autonomous robotics: investigational early development
Personalized surveillance	AAA growth and longitudinal models are emerging; deployed AAA AI has improved follow-up adherence[8,21]	No prospective trial has validated AI-selected surveillance intervals or preemptive reintervention against guideline care	Operational support is plausible; individualized interval selection remains investigational
Digital twins	Recent cardiovascular systematic review included 42 original studies; meta-review included 25 reviews.[26,27] Data-stewardship barriers have also been described.[28] An aortic-specific framework was published in 2026[29]	Evidence remains mechanistic/heterogeneous; interoperability, calibration, external validation, and patient-outcome trials are major gaps	Conceptual/early translational research; not established procedural decision support

Table 1 Critical appraisal and current clinical maturity of representative vascular AI applications. AI: artificial intelligence; AAA: abdominal aortic aneurysm; PVAT: perivascular adipose tissue; AUROC: area under the receiver operating characteristic curve; CT: computed tomography; PPG: photoplethysmography; ABI: ankle-brachial index; FPR: false positive rate.

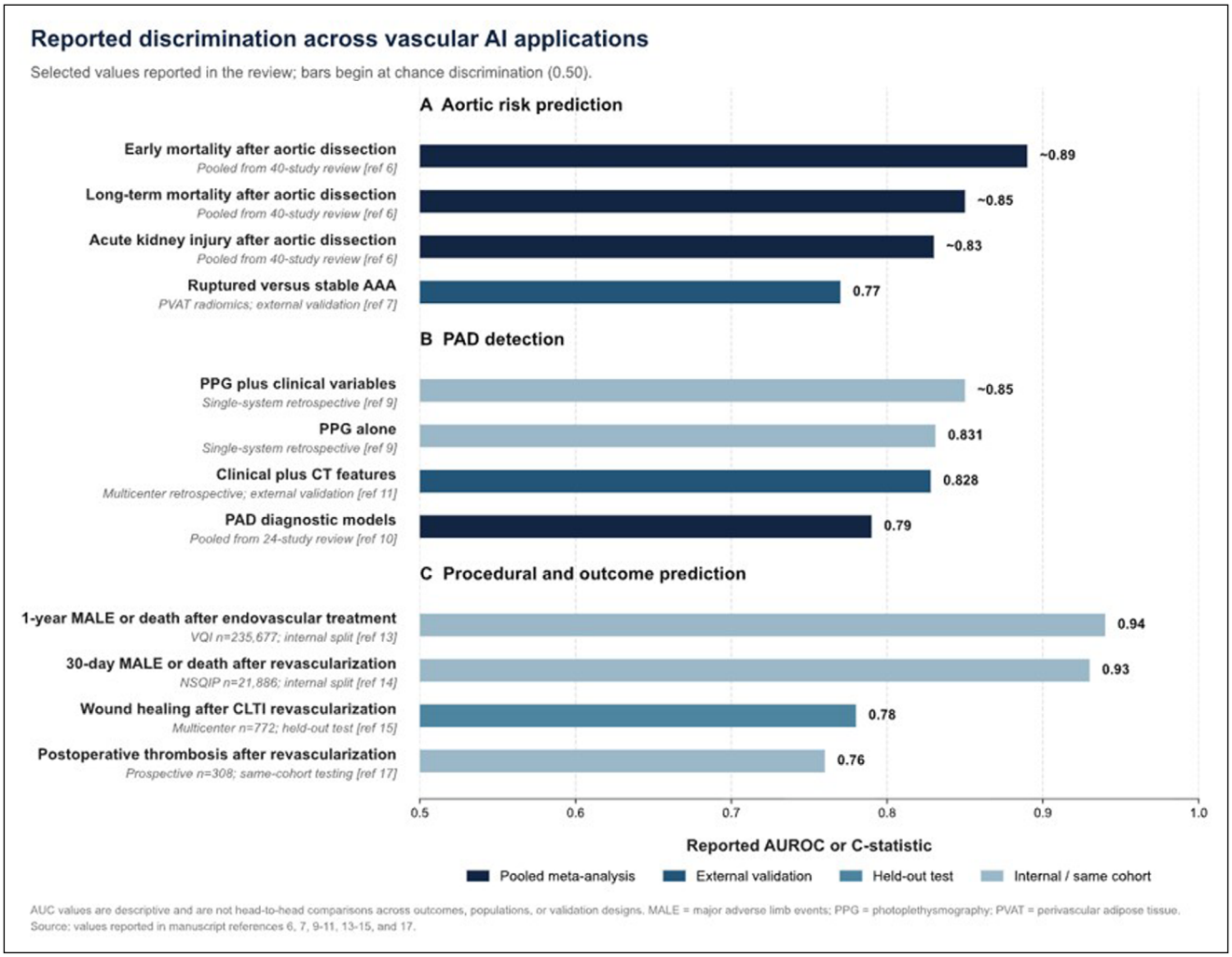


Figure 4 Reported discrimination across vascular artificial intelligence (AI) applications. Selected area under the receiver operating characteristic curve (AUROC) and C-statistic values from the reviewed literature. The chart categorizes algorithmic performance by clinical domain and validation methodology, visually illustrating that high retrospective discrimination (eg, > 0.90) is frequently derived from internal or same-cohort testing, whereas independent external validation typically yields more modest performance. AUROC values are descriptive and do not represent head-to-head comparisons across different clinical outcomes, populations, or validation designs. Original figure created by the authors based on values from manuscript references.[6,7,9-11,13-15,17]

CONCLUSION

AI is becoming an important enabling technology in aortic disease and PAD, but its clinical maturity varies by task. Automated image analysis and AI-assisted AAA case finding are closest to routine workflow integration; most prognostic, radiomic, CLTI, personalized-surveillance, robotic, and digital-twin applications remain investigational. The decisive step for the field is not another increase in retrospective AUROC but, rather, evidence that externally validated, well-calibrated models improve decisions and patient outcomes in prospective practice. Until that standard is met, current guideline thresholds and surveillance pathways should remain the foundation of vascular care, with AI used as an adjunct rather than an independent decision-maker.

KEY POINTS

- High retrospective discrimination does not establish clinical benefit; vascular artificial intelligence (AI) studies should report external validation, calibration, comparison with established standards, and prospective utility.
- AI-assisted aortic segmentation and opportunistic abdominal aortic aneurysm (AAA) detection have the most mature evidence, with nonrandomized data showing improved follow-up after AI-supported case finding.
- Peripheral artery disease (PAD) evidence is expanding across photoplethysmography screening, revascularization outcomes, chronic limb-threatening ischemia wound healing, and surveillance, but most models remain retrospective and have not been shown to improve limb outcomes prospectively.

- Current AAA repair thresholds and PAD/aortic surveillance intervals should not be changed solely on the basis of investigational radiomics or machine learning predictions.
- Image-fusion guidance has clinical procedural evidence, whereas autonomous endovascular robotics, ambient intraoperative decision support, and digital twins remain early-stage or conceptual.

COMPETING INTERESTS

The authors have no competing interests to declare.

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