Texas Heart Institute Journal

*Artificial Intelligence In Cardiovascular Medicine*

# Artificial Intelligence in Echocardiography

Stephanie A. Coulter, MD[1]; Karla Campos, MD[1]

[1]Center for Women's Heart and Vascular Health, Texas Heart Institute, Houston, Texas

*Artificial intelligence in diagnostic cardiac-imaging platforms is advancing rapidly. In particular, artificial intelligence algorithms have increased the efficiency and accuracy of echocardiographic cardiovascular imaging, resulting in more complex echocardiographic imaging techniques and expanded use among noncardiologists. Here, we provide an overview of real-world applications of artificial intelligence in echocardiography including automatic high-quality computer-optimized image acquisition sequences, automated measurements, and algorithms for the rapid and accurate interpretation of cardiac physiology. These advances will not replace physicians but will improve their productivity, workflow, and diagnostic performance.* ***(Tex Heart Inst J 2022;49(2):e217671)***

The development and implementation of artificial intelligence (AI) in medicine—specifically in diagnostic cardiac-imaging platforms—are advancing rapidly. In particular, ultrasound-equipment companies are driving AI research and development, which has led to the incorporation of AI into daily clinical practice with real-world clinical applications. As a result, echocardiographic cardiovascular imaging is becoming more complex, while its use among noncardiologists is expanding. Real-world applications of AI in echocardiography include automatic high-quality computer-optimized image acquisition sequences, automated measurements, and algorithms for the rapid and accurate interpretation of cardiac physiology. Artificial intelligence algorithms can increase efficiency and accuracy in echocardiography by reducing human variability.[1]

## Artificial Intelligence in Cardiac Imaging

### Image Optimization and Acquisition

In cardiac imaging, image optimization is the foundation for all higher-order AI algorithms. Currently, echocardiographic images are optimized manually with image quality that depends on the skill level of the cardiac sonographer. Image optimization and acquisition performed by a computer algorithm instead of a sonographer enable the delineation of cardiac structures by using an automated recognition sequence with prespecified rules, algorithms, or instructions. The use of AI algorithms to optimize image quality reduces sonographic scanning time, eliminates artifacts, decreases interobserver and intraobserver variability, and improves diagnostic accuracy.[2,3]

### Segmentation

In echocardiographic interpretation, the next essential step is the classification of standardized transthoracic echocardiographic views. Madani and colleagues[4] used a training set of 247 real-world echocardiograms with 200,000 images acquired for clinical purposes to derive a single vendor-agnostic deep-learning model. They used this model to correctly classify 15 major transthoracic views with 98% accuracy, which exceeded that of board-certified echocardiographers given the same task.

### Measurements

Automated measurement protocols for 2-dimensional (2D) and 3-dimensional (3D) echocardiographic datasets are commercially available and are currently used by

**Citation:**
Coulter SA, Campos K. Artificial intelligence in echocardiography. Tex Heart Inst J 2022;49(2):e217671. doi: 10.14503/THIJ-21-7671

**Key words:**
Algorithms; artificial intelligence; cardiac imaging techniques/methods; deep learning; diagnosis, computer-assisted; echocardiography; image interpretation, computer-assisted; imaging, three-dimensional; investigative techniques

**Corresponding author:**
Stephanie A. Coulter, MD, Texas Heart Institute, P.O. Box 20345, MC 3-116, Houston, TX 77225.

**E-mail:**
scoulter@texasheart.org

*© 2022 by the Texas Heart® Institute, Houston*



http://prime-pdf-watermark.prime-prod.pubfactory.com/ | 2025-02-04

multiple vendors. Automated measurement packages help to standardize reproducibility by reducing human error. Traditional 2D echocardiographic determination of ejection fraction (EF) by the manual tracing of endocardial borders is both time-consuming and operator-dependent. Furthermore, visual assessment of EF by expert readers is subjective. Automated border-detection algorithms combined with the identification of end-systolic and end-diastolic frames from the electrocardiogram facilitate the measurement of cardiac-chamber dimensions and volumes, stroke volume, EF, and wall thickness. Machine learning–assisted, 3D automated assessment of left ventricular (LV) and right ventricular volumes and EF is feasible, with the advantage of one-minute acquisitions and the limited need for manually editing endocardial borders (Fig. 1). Two training and validation studies have demonstrated the accuracy of automatic cine-derived LVEF, with correlation at or better than 90% when compared with that of conventional volume-derived EF determined by clinical readers.[2,5] The accuracy of EF determined by echocardiographically derived automated measurement is now more consistent with the reference standard of EF determined by using cardiac magnetic resonance (CMR) imaging.[2,5-8] In its recent guidelines,[9] the American Society of Echocardiography has recommended the expanded use of 3D echocardiography to quantify ventricular cavity volumes. The incorporation of AI for 3D echocardiography into clinical practice may be an important step that decreases the need for CMR imaging, which is not readily available outside of most large tertiary medical centers.

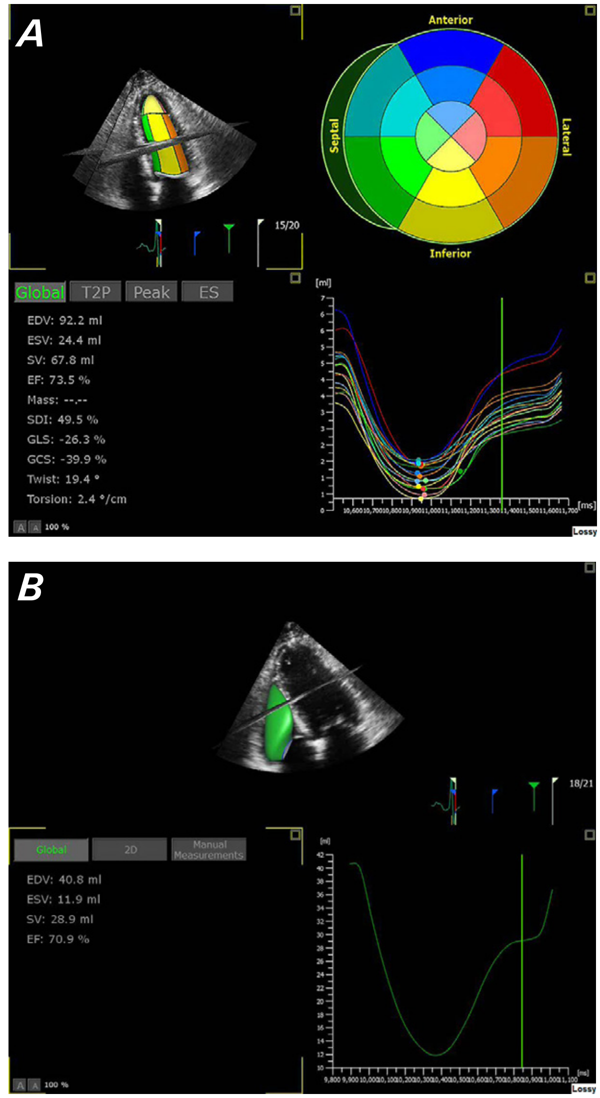


***Fig. 1*** *Three-dimensional echocardiograms, acquired with use of the GE Vivid T9 Ultra Edition System, show **A**) left and **B**) right ventricular volumes and ejection fraction.*

*Supplemental motion images are available for Figures 1A and 1B.*

## Global Longitudinal Strain

Fully automated measurement of 2D LV global longitudinal strain (GLS) is a widely used application of AI in echocardiography.[10,11] Automated EF with simultaneous 2D LV GLS can be assessed rapidly (i.e., in 8 seconds) with high feasibility (98%) and accuracy by using AI to automatically identify and classify standard views, trace the myocardium for motion estimation, and evaluate GLS in patients with acute myocardial infarction or heart failure (Fig. 1).

## Disease Detection

The ability of a computer to recognize a captured image and categorize it (e.g., 2D, 3D, Doppler) according to clinical utility enables the use of algorithms for disease detection. Algorithms derived to incorporate Doppler measurements with 2D or 3D measurements can facilitate the analysis of diastolic function, the classification of heart failure, and the evaluation of valvular lesions (stenosis or regurgitation). Algorithms for detecting disease-specific echocardiographic patterns in hypertrophic cardiomyopathy, amyloidosis, or pulmonary hypertension have been identified; and their diagnostic accuracy is comparable with that obtained by expert clinical readers.[12] Furthermore, algorithms are being developed to determine automatically the severity of valvular disease. Moghaddasi and Nourian[13] used a machine-learning AI technique to grade mitral valve regurgitation by severity among 139 patients; they reported 99.5% accuracy for identifying a normal mitral valve and 99.38%, 99.31%, and 99.59% accuracy for identifying mild, moderate, and severe mitral regurgitation, respectively (overall sensitivity, 99.38%; specificity, 99.63%). Playford and colleagues[14] compared the accuracy of the traditional continuity equation with that of an AI algorithm used to identify severe high-gradient aortic stenosis, by using phenotypic characteristics to assist in the diagnosis of aortic stenosis without reference to LV outflow tract (LVOT)


http://prime-pdf-watermark.prime-prod.pubfactory.com/ | 2025-02-04

dimension or velocity. The AI algorithm correctly graded the severity of aortic stenosis in 95.3% of patients with varying degrees of LV systolic function and stroke volumes, whereas the continuity equation correctly graded the severity in 73.9%. The phenotypic AI algorithm was also a significant predictor of long-term mortality, even after adjustment for transaortic gradients and stroke volume index.[14]

## Periprocedural Assessment

Artificial intelligence has also been implemented to assess the suitability of the aortic annulus in patients who are undergoing transcatheter aortic valve replacement. In a single-center study of 47 patients,[15] periprocedural aortic annular measurements obtained by using AI software were compared with those acquired by using traditional 2D transesophageal echocardiography or cardiac computed tomography. Measurements made by AI software correlated well with cardiac computed tomographic data and performed better than transesophageal echocardiographic measurements did (r=0.84; $P$ <0.0001).[15]

Vendor-specific AI protocols are available that can be used to evaluate the anatomy of the mitral valve and perform automated measurements that are useful for periprocedural mitral clip assessment.[16] These algorithms emphasize precise sizing and real-time imaging guidance (Fig. 2).

## Workflow in the Echocardiography Laboratory

With the use of AI, the sequence in which echocardiograms are interpreted will change. Currently, the physician performs conventional echocardiographic interpretation after the sonographer performs a standardized image-acquisition protocol that includes parasternal imaging and apical, subcostal, suprasternal, off-axis, and nonimaging Doppler. The interpreter must integrate nonconsecutive 2D, 3D, and Doppler images in order to make accurate assessments of wall motion, systolic and diastolic function, valvular stenosis, and regurgitation. With advances in AI, image-acquisition protocols will group relevant images according to clinical relevance. For example, an LV-wall motion assessment query would display all cine images of the LV serially. Alternatively, a query for aortic valve stenosis would display the 2D or 3D LVOT images and juxtapose these with the pulse-wave stroke volume transvalvular Doppler tracings and the peak aortic valve transvalvular Doppler images. Advances in image interpretation will also facilitate the calculation of aortic stenosis severity, with accurate consideration of stroke volume index (assessed by using both LVOT Doppler and Simpson's volumetric calculation) and LV function (assessed by using 3D volume, perhaps with consideration of LV GLS).[8,9]

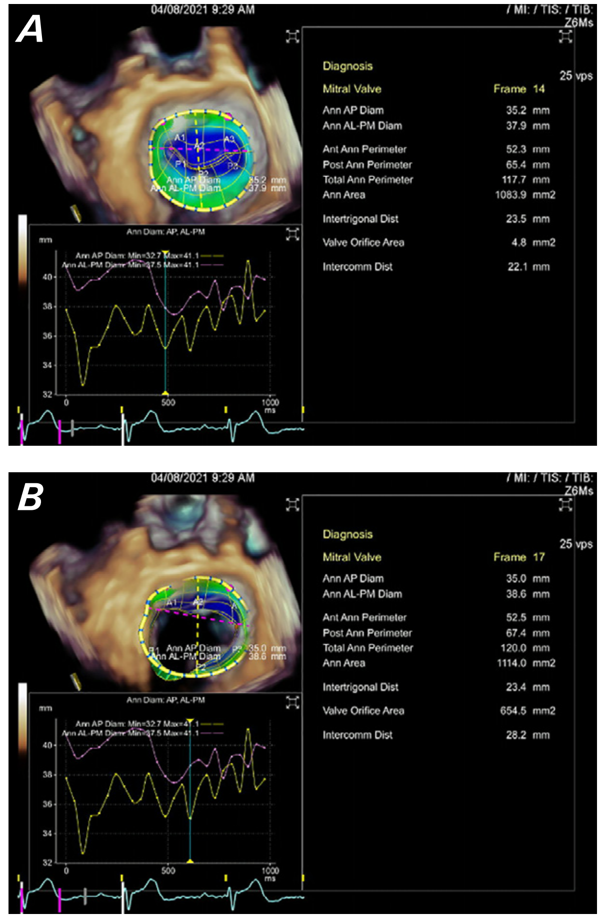


*Fig. 2 Three-dimensional echocardiograms, acquired with use of the GE Vivid T9 Ultra Edition System, show the mitral valve before mitral valve clip placement.* ***A****) The system's artificial intelligence program automatically labels the mitral leaflet segments during systole, then* ***B****) planimetrically calculates the mitral valve area during diastole.*

*Supplemental motion image is available for Figure 2.*

Notably, AI will make comparisons with images from prior studies automated and less time-consuming. For example, an algorithm may enable rapid, side-by-side comparison with similar images from a prior study. This will reduce the time requirements involved in loading and comparing studies in real time. Comparison with images and not with a prior report will improve accuracy and also help meet laboratory accreditation requirements.[16]

Advances in AI will also change the sequence in which echocardiograms are read in a busy echocardiography laboratory. Currently, unread echocardiograms are triaged for interpretation according to length-of-stay considerations (i.e., day of discharge from the hospital) and presumed study acuity with designations of "stat," "intensive care unit," and "routine." In the future, the most urgent, clinically pertinent unread echocardiograms will be given higher priority. Key echocardiographic


http://prime-pdf-watermark.prime-prod.pubfactory.com/ | 2025-02-04

features such as a large pericardial effusion or cardiogenic shock can be identified by AI and potentially designated for immediate physician interpretation.

### Artificial Intelligence for Novice Users

As cardiovascular disease continues to grow more complex, the need for accurate image acquisition and interpretation will also increase.[17] Smaller and less expensive echocardiographic devices marketed as point-of-care ultrasound devices will further expedite the use of echocardiography in settings where resources are limited and where immediate acquisition and interrogation will be made by physicians or nonphysicians who have limited echocardiographic training. The incorporation of AI software will be essential for training these novice users. A new deep-learning software program (Caption Health)[18] provides novice sonographers with guidance for acquisition of standard echocardiographic images in real time. Images are automatically acquired when deemed diagnostic by the software.[2] Incorporation of these AI tools shortens acquisition time, limits musculoskeletal stress to the sonographer, optimizes the images acquired, and standardizes measurements.[19] More accurate disease detection, increased access in rural areas, and expanded use by noncardiologists are all on the horizon.

## Conclusion

Echocardiography is the cornerstone of cardiac imaging. Inconsistencies in echocardiographic quality, image acquisition, and interpretation have increased the skill level required of the physician reader. The complexity of imaging techniques and the number of echocardiographic parameters used in routine examinations will continue to increase. Artificial intelligence is evolving to meet more complex imaging needs, as evidenced by improvements in quality image acquisition and the commercial availability of automatic 2D, 3D, and GLS measurements. These advances will not replace physicians but will improve their productivity, workflow, and diagnostic performance.[20] Importantly, AI can reduce the cost of echocardiograms while improving their safety and increasing their value.[21]

## Acknowledgment

The authors thank Nicole Stancel, PhD, ELS(D), of the Department of Scientific Publications at the Texas Heart Institute, for her editorial support.

**Published:** 28 April 2022

**Conflict of interest disclosure:** None

**Funding/support:** None

**Section editor:** Zvonimir Krajcer, MD

## References

1. Nagata Y, Kado Y, Onoue T, Otani K, Nakazono A, Otsuji Y, Takeuchi M. Impact of image quality on reliability of the measurements of left ventricular systolic function and global longitudinal strain in 2D echocardiography. Echo Res Pract 2018;5(1):27-39.
2. Asch FM, Poilvert N, Abraham T, Jankowski M, Cleve J, Adams M, et al. Automated echocardiographic quantification of left ventricular ejection fraction without volume measurements using a machine learning algorithm mimicking a human expert. Circ Cardiovasc Imaging 2019;12(9):e009303.
3. Alsharqi M, Woodward WJ, Mumith JA, Markham DC, Upton R, Leeson P. Artificial intelligence and echocardiography. Echo Res Pract 2018;5(4):R115-25.
4. Madani A, Arnaout R, Mofrad M, Arnaout R. Fast and accurate view classification of echocardiograms using deep learning. NPJ Digit Med 2018;1:6.
5. Behnami D, Liao Z, Girgis H, Luong C, Rohling R, Gin K, et al. Dual-view joint estimation of left ventricular ejection fraction with uncertainty modelling in echocardiograms. In: Shen D, Liu T, Peters TM, Staib LH, Essert C, Zhou S, et al., editors. Medical Image Computing and Computer Assisted Intervention – MICCAI 2019; Cham: Springer; Lecture Notes in Computer Science (vol. 11765); 2019. p. 696-704.
6. Medvedofsky D, Mor-Avi V, Amzulescu M, Fernández-Golfín C, Hinojar R, Monaghan MJ, et al. Three-dimensional echocardiographic quantification of the left-heart chambers using an automated adaptive analytics algorithm: multicentre validation study. Eur Heart J Cardiovasc Imaging 2018;19(1):47-58.
7. Tsang W, Salgo IS, Medvedofsky D, Takeuchi M, Prater D, Weinert L, et al. Transthoracic 3D echocardiographic left heart chamber quantification using an automated adaptive analytics algorithm. JACC Cardiovasc Imaging 2016;9(7):769-82.
8. Narang A, Mor-Avi V, Prado A, Volpato V, Prater D, Tamborini G, et al. Machine learning based automated dynamic quantification of left heart chamber volumes. Eur Heart J Cardiovasc Imaging 2019;20(5):541-9.
9. Lang RM, Badano LP, Mor-Avi V, Afilalo J, Armstrong A, Ernande L, 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. J Am Soc Echocardiogr 2015;28(1):1-39.e14.
10. Knackstedt C, Bekkers SC, Schummers G, Schreckenberg M, Muraru D, Badano LP, et al. Fully automated versus standard tracking of left ventricular ejection fraction and longitudinal strain: the FAST-EFs multicenter study. J Am Coll Cardiol 2015;66(13):1456-66.
11. Salte IM, Oestvik A, Smistad E, Melichova D, Nguyen TM, Brunvand H, et al. 545 Deep learning/artificial intelligence for automatic measurement of global longitudinal strain by echocardiography. Eur Heart J Cardiovasc Imaging 2020;21(Suppl 1):jez319.279.
12. Zhang J, Gajjala S, Agrawal P, Tison GH, Hallock LA, Beussink-Nelson L, et al. Fully automated echocardiogram interpretation in clinical practice. Circulation 2018;138(16):1623-35.
13. Moghaddasi H, Nourian S. Automatic assessment of mitral regurgitation severity based on extensive textural features on 2D echocardiography videos. Comput Biol Med 2016;73:47-55.



http://prime-pdf-watermark.prime-prod.pubfactory.com/ | 2025-02-04

14. Playford D, Bordin E, Mohamad R, Stewart S, Strange G. Enhanced diagnosis of severe aortic stenosis using artificial intelligence: a proof-of-concept study of 530,871 echocardiograms. JACC Cardiovasc Imaging 2020;13(4):1087-90.
15. Thalappillil R, Datta P, Datta S, Zhan Y, Wells S, Mahmood F, Cobey FC. Artificial intelligence for the measurement of the aortic valve annulus. J Cardiothorac Vasc Anesth 2020;34(1):65-71.
16. Davis A, Billick K, Horton K, Jankowski M, Knoll P, Marshall JE, et al. Artificial intelligence and echocardiography: a primer for cardiac sonographers. J Am Soc Echocardiogr 2020;33(9):1061-6.
17. Narang A, Sinha SS, Rajagopalan B, Ijioma NN, Jayaram N, Kithcart AP, et al. The supply and demand of the cardiovascular workforce: striking the right balance. J Am Coll Cardiol 2016;68(15):1680-9.
18. Narang A, Bae R, Hong H, Thomas Y, Surette S, Cadieu C, et al. Utility of a deep-learning algorithm to guide novices to acquire echocardiograms for limited diagnostic use. JAMA Cardiol 2021;6(6):624-32.
19. Cheema B, Hsieh C, Adams D, Narang A, Thomas JD. Automated guidance and image capture of echocardiographic views using a deep learning-derived technology [abstract]. Circulation 2019;140(Suppl 1):A15694-A.
20. He J, Baxter SL, Xu J, Xu J, Zhou X, Zhang K. The practical implementation of artificial intelligence technologies in medicine. Nat Med 2019;25(1):30-6.
21. Badano LP, Keller DM, Muraru D, Torlasco C, Parati G. Artificial intelligence and cardiovascular imaging: a win-win combination. Anatol J Cardiol 2020;24(4):214-23.



http://prime-pdf-watermark.prime-prod.pubfactory.com/ | 2025-02-04