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Caption AI™ AutoEF

Automated echocardiographic quantification of left ventricular ejection fraction: A deep learning solution mimicking the human eye

Background

Left ventricular ejection fraction (LVEF) remains the primary clinical echocardiographic measure of LV function. Current echocardiography guidelines[1] emphasize the importance of accurate quantification of LV EF, as multiple indications for therapeutic interventions rely on precise cutoff values of this parameter.

Traditionally, EF measurements utilize either manual or automated identification of endocardial boundaries followed by model-based calculation of end-systolic and end-diastolic LV volumes. However, border detection of the entire blood-tissue interface throughout the cardiac cycle is difficult and prone to errors: suboptimal image quality, artifacts, and unusual LV shape in different pathologies all contribute to considerable interobserver variability.

We hypothesized that instead of identifying endocardial boundaries and calculating ventricular volumes, computers could be "trained" to directly estimate the dimensionless degree of ventricular contraction and expansion, similar to what a human eye and brain do.

Accordingly, we developed a fully automated machine learning algorithm that completely circumvents border detection and instead estimates the degree of ventricular contraction much like an expert human reader.

Key points

- Rather than tracing endocardial borders and calculating ventricular volumes, the Caption AI AutoEF algorithm mimics an experienced human reader's ability to **visually estimate left ventricular ejection fraction**.
- The Caption AI AutoEF algorithm was trained on >50,000 echocardiographic studies and has been clinically validated to calculate ejection fraction with a **high degree of accuracy**, comparable to conventional volume-based measurements.
- Because it can reliably estimate ejection fraction from any combination of AP2, AP4, and PLAX views, the Caption AI AutoEF algorithm is particularly **well suited for point-of-care settings**.

Solution

Our approach assumes that the ventricle contracts throughout systole simultaneously along its long axis and in the radial direction, so that its corresponding dimensions **L** and **R** change over time according to two dimensionless contraction coefficients $\mathbf{C_L}$ and $\mathbf{C_R}$ *(Figure 1)*.

Using these coefficients, LV volume at end-systole can be described by: $\mathbf{V(ES) = V(ED) \cdot C_L \cdot C_R}$, where V(ED) is the volume at end-diastole.

By definition of LV EF as the difference between **V(ED)** and **V(ES)** normalized by the former, it can be expressed in terms of the above two contraction coefficients as follows: $\mathbf{EF = [V(ED) - V(ES)] / V(ED) = 1 - V(ES) / V(ED) = 1 - C_L \cdot C_R}$, which allows for the estimation of EF without measuring LV end-systolic and end-diastolic volumes.

The Caption AI AutoEF algorithm was developed and trained to automatically estimate LV EF using the above approach on a database of >50,000 echocardiographic studies of variable quality depicting a wide range of pathologies. Training consisted of identifying image features and patterns and associating them with the position of the endocardial boundary. It included the use of multiple apical 2-chamber (AP2), apical 4-chamber (AP4), and parasternal long-axis (PLAX) views available as part of each individual exam along with LV EF values measured over the years by the clinicians interpreting these studies using conventional methodology.

Importantly, our deep learning approach does not use any type of explicit tracking methodology, but instead lets the neural network decide from the data itself what the best approach to handle it is. In other words, the algorithm was not guided by the developers as to what should be detected or tracked throughout the cardiac cycle. Instead, the algorithm was allowed to derive from the thousands of images the features and visual patterns necessary to estimate EF in agreement with the reference values obtained by human readers using conventional methodology.

Following this training, the algorithm was designed to provide fully automated estimates of LV EF from any combination of AP2, AP4, and PLAX views of sufficient quality *(Figure 2)*. The AutoEF calculation is accompanied by an "expected error range" in parenthesis, indicating the estimated range in which the true ejection fraction is expected to lie based on the image quality of the study; studies with higher-quality images and studies that include at least two views that can be used for an EF assessment typically have smaller error ranges. The software also displays a qualitative assessment of global LV function, mapped to categories (hyperdynamic, normal, reduced, severely reduced) based on American Society of Echocardiography (ASE) and American College of Emergency Physicians (ACEP) guidelines,[1,2] along with a "confidence estimate" showing the likelihood [probability] that the true ejection fraction falls within the predicted category, taking into account the expected error range.

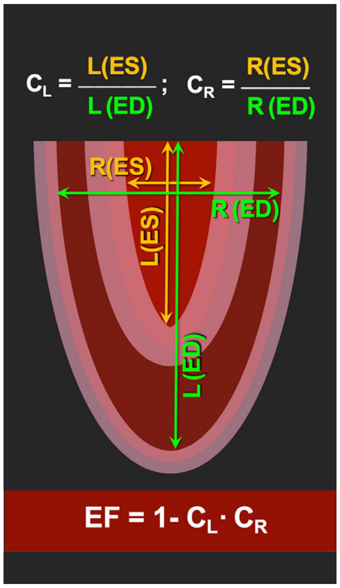

Figure 1. Schematic depiction of the principle of the Caption AI AutoEF algorithm.

Contraction coefficients in the longitudinal and radial directions, C_L and C_R, defined as the ratios between ventricular dimensions, L and R, at end-systole (ES) and end-diastole (ED) are estimated and used to calculate ejection fraction (EF). This is based on the assumption that LV volume changes from ED to ES according to the changes in these dimensions, i.e. $\mathbf{V(ES) = V(ED) \cdot C_L \cdot C_R}$.

For example, if during systole, the ventricle shortens by 14%, C_L would be 0.86, and if at the same time its radial dimension shortens by 30%, corresponding to C_R value of 0.70, this would result in an EF of 40%: $\mathbf{EF = 1 - [0.86 \cdot 0.70] = 1 - 0.60 = 0.40}$.

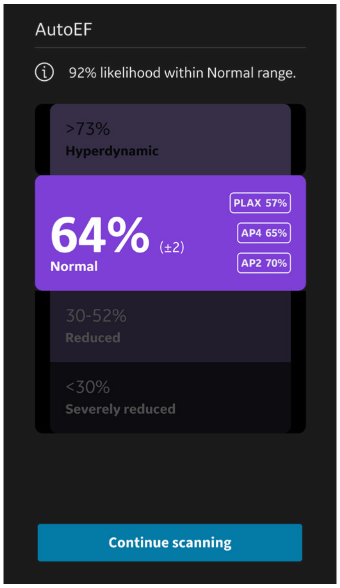

Figure 2. Screenshot of Caption AI software showing AutoEF calculation with expected error range and confidence estimate.

Validation

Caption AI AutoEF received 510(k) clearance from the U.S. FDA in 2020, and results from performance testing have been published in two peer-reviewed studies.[3,4] First, testing was performed on an independent group of 99 patients with diverse body habitus and LV function. Automated EF values generated using AP2 and AP4 views were compared with reference values obtained by sonographers using conventional volume-based methodology (biplane Simpson technique) and overread by three expert cardiologists. Inter-technique agreement was assessed using linear regression and Bland-Altman analysis. Consistency was assessed using mean absolute deviation (MAD) among automated estimates from different combinations of apical views. Finally, sensitivity and specificity of detecting of EF ≤35% were calculated. These metrics were compared side-by-side against the same reference standard to those obtained through conventional EF measurements by clinical readers.

Automated estimation of LV EF was feasible in all patients. AutoEF values showed high consistency (MAD = 2.9%) and excellent agreement with the reference values *(Figure 3)*: ***r*** **= 0.95**, **bias = 1.0%**, **limits of agreement = ±11.8%**, with sensitivity 0.90 and specificity 0.92 for detection of EF ≤35%. This was similar to clinicians' measurements: ***r*** **= 0.94**, **bias = 1.4%**, **limits of agreement = ±13.4%**, sensitivity 0.93, specificity 0.87.

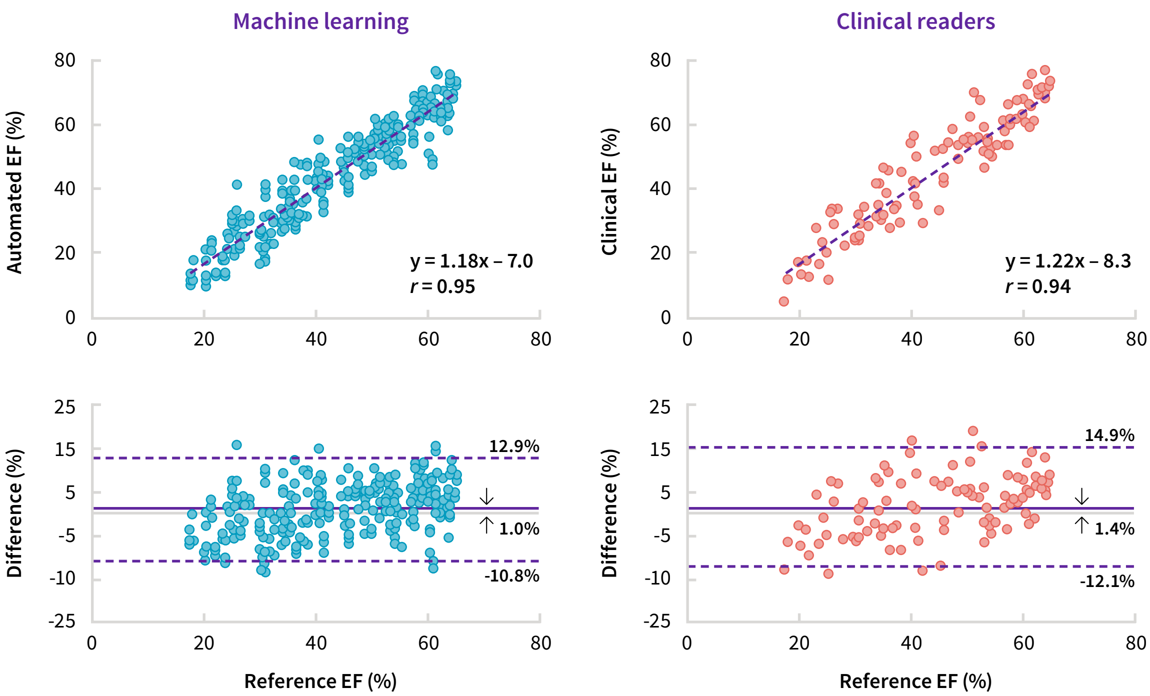

Figure 3. Agreement between the automated EF measurements (left), side-by-side with the clinical measurements (right) against reference values obtained by averaging measurements by a panel of 3 experts: linear regression (top) and Bland-Altman analysis (bottom).

In point-of-care (POC) settings, acquisition of AP2 and AP4 views by non-echocardiographers can be challenging. As a result, most POC clinicians tend to rely on visual assessment of easier-to-obtain views, such as PLAX, for evaluation of LV function. Thus, the software was modified to quantify LV EF from any one of the aforementioned three views alone or from any combination of these views available in an individual patient.

The updated version of the algorithm underwent similar performance testing on an independent group of 166 patients. Reference EF was obtained using conventional measurements by experts, and both automated and reference EF values were used to categorize LV function. Additionally, LV function was visually estimated for each view by a group of 10 physicians, including three trained imaging cardiologists and seven POC clinicians, and the accuracy of detection of reduced LV function (EF <53%) by the algorithm and the physicians was assessed against the reference classification.

The algorithm was able to analyze at least one view in all patients. Agreement with the reference EF values was very good (intraclass correlation, 0.86–0.95), with minimal biases (<2%) *(Figures 4 and 5)*. Automated EF classification showed similar accuracy to that by physicians in most views, with only 10% to 15% cases where it was less accurate. All MAD values were <7%, including those based on a single PLAX view, for which the largest difference was noted; this was similar to MAD between the experts' individual biplane measurements, which was 9%.

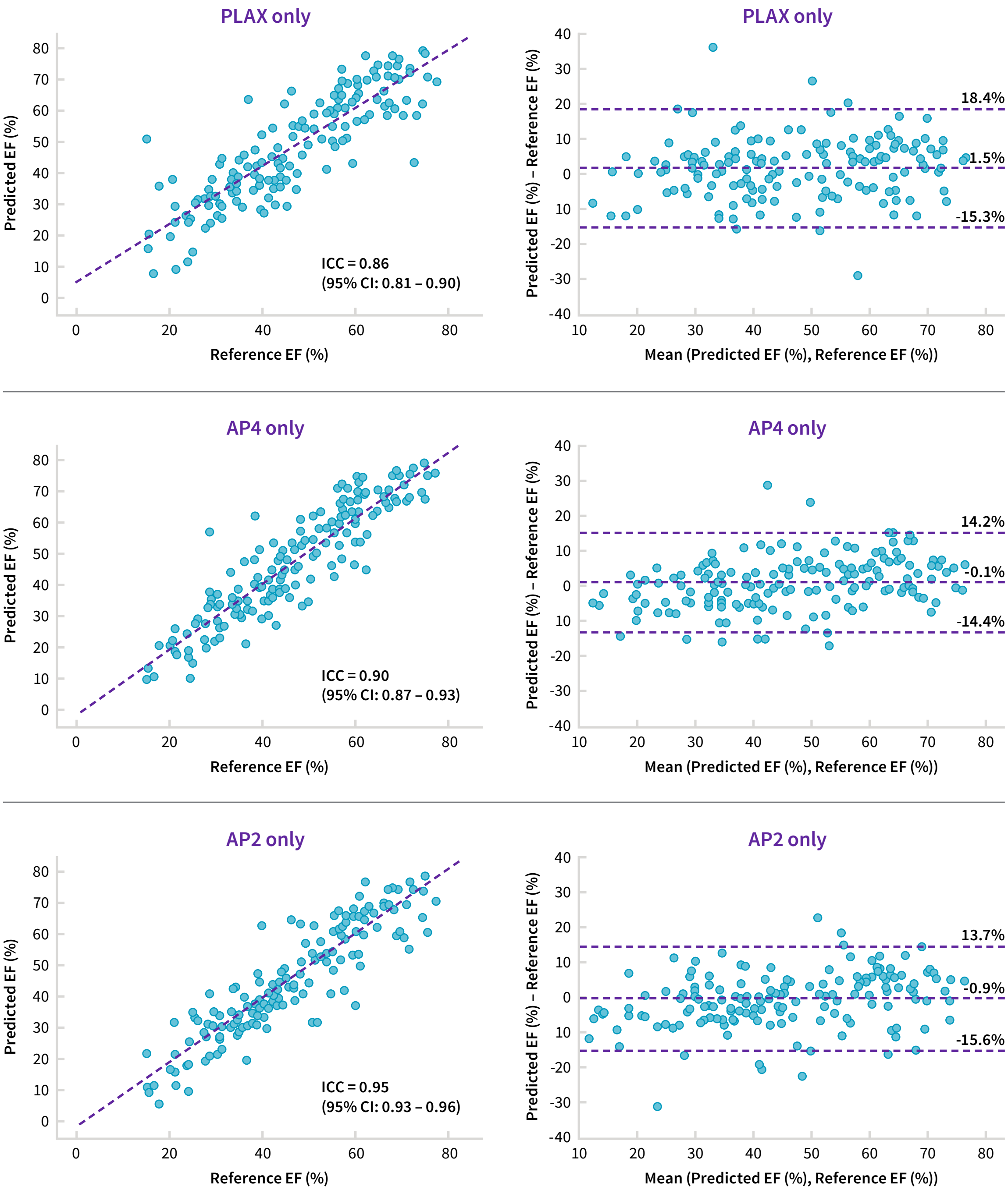

Figure 4. Agreement between automated ejection fraction measurements and reference values: intraclass correlation (ICC, left) and Bland-Altman analysis (right). Data shown for the 3 single views.

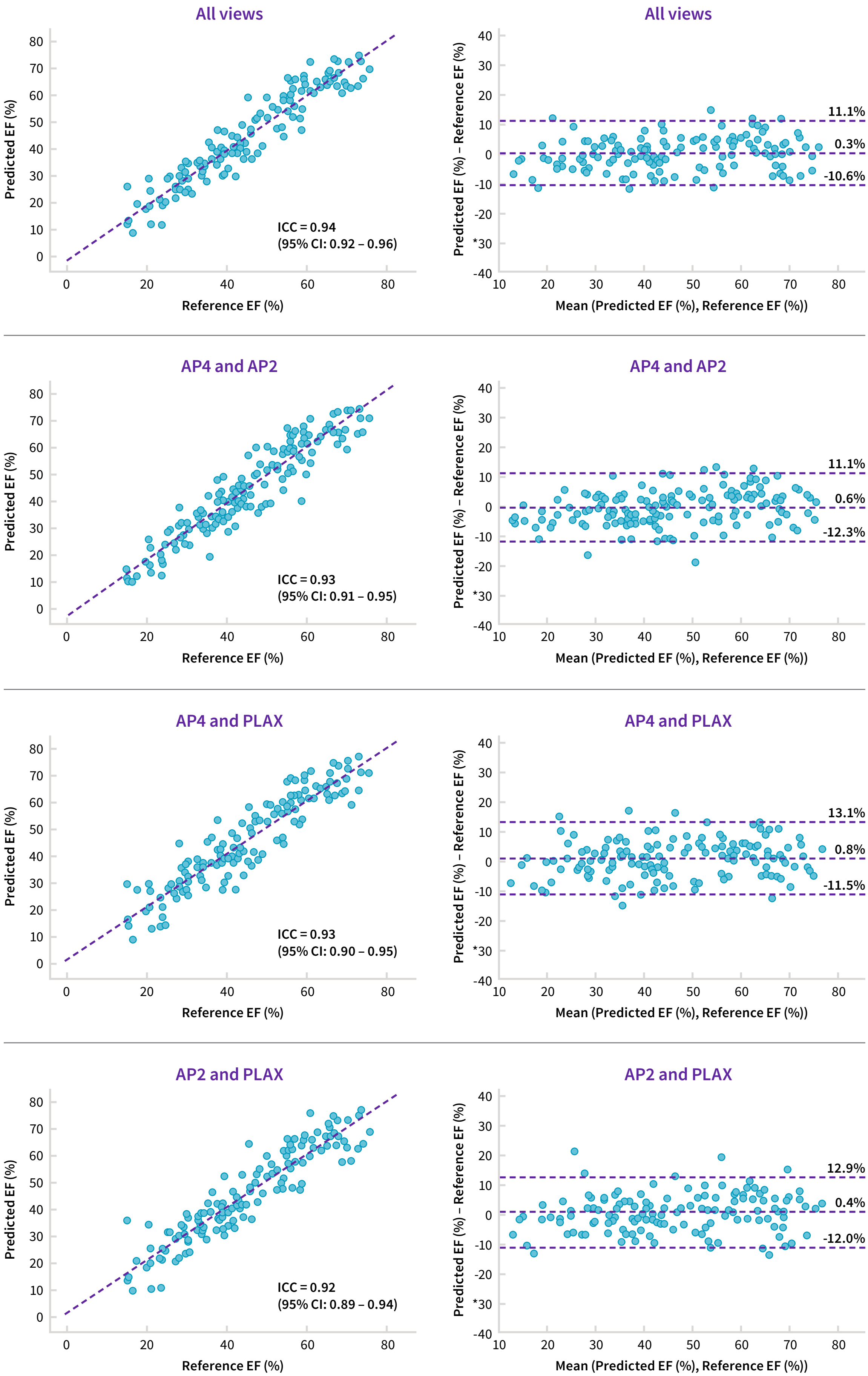

Figure 5. Agreement between the automated ejection fraction measurements and reference values: intraclass correlation (ICC, left) and Bland-Altman analysis (right). Data shown for the 4 possible combinations of 2 and all 3 views.

Caption AI AutoEF on Vscan Air™ SL

Performance of Caption AI AutoEF on the Vscan Air SL was validated on a dataset of 102 subject studies,[5] assembled to represent a balance of males and females, a range of ejection fraction values, and a significant portion of high body mass index patients as is typically associated with technically difficult studies.

All single-view AutoEF results (PLAX, AP4, AP2) surpassed the single-view root mean square deviation (RMSD) performance target of 11%, and all view combination results (AP4 & AP2; AP4 & PLAX; AP4, AP2 & PLAX; AP2 & PLAX) surpassed the combined views performance target of 9.2%. Notably, single-view AutoEF values met not only the plan acceptance criteria of 11%, but also met the stricter acceptance criteria for combined views of 9.2%, demonstrating good performance even on single-view AutoEF calculations.

Impact

As the number of clinicians performing bedside echocardiograms in point-of-care settings grows, the need for accurate determination of LV EF increases in parallel. Caption AI AutoEF software was designed to address this need. This technology can support healthcare personnel who are developing their ultrasound skills to confidently interpret bedside cardiac ultrasound examinations, particularly when combined with technologies aimed at assisting image acquisition, such as Caption AI scan guidance (DEN190040, K201992).

1. Lang RM, Badano LP, Mor-Avi V, 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. doi:10.1016/j.echo.2014.10.003.
2. ACEP Emergency Ultrasound Standard Reporting Guidelines. June 2018.
3. Asch FM, Poilvert N, Abraham T, 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. doi:10.1161/CIRCIMAGING.119.009303.
4. Asch FM, Mor-Avi V, Rubenson D, et al. Deep Learning-Based Automated Echocardiographic Quantification of Left Ventricular Ejection Fraction: A Point-of-Care Solution. *Circ Cardiovasc Imaging.* 2021;14(6):e012293. doi:10.1161/CIRCIMAGING.120.012293.
5. Caption AI Echocardiography Guidance Software User Manual. Part Number 734-01562 Rev 04. Caption Health/GE HealthCare.

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February 2026
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