Cardiovascular Ultrasound

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The diagnostic accuracy of left ventricular ejection fraction assessment between visual and artificial intelligence-based algorithms on bedside ultrasound

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Abstract

Background Focused cardiac ultrasound (FoCUS) has become the standard of care for bedside assessments of cardiac function. With the integration of artificial intelligence (AI), there is limited evidence comparing it to bedside visual assessments by experienced users.

Methods In our prospective study conducted at Tufts Medical Center in Boston, Massachusetts from December 2020 to March 2022, patients ≥ 18 years requiring a TTE were recruited by convenience sampling. They each underwent FoCUS LVEF classification by AI and bedside visual assessment, with TTE as reference. LVEF was calculated by Simpson's biplane method of disks in AI-FoCUS and TTE, and visual global assessment by the bedside sonographer. Data analysis was completed in October 2025.

Results Our 215 participants had a median age of 63 (IQR 49–73) years with 83 (38.6%) being female. AI-FoCUS assessments showed good agreement with TTE (intraclass correlation coefficient 0.84, 95% CI: 0.80–0.88), while visual assessments had stronger concordance (intraclass correlation coefficient 0.97, 95% CI: 0.96–0.98). Categorization of LV dysfunction severity showed excellent agreement with TTE for both AI-FoCUS (kappa 0.89, 95% CI: 0.84–0.94) and visual estimate (kappa 0.96, 95% CI: 0.92–0.99). For AI-FoCUS, the area under the curve (AUC) for identifying an abnormal LVEF (< 50%) was 0.9779 (95% CI: 0.9591–0.9967) with sensitivity 90.9% (95% CI: 88.1–100), specificity 95.6% (95% CI: 92.6–98.6), positive predictive value (PPV) 0.79 (95% CI: 0.66–0.92) and negative predictive value (NPV) 0.98

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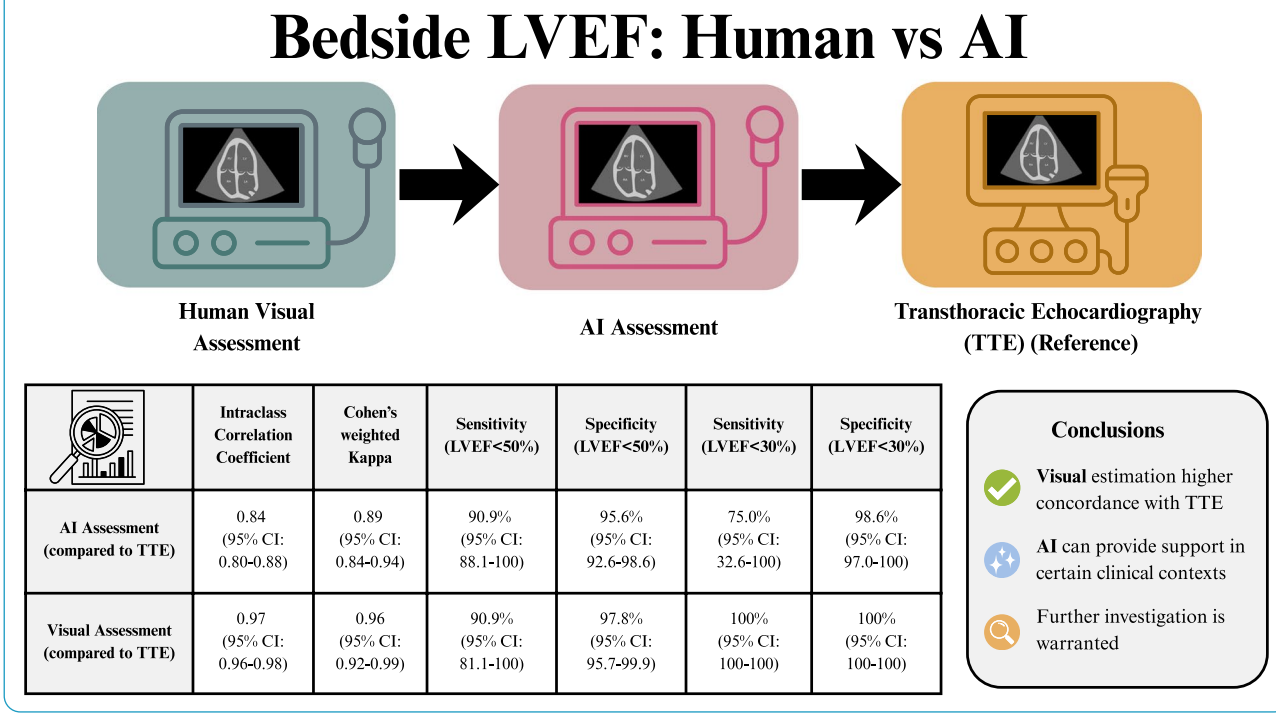
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(95% CI: 0.96–1.00). For visual estimate, the AUC was 0.9961 (95% CI: 0.9915–1.000) with sensitivity 90.9% (95% CI: 88.1–100), specificity 97.8% (95% CI: 95.7–99.9), PPV 0.88 (95% CI: 0.77–0.99) and NPV 0.98 (95% CI: 0.96–1.00).

Conclusion AI-assisted FoCUS LVEF assessments provide accurate estimates for the presence and severity of LV dysfunction but are outperformed in the latter by experienced bedside users.

Keywords Echocardiography, Point-of-care ultrasound, Left ventricular ejection fraction, Heart failure, Artificial intelligence, Diagnostic accuracy

Graphical Abstract



Background

Assessment of cardiac function is fundamental in the assessment of cardiovascular disease [1–4]. Transthoracic echocardiography (TTE) is the most commonly used cardiac imaging modality, providing comprehensive information on structure and function [5, 6]. Due to potential logistical constraints and the requirement of specialized expertise, formal TTE is often not readily available in a number of settings such as emergency departments, critical care and inpatient wards, where it has been shown to significantly impact patient care and management [7–9]. Focused cardiac ultrasound (FoCUS) is an alternative method to assessing cardiac structure and function with the use of portable ultrasound devices, and has become part of the standard of care for bedside cardiovascular assessments as an adjunct to physical examination [10–12]. Newer bedside ultrasound devices have integrated artificial intelligence (AI), providing novel opportunities to enhance both the acquisition and interpretation of FoCUS studies [13–16].

The integration of AI into clinical practice continues to grow, influencing how clinicians acquire, interpret, and respond to diagnostic data [17, 18]. The role of AI has also expanded, as various algorithms have been validated in image interpretation and clinical care [19, 20]. These technologies offer the potential to help improve diagnostic accuracy, especially in settings with minimal resources and few experienced personnel [21, 22].

Though FoCUS is becoming increasingly common in clinical settings, its effectiveness is limited by operator dependency [22, 23]. The risks of misinterpretation influenced by operator experience and clinical setting contribute to ongoing challenges in bedside FoCUS assessments [24, 25]. AI may serve as a useful tool to assist diagnosis in such scenarios, helping to improve clinical workflow and patient care. However, its integration into routine care requires validation studies and comparison to the current standard of care, physician bedside assessments, to determine if it improves diagnostic accuracy.

The objective of our prospective observational study was to evaluate the diagnostic accuracy of LVEF assessment by FoCUS using both visual and AI assessments with formal TTE as reference, to better define the

capabilities and limitations of AI-enabled point-of-care cardiac imaging.

Study design and methods

Ethical approval

Informed verbal consent was provided by all participants, or their substitution decision maker, prior to enrollment. Ethics approval was obtained from the Tufts Institutional Review Board.

Study design

This is a secondary analysis of a prospective, single-center observational study conducted at the Tufts Medical Center (Boston, United States). Patients who were 18 years or older and scheduled to receive a formal TTE were eligible for study inclusion. There were no exclusion criteria. Due to hospital workflow constraints a convenience series was used for participant enrollment, occurring from December 2020 to March 2022.

Every FoCUS assessment was completed by a trained cardiac sonographer within 48 h of formal TTE where LVEF was calculated by visual estimate first, and then AI interpretation. Most participants were imaged in the left lateral decubitus position. If this was not possible, assessments were completed with the patient supine or sitting upright. If at least one of the FoCUS assessments was incomplete – either due to non-diagnostic images or the AI device being unable to calculate an LVEF – these participants were excluded from data analysis.

Visual bedside LVEF assessment

Patients had a bedside visual assessment of their LVEF using the EchoNous KOSMOS point-of-care ultrasound machine device (Redmond, United States). KOSMOS is a hand-held, 64-channel diagnostic medical ultrasound system that uses a machine-learning workflow. The bedside users were trained cardiac sonographers that acquired apical four-chamber and two-chamber views, if possible, and estimated the LVEF based on their global assessment. This assessment was completed prior to both AI-LVEF assessment and cart-based TTE image acquisition, as to not bias interpretation. The visual LVEF assessment was completed immediately prior to the AI-based assessment. Formal cart-based LVEF image acquisition was completed at that time as well.

FoCUS AI LVEF assessment

All of the AI-FoCUS LVEF assessments were completed using only the EchoNous KOSMOS point-of-care ultrasound machine device. The methods and workflow of our study have been previously described [16]. In brief, following the acquisition of apical four- and two-chamber views and identification of the end-diastolic and end-systolic frames, LVEF was calculated with the modified Simpson's biplane method of disks. As the studies were conducted back-to-back, image quality was congruent between visual and AI assessment. All AI-acquired tracings and image frames were left unmodified, meaning that the echocardiographers were unable to manually correct the measurements.

Transthoracic echocardiography LVEF assessment

An experienced level-three echocardiographer performed the TTE studies with a cart-based system. As with the AI-assisted FoCUS assessments, LVEF was calculated in the apical four-chamber and two-chamber views by the modified Simpson's biplane method of disks.

Statistical analysis

Means and standard deviations (SD) were used to summarize continuous variables with normal distributions, while median and interquartile range (IQR) were used for non-normal distributions. Frequencies and percentages summarized categorical variables.

Intraclass correlation coefficients (ICC) were used to analyze agreement between both bedside AI and visual estimates of LVEF, compared to formal TTE LVEF as the reference standard. We performed a Bland–Altman plot and calculated the level of agreement and bias between AI-FoCUS and TTE LVEF, as well as between visual estimates and TTE LVEF. A Cohen's weighted kappa coefficient was calculated to determine categorical agreement for the severity of LV dysfunction. Categories of LVEF were determined as normal (≥ 50%), mild (40–49.9%), moderate (30–39.9%) or severe dysfunction (< 30%). A receiver operating characteristic (ROC) curve was used to assess bedside AI-FoCUS LVEF measurement and visual assessment identifying abnormal (< 50%) and severely reduced (< 30%) LVEF. We determined the sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) for abnormal and severely reduced LVEF for both AI and visual assessments. All reported p-values are two-sided, and a value less than 0.05 was considered to indicate statistical significance. Analyses were performed using SAS 9.4. Devices used in our study for obtaining bedside AI-FoCUS LVEF were provided by Echonous. Findings are presented in accordance with the STARD reporting guidelines.

Results

Baseline characteristics

Of the 222 patients enrolled in our study, seven participants were excluded due to non-diagnostic image quality in FoCUS imaging, leaving 215 patients for our analysis. The median age of all participants was 63 years (IQR 49–73) with 83 (38.6%) being female (Table 1). The median weight was 82.2 kg (IQR 70.3–93.8) and median BMI was 27.3 kg/m^2 (IQR 24.3–32.8). 25 (11.6%)

Table 1 Baseline patient characteristics

Characteristic	All studies (*N* = 215)
Age (years), median (IQR)	63 (49–73)
Female Sex (%)	83 (38.6)
BMI (kg/m^2), median (IQR)	27.3 (24.3–32.8)
Weight (kg), median (IQR)	82.2 (70.3–93.8)
Smoking History	
Never (%)	146 (67.9)
Current (%)	21(9.8)
Former (%)	48 (22.3)
Hypertension (%)	142 (66.1)
Diabetes Mellitus (%)	51 (23.7)
Congestive Heart Failure (%)	80 (37.2)
Chronic Obstructive Pulmonary Disease (%)	19 (8.9)
Hyperlipidemia (%)	128 (59.5)
Previous Myocardial Infarction (%)	29 (13.5)
Previous Transient Ischemic Attack/Cerebrovascular Accident (%)	14 (6.5)
Previous Coronary Artery Bypass Grafting (%)	11 (5.1)
Previous Percutaneous Coronary Intervention (%)	20 (9.3)
≥ moderate Mitral Regurgitation (%)	8 (3.7)
≥ moderate Mitral Stenosis (%)	1 (0.5)
≥ moderate Aortic Regurgitation (%)	1 (0.5)
≥ moderate Aortic Stenosis (%)	13 (6.1)
Echo contrast needed (%)	25 (11.6)
Formal Transthoracic Echocardiogram Assessment	
Left ventricular ejection fraction, median (IQR)	60% (52.2–63.1)
Abnormal left ventricular ejection fraction < 50% (%)	33 (15.4)
Mildly reduced left ventricular ejection fraction 40–49.9% (%)	16 (7.4)
Moderately reduced left ventricular ejection fraction 30–39.9% (%)	13 (6.1)
Severely reduced left ventricular ejection fraction < 30% (%)	4 (1.9)

Abbreviations: IQR Interquartile range, *BMI* Body mass index

participants required an echocardiogram with contrast during their visit. There were 19 (8.9%) participants with a previous diagnosis of chronic obstructive pulmonary disease (COPD).

The median LVEF, measured on formal TTE, was 60% (IQR 52.2–63.1). There were 33 (15.4%) participants with abnormal LVEF (< 50%), of which only four (1.9%) were classified to have severely reduced LVEF (< 30%).

Assessing the presence of LV systolic dysfunction

Identifying the presence of LV systolic dysfunction, defined as a LVEF < 50%, using bedside visual assessment had an AUC of 0.9961 (95% CI: 0.9804–1.0000) (Fig. 1). This corresponds with a sensitivity of 90.9% (95% CI: 88.1–100) and specificity of 97.8% (95% CI: 95.7–99.9) when compared to formal TTE (Table 2).

With respect to AI-FoCUS assessments, the AUC was 0.9779 (95% CI: 0.9591–0.9967) with a sensitivity of 90.9% (95% CI: 88.1–100) and specificity of 95.6% (95% CI: 92.6–98.6) when compared to formal TTE (Fig. 1, Table 2).

Assessing the severity of LV systolic dysfunction

When comparing AI-FoCUS to formal TTE, there was good reliability with an ICC of 0.84 (95% CI: 0.80–0.88). In comparison, visual estimates produced a higher ICC of 0.97 (95% CI: 0.96–0.98). On average, LVEF from AI-FoCUS is 1.16% (SD 5.36%) less than LVEF derived from formal TTE, while Mean LVEF from the visual assessment is 0.08% (SD 2.60%) greater than formal TTE (Fig. 2).

With respect to grading the severity of LV dysfunction as normal, or mildly, moderately or severely reduced, there were no cases where the grading difference between AI and visual assessments were off by more than one category in comparison to TTE (Table 3). The Cohen's weighted kappa for LVEF by AI-FoCUS was 0.89 (95% CI: 0.84–0.94) and the visual assessment was 0.96 (95% CI: 0.92–0.99). For detection of severe LV dysfunction (< 30%), AI-FoCUS had an AUC of 0.9923 (95% CI: 0.9915–1.0000) (Fig. 1), which correlates to a sensitivity of 75.0% (95% CI: 32.6–100) and specificity of 98.6% (95% CI: 97.0–100) when compared to formal TTE. Meanwhile, visual estimate had an AUC of 1.0000 (95% CI: 1.0000–1.0000) (Fig. 1) with a corresponding sensitivity of 100% (95% CI: 100–100) and specificity of 100% (95% CI: 100–100) when compared to formal TTE (Table 2). It should be noted that these statistics are applied to a small sample of only four patients found to have severe LV dysfunction.

Discussion

In our prospective study of 215 patients, we found that LVEF assessments by FoCUS with visual estimate by the bedside user were closer in comparison to formal TTE assessments than AI-FoCUS assessments. While AI-assisted LVEF assessments demonstrated good accuracy in identifying the presence and severity of LV dysfunction, visual assessments were superior with grading the severity of LV dysfunction. Although, the number of participants with severe LV dysfunction (LVEF < 30%) was small, limiting the interpretation of results for this specific subgroup.

Prior studies have demonstrated that AI-guided handheld ultrasound devices can be effective in automating image analysis [16, 26, 27]. In the case of FoCUS, it has been primarily used to streamline image acquisition and improve reproducibility, both of which are traditionally

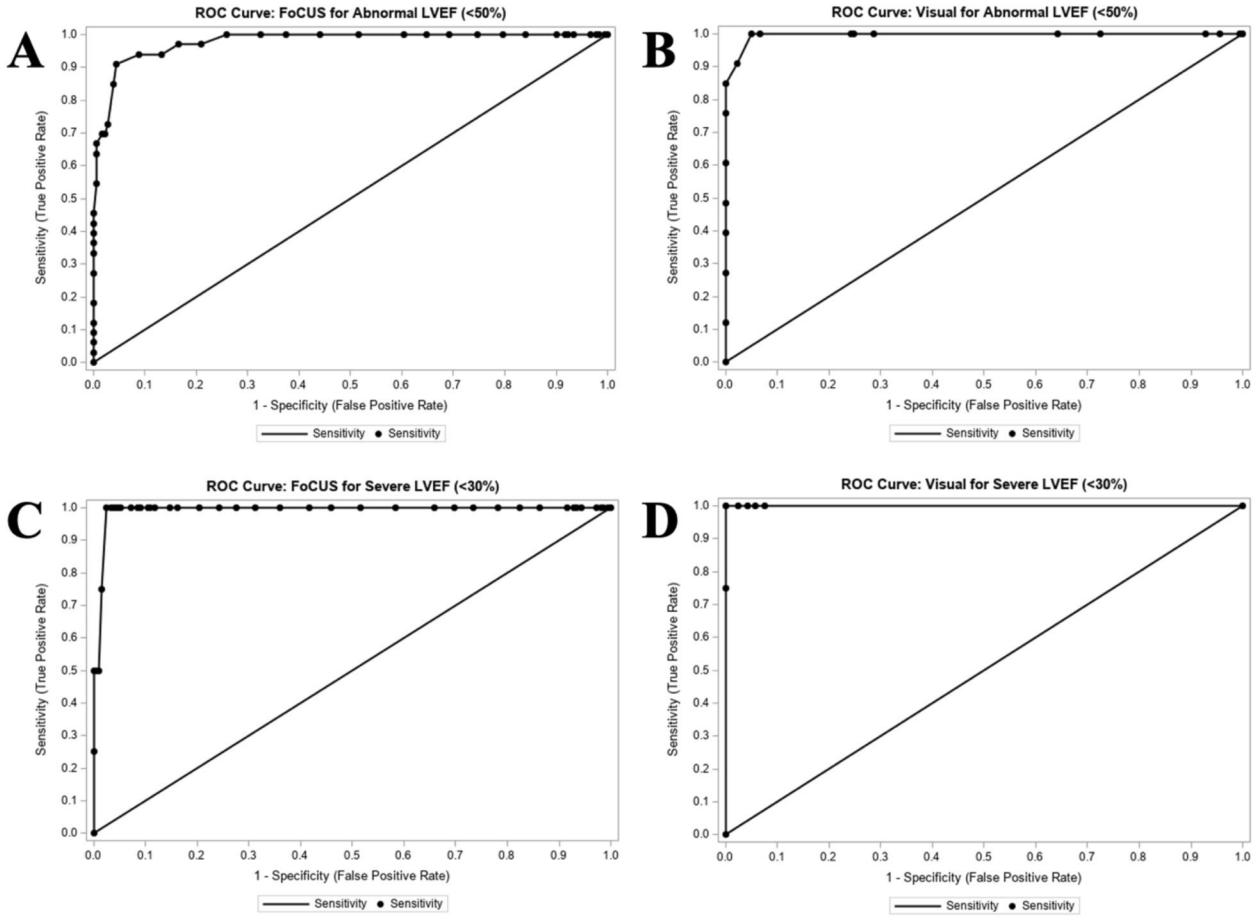


Fig. 1 ROC Curves for diagnosing LV dysfunction. Identification of abnormal LVEF (< 50%) by **A**) AI-FoCUS and **B**) visual assessment, as well as identification of severely reduced LVEF (< 30%) by **C**) AI-FoCUS and **D**) visual assessment

limited by operator experience [28, 29]. A multicenter diagnostic study investigating a novel deep-learning (DL) algorithm found that most clinical parameters assessed by novice nurses using the DL algorithm had greater than 90% agreement in comparison to scans by trained sonographers [13]. This illustrates the potential for AI to help close the gap between novice and more experienced technicians. Another diagnostic study analyzing the accuracy of AI-FoCUS LVEF assessments determined that novice and experienced operators showed consistent reliability when compared to TTE, with ICC values of 0.921 and 0.845, respectively [16]. These findings suggest that AI assistance in cardiovascular assessment can help provide diagnostic accuracy for operators of varied experience. As FoCUS becomes more widely adopted, especially among clinicians with variable training, AI has the potential to improve the quality and consistency of cardiovascular assessments.

Our findings highlight that current AI-assisted imaging still falls short of matching the performance of trained bedside users as it does not match the accuracy of trained echocardiography technologists when assessing LVEF. Of note, the cardiac sonographers in our study have formal training, which is not completely reflective of the diversity of real-world FoCUS users. As such, the difference in performance between AI and visual assessment in our study may not be consistent with the real-world FoCUS users. While AI has not surpassed expert human interpretation, it may still provide support in certain clinical environments. AI can serve as a valuable adjunct for early learners, trainees, or clinicians practicing in settings with limited access to formal imaging. In such clinical contexts, AI-FoCUS can help bridge gaps in expertise. It offers the potential for standardized, reproducible LVEF assessment and may support diagnostic confidence in uncertain cases [30]. Furthermore, AI integration has the potential to streamline workflow by automating measurements and allowing echocardiographers more time for complex pathology [31, 32]. However, it is crucial to mitigate the introduction of bias into AI imaging models before their wide adoption in the clinical setting [33]. Moving forward, continued advancements in algorithm training and real-world validation are needed before AI can rival

Table 2 Summary of comparative statistics

Comparative Statistic	AI (compared to TTE)	Visual Assessment (compared to TTE)	*p*-value
Bland–Altman Statistics			
Mean Difference	−1.16%	0.08%	
SD of Difference	5.36%	2.60%	
Interval of Agreement	−11.66% to 9.34%	−5.03% to 5.18%	
Measures of Agreement			
Intraclass Correlation Coefficient (95% CI)	0.84 (0.80–0.88)	0.97 (0.96–0.98)	
Cohen's weight Kappa (95% CI)	0.89 (0.84–0.94)	0.96 (0.92–0.99)	
Difference in ICCs	−0.08 (−0.14–0.02)		
Accuracy in identifying LV dysfunction (LVEF < 50%)			
Sensitivity (95% CI)	90.9% (88.1–100)	90.9% (81.1–100)	
Specificity (95% CI)	95.6% (92.6–98.6)	97.8% (95.7–99.9)	
Positive Predictive Value (95% CI)	0.79 (0.66–0.92)	0.88 (0.77–0.99)	
Negative Predictive Value (95% CI)	0.98 (0.96–1.00)	0.98 (0.96–1.00)	
AUC (95% CI)	0.9779 (0.9591–0.9967)	0.9961 (0.9804–1.0000)	0.03
Accuracy in identifying severe LV dysfunction (LVEF < 30%)			
Sensitivity (95% CI)	75.0% (32.6–100)	100% (100–100)	
Specificity (95% CI)	98.6% (97.0–100)	100% (100–100)	
Positive Predictive Value (95% CI)	0.50 (0.10–0.90)	1.00 (1.00–1.00)	
Negative Predictive Value (95% CI)	1.00 (0.99–1.00)	1.00 (1.00–1.00)	
AUC (95% CI)	0.9923 (0.9915–1.0000)	1.0000 (1.0000–1.0000)	0.20

Abbreviations: AI Artificial intelligence, *AUC* Area under the curve, *CI* Confidence interval, *LVEF* Left ventricular ejection fraction, *SD* Standard deviation, *TTE* Transthoracic echocardiogram

expert human interpretation. For now, AI-FoCUS is best viewed as a complementary tool to the physicians' multi-faceted assessment.

Table 3 Classification of LVEF severity by visual estimate and AI interpretation compared to formal TTE

	Visual Estimate				
Formal TTE		Normal (≥ 50%)	Mildly reduced (40–49.9%)	Moderately reduced (30–39.9%)	Severely reduced (< 30%)
	Normal (≥ 50%)	178	3	0	0
	Mildly reduced (40–49.9%)	4	13	1	0
	Moderately reduced (30–39.9%)	0	0	12	0
	Severely reduced (< 30%)	0	0	0	4
	Artificial Intelligence-Assisted				
Formal TTE		Normal (≥ 50%)	Mildly reduced (40–49.9%)	Moderately reduced (30–39.9%)	Severely reduced (< 30%)
	Normal (≥ 50%)	174	8	0	0
	Mildly reduced (40–49.9%)	3	12	1	0
	Moderately reduced (30–39.9%)	0	4	6	3
	Severely reduced (< 30%)	0	0	1	3

Abbreviations: *TTE* Transthoracic echocardiogram

Limitations

Our study has limitations that should be considered. First, participants were enrolled through convenience sampling rather than systematic selection. While this approach allowed for pragmatic data collection, it may also introduce operator bias, especially if the echocardiographer had a pre-existing impression of the patient's LVEF. Second, the single-center design may limit the generalizability of our findings. Although the Tufts Medical Center supports a diverse patient population, replication of this work in a broader range of clinical environments,

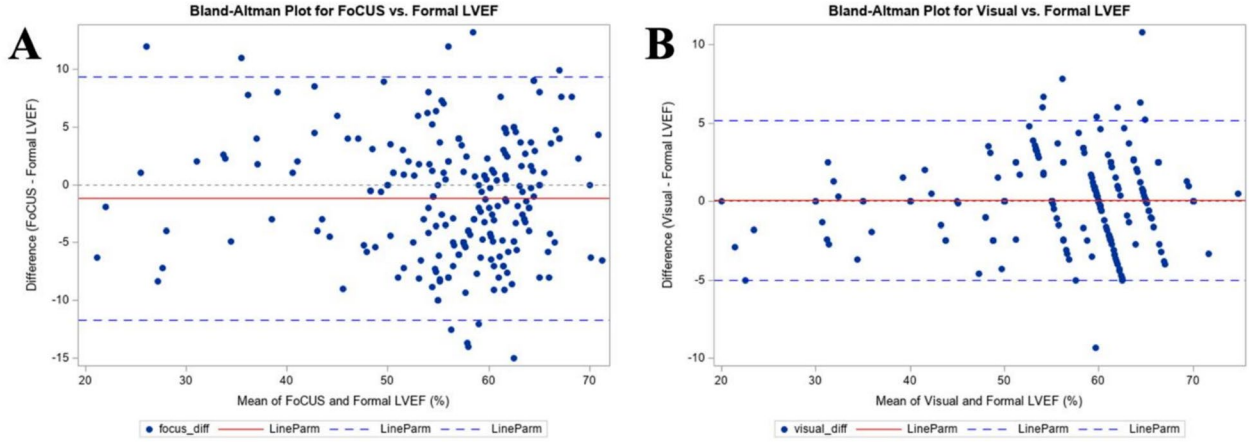


Fig. 2 Bland–Altman plots for LVEF assessment by **A**) AI-FoCUS vs formal TTE and **B**) visual assessment vs formal TTE

including more rural and community settings, will be important for external validity. Future multicenter studies with standardized enrolment protocols may help address both selection and operator bias. Third, while our sample size was adequate for the primary comparisons of LVEF, the number of participants with severely reduced LVEF (< 30%) was very small, with only four in the entire population meeting this threshold. This limits our ability to draw conclusions regarding AI capability for identifying this clinically important subgroup. Lastly, and as previously highlighted, our bedside visual assessments were completed by trained cardiac sonographers. These findings cannot be extrapolated to all users of FoCUS, especially non-cardiologists who do not have the same formal TTE experience or rigorous training in cardiac imaging.

Conclusion

In our single-center prospective study, we found that visual assessments of LVEF by trained echocardiography technicians using FoCUS are more closely aligned with formal TTE assessment than AI-assisted FoCUS. AI demonstrated good diagnostic performance, though it was outperformed by human interpretation across all statistical measures. These findings suggest that AI can provide useful support for bedside cardiac imaging, especially in settings with limited expertise or resources. Further investigation to evaluate AI performance across broader populations is warranted.

Abbreviations

AI	Artificial intelligence
AUC	Area under the curve
BMI	Body mass index
CI	Confidence interval
COPD	Chronic obstructive pulmonary disease
DL	Deep learning
FoCUS	Focused cardiac ultrasound
ICC	Intraclass correlation coefficient
IQR	Interquartile range
LV	Left ventricle
LVEF	Left ventricular ejection fraction
NPV	Negative predictive value
PPV	Positive predictive value
ROC	Receiver operating characteristic
SD	Standard deviation
STARD	Standards for reporting of diagnostic accuracy
TTE	Transthoracic echocardiography

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12947-026-00377-3.

Supplementary Material 1.

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Dr. Jeffrey A Marbach is the guarantor of the content of this manuscript, including the data and analysis.

Authors' contributions

NK, NB, PM, JM were responsible for study design. PM, GPP, SP, PDS, OAR, RJ, WB, MT recruited patients, acquired ultrasound studies and completed data extraction. NB was responsible for data synthesis and analysis. All authors contributed to the data interpretation and drafted the manuscript. All authors contributed to reviewing and editing of the final manuscript. All authors approved the final version of the manuscript.

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Data availability

Due to the strict ethical approvals provided in our study, the data used is available from the corresponding author upon request and after establishment of data sharing agreement between institutions.

Declarations

Ethics approval and consent to participate

Informed verbal consent was provided by all participants, or their substitution decision maker, prior to enrollment. Ethics approval was obtained from the Tufts Institutional Review Board.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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