Towards the Automated Echocardiographic Report: A Review

Joseph Z. Sokol, Roman A. Sandler, PhD

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iCardio.ai Corporation, AI Division
Joseph Sokol and Roman Sandler are co-founders of iCardio.ai.

Correspondence to:
Joseph Sokol, iCardio.ai
joseph@icardio.ai
Los Angeles, CA United States

Introduction

Accurate interpretation of echocardiography is critical for detection and management of cardiovascular diseases. Over the past decade, studies have explored machine learning models applied to echocardiographic images to estimate individual measurements, interpret echocardiographic views, and predict disease. This review synthesizes the field's arc from speckle tracking to modern foundation models, mapping the literature from 2018–2025 across view classification and guidance, quantitative measurement, disease detection, and report generation. We situate academic progress alongside emerging clinical trials, regulatory milestones for radiological interpretive software, and commercial offerings, and we postulate on the field's clear trajectory: the automated echocardiographic report.

Background

Echocardiography is fundamental in the assessment of cardiovascular disorders and represents one of the most ubiquitous imaging modalities in medicine.[1] Nearly every person in the Western world will undergo an echocardiographic examination at least once in their lifetime and elderly persons may receive an echocardiogram at least once or multiple times a year.[2] It is estimated more than 30 million echocardiograms are performed each year in the United States.[3,4] Since its assimilation into clinical medicine, the use of echocardiography has gained significant popularity among scientists; the search term "echocardiography" yields over 200,000 articles on PubMed. Dr. Inge Edler performed the first cardiac ultrasound in Lund, Sweden in 1953, but the first formal systemization of the echocardiogram is credited to Dr. Harvey Feigenbaum, who founded the American Society of Echocardiography (ASE) in 1975. Other than its European, British, and Japaense counterparts, ASE is unique as a scientific society as its focus is entirely on one imaging modality and one organ. At the time of writing of this manuscript, we celebrate its semicentennial, ushering echocardiography's next era: artificial intelligence.

Over the past half-century, echocardiography has been in a continual state of maturation and evolution. Integrating 2D imaging, Doppler signalling, and 3D and 4D capabilities, these modalities allow the echocardiogram to encompass visualization of tissue morphology, muscle motion, and blood flow, providing insight into the entire heart. Its diagnostic faculty is therefore diverse. Unique to this modality, there has been great emphasis on both imaging standards, with canonical protocols put out by several scientific bodies, as well as standardization of the echocardiographic report, which has remained largely consistent over the previous decades. The report includes descriptors that focus foremostly on four chambers, four valves, and four other structures: the pericardium, aortic root, aortic arch, and pulmonary artery. Given the standardization around echocardiography, both in terms of imaging formats and reporting expectations, interpretation of echocardiography is a contained problem, making it particularly well-suited to automation with artificial

[1] Roberto M Lang, Luigi P Badano, Victor Mor-Avi, Jonathan Afilalo, Anderson Armstrong, Laura Ernande, Frank A Flachskampf, Elyse Foster, Steven A Goldstein, Tatiana Kuznetsova, et al. Recommendations for cardiac chamber quantification by echocardiography in adults: an update from the american society of echocardiography and the european association of cardiovascular imaging. European Heart Journal-Cardiovascular Imaging, 16(3):233–271, 2015.
[2] Doherty, John U., et al. "ACC/AATS/AHA/ASE/ASNC/HRS/SCAI/SCCT/SCMR/STS 2019 appropriate use criteria for multimodality imaging in the assessment of cardiac structure and function in nonvalvular heart disease: a report of the American college of cardiology appropriate use criteria task force, American association for thoracic surgery, American heart association, American society of echocardiography, American society of nuclear cardiology, heart rhythm society, society for cardiovascular angiography and interventions, society of ...." Journal of the American College of Cardiology 73.4 (2019): 488-516.
[3] Pearlman, Alan S., et al. "Evolving trends in the use of echocardiography: a study of Medicare beneficiaries." Journal of the American College of Cardiology 49.23 (2007): 2283-2291.
[4] Khan, Hashim A., et al. "Can hospital rounds with pocket ultrasound by cardiologists reduce standard echocardiography?." The American journal of medicine 127.7 (2014): 669-e1.

intelligence.[5,6,7] Yet, for all the expectation around AI in echocardiography, the topic receives only a brief acknowledgement, as an excerpt before the conclusion, in the latest ASE guidelines.[6]

Outpacing guidelines, however, the challenge of automating echocardiographic interpretation has gained popularity among academics across the globe.[8] Publications addressing automated assessment of cardiac function, 2D measurements, disease detection, and, finally, full report generation point to a clear ambition: the automated echocardiographic report. We foresee progress in automated echocardiographic evaluation following the evolution of the electrocardiogram (ECG), which has benefited greatly from automated interpretation. Automated ECG interpretation by computer began in the 1960s, and today tens of millions of ECGs are interpreted by machine.[9,10,11] The aim of the field of AI in echocardiography is to fully automate the creation of the echocardiographic report, eventually to challenge the necessity or efficacy of human interpretation. Amplifying this mission, the nation-wide availability of expertise required to interpret echocardiograms has been in decline, with a -0.4% increase in cardiologists between the years 2016 and 2021.[12] Moreover, a severe sonographer shortage required to meet imaging demand across the country is growing.[13] A solution to reduce the delays and variability in echocardiography is needed to address the surplus of mortality linked to cardiovascular disease.[14,15] Accordingly, automated echocardiographic reporting is regarded as a necessary evolution.

Search strategy and selection criteria

We searched PubMed between January 1st, 2018 and September 29th, 2025 using free-text terms and author linkage to identify relevant articles. Search terms focused on application of AI in echocardiograph and ultrasound. Search focused on terms such as “artificial intelligence in echocardiography”, “deep learning AND”, “machine learning AND”, “echocardiographic view classification”, “echocardiography”, “ultrasound”, “aortic stenosis”, “mitral regurgitation”, “PAH”, “LVH”, “HCM”, “EF”, “LV dysfunction”. We searched conference abstracts from the American Society of Echocardiography, European Society of Echocardiography, and the American College of Cardiology. We also searched FDA filings related to SaMD for AI applications in echocardiography. Additional authors were identified via previous familiarity and interactions with authors. Publications were selected on the basis of their contribution to the field of deep learning applied to echocardiography, their level of evidence, clinical relevance, and date of publication. Preference was given to articles with robust citations, transparency around training datasets used, and general acceptance in the field. Only publications in English were considered.

History of applying computer interpretation to echocardiography

Speckle tracking for assessment of impaired myocardial segments was first published in 1995

[5] Mitchell, Carol, et al. "Guidelines for performing a comprehensive transthoracic echocardiographic examination in adults: recommendations from the American Society of Echocardiography." Journal of the American Society of Echocardiography 32.1 (2019): 1-64.

[6] Taub, Cynthia C., et al. "Guidelines for the Standardization of Adult Echocardiography Reporting: Recommendations From the American Society of Echocardiography." Journal of the American Society of Echocardiography 38.9 (2025): 735-774.

[7] Gardin, Julius M., et al. "Recommendations for a standardized report for adult transthoracic echocardiography: a report from the American Society of Echocardiography's Nomenclature and Standards Committee and Task Force for a Standardized Echocardiography Report." Journal of the American Society of Echocardiography 15.3 (2002): 275-290.

[8] Jiang, Luying, Hou Juan Zuo, and Chen Chen. "Artificial intelligence in echocardiography: Applications and future directions." Fundamental Research (2025).

[9] Pipberger HV, Arms RJ, Stallmann FW. Automatic screening of normal and abnormal electrocardiograms by means of digital electronic computer. Proc Soc Exp Biol Med. 1961;106:130–132.

[10] Ginzton, Leonard E., and Michael M. Laks. "Computer aided ECG interpretation." Images, Signals and Devices. New York, NY: Springer New York, 1987. 46-53.

[11] Schläpfer, Jürg, and Hein J. Wellens. "Computer-interpreted electrocardiograms: benefits and limitations." Journal of the American College of Cardiology 70.9 (2017): 1183-1192.

[12] Association of American Medical Colleges, "Physician Specialty Data Report. 2021." (2021)

[13] Murphey, Susan. "Work related musculoskeletal disorders in sonography." (2017): 354-369.

[14] Cioffi G, Tarantini L, De Feo S, et al. “Functional mitral regurgitation predicts 1-year mortality in elderly patients with systolic chronic heart failure.” Eur J Heart Fail. (2005)

[15] Li, Shawn X., et al. "Trends in utilization of aortic valve replacement for severe aortic stenosis." JACC 79.9 (2022)

and represents one of the early approaches taking advantage of temporal cinegraphic information inherent in the modality of echocardiography.[16] Over the past three decades, computer vision methods have steadily evolved in parallel with advances in computational capacity and algorithmic design. Early computer vision techniques relied on handcrafted features and motion-tracking algorithms, but the advent of machine learning, and more recently deep learning, has dramatically broadened the scope of automated interpretation. The trajectory of deep learning in this field has followed a predictable but accelerating arc: beginning with 2D segmentation- and classification-driven CNNs (especially UNet and VGG-backboned models) in 2018–2019; evolving next into spatiotemporal 3D CNNs and residual networks (R3D, DeepSenseV3) during 2020–2021 to explicitly model motion and cine loops; proceeding through a hybridization phase around 2022–2023 where CNNs, 3D variants, UNet-style decoders, and rudimentary transformer elements coexisted; and finally arriving in 2024–2025 at the "transformer era," where ViTs, R(2+1)D, SAM, hybrid CNN-Transformer models, diffusion-augmented UNets, and task-specific segmentation architectures dominate research. This decades-long shift mirrors broader trends in medical imaging: CNNs are being supplanted by attention-based models capable of modeling long-range dependencies and cross-frame interactions more naturally (as surveyed in the Vision Transformer medical imaging literature).[17] In echocardiography specifically, recent reviews note that modern deep learning approaches increasingly emphasize temporal modeling, generalization across devices, and multimodal integration–all of which align with the shift toward Transformers and hybrid architectures.[18]

Challenges in applying AI to echocardiography

Despite its widespread use, ultrasound is both literally and statistically noisy, with the interpretation of echocardiography often suffering from poor inter-rater reliability, as reflected in low kappa agreements.[19,20] Unlike other radiological modalities, echocardiography is characterized by cone-shaped ultrasound beams in which spatial resolution is highest proximally but declines distally, leading to heterogeneous information density across the image. Echocardiography is also cinegraphic, requiring analysis of temporal dynamics that are less relevant to static modalities such as CT or radiography. Cardiac motion introduces further complexity: the heart contracts in a three-dimensional helical pattern, causing anatomy to shift within the field of view. The heart also has distinct morphological intra-heartbeat cycle characteristics: valve leaflets coapt, myocardial segments stretch and contract, chamber sizes oscillate, and blood movement varies dynamically, particularly in the setting of disease. Algorithms designed to consider these changes may struggle in the setting of cardiac arrhythmias, where cardiac cycles are less predictable. Congenital anomalies, tumors, thrombi, rare cardiac disease, and prostheses pose another difficulty, and speak to the long-tail statistical distribution challenge for algorithmic generalization to all permutations of cardiac presentation. Training on simulated and synthetic data is a proposed direction.[21]

Regulatory and reimbursement

Despite echocardiography's worldwide ubiquity in cardiology, algorithms for automated assessment of echocardiography represent less than 2% of Software as a Medical Device (SaMD)-regulated devices for automated radiological interpretation.[22] Public FDA records for SaMD for automated echocardiography assessment stretch as early as DiaCardio's "Dia-Analysis", a precursor to Philips

[16] Bohs, Laurence N., Barry H. Friemel, and Gregg E. Trahey. "Experimental velocity profiles and volumetric flow via two-dimensional speckle tracking." Ultrasound in medicine & biology 21.7 (1995): 885-898.

[17] Transforming medical imaging with Transformers? A comparative review of key properties, current progresses, and future perspectives

[18] Sanjeevi, G., et al. "Deep learning supported echocardiogram analysis: A comprehensive review." Artificial Intelligence in Medicine 151 (2024): 102866.

[19] Cecaro, Fabrizio. "What are the components that contribute to variability in echocardiographic measurements in aortic stenosis?." (2013).

[20] Pellikka, Patricia A., et al. "Variability in ejection fraction measured by echocardiography, gated single-photon emission computed tomography, and cardiac magnetic resonance in patients with coronary artery disease and left ventricular dysfunction." JAMA network open 1.4 (2018): e181456-e181456.

[21] Al Khalil, Yasmina, et al. "On the usability of synthetic data for improving the robustness of deep learning-based segmentation of cardiac magnetic resonance images." Medical Image Analysis 84 (2023): 102688.

[22] Health AI Register. "Radiology AI Products." Health AI Register, https://healthairegister.com/radiology/products . Accessed 30 Sept. 2025.

QLAB cardiac quantification plug-in (K070792), which was cleared in 2007, and DiaCardio's LVivo EF software was cleared via 510(k) in 2013 (K130779). But the regulatory landscape has matured considerably since then, and additional software approvals have appeared with increased cadence over the last five years. Over that time period, regulatory clearance for SaMDs in cardiology has faced a number of challenges. Modern challenges include: difficulties aligning adaptive or continuously learning algorithms with FDA's traditional static "locked model" clearance paradigm, given that changes over time may introduce unpredictability of performance;[23] the ambiguity in how to satisfy "substantial equivalence" or predicate device requirements when newer models diverge substantially in architecture or training data;[24] the need for transparency, risk management, and explainability in AI models (e.g. documenting training data diversity, performance drift, and robustness across patient subgroups) under the latest proposed FDA frameworks;[25] and limited consistency and reporting in FDA summaries and public documents about how the AI aspects were validated, especially in post-market performance, demographic biases, and real-world generalizability.[26] These challenges complicate the pathway for AI echocardiography systems today and contribute to the barrier to clinical adoption of AI.

Despite these regulatory challenges, automated interpretation of echocardiography has in recent years been embraced within public reimbursement frameworks. In 2021, CPT code 93356 was introduced to reimburse quantitative assessment of myocardial strain imaging, marking the first major inclusion of an automated image-analysis technique within echocardiography's procedural lexicon. This represented an early acknowledgment of computer-assisted interpretation as a reimbursable component of cardiac ultrasound. In 2025, the American Medical Association (AMA) approved Category III CPT code 0932T for use in automated detection of restrictive cardiomyopathy within echocardiography. Algorithms designed for interpretation of heart failure with preserved ejection fraction (HFpEF) and other restrictive cardiomyopathies, including cardiac amyloidosis, sarcoidosis, and idiopathic restrictive cardiomyopathies, may fall under this designated code, reflecting the growing acceptance of artificial intelligence as a billable adjunct to clinical echocardiographic analysis. While these codes may offer reimbursement for usage, they are limited to their respective pathologies or applications. Development of future codes to cover broader AI reporting, such as in the case of reimbursement for an entire echocardiographic report, is an ongoing discussion.[27]

Trends of applying AI to the modalities of echocardiography

Coinciding with innovations in deep learning and its applications in adjacent fields of medical imaging,[28,29,30] deep learning applied to echocardiography has seen rapid progress. Echocardiography is unique among other radiological modalities for its multimodal nature. Signals like muscle motion, tissue morphology, and hemodynamics (blood flow) are illustrated through a broad spectrum of modalities: 1D+time (m-mode, cw-doppler, pw-doppler, and tissue doppler); 2D still frames (and annotations of those frames); 2D+time (b-mode); 2D+time with integrating color doppler representing blood flow direction, velocity, eccentricity, and distance (c-mode). Other modalities, like 3D and 4D ultrasound, are also available as proprietary software from incumbent ultrasound vendors, though AI applied to these

[23] U.S. Food and Drug Administration. "Artificial Intelligence / Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD)." FDA, https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-software-medical-device

[24] Santra, Snigdha, et al. "Navigating regulatory and policy challenges for AI enabled combination devices." Frontiers in Medical Technology 6 (2024): 1473350.

[25] U.S. Food and Drug Administration. Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD): Proposed Regulatory Framework. U.S. Food and Drug Administration, 2023. https://www.fda.gov/media/184856/download

[26] Muralidharan, Vijaytha, et al. "A scoping review of reporting gaps in FDA-approved AI medical devices." NPJ Digital Medicine 7.1 (2024): 273.

[27] Dogra, Siddhant, Ezequiel Silva, and Pranav Rajpurkar. "Reimbursement in the age of generalist radiology artificial intelligence." npj Digital Medicine 7.1 (2024): 1-5.

[28] Liu, X. et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and metaanalysis. Lancet Digit. Health 1, e271–e297 (2019)

[29] Esteva, A. et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 542, 115–118 (2017).

[30] McKinney, S. M. et al. International evaluation of an AI system for breast cancer screening. Nature 577, 89–94 (2020).

modalities are seldom reflected in the corpus of literature on this topic. Given the plurality of interpretation challenges and opportunities across echocardiographic domains, the trajectory of these applications mirrors the scaling laws of deep learning itself: tasks requiring limited data and modest computational resources were addressed earliest, whereas complex problems demanding large-scale datasets and high-performance GPUs have only recently become tractable. A complete, end-to-end interpretation of the echocardiogram is the ambition of many researchers in the domain of AI for echocardiography, which may be solved in a similar step-wise fashion.

Steps to automate the echocardiographic report

Echocardiographic images are obtained by placing an ultrasound probe at various positions on the thoracic cavity and tilting or rotating the transducer axially about the cardiac chamber.[31] In the United States, echocardiograms are reviewed by two clinicians, first the ultrasound technician, who may be tasked with creating initial measurements, and then, by a physician qualified to produce an echocardiographic report. Evaluation of echocardiography requires that the interpreting physician draw a complete narrative from all the echocardiographic signals, which may contain complementary and conflicting information. Finalizing the echocardiographic report incorporates a multitude of quantitative parameters, independent descriptors of cardiac anatomy, and a report summary.

We consider the steps to automate the echocardiographic report to begin after the image acquisition phase, and thus firstly must address view classification. This would inform spatial and anatomical context for measurements and other qualitative assessments. Proceeding, therefore we then automate quantitative and qualitative assessment. Calculation-derived parameters and measurement-directed disease guidelines can also be referenced. Taken together, these outputs would be used to produce the report verbiage. A final step would entail organizing report verbiage into a report conclusion (Figure 1.). Each component of this pipeline is discussed in the proceeding sections.

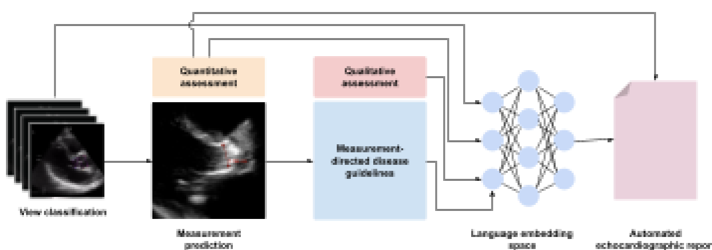


Figure 1. Steps towards the automated echocardiographic report

View classification

Classification of echocardiographic views is a foundational task, essential for nearly all downstream deep learning applications. Large-scale datasets needed for disease detection models require tens of thousands of consistently labeled views—an effort impractical to perform manually and thus dependent on machine-generated labels. Further, because view taxonomy is at the core of echocardiography, the problem is both well-suited to the task of classification with deep learning, and models are transferable across datasets, institutions, and downstream target tasks.[32] View tagging, however, is not a component of routine clinical interpretation of echocardiography (despite DICOM LOINC values allotted for such information).[33] Thus, view classification is a critical infrastructure towards the automated echocardiographic report. The challenge of view classification benefits from the data availability of the standard echocardiogram, which consists of 40-60 DICOMs many of which are cinagraphic, containing collectively 1000s of frames. Owing to the low single-to-noise ratio inherent in echocardiographic imaging, each frame of a cine is visually distinct, and as such, labeling a single cine propagates labels to hundreds of frames, offering an avenue for rapid dataset assembly. As such, even a modest number of echocardiographic studies can yield a considerable image dataset appropriate for deep learning. However, because echocardiography is inherently a mobile imaging modality, large datasets of echocardiographic studies have not historically been amassed. Consequently, early

[31] Mitchell, Carol, et al. "Guidelines for performing a comprehensive transthoracic echocardiographic examination in adults: recommendations from the American Society of Echocardiography." Journal of the American Society of Echocardiography 32.1 (2019): 1-64.

[32] Mitchell, Carol, et al. "Guidelines for performing a compreinterpretationhensive transthoracic echocardiographic examination in adults: recommendations from the American Society of Echocardiography." Journal of the American Society of Echocardiography 32.1 (2019): 1-64.

[33] DICOM interpretation Standards Committee. CID 12226 Echocardiography Image View. DICOM PS3.16 2020a: Content Mapping Resource, 2020, https://dicom.nema.org/medical/Dicom/2020a/output/chtml/part16/sect_CID_12226.html

endeavors into applying deep learning to echocardiography naturally exploited these advantages to enable automated classification of standardized echocardiographic views.[34,35]

Diving further into view classification, scientific guidelines are decisive to establish the optimal echocardiographic views to assess pathology. Certain deep learning studies have revealed however that alternative views may be more informative. Take for instance Vukadinovic and colleagues' findings that in view-informed attention network,

View guidance

Automated echocardiogram view guidance systems use deep learning–based feedback to direct probe orientation toward standardized views, reducing operator variability and improving image quality. Early studies show these systems enable novices to acquire diagnostic-quality images, highlighting their potential to expand echocardiography use in point-of-care and resource-limited settings.[36] While image acquisition is a crucial component in the echocardiogram lifecycle, for the purposes of this review, we are focused on image interpretation.

Measurements

Proceeding from view classification, quantitative measurement represents the rudimentary function of echocardiographic assessment. Measurements are performed manually and involve linear and area measurements by hand-drawn placement of calipers or hand-planimetry by visual estimation. As a result of human dependence, echocardiographic measurements are variable, time-consuming, and have poor reproducibility, a drawback of the modality's complexity and low signal-to-noise ratio.[37,38] Improving measurement quality is a motivation behind accreditation bodies, and is linked to higher reimbursement and fewer denials among payors in the United States.[39,40] But measurement variability plagues even the most reputable institutions. In an analysis of 24,948 paired follow-up studies performed at Stanford University and interpreted by board-certified, level III echocardiographers, each designated in the report as showing 'no significant change,' Pillai and colleagues documented systematic variability, defined as coefficient of variation (CV): linear measurements exhibited the greatest precision (median CV ~3–5%), variability increased in area-derived measures (~8–12%) and calculated indices (~12–20%), and reached its highest magnitude in Doppler-derived parameters, which frequently exceeded 20–30% CV.[41]

Because left ventricular ejection fraction is central to assessment of cardiovascular function, for much time, quantification of left ventricular values has been a core focus of automated echocardiographic

[34] Madani, Ali, et al. "Fast and accurate view classification of echocardiograms using deep learning." NPJ digital medicine 1.1 (2018): 6.

[35] Zhang, Jeffrey, et al. "Fully automated echocardiogram interpretation in clinical practice: feasibility and diagnostic accuracy." Circulation 138.16 (2018): 1623-1635.

[36] Narang, A., R. Bae, H. Hong, Y. Thomas, S. Surette, C. Cadieu, et al. "Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use." JAMA Cardiology, vol. 6, no. 6, 2021, pp. 624–32. doi:10.1001/jamacardio.2020.7422.

[37] Anderson D.R., Blissett S., O'Sullivan P., Qasim A. Differences in echocardiography interpretation techniques among trainees and expert readers. J Echocardiogr. 2021;19:4: 222-231.

[38] Virnig, B. A., et al. "Trends in the Use of Echocardiography, 2007 to 2011. Echocardiography Trends. Data Points# 20 (prepared by the University of Minnesota DEcIDE Center, under Contract No. HHSA290201000131)." (2014).

[39] Thaden, J. J., et al. "Association between echocardiography laboratory accreditation and the quality of imaging and reporting for Valvular heart disease. Circ Cardiovasc Imaging. 2017; 10: e006140."

[40] Yang, Jesse X., et al. "The impact of IAC-Echo accreditation and required quality assurance initiatives on transthoracic echocardiogram interpretation errors." JACC: Cardiovascular Imaging 12.10 (2019): 2090-2092.

[41] Pillai, Balakrishnan, et al. "Precision of echocardiographic measurements." Journal of the American Society of Echocardiography 37.5 (2024): 562-563.

measurements.[42,43,44,45] Not until the present decade have become available an increasing number of commercial and academic software systems offering a comprehensive suite of echocardiographic measurements.[46,47,48] Studies assessing intraclass correlation coefficients (ICCs) have demonstrated that AI-derived echocardiographic measurements consistently exhibit higher reproducibility than human readers. In particular, when comparing the agreement between AI and a group of humans, the variability is often lower than the variability observed between human readers.[49,50] This reliability of AI systems to produce stabilized measurements can reduce interobserver variability, particularly on follow on longitudinal studies, and as such may pave an avenue for an AI core laboratory, where precision is paramount.

Disease detection

The advantages of deep learning over manual interpretation of echocardiography are most compelling in the setting of evaluation of disease. Deep learning offers an opportunity to learn from image factors that are beyond those known in disease guidelines.[51] Morphological factors considered by "black-box" deep learning models elude researchers and are an active area of investigation, though methods like Grad-CAM visualizations may provide insight into the features models appraise towards their classification (Figure 1).

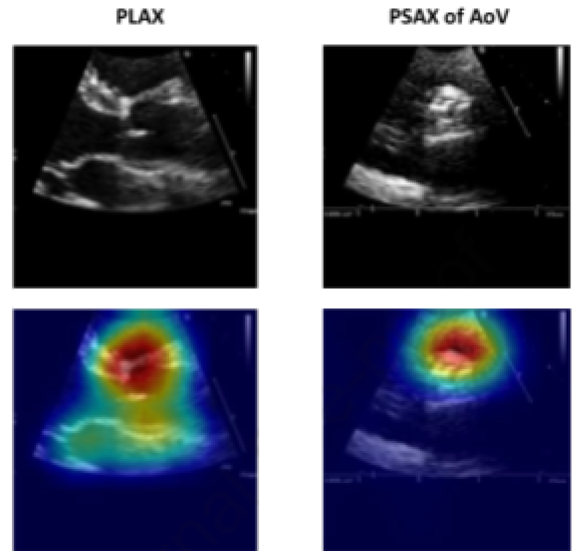


Figure 1. Grad-CAM Visualization for View Detection of PLAX vs PSAX (Wessler, et al.). Heatmap revealing area of attention.

Pathological signatures are visually distinct in echocardiography and thus well-suited for automated recognition by deep learning computer vision approaches: myocardial tissue impacted by fibrosis and infiltrative amyloid fibril deposition, both often presenting with left ventricular hypertrophy and appear echogenic, relative to healthy myocardium; calcification of valvular leaflets implicated in restrictive valvular motion, valvular sclerosis and stenosis appears distinctly echogenic; and, because each red blood cell is a specular reflector, c-mode color Doppler appears dense in the setting of valvular regurgitation. Further, as deep learning models assess image morphology for disease classification beyond known risk factors, they may be particularly well-suited to classification of out-of-guideline disease phenotypes.[51]

[42] Kaluzynski, K., et al. "Strain rate imaging using two-dimensional speckle tracking." IEEE transactions on ultrasonics, ferroelectrics, and frequency control 48.4 (2001): 1111-1123.

[43] Madani, Ali, et al. "Deep echocardiography: data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease." NPJ digital medicine 1.1 (2018): 1-11.

[44] Leclerc, Sarah, et al. "Deep learning for segmentation using an open large-scale dataset in 2D echocardiography." IEEE transactions on medical imaging 38.9 (2019): 2198-2210.

[45] Ouyang, David, et al. "Video-based AI for beat-to-beat assessment of cardiac function." Nature 580.7802 (2020): 252-256.

[46] U.S. Food and Drug Administration. K210791: Us2.v1 510(k) Premarket Notification. 2021, https://www.accessdata.fda.gov/cdrh_docs/pdf21/K210791.pdf

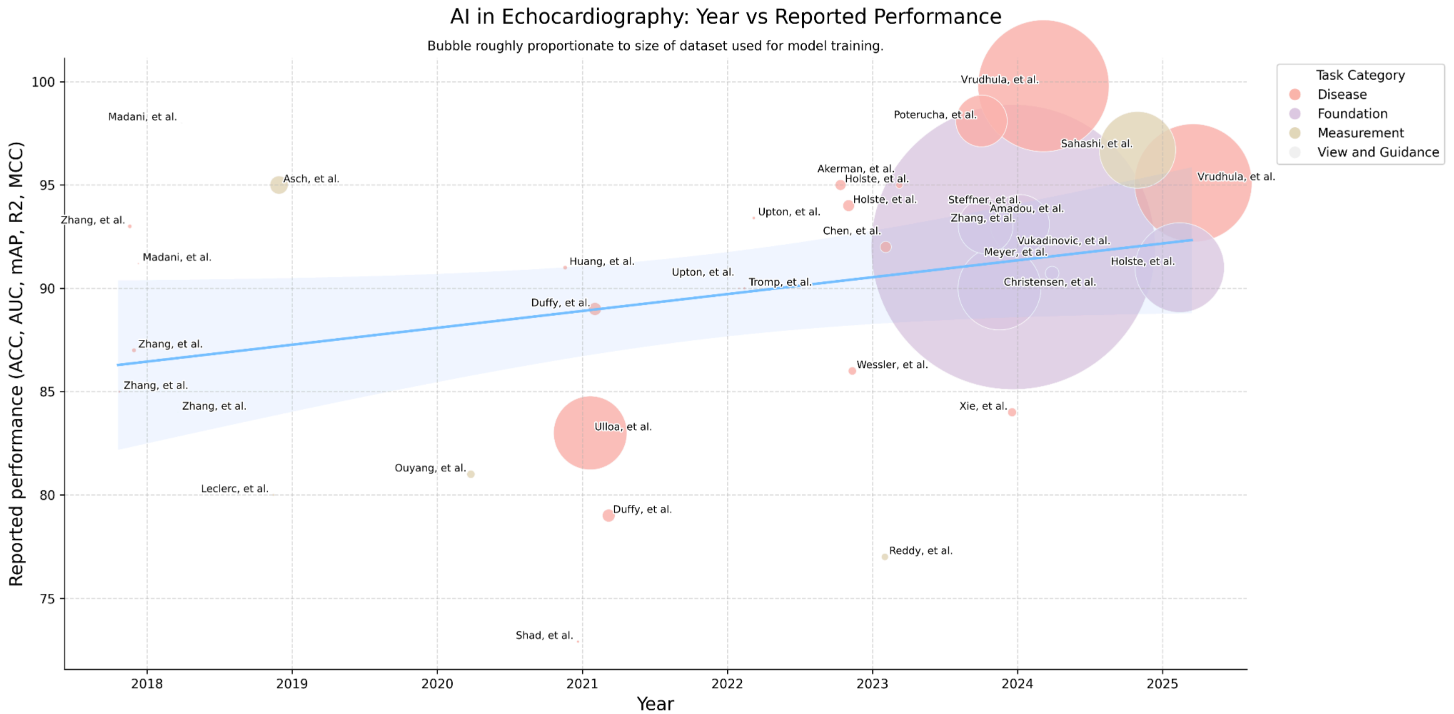
[47] U.S. Food and Drug Administration. 510(k) Premarket Notification Summary: EchoMeasure (K241430), 2024, https://www.accessdata.fda.gov/cdrh_docs/pdf24/K241430.pdf

[48] Holste, Gregory, et al. "PanEcho: Complete AI-enabled echocardiography interpretation with multi-task deep learning." medRxiv (2025): 2024-11.

[49] Sahashi, Yuki, et al. "Artificial intelligence automation of echocardiographic measurements." medRxiv (2025).

[50] Lafitte, Stéphane, et al. "Integrating artificial intelligence into an echocardiography department: Feasibility and comparative study of automated versus human measurements in a high-volume clinical setting." Archives of Cardiovascular Diseases (2025).

[51] Akerman, Ashley, et al. "Comparison of clinical algorithms and artificial intelligence applied to an echocardiogram to categorize risk of heart failure with preserved ejection fraction (HFPEF)." Journal of the American College of Cardiology 81.8_Supplement (2023): 360-360.



In the modern era of deep learning, the use of increasingly large datasets has driven a clear trend toward improved performance and robustness in disease detection models, with AUC reported for detection of clinical significant versus non-signficant mitral regurgitation approaching its upper theoretical asymptote. For instance, Vrudhula, et al. demonstrated a model trained in excess of two and a half million DICOMs showed AUCs of 0.998.[52] The function of disease classification models have been overwhelmingly towards binary classification of disease, and deep learning models demonstrated to stratify disease severity reveal the challenge implicit in the intersubjective nature of echocardiographic interpretation.[53,54]

Foundation models towards generation of the full echo report

As we progress from view classification, measurement, and disease detection, we move to the foundation model. Over the past decade, studies have explored these expert tasks, however, these image processing algorithms, while precise in their narrow focus, fall short in mirroring the holistic and interconnected clinical judgment typical of human echocardiographers in producing a full qualitative echocardiographic report. Vision-language models are a fundamental advance in the field of deep learning with implications for a host of applications in medical imaging. They promise to encapsulate not just discrete data points typical in traditional machine learning, but also the complex contextual interrelations in clinical diagnosis. Foundation models portend several advantages over discreet tasks methods: they can be trained on large, unlabeled datasets; they can be multi-modal, accepting as input still-frame and cines, exploiting the temporal information embedded between interconnected frames; and they can be trained to consider the plethora of modalities inherent in echocardiography. Concepts exploiting this phenomenon have been demonstrated, with several foundation models published over the past

[52] Vrudhula, Amey, et al. "High-throughput deep learning detection of mitral regurgitation." Circulation 150.12 (2024): 923-933.

[53] Poterucha, Timothy, et al. "DELINEATE-MR: Deep learning for automated assessment of mitral regurgitation from echocardiography." Journal of the American College of Cardiology 83.13_Supplement (2024): 2124-2124.

[54] Uretsky, Seth, et al. "Discordance between echocardiography and MRI in the assessment of mitral regurgitation severity: a prospective multicenter trial." Journal of the American College of Cardiology 65.11 (2015): 1078-1088.

year.[55,56,57,58] Concepts of the foundation model in echocardiography point not only to increased performance for discrete measurement and regression tasks, disease classification and severity stratification, but towards a productive step in the creation of the full report. It remains to be seen which pipeline architecture will yield a fully automated echocardiographic report that is accepted into clinical practice, though a qualitative trend suggests the field is moving towards solving an automated report (Figure 2).

Figure 2. Each bubble represents one peer-reviewed model. Bubble size roughly corresponds to dataset size used in training, color corresponds to target task, trend line indicates lines of best fit of reported performance values, with 95% confidence band illustrated over regression line. Size of validation data cohorts also scale with training dataset size.

Language of the echocardiographic report

As we near the end of the discussion on components required to produce the automated echocardiographic report, we move to the report language itself. Despite efforts to ground many aspects of echocardiographic interpretation in quantifiable endpoints, language is ultimately the medium of echocardiographic reporting. Guidelines have been published around the recommended components of an echocardiographic structured report, though–in the context of language embedding models–these guidelines also serves a serendipitous secondary purpose of constraining the language diversity used in report text.[6,7] For all the focus of language in qualitative interpretation of echocardiographic reporting, peer-reviewed literature exploring metalinguistic trends of structured reports is sparse. Vukadinovic and colleagues report among 275,442 studies from Cedars-Sinai Medical Center, 67,756,876 words are present and, from the same group, Christensen et. al. developed a custom domain-specific echocardiography text tokenizer to standardize heterogeneity across reporting language, though the details of this aspect are not discussed.[59] Certain wording templates plague echocardiographic reports, a vestige of macros and templated language from mainstream Picture and Archiving Communication systems (PACs). As a result, language heterogeneity among echocardiographic reports follows a long-tailed statistical distribution. Exploring this concept, we analyzed a subset of data sources from a national ultrasound diagnostic company collected between 2009 and 2024 containing 82,456 TTE studies, approximating 870,000 descriptors of chambers, valves, and other structures (aortic root, aortic arch, pericardium, and pulmonary artery). We indexed each descriptor by the instances it appears and enumerated unique descriptors (Figure 1).

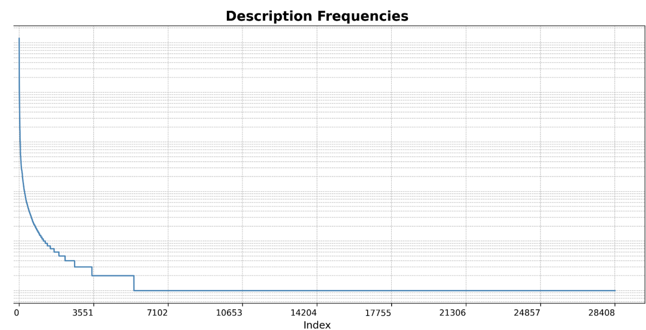


Figure 1: Illustration of the long-tailed distribution of descriptors. We found the phrase "Normal dimensions. No suggestion of mass or thrombus." to occur 122,874 times, being the most prevalent. Index 3551 from the end of the first quartile revealed the phrase "Moderate aortic stenosis, with a peak gradient of 26 mmHg, mean of 12, AVA of 1.2." appearing just 2 times, illustrating the precipitous dropoff of the number of repeating phrases, (in this case, partly owing to the specificity of the quantities contained within this descriptor). Index 7102 reads: "There is posterior mitral leaflet prolapse, with moderate mitral regurgitation and a very eccentric anteroseptally-directed jet." occuring just once, likely owing to the specific nature of the finding. Index 28408, also appearing once, was unique likely owing to its spelling errors: "Milddilation of aortci root".

Language remains the fundamental expression of echocardiographic interpretation, capturing

[55] Amadou, Abdoul Aziz, et al. "Echoapex: A general-purpose vision foundation model for echocardiography." arXiv preprint arXiv:2410.11092 (2024).
[56] Zhang, Ziyang, et al. "Echo-Vision-Fm: A Pre-Training and Fine-Tuning Framework for Echocardiogram Video Vision Foundation Model." medRxiv (2024): 2024-10.
[57] Kim, Sekeun, et al. "EchoFM: Foundation model for generalizable echocardiogram analysis." arXiv preprint arXiv:2410.23413 (2024).
[58] Holste, Gregory, et al. "PanEcho: Complete AI-enabled echocardiography interpretation with multi-task deep learning." medRxiv (2025): 2024-11.

[59] Christensen, Matthew, et al. "Vision–language foundation model for echocardiogram interpretation." Nature Medicine 30.5 (2024): 1481-1488.

subtleties both explicit and implied. Ultimately, the fully automated echocardiographic report will require not only accurate visual and quantitative inference, but also a mechanism developed on account of great exploration into the lexical diversity and structure of the echocardiographic language. Satisfactorily accomplishing this would result in encoding the latent semantics of diagnostic phrasing, which contains the gradations of certainty, emphasis, and relational context of echocardiographic report language.

Use of major windows to reduce the complexity of echocardiography

It is interesting to note the focus on the use of major echocardiographic views for many of the deep learning studies reviewed here. As disease can be classified with lower-order information, this points to the potential of a future of a simplified echocardiogram, where the diagnostic information required to assess the complete echocardiogram may be available in a simpler examination.[60] Take for instance, the parasternal long axis window (PLAX), the first acquired perspective in the canonical thranthoracic echocardiographic protocol, whereby three chambers, two valves, and other structures are in view. A suite of algorithms focused entirely on automated interpretation of the PLAX view may be feasible for production of a preliminary left-sided echocardiographic report,[61] and may offer a critical avenue in the utility of portable Point-of-Care (POCUS) hardware. Evangelos and colleagues showed an AI model can capture HCM and ATTR amyloidosis from simplified echocardiographic examinations (PLAX, PSAX, A4C views only) taken in the emergency setting demonstrating feasibility in capturing diagnoses of non-acute cardiomyopathies from POCUS examinations which would otherwise be relegated to more comprehensive TTE examinations.[62] Emerging studies point to the direction of predicting cardiac magnetic resonance (CMRI)-derived findings from echocardiographic images suggesting an additional research direction to expand on the clinical utility of artificial intelligence applied to echocardiography. [63]

Clinical trials of AI echocardiography

Formal clinical trials evaluating AI in production are emerging. Early clinical trials (NCT03936413) demonstrated feasibility in image acquisition tasks concluding minimally trained operators guided by AI produced significantly more adequate standard views. A randomized trial by Narang et al. (Nature, 2023) showed that AI-derived ejection fraction estimates were non-inferior to sonographer measurements, supporting integration of automation into quantification workflows. Building on these findings, ongoing studies are expanding into broader clinical contexts: NCT05558605 is assessing AI guidance during routine patient care, NCT07144189 is applying AI to the diagnostic challenge of low-gradient aortic stenosis, and the AI-ECHO/ACCEL Lite crossover trial is evaluating workflow efficiency, reproducibility, and interpretation time. Collectively, completed studies confirm that AI can enhance acquisition and quantification, while ongoing trials aim to validate its impact on clinical care and laboratory operations. (Table 1.)

Commercial offerings

Growing market expectation for AI integration into clinical workflows has spurred the emergence of startups seeking to capture its potential value. These efforts span the entire imaging continuum, from acquisition to interpretation. Startups and academic groups represent efforts from the United States, the United Kingdom, Singapore, Israel, Lithuania, France, China, and the United Arab Emirates, reflecting a worldwide “space race” towards automated echocardiography. Table 3.

Study limitations

[60] Bughrara, Nibras, et al. "Comparison of qualitative information obtained with the echocardiographic assessment using subcostal-only view and focused transthoracic echocardiography examinations: a prospective observational study." Canadian Journal of Anaesthesia/Journal canadien d'anesthésie 69.2 (2022): 196-204.

[61] Ulloa Cerna, Alvaro E., et al. "Deep-learning-assisted analysis of echocardiographic videos improves predictions of all-cause mortality." Nature Biomedical Engineering 5.6 (2021): 546-554.

[62] Oikonomou, Evangelos K., et al. "Artificial intelligence-guided detection of under-recognised cardiomyopathies on point-of-care cardiac ultrasonography: a multicentre study." The Lancet Digital Health 7.2 (2025): e113-e123.

[63] Sahashi, Yuki, et al. "Using deep learning to predict cardiovascular magnetic resonance findings from echocardiography videos." Journal of the American Society of Echocardiography (2025).

This review is subject to several limitations. First, as reporting standards for AI studies in echocardiography are heterogeneous, performance metrics are not directly comparable across studies, and heterogeneity in dataset size, curation, and external validation limits generalizability. This study attempts to broadly link non-comparable performance metrics to understand the trend of performance of deep learning algorithms in echocardiography over time. Second, most published studies remain retrospective and rely on single-center or convenience datasets, thus this review does not assess concerns regarding bias, robustness across imaging vendors, and applicability to diverse patient populations in real-world clinical applications. Finally, the rapidly evolving nature of the field means that new methods and commercial offerings may emerge after the time of writing.

Conclusion

In sum, the standardized structure of echocardiographic imaging and reports, combined with the ubiquity of echocardiography and its central role in cardiovascular care, have made it a focus of intense global academic activity. In this review, we have traced the evolution of artificial intelligence in echocardiography from nascent myocardial motion analysis to multimodal foundation models capable of parsing cine loops, quantifying disease, and generating structured text. The next frontier lies in unifying these elements to capture not only anatomy, but intent, emphasis, and uncertainty. The aspiration of the automated echocardiographic report speaks to the arc of artificial intelligence drawing ever closer to the art of echocardiographic interpretation. Yet in doing so, it invites a deeper reflection on the spirit of our own interpretive art, and thus brings into question how narrow the gap between man and machine may truly be.

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Identifier / Trial Name	Description / Aim	Status / Key Findings
NCT03936413 — Artificial Intelligence in Echocardiography[1]	To determine whether a Bay Labs AI system can be used by minimally trained operators to obtain diagnostic echo images	Registered clinical trial
NCT05558605 — Use of Artificial Intelligence-Guided Echocardiography to Triage / Manage Patients[2]	To test AI-based echo guidance in patients with known or suspected heart disease	Ongoing trial
AI Assessment of Low-Gradient Aortic Stenosis Severity (NCT07144189)[3]	Evaluate AI methods for grading aortic stenosis severity in low-gradient cases	Registered trial (specific to echo / valve disease)
AI-ECHO / ACCEL Lite: randomized crossover trial[4]	Evaluate how AI-based automated echo measurements affect sonographer workflow, time, and quality	Reported / ongoing trial
Blinded randomized trial: sonographer vs AI for LVEF assessment[5]	Compare initial LVEF measurement by AI vs by sonographers and see effect on final cardiologist interpretation	Completed, published in Nature
Artificial Intelligence-based Automated Echocardiography (preprint / trial)[6]	Integrates AI into real clinical echo workflows to evaluate performance and outcomes	Preprint / ongoing randomized evaluation
Study with novice users acquiring echo using AI guidance[7]	Assess whether nurses without echo experience can acquire diagnostic images with AI assistance	Prospective evaluation

1. "Artificial Intelligence in Echocardiography (NCT03936413)." ClinicalTrials.gov, U.S. National Library of Medicine, https://clinicaltrials.gov/study/NCT03936413
2. "Use of Artificial Intelligence-Guided Echocardiography to Triage and Manage Patients (NCT05558605)." ClinicalTrials.gov, U.S. National Library of Medicine, https://clinicaltrials.gov/study/NCT05558605
3. "Artificial Intelligence Assessment of Low-Gradient Aortic Stenosis Severity (NCT07144189)." ClinicalTrials.gov, U.S. National Library of Medicine, https://clinicaltrials.gov/study/NCT07144189
4. "ACCEL Lite: Artificial Intelligence-based Automated Echocardiographic Measurements." ACC.org, American College of Cardiology, 11 Feb. 2025, https://www.acc.org/Latest-in-Cardiology/Articles/2025/02/11/16/30/accel-lite-11feb2025
5. Narang, Apoorva, et al. "Blinded Randomized Trial of Artificial Intelligence-Derived vs Sonographer-Derived Echocardiographic Measurements of Left Ventricular Ejection Fraction." Nature, vol. 616, 2023, pp. 1-7. doi:10.1038/s41586-023-05947-3.
6. Holste, Gregory, et al. "Complete AI-Enabled Echocardiography Interpretation With Multitask Deep Learning." JAMA, 2025. doi:10.1001/jama.2025.1459. PubMed, https://pubmed.ncbi.nlm.nih.gov/40549400/
7. Lafitte, S., et al. "Artificial intelligence empowers Novice Users to acquire Diagnostic-Quality echocardiography." Archives of Cardiovascular Diseases 118.6-7 (2025)

Table 1. Completed and ongoing trials of AI in echocardiography

Software	Company	Country	Main Functions	Notes
Probe Guidance				
Vscan Air SL w/ Caption AI	GE	USA	Probe placement assistance	Standardization of acquisition
UltraSight AI Guidance	UltraSight	Israel	Probe placement assistance	Standardization of acquisition
HeartFocus	DESKi	France	Probe placement assistance	Standardization of acquisition
Interpretation				
Libby Echo:Prio	DyadMed	USA	EF	Company defunct
LVivo EF	DiaAnalysis	Israel	EF and view classififcation	Acquired by Philips
Philips / Tomtec	Philips	USA	3D echo, multimodality integration	Advanced reconstructions
GE EchoPAC	GE	USA	Automated measurements, reporting	On hardware deployment
Imacor	Imacor	USA	Myocardial strain, 3D TEE, hemodynamics (ICU)	ICU-focused
InVision Precision Cardiac Amyloid	InVision Medical	USA	Amyloid detection, EF analysis	Disease detection
EchoMeasure	iCardio.ai	USA	View classification, quality, LV/RV/AS measurements	Core echocardiographic measurements
EchoApex	Siemens Healthineers	USA	View classification, LV measurements, EF	Foundation model
Us2.ai	Us2.ai	Singapore	View classification, quality, chamber, Doppler measurements	Core echocardiographic measurements
Ultromics EchoGo	Ultromics	United Kingdom	HFpEF detection, Amyloid detection, GLS analysis, reporting	Disease detection
Ventripoint VMS	Ventripoint Diagnostics	Canada	2D/3D reconstruction, EF, single ventricle	Knowledge-based reconstruction
EchoConfidence	MyCardium	United Kingdom	View classification, chamber, Doppler measurements	Core echocardiographic measurements
EchoNous Kosmos	EchoNous	USA	Real-time labeling, auto measurement	POCUS focus
EchoCoTr	MBZUAI	United Arab Emirates	EF and view classification	Research-level
Ligence Heart	EchoIQ	Lithuania	View classification, chamber, Doppler measurements	Core echocardiographic measurements
EchoSolv AS		Australia	Aortic stenosis detection	Valve phenotyping

Table 2. Commercial offerings in AI for echocardiography with regulatory clearances

Paper	Year	Problem	Target Task	Architecture	Perspective	Studies	Videos	Metric	Result
Madani, et al.	2018	View and Guidance	View Classification		View prediction	267		ACC	98
Madani, et al.	2018	Disease	LVH	UNet	View prediction	455		ACC	91.2
Zhang, et al.	2018	View and Guidance	View Classification	UNet, VGG13	A2C, A4C, PLAX, PSAX, A3C	227		ACC	84
Zhang, et al.	2018	Disease	HCM	UNet, VGG13	A2C, A4C, PLAX,	2739		AUC	93

					PSAX, A3C				
Zhang, et al.	2018	Disease	Amyloid	UNet, VGG13	A2C, A4C, PLAX, PSAX, A3C	3071		AUC	87
Zhang, et al.	2018	Disease	PAH	UNet, VGG13	A2C, A4C, PLAX, PSAX, A3C	983		AUC	85
Leclerc, et al.	2019	Measurement	LV Function	UNet	A2C, A4C	500	1000	MCC	80
Asch, et al.	2019	Measurement	LV Function	CNN	A4C	50,000		R2	95
Ouyang, et al.	2020	Measurement	LV Function	DeepSenseV3, R3D	A4C	10,030	10,030	R2	81
Jafari, et al.	2020	Enhancement		UNet, CycleGan	A2C				
Wang, et al.	2021	Disease	VSD, ASD		Pediatric (multiview)	1308	6540	AUC	94.2
Huang, et al.	2021	Disease	Aortic Stenosis	ResNet	PLAX, PSAX	2905		AUC	91
Degerli, et al.	2021	Pathology	MI	UNet	A4C				
Shad, et al.	2021	Disease	RV Function	ResNet	A4C	723	1223	AUC	72.9
Ulloa, et al.	2021	Mortality	Mortality		View agnostic	34,362	812,278	AUC	83
Upton, et al.	2022	Disease	CAD	UNet	A2C, A3C, A4C	1498		AUC	93.4
Duffy, et al.	2021	Disease	Amyloid	R3D	PLAX	24,804		AUC	79
Duffy, et al.	2021	Disease	HCM	R3D	PLAX	24,804		AUC	89
Tromp, et al.	2022			CNN	A2C, PLAX, A4C	602			
Upton, et al.	2022	Disease	CAD	CNN	A4C	578		AUC	90
Tromp, et al.	2022			CNN	A2C, PLAX, A4C, 2D other	1145		AUC	90
Wessler, et al.	2023	Disease	AS		PLAX	577	10253	AUC	86
Akerman, et al.	2023	Disease	HFpEF	ResNet	A4C	6,756			
Holste, et al.	2023	Disease	AS	R3D	PLAX	20,500	20,500	AUC	94
Akerman, et al.	2023	Disease	HfPEF / HFrEF		A4C	7,249	7,249	AUC	95
Holste, et al.	2023			3D-ResNet-18	PLAX	5257	17,570	AUC	95
Chen, et al.	2023	Measurement			A4C, A2C, PW-Doppler Transmitral, CW-Doppler transtricuspid, Tissue Doppler IVS, Tissue Doppler Lateral Wall	2238	18,992	ACC	92
Reddy, et al.	2023	Pediatrics	LV Function		A4C, PSAX	4467	7643	R2	77
Jiang, et al.	2024	View and Guidance			PLAX, PSAX-AV, PSAX-MV	110	151,000		
Alajrami, et al.	2024	Segmentation	LV Function	MCD U-Net	A4C				
Steffner, et al.	2024	View and Guidance	View Classification	R2+1D	TEE (8 views)	2967	2967	AUC	91.9
Amadou, et al.	2024	View and Guidance, Measurement, Disease	View Classification, Segmentation, Pathology, LV Function		View agnostic to 18 views	26,704	450,338	AUC	93
Zhang, et al.	2024	Measurement	LV Function, Measurements	ViT, STFF-Net	View agnostic to 12 views				
Alvén, et al.	2024	Measurement	LV Function	I3D	A2C, A3C, A4C, PLAX				
Fadnavis, et al.	2024	Disease	PAH	ViT-B/16		6500	286,080	AUC	80

Meyer, et al.	2024	Foundation		ViT			28,000	mAP	90.73
Kim, et al.	2024		Foundation	ViT	A2C, A4C, PLAX, PSAX, "Others"	6500	286,080		
Vukadinovic, et al.	2024	Foundation, View and Guidance, Measurement, Disease, Report Generation	Foundation, View Classification, Out of Domain, Pathology, Report Generation	mVIT	View agnostic	275,442	12,124,168	AUC	92
Zhang, et al.	2024	Foundation	Segmentation		A2C, A4C, PLAX, PSAX, others	7243	525,328	AUC	93.1
Ravishankar, et al.	2023	Foundation	Segmentation	ViT-B					
et al.	2024	Disease	MR	CNN	A4C	61,689	399,454	AUC	98.1
Christensen, et al.	2024	Foundation, View and Guidance, Measurement, Disease, Report Generation	Foundation, View Classification, Out of Domain, Pathology, Report Generation	ConcNexT	View agnostic	224,685	1,032,975	AUC	90
Huang, et al.	2024	Measurement	LV Function		A4C			AUC	88
Vrudhula, et al.	2024	Disease	MR	R(2+1)D	A4C with color Doppler	58,614	2,587,538	AUC	99.8
Sanabria, et al.	2024	Disease	AS	LightGBM				AUC	83
Xie, et al.	2024	Disease	TR		CW-Doppler TR	11,654		AUC	84
Holste, et al.	2025	Foundation, View and Guidance, Measurement, Disease, Report Generation	Foundation, View Classification, Out of Domain, Pathology, Report Generation	CNN-Transformer hybrid		32,265	1,200,000	AUC	91
Vrudhula, et al.	2025	Disease		R(2+1)D CNN	A4C with color Doppler	47,312	2,079,898	AUC	95.1
Chao, et al.	2025	Segmentation	Segmentation		A4C, A2C		10,030+		
Sahashi, et al.	2025	Measurement	LV Function, Measurements	DeepLabv3	PLAX, A4C, A2C, PSAXA Zoomed Out, CW-Doppler, PW-Doppler	155,215	877,983 (likely overlapping)	R2	96.7
Park, et al.	2025	Disease	AS	3D-CNN and SegFormer	PLAX, PSAXA				
Park, et al.	2025	Disease	AS	3D-CNN and SegFormer	PLAX, PSAXA, Ao CW-Doppler, Ao PW-Doppler, LVOT PW Doppler	30,000		AUC	0.97

Table 3. Publications with independently reported models, year of publication, problem category, target task, deep learning architecture, echocardiographic perspective, number of unique TTE studies used, number of unique cine DICOMs used (if reported) reported performance metric, performance.

ASD=atrial septal defect, VSD=ventricular septal defect, LVH=left ventricular hypertrophy, HCM=hypertrophic cardiomyopathy, PAH=pulmonary arterial hypertension, MI=myocardial infarction, AS=aortic stenosis, MR=mitral regurgitation, TR=tricuspid regurgitation, CAD=coronary artery disease, HFpEF=heart failure with preserved ejection fraction, HFrEF=heart failure with reduced ejection fraction, A2C=apical 2-chamber, A3C=apical 3-chamber, A4C=apical 4-chamber, PLAX=parasternal long axis, PSAX=parasternal short axis, PSAX-AV=parasternal short axis at aortic valve level, PSAX-MV=parasternal short axis at mitral valve level, TEE=transesophageal echocardiography, LV=left ventricle, LVOT=left ventricular outflow tract, IVS=interventricular septum, Ao=aortic, PW-Doppler=pulsed-wave Doppler, CW-Doppler=continuous-wave Doppler, ACC=accuracy, AUC=area under the ROC curve, MCC=Mean correlation coefficient, R^2=coefficient of determination, mAP=mean average precision