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Artificial Intelligence in Valvular Heart Disease: Imaging, Quantification, Risk Prediction, and Potential Clinical Decision Support

REVIEW

YEVA FAKIKH, MD
MAAN MALAHFJI, MD
*Author affiliations can be found in the back matter of this article

HOUSTON Methodist DEBAKEY HEART & VASCULAR CENTER

ABSTRACT

Valvular heart disease (VHD) affects a substantial proportion of the population and remains a major cause of cardiovascular morbidity and mortality worldwide. Despite advances in surgical and transcatheter therapies, important challenges persist. VHD remains underdiagnosed, assessment of disease severity is often variable, and the optimal timing of intervention continues to evolve. Artificial intelligence (AI) has emerged as a promising tool across the spectrum of VHD care. AI-based electrocardiogram analysis can identify both existing and future VHD, while AI-guided point-of-care ultrasound extends screening to nonspecialist settings. Across multimodality imaging, machine learning (ML) and deep learning algorithms enable automated, reproducible assessment of VHD. In echocardiography, AI supports grading of disease severity across the main valvular lesions, including Doppler interpretation and automated report generation. AI-enhanced cardiac magnetic resonance facilitates automated assessment of ventricular remodeling and myocardial fibrosis, while AI-assisted cardiac computed tomography improves procedural planning for transcatheter interventions. In parallel, ML has identified distinct patient phenotypes in multiple valvular lesions with differing clinical trajectories and responses to intervention. This review summarizes current applications of AI in detection, multimodality imaging, and potential clinical decision support for VHD and discusses opportunities and challenges for integration into routine practice.

CORRESPONDING AUTHOR:
Maan Malahfji, MD
Houston Methodist DeBakey Heart & Vascular Center, Houston Methodist, Houston, Texas, US
mmalahfji@houstonmethodist.org

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INTRODUCTION

Valvular heart disease (VHD) is a growing global health challenge, driven primarily by population aging in high-income countries and the persistent burden of rheumatic heart disease in lower-resource settings.[1] Rheumatic heart disease is still the single most common form of VHD globally, with close to 41 million people affected, while calcific aortic valve disease has nearly tripled in prevalence since 1992.[1-4] Early United States (US) cohort data estimated the prevalence of moderate or severe VHD at 2.5% among adults overall, rising to 13.2% in those over 75 years.[5] However, recent community-based screening studies suggest a higher burden, with moderate or severe VHD affecting up to 22.5% of adults older than 75 years.[6] The 2023 Global Burden of Disease analysis estimated that more than 84 million people are affected by VHD worldwide, with this burden projected to double by 2050.[2,3] A community-based screening study of adults aged 65 years or older identified previously unrecognized clinically significant VHD in 6.4% of participants.[7] The likelihood of undiagnosed VHD was higher in lower socioeconomic groups, which highlights the importance of social determinants of health in VHD detection.[7]

Despite progress in surgical and transcatheter therapies, a substantial treatment gap remains, with many patients remaining undiagnosed, inadequately surveilled, or referred only after irreversible ventricular remodeling or damage has occurred.[8-10] Consequently, artificial intelligence (AI) offers an opportunity to address these gaps by enabling earlier disease detection, more consistent severity assessment, and perhaps timely referral for intervention.[8-10] Advances in machine learning (ML), deep learning (DL), large-scale multimodal imaging datasets, and digital health technologies have accelerated the integration of AI across the spectrum of VHD care, ranging from community-based screening to procedural planning.[9-12]

For the purposes of this review, AI encompasses ML approaches, including DL and unsupervised learning, as well as automated image acquisition, analysis, and quantification methods that rely on learned models. Within this framework, we examine current applications of AI in multimodality imaging and potential clinical decision support for VHD, highlighting their potential to improve disease detection and risk stratification while addressing challenges to clinical implementation.

AI FOR SCREENING AND EARLY DETECTION

ELECTROCARDIOGRAM-BASED DETECTION

The electrocardiogram (ECG) is among the most widely used cardiovascular tests worldwide and represents an attractive platform for population-level VHD screening. Early work showed a DL model could identify moderate or severe aortic stenosis (AS) directly from a standard ECG, with even false-positive cases (no AS on concurrent echocardiogram) carrying an elevated future risk of developing AS, suggesting a role for AI-ECG in risk prediction and diagnosis.[13] More recent DL models applied to standard 12-lead ECGs have extended that ability to a broader range of existing and future valvular disease.

In a large international study of nearly 1 million ECG-echocardiogram pairs, AI-ECG models accurately detected and predicted significant mitral regurgitation (MR), tricuspid regurgitation (TR), and aortic regurgitation (AR), with high-risk individuals demonstrating substantially greater risk of developing clinically significant VHD over time, supporting its potential as a nonimaging pathway to identify patients who may benefit from closer surveillance.[14] DL applied to the 12-lead ECG detected individual left-sided valvular lesions with area under the receiver operating characteristic curve (AUROC) between 0.77 to 0.88 and a negative predictive value exceeding 97%, supporting its potential as a rule-out screening tool.[15]

A complementary approach, called rECHOmmend, achieved an AUROC of 0.91 for identifying previously unrecognized structural heart disease, including VHD, by incorporating ECG tracings alongside demographic data.[16] Building on a large dataset, EchoNext, which utilized over 1 million ECG-echocardiogram pairs, detected a broad range of structural heart disease including VHD.[17] A subsequent meta-analysis confirmed the overall diagnostic potential of AI-ECG while highlighting the need for prospective validation across diverse clinical settings prior to widespread implementation.[18]

DIGITAL AUSCULTATION AND POINT-OF-CARE ULTRASOUND

AI-augmented digital stethoscopes improve detection of pathological murmurs and may enhance VHD screening beyond conventional auscultation.[9] DL algorithms applied to phonocardiographic recordings can identify patients with underlying structural heart disease and have demonstrated good performance in external validation

studies.[19-21] Similarly, AI-guided point-of-care ultrasound (POCUS) enables nonexperts to acquire diagnostic-quality cardiac images and has been successfully implemented in both tertiary care settings and community-based rheumatic heart disease screening programs.[22,23] Together, these technologies may expand access to early VHD detection in underserved settings, representing a crucial yet unmet need.

AI IN ECHOCARDIOGRAPHY

Echocardiography serves as the primary imaging modality for evaluating VHD. It remains central to diagnosis, disease surveillance, and procedural planning and guidance. Nevertheless, its performance is highly operator dependent, and certain assessments are often subjective and can vary across readers, particularly when quantifying regurgitant lesions.[24] These limitations have fueled growing interest in AI-based approaches that can streamline image acquisition, automate quantitative measurements, and support more standardized interpretation.

IMAGE ACQUISITION

Accurate echocardiographic diagnosis depends on high-quality image acquisition, which requires considerable operator effort and expertise. AI-guided algorithms embedded within POCUS provide real-time feedback on probe positioning and image quality, enabling nonexperts—including nurses, medical students, and physicians—to acquire diagnostic-quality studies.[22,25] A prior study demonstrated that AI-guided image acquisition by novice users produced studies of sufficient quality for limited diagnostic use.[22] Subsequent studies showed that real-time AI guidance generated images suitable for diagnostic interpretation and quantitative analysis across a range of operators.[25] In resource-limited settings, AI-guided POCUS has facilitated community-based screening for rheumatic heart disease, a major cause of premature cardiovascular morbidity and mortality in regions where access to cardiologists and cardiac care remains limited.[23]

ECHOCARDIOGRAPHIC INTERPRETATION

Once quality images are acquired, AI can facilitate automated interpretation of echocardiographic data. Early studies demonstrated the feasibility of fully automated image analysis in clinical practice, with subsequent DL models extending these capabilities across multiple echocardiographic views and cardiac pathologies.[26,27] EchoNet-Dynamic is a video-based DL model that provides automated beat-to-beat assessment of left ventricular (LV) ejection fraction using apical four-chamber videos.[28] A blinded randomized trial using EchoNet-Dynamic—the first in this field—demonstrated noninferior performance compared with trained sonographers with respect to LV ejection fraction measurements.[29] Recent advances have moved AI beyond single-task algorithms toward foundation models capable of comprehensive echocardiographic interpretation. PanEcho simultaneously performs 39 assessment tasks across the cardiac chambers and valves, with validation extending to POCUS.[30] EchoPrime, which trained on more than 12 million echocardiographic video-report pairs, has demonstrated state-of-the-art performance across multiple healthcare systems.[31] Together, these models represent an important step toward comprehensive AI-assisted echocardiographic interpretation, although prospective clinical validation remains essential before routine implementation.

VALVULAR DISEASE DETECTION AND SEVERITY ASSESSMENT

An early study applied a three-stage DL framework to color Doppler imaging, extending the use of AI to the assessment of valvular lesions. The model simultaneously screened for mitral stenosis (MS), MR, AS, and AR, achieving AUROCs ranging from 0.88 to 0.99 in a prospective validation cohort.[32] AI-based assessment has since been extended across multiple valve lesions.

Mitral Regurgitation

Several distinct approaches have emerged for automated MR severity grading. DELINEATE-MR uses all color Doppler clips across multiple views from a complete transthoracic echocardiogram and integrates video-level predictions into a four-step ordinal severity grade, achieving an AUROC of 0.98 for detecting moderate or greater regurgitation.[33] EchoNet-MR operates exclusively on single apical four-chamber color Doppler videos, classifying MR as a binary outcome with AUROCs of 0.92 and 0.95 in independent cohorts, prioritizing scalability for high-throughput screening.[34] Notably, neither model measures traditional MR-specific parameters, with both deriving severity directly from raw color Doppler pixel patterns, offering speed of application but limited interpretability. In contrast, a multiparametric approach incorporating AI-based measures of nine guideline-recommended parameters—including vena contracta, regurgitant area ratio, and continuous-wave Doppler jet density—achieved 80% accuracy for MR severity grading and 97% accuracy for identifying moderate or greater MR, preserving transparency and alignment with current clinical practice.[35]

Aortic Regurgitation

In a preprint, EchoNet-AR extended automated color Doppler analysis to AR across five standard echocardiographic views without measuring traditional severity indices. The model

achieved AUROCs of 0.95 and 0.97 in internal validation for moderate or greater and severe AR, respectively, and 0.92 and 0.94 in an external cohort.[36] Notably, saliency mapping revealed that the model appropriately weighted hemodynamically significant regions, including the proximal convergence zone and vena contracta, supporting its mechanistic plausibility despite the absence of explicit parameter measurement.[36]

Tricuspid Regurgitation

EchoNet-TR extended the single-view pixel-based approach to the tricuspid valve, detecting moderate or severe TR with AUROCs of 0.928 and 0.951 in internal and external cohorts, respectively, and severe TR with AUROCs of 0.956 and 0.980.[37]

Combined Regurgitant Lesions

Across all three regurgitant lesions, the DELINEATE-Regurgitation study demonstrated substantial agreement with cardiologist interpretation, with AUROCs ranging from 0.95 to 0.99 for moderate or greater AR, MR, and TR.[38]

Aortic Stenosis

An initial DL model relying on parasternal long-axis 2-dimensional (2D) videos without Doppler demonstrated AUROCs of 0.94 to 0.98 for severe AS detection across independent cohorts.[39] Building on this framework, PanEcho achieved AUROCs of 0.98 and 1.00 for severe disease detection in internal and external validation cohorts, respectively.[30] Notably, PanEcho did not measure traditional hemodynamic parameters such as peak velocity, mean gradient, or valve area, instead learning visual and temporal features through end-to-end DL. Beyond disease classification, a DL-derived AS continuum index, validated in 2,373 patients across 7,371 echocardiograms, was independently associated with progression to severe AS, supporting a potential role for AI in longitudinal disease surveillance and risk stratification.[40] Separately, the Digital Aortic Stenosis Severity Index (DASSi)—derived from single parasternal long-axis views without Doppler—displayed a continuous severity score that predicted faster aortic valve velocity progression and a significantly higher risk of aortic valve replacement (AVR) independent of traditional Doppler parameters.[41]

Mitral Stenosis

AI application in MS has lagged relative to other valvular lesions, reflecting its lower prevalence in high-income countries and the complexity of multiview hemodynamic integration. In a preprint, EchoNet-MS was trained on over 431,000 echocardiographic videos and achieved automated assessment of MS severity with AUROCs of 0.937 to 0.994 across four independent validation cohorts.[42] The model also classified rheumatic versus non-rheumatic etiology with AUROCs of 0.890 to 0.967, representing a meaningful step toward scalable etiology-informed MS assessment.[42]

QUANTIFICATION OF ECHOCARDIOGRAPHIC PARAMETERS

Beyond disease detection, AI has been applied to automate quantitative echocardiographic measurements. Automated quantification of 18 parameters has been validated across nearly 900,000 measurements, demonstrating consistent performance across diverse patient populations and imaging platforms.[43] However, these parameters predominantly comprise linear cardiac dimensions and Doppler velocities—including chamber diameters, tissue Doppler indices, and peak aortic, mitral, and tricuspid valve velocities—rather than valve-specific severity measures.

Among lesion-specific applications, automated quantification is most established in AS, with strong agreement between AI- and expert-derived measurements of peak aortic velocity, transvalvular gradient, and aortic valve area ($r = 0.88$-0.97).[44] Subsequent work in MR has extended automated quantification to some MR-specific measures, including vena contracta width and regurgitant area ratio.[35] However, AI-based quantification of lesion-specific parameters in MS, AR, and TR remains comparatively less developed and validated. Further work is needed to establish robust and generalizable automated quantification across individual valve lesions.

AI IN CARDIAC MAGNETIC RESONANCE IMAGING

Cardiac MRI (CMR) occupies a unique role in VHD imaging, enabling direct quantification of regurgitant volumes and tissue characterization. Late gadolinium enhancement (LGE) and T1 mapping are established markers of replacement and interstitial fibrosis, both carrying independent prognostic significance in VHD.

FLOW QUANTIFICATION

AI is increasingly applied to CMR acquisition, reconstruction, and interpretation. Vista AI, a platform approved by the US Food and Drug Administration (FDA) and evaluated across 6,545 CMR studies, automates scan plane prescription, cardiac segmentation, artifact detection, and acquisition parameter optimization.[45] Compared with standard operator-dependent scanning, AI-assisted acquisition

achieved a 23% reduction in scan time, a 27% improvement in image quality scores, and a 31% reduction in scan time variability, with benefits consistent across all indications, including a 28.9% scan time reduction specifically for VHD, and independent of operator experience level.[45] DL-based image reconstruction represents a complementary advance, reducing acquisition time by 62% to 73% and overall protocol time by up to 57% while preserving diagnostic image quality and functional accuracy, enabling single-breath-hold and free-breathing acquisitions that improve patient tolerance and expand access.[46,47]

IMAGE ANALYSIS

Several barriers to broader CMR adoption, such as processing time, are being addressed by AI. DL models enable automated chamber segmentation and volumetric quantification with accuracy comparable to expert readers while substantially reducing analysis time.[48] For example, a fully automated model brought the time needed to assess LV structure and global systolic function down from 13 minutes manually to roughly 20 seconds.[49] These capabilities are critical in VHD, where accurate and reproducible ventricular measurements guide decision making on surveillance frequency and intervention timing.

CONTRAST-FREE MYOCARDIAL TISSUE CHARACTERIZATION

Beyond acquisition and analysis, Cine2LGE derives late enhancement-equivalent images from contrast-free CMR, achieving AUROCs of 0.906 and 0.895 across internal and external cohorts, respectively, offering a viable alternative for patients with gadolinium contraindications.[50] Complementary ML approaches have demonstrated strong correlation with conventional LGE for scar quantification ($R = 0.89$), further supporting the feasibility of contrast-free fibrosis assessment.[51,52] Radiomic approaches applied to native T1 mapping have additionally demonstrated AUROCs of 0.82 to 0.85 for detecting myocardial infarction without contrast across multicenter validation cohorts.[53]

PHENOTYPING AND RISK STRATIFICATION

In patients with AS, combined echocardiographic and CMR data using an unsupervised ML framework was able to flag phenotypes with markedly different outcomes.[54] The highest-risk phenotype demonstrated worse survival despite the absence of symptoms, highlighting the ability of ML to refine risk assessment beyond conventional metrics.[54] As CMR protocols become more standardized and AI tools undergo prospective validation, automated flow quantification, tissue characterization, and ML-based phenotyping may further strengthen the role of CMR in VHD risk stratification.

AI IN CARDIAC COMPUTED TOMOGRAPHY

Cardiac computed tomography (CT) is central to transcatheter intervention planning, and AI is increasingly integrated throughout the process. The Society of Cardiovascular Computed Tomography has emphasized the expanding applications of AI in transcatheter aortic valve replacement (TAVR) planning, from automated evaluation of the aortic annulus and coronary ostia to better estimation of procedural risk.[55]

PROCEDURAL PLANNING

A DL algorithm externally validated across 19 hospitals demonstrated excellent agreement with expert aortic valve complex measurements (Intraclass Correlation Coefficient, or ICC, up to 0.998), and high accuracy for identifying high-risk anatomical features (ICC up to 0.989).[56] Additionally, a dual 3D U-Net model achieved automated aortic root segmentation with a Dice score of 0.93 and area-derived annular diameter bias of 0.07 mm.[57] A fully automated DL platform demonstrated excellent agreement with conventional planning software for annular measurements (all ICCs > 0.95), although assessment of coronary ostial distances was less precise.[58]

CALCIUM QUANTIFICATION AND DISEASE CHARACTERIZATION

AI has also enhanced CT-based assessment of aortic valve calcification. A DL pipeline combining aortic segmentation and calcium quantification demonstrated excellent agreement with manual Agatston scoring (Pearson correlation 0.93) and 90% accuracy for identification of severe AS using sex-specific thresholds.[59] Notably, these results were achieved using contrast-enhanced CT alone, eliminating the need for a dedicated noncontrast acquisition.[59]

Additionally, automated tissue characterization from CT angiography (CTA) can differentiate fibrotic from calcific aortic valve components using density-based modeling—an approach prospectively validated against explanted valve histology in patients undergoing surgical AVR.[60] Fibrocalcific composition derived from CTA showed strong agreement with pathologic findings, with excellent intermodality concordance and near-perfect interobserver reproducibility, supporting its potential role as a noninvasive tool for tissue-level disease characterization beyond what conventional calcium scoring provides.[60] Taken together, these calcium- and tissue-based applications are expanding what CT contributes to VHD risk assessment beyond anatomy alone. The major AI applications across echocardiography, CMR, and CT in VHD are summarized in Table 1.

MODALITY	VALVE LESION	AI APPLICATION	PERFORMANCE	KEY FINDING/CLINICAL IMPLICATION	AUTHOR (YEAR)
Echo[32]	MS/MR/ AS/AR	Simultaneous four-valve screening via color Doppler DL framework	AUROC 0.88-0.99	First AI model to screen all four valves simultaneously in a prospective real-world cohort	Yang et al. (2022)
Echo[33-35]	MR	Automated severity grading (≥ moderate vs not) • DELINEATE-MR: multiview, 4-step ordinal grade • EchoNet-MR: single A4C, binary classification • Multiparametric/guideline-based parameters	DELINEATE-MR: AUROC 0.98 EchoNet-MR: AUROC 0.92-0.95 Multiparametric: 80-97% accuracy	Parameter-free models offer scalability; parameter-based models preserve guideline alignment and interpretability	Long et al. (2024); Vrudhula et al. (2024); Sadeghpour et al. (2025)
Echo[36] [preprint]	AR	EchoNet-AR: automated severity grading across 5 color Doppler views; end-to-end, no traditional parameters measured	AUROC 0.95-0.97 (internal) AUROC 0.92-0.94 (external)	Saliency maps confirmed focus on proximal convergence zone and vena contracta	Binder et al. (2025)
Echo[37]	TR	EchoNet-TR: single A4C color Doppler view, end-to-end pixel-based severity grading	≥ Moderate TR: AUROC 0.928-0.951 Severe TR: AUROC 0.956-0.980	Consistent performance across internal and external cohorts	Vrudhula et al. (2025)
Echo[38]	AR/TR/MR	DELINEATE-Regurgitation: multiview combined regurgitant lesion grading (≥ moderate vs not)	AUROC 0.95-0.99	Substantial agreement with cardiologist interpretation across all three regurgitant lesions	Long et al. (2025)
Echo[30,39-41]	AS	Severe AS detection and longitudinal surveillance • PanEcho: view-agnostic, no traditional hemodynamic parameters • DLi-ASc and DASSi: continuous AI-derived severity indices, PLAX-based, no Doppler	PanEcho: AUROC 0.98-1.00 DLi-ASc: AUROC 0.91-0.99 DASSi: HR 1.42 for AVR	End-to-end black-box approach; continuous indices predict AS progression and AVR risk independent of Doppler parameters	Holste et al. (2023); Holste et al. (2025); Park et al. (2026); Khera et al. (2024)
Echo[42] [preprint]	MS	EchoNet-MS: multiview; automated severity grading and rheumatic etiology classification	Severity: AUROC 0.937-0.994 Etiology: AUROC 0.890-0.967	Validated across four independent cohorts; first model to classify rheumatic vs non-rheumatic etiology at scale	Ieki et al. (2026)
CMR[45-47,50]	VHD, general	AI-assisted acquisition (Vista AI, FDA-approved) and DL image reconstruction Contrast-free LGE prediction (Cine2LGE)	Vista AI: 23% scan time reduction, 27% image quality improvement DL reconstruction: 62-73% cine time reduction Cine2LGE: AUROC 0.906 (internal)/0.895 (external)	Standardized acquisition independent of technologist experience; contrast-free fibrosis assessment viable for patients with gadolinium contraindications	Kwong et al. (2026); Hua et al. (2026); Kong et al. (2025); Xie et al. (2026)
CMR/Echo[54]	AS	Unsupervised ML phenotyping using combined echocardiographic and CMR data	High-risk asymptomatic phenotype with markedly worse survival	Biological heterogeneity not captured by conventional grading; high-risk phenotype identified despite absence of symptoms	Sengupta et al. (2021)
CT[56-58]	TAVR planning	Automated aortic valve complex measurement, anatomic risk identification	ICC up to 0.998; Dice 0.93	Near-expert TAVR planning accuracy	Wang et al. (2023); Saitta et al. (2023); Arsalan et al. (2026)
CT[59,60]	AS	Calcium quantification and fibrocalcific tissue characterization • Agatston scoring on contrast-enhanced CT • CTA density-based modeling vs. histology	Calcium: Pearson r = 0.93; 90% accuracy Tissue: ICC 0.94 vs histology; interobserver ICC 0.99	Calcium scoring achieved without dedicated noncontrast acquisition; tissue characterization prospectively validated against explanted valve histology	Park et al. (2025); Grodecki et al. (2024)

Table 1 Summary of AI applications across imaging modalities in valvular heart disease**.** MS: mitral stenosis; MR: mitral regurgitation; AS: aortic stenosis; AR: aortic regurgitation; DLi-ASc: DL-derived AS continuum index; AUROC: area under the receiver operating characteristic curve; AI: artificial intelligence; TR: tricuspid regurgitation; TAVR: transthoracic aortic valve replacement; CT: computer tomography: CTA: CT angiography; LGE: late gadolinium enhancement; FDA: Food and Drug Administration

COMPARING AI APPROACHES AND CLINICAL APPLICATIONS

Some of the studies described above highlight important differences in how AI-derived information is generated and how it may ultimately be used clinically. End-to-end DL models derive disease classifications or continuous severity estimates directly from raw imaging data without explicitly measuring conventional parameters. In echocardiography, for example, models such as EchoNet-MR, EchoNet-AR, EchoNet-TR, and PanEcho infer valvular disease severity directly from image or video features rather than reproducing traditional Doppler measurements.[30,34,36,37] This approach may facilitate rapid, scalable screening and capture imaging features beyond predefined measurements, but it provides less transparency regarding the basis of an individual prediction. In contrast, parameter-based approaches automate established measurements and preserve alignment with guideline-based thresholds, allowing clinicians to review the individual parameters contributing to a severity classification.[35,43,44] However, these approaches remain dependent on predefined measurements and may therefore retain limitations inherent to conventional grading criteria.

The relative clinical value of each approach depends on the intended task. End-to-end models may be particularly useful for screening, automated disease detection, and triage, where scalable identification of patients with possible VHD is prioritized. Parameter-based approaches may be more readily incorporated into confirmatory assessment and longitudinal surveillance, where interpretability and comparison with established severity thresholds are important. Across CMR and CT, many AI applications instead focus on automated acquisition, segmentation, quantitative measurement, tissue characterization, or procedural planning rather than direct classification of valvular severity, and their clinical value should therefore be assessed according to these specific tasks. These approaches are not mutually exclusive, and hybrid strategies combining conventional measurements with image-derived features may ultimately balance interpretability with the ability to capture information beyond established parameters. Accordingly, AI models should be evaluated not only by discriminatory metrics such as AUROC but also by their intended clinical role, interpretability, generalizability, and ultimately whether their use improves clinical decision-making and patient outcomes.

RISK STRATIFICATION AND POTENTIAL CLINICAL DECISION SUPPORT

The valve-specific studies discussed below primarily establish a framework for AI-based phenotyping, prognostication, and risk stratification that may ultimately inform clinical decision-making. By identifying disease phenotypes and patients at increased risk of progression, adverse outcomes, or future intervention, these approaches could potentially support decisions regarding surveillance, referral, and timing of intervention. However, risk prediction should be distinguished from validated clinical decision support, which requires evaluation of whether model-derived information is incorporated into and changes a defined clinical action. To date, most AI studies in VHD have not prospectively evaluated changes in surveillance, referral, or intervention decisions resulting from AI-guided management. Nevertheless, these studies provide important groundwork for the development and prospective evaluation of future AI-based decision-support strategies. These applications are summarized by valve lesion in Table 2.

AORTIC STENOSIS

This convergence of AI across imaging modalities has been most fully realized in AS, making it among the most extensively studied applications of AI in VHD. Unsupervised ML has identified distinct AS phenotypes with differing patterns of ventricular remodeling, disease progression, and clinical outcomes, highlighting biological heterogeneity not captured by conventional severity classifications.[61,62] Network analyses further suggest that myocardial dysfunction may precede severe valve obstruction, challenging traditional disease paradigms.[61] These approaches may improve identification of asymptomatic patients at increased risk despite not meeting guideline-based intervention thresholds.[40,63,64]

Complementing phenotype-based risk stratification, ML models have demonstrated robust performance for predicting AS progression and clinical outcomes. In the PROGRESSA cohort, an ML model achieved a 5-year AUROC of 0.83, outperforming models based solely on clinical variables (AUROC 0.67).[63] Consistent findings were observed in a primary cohort comprising around 10,000 patients, with AUROCs of approximately 0.83 for both short- and long-term outcome prediction.[64] ML models have similarly shown promise in procedural risk assessment for TAVR, improving prediction of paravalvular leak, conduction abnormalities, and mortality beyond conventional risk scores such as EuroSCORE II and the Society of Thoracic Surgeons model.[65]

VALVE	AI APPLICATION	KEY FINDING	AUTHOR (YEAR)
AS[61,62]	Unsupervised ML phenotyping and network analysis	Distinct phenotypes with differing ventricular remodeling, disease progression, and outcomes; myocardial dysfunction may precede severe valve obstruction	Casaclang-Verzosa et al. (2019); Lachmann et al. (2021)
AS[63,64]	ML-based progression and outcome prediction	5-year AUROC 0.83 in PROGRESSA cohort (vs 0.67 for clinical variables); consistent in external cohorts	Sanabria et al. (2024); Shimoni et al. (2024)
AS[66]	AI biomarker prospective trial validation DASSi post-hoc analysis of SALTIRE-2	Independently associated with multimodality disease severity, 24-month progression, and AVR risk over 5.5 years; proposed as enrichment biomarker for future clinical trials	Oikonomou et al. (2026)
AR[67]	Unsupervised ML phenotyping	Female-predominant subgroup appeared less severe by conventional grading yet experienced worse outcomes, suggesting current grading schemes may underestimate risk in some patients	Malahfji et al. (2025)
MS[23]	AI-guided POCUS screening for rheumatic heart disease	Enables community-based detection by nonexpert operators in resource-limited settings; potential equity tool where specialist access is scarce	Peck et al. (2023)
MR[69,70] (primary)	ML prediction of repairability, recurrence, and adverse outcomes in mitral valve prolapse	Predicts surgical repairability, recurrence after repair, and adverse events; supports individualized risk assessment and procedural planning	Huttin et al. (2023); Penso et al. (2021)
MR[72] (secondary)	EuroSMR AI risk score 18-variable ML model	AUROC 0.789 for 1-year mortality and lack of clinical improvement after M-TEER; identified high-risk subgroup with event rates exceeding 70%	Hausleiter et al. (2024)
TR[73,74]	Unsupervised ML phenotyping and CT-based procedural planning	Five distinct TR phenotypes identified; preserved RV function subgroup had substantially better prognosis. Longer CT-derived RV length associated with lower technical success and 4-fold higher risk of mortality or reintervention after tricuspid TEER	Anand et al. (2023); Bartkowiak et al. (2024)

Table 2 Summary of AI-based risk stratification and potential clinical decision support by valve lesion. ML: machine learning; AS: aortic stenosis; AI: artificial intelligence; AR: aortic regurgitation; MS: mitral stenosis; POCUS: point-of-care ultrasound; TR: tricuspid regurgitation; CT: computed tomography

Despite these advances, no prospective clinical trial has yet used an AI-derived tool to directly guide intervention timing or surveillance in AS. The post-hoc validation of DASSi within the SALTIRE-2 trial represents the closest precedent, demonstrating independent associations with multimodality disease severity, 24-month progression, and AVR risk over 5.5 years, positioning it as a potential enrichment biomarker for future clinical trials in early AS.[66] Prospective, AI-guided clinical decision-making remains the critical next step for the field.

AORTIC REGURGITATION

Aortic regurgitation presents one of the most clinically vexing management challenges in VHD: prevalent, often chronic, frequently asymptomatic for years, and governed by guideline thresholds that may not reliably identify the optimal intervention window. By the time conventional markers for intervention are reached, subclinical myocardial damage may already be present and irreversible.

Unsupervised ML has identified distinct AR phenotypes with markedly different clinical trajectories.[67] Notably, one subgroup composed predominantly of women appeared less severe by conventional parameters yet experienced worse outcomes, with mortality risk comparable to patients with overt ventricular dysfunction, suggesting that current grading schemes may underestimate risk in some patients.[67]

MITRAL STENOSIS

The greatest opportunity in MS may be in rheumatic heart disease screening, where AI-guided POCUS enables detection by nonexpert operators in resource-limited settings.[23] Whether these tools can meaningfully improve access to care and reduce progression to advanced rheumatic valve disease remains an important question.

MITRAL REGURGITATION

An ongoing challenge in primary MR is identifying patients who may benefit from intervention before irreversible ventricular remodeling occurs. Network analyses have highlighted diastolic dysfunction as an important marker of adverse remodeling that is not fully captured by conventional severity assessment.[68] ML models have also demonstrated the ability to predict repairability, recurrence following surgical repair, and adverse outcomes in patients with mitral valve prolapse, supporting a more individualized approach to risk assessment and procedural planning.[69,70]

In secondary MR, AI-derived risk scores have improved prediction of outcomes following mitral transcatheter edge-to-edge repair (M-TEER) and may provide incremental decision support beyond conventional surgical risk models in a population where treatment selection remains complex.[71] The EuroSMR score, an AI-based risk model built on 18 variables in 4,600 patients with secondary MR, predicted 1-year mortality and lack of clinical improvement after M-TEER with an AUROC of 0.789 and identified a high-risk subgroup with event rates exceeding 70%, outperforming existing risk models.[72]

TRICUSPID REGURGITATION

There is growing interest in using ML to support patient selection and risk stratification for TR, particularly given the growth of transcatheter options. Unsupervised ML has identified distinct TR phenotypes with differing patterns of right heart remodeling, functional status, and long-term outcomes.[73] Notably, some patients with severe TR and preserved right ventricular (RV) function appear to have substantially better outcomes than other severe TR phenotypes, suggesting that TR severity alone may be insufficient for decision-making.[73]

This same emphasis on right heart anatomy extends to procedural planning. In a study using DL-based CT measurements, longer RV length was independently associated with lower technical and procedural success in tricuspid TEER, and patients with greater RV length had a substantially higher risk of mortality, hospitalization for heart failure, and 2-year reintervention.[74] Consequently, ML-derived phenotyping may identify which patients with severe TR are most likely to benefit from transcatheter intervention, a question of growing urgency as options expand.

LIMITATIONS AND THE PATH FORWARD

The growing evidence for AI in VHD must be balanced against important limitations. Most models have been developed using retrospective datasets that underrepresent women, older adults, and racial/ethnic minority groups, potentially limiting generalizability.[12] The evidence base is also uneven across imaging modalities and valve lesions, with studies concentrated predominantly on echocardiography and AS. In contrast, many CMR and CT applications focus on broader automation tasks that support VHD assessment rather than valve-specific diagnosis or management, while evidence for AI-based risk stratification and clinical decision support remains comparatively limited in AR, MR, TR, and MS. Emerging studies in less extensively investigated lesions, particularly AR, nevertheless suggest that AI may identify clinically relevant patterns not readily captured by conventional approaches, highlighting opportunities for further investigation.[67] In addition, some DL models are difficult to interpret depending on their approach, limiting acceptance by some operators and clinicians, and explainable AI methods may require further validation before widespread adoption.[75]

A consistent pattern across published studies is strong performance for detecting hemodynamically significant disease, although most models report performance at binary thresholds rather than specifically evaluating the clinically critical moderate-versus-severe boundary, where management decisions are most consequential.[33,38] Performance in patients with prosthetic valves remains largely uncharacterized because acoustic shadowing and eccentric or paravalvular jets are underrepresented and difficult to assess in current training datasets.[76] Direct comparison of AI-derived severity grades with CMR is largely absent, and given the known modest concordance between echocardiographic and CMR-based regurgitant quantification, current models risk perpetuating rather than resolving existing intermodality discordance.[77]

Perhaps the most important limitation is that most AI tools have been evaluated thus far using diagnostic performance metrics rather than clinical outcomes. Demonstrating accurate disease classification is insufficient if these tools do not ultimately improve patient management or outcomes. Prospective studies, some of which are now ongoing, are therefore needed to determine whether AI-guided approaches improve intervention timing, reduce adverse events, or enhance survival.[10]

Finally, challenges related to workflow integration, reimbursement, regulation, and clinician adoption remain important barriers to implementation.[11] Beyond these barriers, successful implementation will require evaluation beyond discrimination metrics, including model calibration and prevalence-dependent measures such as positive and negative predictive values in the intended clinical population, as well as external validation across institutions, imaging platforms, and patient populations.[78,79] Performance should also be monitored after deployment to identify model drift.[11,79] Importantly, implementation studies should define appropriate downstream actions following abnormal AI results and assess whether large-

scale deployment increases referrals, confirmatory testing, or other healthcare resource utilization.[11,80]

Despite these challenges, the future of AI in VHD is promising. As datasets become more diverse, models more interpretable, and prospective evidence grows, AI is increasingly positioned to become an integral part of VHD care. Rather than replacing clinical decision-making, its greatest value lies in automating time-intensive image analysis, allowing clinicians to focus more time and effort on interpretation of complex studies, and patient care. The progress already seen in AS provides a roadmap for broader implementation across other valve lesions, with the potential to move VHD assessment beyond a single severity grade toward more personalized risk stratification.

CONCLUSION

Artificial intelligence is increasingly being integrated across the spectrum of VHD care, from screening and multimodality imaging to risk stratification and potential clinical decision support. Beyond improving efficiency, AI has the potential to identify high-risk patient subgroups, uncover disease patterns not captured by conventional classifications, and support more individualized management approaches. Future studies must establish whether AI-guided strategies improve clinical decision-making, optimize intervention timing, and ultimately enhance patient outcomes. If successfully validated and thoughtfully implemented, AI may become an important adjunct to contemporary VHD care. The pixels on a cardiac image have always contained more information than the human eye alone could extract. Artificial intelligence is beginning to see what we have been missing.

KEY POINTS

- Artificial intelligence (AI)-electrocardiogram and AI-guided point-of-care ultrasound may facilitate earlier detection of valvular heart disease (VHD), including in nonspecialist and resource-limited settings.
- AI has expanded the role of echocardiography through automated assessment of valvular lesions, improving the reproducibility and efficiency of VHD evaluation.
- AI-enhanced cardiac computed tomography and cardiac magnetic resonance imaging enable automated quantification, procedural planning, and tissue characterization, providing incremental information for diagnosis, risk stratification, and intervention planning.
- Machine learning has identified clinically relevant patient subgroups that are not captured by conventional classifications, including high-risk patients who may be underrecognized by current grading approaches.
- Although diagnostic performance is promising, prospective studies are needed to determine whether AI-guided approaches improve clinical decision-making and patient outcomes.

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR AFFILIATIONS

Yeva Fakikh, MD orcid.org/0009-0002-3069-9759
Houston Methodist DeBakey Heart & Vascular Center, Houston Methodist, Houston, Texas, US

Maan Malahfji, MD orcid.org/0000-0002-2701-8783
Houston Methodist DeBakey Heart & Vascular Center, Houston Methodist, Houston, Texas, US

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