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Review article

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Artificial intelligence-enhanced echocardiography in cardiovascular disease management

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Abstract

Artificial intelligence (AI) is transforming echocardiography, ushering in an era of improved diagnostic precision, efficiency and patient care. In this Review, we present an in-depth exploration of AI applications in echocardiography, highlighting the latest advances, practical implementations and future directions. We discuss the integration of AI throughout the echocardiographic workflow, from image acquisition and analysis to interpretation. We outline the potential of AI to automate routine measurements and calculations, enable task shifting, recognize disease-specific patterns and uncover new phenogroups that might surpass current diagnostic classifications. Moreover, we address the aspects needed to create trustworthy AI systems, through careful validation, navigating regulatory requirements and upholding ethical standards, thereby presenting a balanced perspective on the advantages and limitations of this rapidly evolving technology. Through an examination of current AI applications, clinical studies and technological breakthroughs, we offer a comprehensive understanding of the evolving role of AI in the future of echocardiography and its capacity to advance cardiovascular care, while also acknowledging the current limitations of the widespread clinical implementation of AI-supported echocardiography.

Sections

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Key points

- Echocardiography is a crucial tool in cardiology, but is time intensive, produces variable results and requires technical expertise, and current workforce shortages worldwide create delays in patient care.
- Artificial intelligence (AI) technologies offer transformative solutions for echocardiography, allowing automated image classification, segmentation and measurement.
- AI methods have shown potential in guiding image acquisition, automating routine echocardiographic measurements such as left ventricular function and detecting cardiovascular diseases such as cardiac amyloidosis, hypertrophic cardiomyopathy and valvular heart disease.
- Beyond improving workflows and standardization in echocardiography laboratories, potential clinical applications include screening and monitoring for cardiovascular diseases, improving efficacy in clinical trials, task shifting and the expanded use of mobile devices.
- AI-enhanced echocardiography is advancing rapidly and being integrated into clinical practice at leading centres, but further research is warranted to address its limitations.
- Developers of AI-enhanced echocardiography should prioritize creating trustworthy applications that support the implementation of user-friendly AI to improve patient care.

Introduction

Echocardiography is a cornerstone of cardiovascular imaging, providing real-time, non-invasive assessment of cardiac structure and function. However, the acquisition and interpretation of echocardiograms is time consuming, expert dependent and prone to variability[1–3]. Furthermore, echocardiographic advances in the past decade have included new techniques (such as strain imaging) and new clinical indications (for example, cardio-oncology), introducing even more specialized requirements for imaging and interpretation, leading to longer and more complex echocardiographic studies. With the growing burden of cardiovascular disease, the limitations of current echocardiography workflows have led to workforce shortages, sonographer injuries and extended waiting times for patients[4].

Artificial intelligence (AI) technology offers promising solutions to these challenges, driving a paradigm shift in how echocardiographic examinations are performed and interpreted[5]. Although AI in medical imaging is not entirely new, its application to echocardiography has necessitated navigating several unique challenges. Instead of a single still image, a typical echocardiographic study consists of ~70 videoclips collected from different transducer positions on the chest, approximating a 3D moving object using multiple 2D cross-sectional images, with variability from one video to another, as well as beat-to-beat variability within each video. Key advances in AI (Box 1) paved the way for AI-enhanced echocardiographic quantification and interpretation over the past decade. Machine learning, a core technology within AI, enabled systems to learn and improve from data, unlike traditional programming, which followed fixed instructions[6]. Deep learning, an advanced form of machine learning, utilizes neural networks inspired by the human brain to process complex data such as text, images and videos. These models can be trained using supervised learning, in which labelled data guide the algorithm, or unsupervised learning, in which patterns are discovered from unlabelled data (Fig. 1). Pioneering applications of deep learning in echocardiography were the automatic segmentation of the left ventricle in echocardiography images in 2012[7] and the development of convolutional neural networks models that could accurately classify echocardiographic standard views from images and videos[8–10]. These advances provided the foundation for subsequent AI applications to isolate specific heart structures, such as chambers, valves and myocardium, in the echocardiography images and subsequent interpretation and measurements of the images[11].

Just as AI is revolutionizing electrocardiography[12], its integration into echocardiography could democratize access to high-quality, efficient echocardiography. Indeed, rapid advances in AI are transforming echocardiography by improving standardization, accuracy, and efficiency in image acquisition and analysis, improving disease detection and facilitating cardiovascular care. AI approaches can be applied at multiple levels in echocardiography, including mathematical modelling of tabular data from structured reports and natural language processing to extract data from unstructured text. In this Review, we explore the current state of AI in echocardiography, with a focus on AI applications that use echocardiographic image data (Fig. 2) and highlight its clinical applications, challenges and future directions.

AI in echocardiography image analysis

AI holds the potential to transform the workflow in echocardiography, from image acquisition and analysis, to interpretation, reporting and clinical decision-making (Fig. 2). Each step in the conventional workflow is labour intensive and time consuming, with an operator dependency that leads to high variability in assessment[1–3]. AI-assisted image analysis offers important potential benefits such as improved precision, reduced user variability and substantial time savings[13–15]. Several fully automated measurement methods based on AI are already commercially available, and the field is rapidly expanding.

Multistep versus end-to-end models for image analysis

Two main approaches have emerged in AI-assisted image analysis: multistep and end-to-end models[16] (Fig. 1). Multistep models use dedicated neural networks to solve specific tasks sequentially. For example, fully automated methods have been developed to first classify relevant image views, then identify end systole and end diastole, perform myocardial segmentation, label cardiac chambers and, finally, quantify cardiac structure and function[11,13,15,17–21]. Visualizing the predictions at each step, such as the identification of views and structures and performing measurements, can improve explainability, which is key to engendering trust and clinical adoption. Advances in explainable AI aim to build trust in these models by making their internal processes more understandable[22]

By contrast, end-to-end models, often referred to as 'black box' models, predict outcomes directly from images without the intermediate steps[23–26]. For instance, an algorithm was developed and trained to automatically estimate left ventricular (LV) ejection fraction (EF) from a database of >50,000 echocardiographic studies without the need for endocardial delineation (that is, the algorithm was not guided by developers as to where the endocardial border should be traced). Instead, the algorithm was allowed to learn from the thousands of images, features and visual patterns necessary to estimate EF in agreement with the reference values obtained by human readers using conventional

Box 1 | Key advances in AI and their application in echocardiography

- The pioneering theories of British mathematician Alan Turing during the 1930s laid the foundation for modern computing and artificial intelligence (AI)[143]. Advances in AI, along with increased processing power and reduced costs, are now 'democratizing' AI, making it more accessible[144,145]. However, developing safe and effective AI applications for medical use still demands substantial expertise and resources. Moreover, clinicians must understand AI principles, including machine learning, deep learning and model validation, to ensure safe and effective implementation[128,146].
- Machine learning, a core technology within AI, enables systems to learn and improve from data, unlike traditional programming, which follows fixed instructions[6]. This adaptability is particularly valuable in medical imaging, where data are complex and varied. For example, machine learning models can analyse each pixel in an echocardiography image, assess its relationship with surrounding pixels and integrate patterns across sequences of images.
- Deep learning, an advanced form of machine learning, utilizes neural networks inspired by the human brain to process complex data, such as text, images and video. These networks consist of interconnected layers that process different aspects of the data and learn through iterative adjustments of network weights[16,147]. Three primary deep learning approaches exist:
  - Supervised learning, whereby algorithms learn by analysing data for which the answers are already known, such as identifying left ventricular myocardium in echocardiographic images. In this approach, the model learns by itself which features in the images are associated with specific structures. Supervised learning is the most widely used method in AI echocardiography.
  - Unsupervised learning, whereby the algorithm explores patterns in the data without predefined answers or labels. Although promising for discovering novel patterns and hidden structures, the application of unsupervised learning is highly challenging, particularly because of the difficulty of interpreting its predictions and understanding the underlying reasoning.
  - Reinforcement learning, where algorithms improve through trial and error by receiving rewards for correct decisions and penalties for mistakes. This approach encourages the system to identify the best strategy for maximizing the overall reward over time[146,148].

Despite the power of deep learning approaches, there are challenges in their application. One particular pitfall is the management of uncertainty because these models often produce predictions even when input data are insufficient. In addition, deep learning models rely heavily on the training data, particularly the accuracy of labels, whether anatomical structures or disease categories. This reliance can propagate biases or errors present in the training dataset, potentially leading to incorrect predictions.

- Generative AI, a more recent extension of deep learning, creates new data, such as text or images, by identifying patterns in existing datasets. Combined with natural language processing, large language models have the potential to automate tasks, such as summarizing echocardiographic reports, suggesting diagnoses and recommending therapies, thereby streamlining the echocardiography workflow[149–151]. However large language models also have limitations. A key challenge is their tendency to produce unreliable predictions, often referred to as 'AI hallucinations', in which the system generates plausible-sounding but incorrect information. Additionally, large language models require extensive training on diverse and representative datasets to minimize biases and ensure generalizability, and they offer limited human oversight, raising concerns about accountability in clinical decision-making.
- Foundation models, trained on large datasets through self-supervision, are a recent advance in deep learning. Unlike traditional task-specific models, foundation models are highly adaptable and can be fine-tuned for various applications, offering versatility across domains. For instance, using multimodal learning (for example, text and imaging data), trained models can analyse echocardiographic data and predict variables such as ejection fraction without being specifically trained for that task[129,152,153]. However, this technology is still in the early stages and, like traditional 'black box' models, foundation models often lack transparency in their feature extraction.

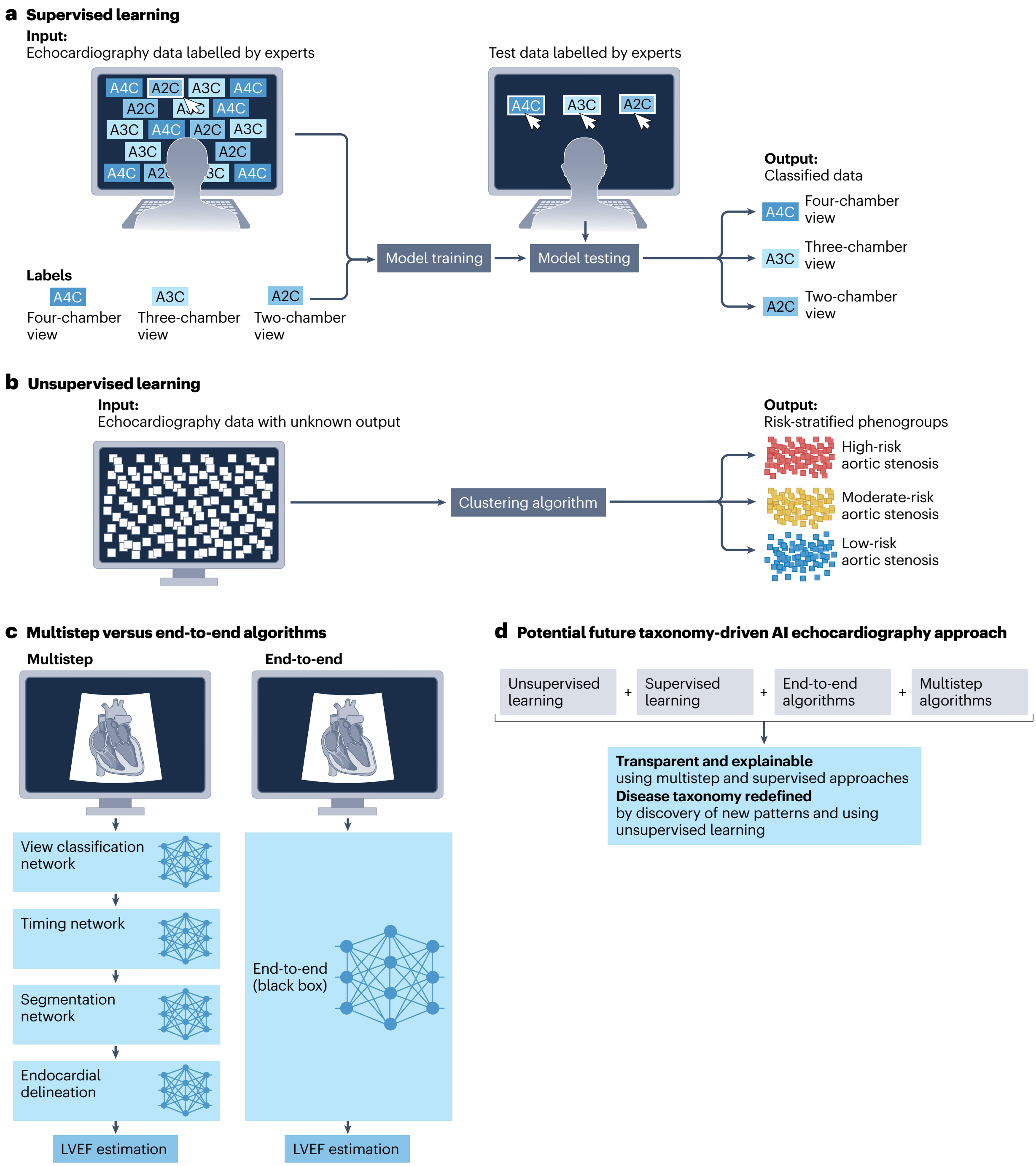
methodology[25]. Whereas multistep approaches offer transparency at each stage, end-to-end models can be more challenging for clinicians to interpret and trust. Another challenge in developing generalizable end-to-end models is that they require more training data than multistep models, often necessitating tens of thousands of labelled images.

LV systolic function

Automating the quantification of LV systolic function has been one of the most successful applications of AI in echocardiography so far (Table 1). Both multistep[13,15,17] and end-to-end[25] models have been used for the calculation of LVEF. Such methods have demonstrated good agreement with the reference measurements of experts[18,21], with better reproducibility and reduced variability compared with human readers[13,15,18]. AI algorithms in 2D echocardiography have also demonstrated good concordance with reference measurements of 3D LV volumes and EF[27]. Moreover, AI automation can provide real-time results during scanning, as well as reduce the time needed to perform and analyse routine echocardiograms by 70–80%, without sacrificing accuracy[15,28].

Most AI methods estimate LVEF using labelled views, such as the apical four-chamber and two-chamber views[15,18,25,27,29,30], or only the four-chamber view[21,23,31]. However, these views are not always available or lack sufficient image quality, limiting the accuracy of the estimation. A more robust approach might involve models trained on a broader range of views. One such model, trained on 12,648 examinations, automatically identified the parasternal and the three apical long-axis views, and estimated LVEF based on the available views with an R^2 of 0.84 and a mean absolute error of 4.0%, making this model more resilient than previous AI methods to missing or suboptimal images[32].

AI models are also accurate for quantifying LV global longitudinal strain without any human input, which differs from the traditionally used semiautomatic methods. A fully automated, multistep deep learning-based method calculated global longitudinal strain from apical views, showing excellent correlation with traditional semiautomatic



measurements in diverse pathologies (Pearson's $R = 0.93$)[33]. Of note, the minimal detectable change in global longitudinal strain between repeated examinations, which is crucial for monitoring cardiac function, such as in patients with cancer receiving cardiotoxic treatment, was reduced from 5.5 to 3.7 (ref. 34). Using a novel point-tracking deep learning technology, the reproducibility of regional strain measurement improved, matching the interobserver reproducibility of global longitudinal strain measurements from commercial semiautomatic software, with a calculation time of <1 s, making routine regional strain assessment a practical reality[35]. Furthermore, AI automation of LV strain measurements has been extended to include accurate quantification in patients with diverse pathologies, including heart failure (HF) and myocardial infarction[19]. Although some models estimate global longitudinal strain with an accuracy comparable to that of human experts (correlation 0.85 and median absolute error 2.0 global longitudinal strain percentage units)[36], other models have demonstrated a more modest agreement with manual measurements (correlation 0.56 and bias −3.3%)[37].

AI-based image analyses are paving the way for innovative uses of echocardiography in new clinical settings. For instance, acquisition and

Fig. 1 | Overview of AI approaches in echocardiography. Key artificial intelligence (AI) approaches for echocardiography analysis. **a**, Supervised learning. Labelled echocardiography data are used to train an AI model for view classification, enabling the automatic identification of the apical four-chamber (A4C), two-chamber (A2C) and three-chamber/long-axis (A3C) views. Supervised learning models excel at predicting outcomes within well-defined categories but can encounter challenges as classifications and clinical definitions evolve. **b**, Unsupervised learning. The AI model clusters unlabelled echocardiography data into phenogroups that are based on the risk of adverse events in patients with aortic stenosis, potentially discovering new disease subclasses. This method can refine disease taxonomies by identifying patterns without predefined categories, particularly in complex conditions such as heart failure, diastolic dysfunction and aortic stenosis, for which clinical definitions are evolving. **c**, Differences between multistep and end-to-end approaches for the estimation of left ventricular ejection fraction (LVEF). In the multistep approach, AI sequentially performs tasks such as view classification, structure labelling and LVEF calculation, offering transparency (allowing clinicians to verify the accuracy at each step). This transparency increases trust and ensures human oversight during the analysis. By contrast, the end-to-end model directly predicts LVEF from raw images without manual labelling or intermediate steps, which makes the process more efficient, but with the internal processes less visible to clinicians. This method requires explainable AI advances to increase trust because the decision-making process is harder to trust. **d**, The possible future approach in which a combined model integrates both supervised and unsupervised learning with multistep and end-to-end methods, leveraging the strengths of each to advance echocardiographic analyses by offering adaptability, accuracy and transparency across varied clinical scenarios.

analysis of images to evaluate LVEF was feasible for novice health-care staff, such as medical students and nurses, demonstrating their potential for use in echocardiographic screening in non-specialized settings[38–40]. A deep learning-based model for automatic and continuous measurements of mitral annular plane systolic excursion using hands-off transoesophageal echocardiography (TEE) demonstrated good agreement with manual measurements and identified haemodynamic alterations, thereby showcasing the potential for haemodynamic monitoring in intensive care units[41,42].

Quantification of chamber dimensions

Quantification of LV dimensions has a crucial role in guideline-directed follow-up, prognostication and therapeutic decision-making for patients with HF, valvular heart disease, congenital heart disease or cardiomyopathies. Automating these measurements would improve workflow efficiency and accuracy. A multistep deep learning-based model trained in 64,028 echocardiograms showed good accuracy in predicting LV end-diastolic diameter (mean absolute error 2.09 mm), LV end-systolic diameter (mean absolute error 2.04 mm), wall thicknesses (mean absolute error 0.99 mm and 0.93 mm) and left atrial anteroposterior diameter (mean absolute error 2.52 mm)[43]. Comparable accuracy was achieved using end-to-end models in parasternal long-axis images from various patient populations[44,45].

AI has also showed promising results for estimating chamber volumes. A multistep model trained in 600 individuals, including patients with HF, demonstrated strong agreement between the AI and expert's measurements of LV end-diastolic volume, LV end-systolic volume and left atrial end-systolic volume (intraclass correlations of 0.83, 0.85 and 0.85, respectively)[18]. The variability between automated and human measurements was lower than the variability among humans (individual equivalence coefficients of −0.81, −0.79 and −0.61, respectively).

LV diastolic function

Although a key task in echocardiography, clinical assessment of LV diastolic function is challenging and hampered by observer-related variability[3]. Specific challenges for implementation of AI models in image analysis for diastolic function evaluation are related to the use of spectral Doppler imaging, including poor signal-to-noise ratio, optimal beam alignment, or automatically identifying the location of Doppler sampling and timing of key cardiac events.

Models have been developed to assess LV diastolic function directly from echocardiographic images, performing both automated measurements and integrating the results to grade diastolic function without the need for manual input[20,46–50]. For instance, a multistep deep learning method identified patients with an E/e' ratio of ≥13 with area under the curve (AUC) of 0.91 in a large external dataset[13]. In another study, a multistep deep learning-based model using B-mode and Doppler images was trained to calculate and integrate LVEF, left atrial volume and Doppler parameters, and demonstrated an AUC of 0.88 for algorithmic classification of diastolic function[20]. Another multistep method that integrated automated diastolic parameters from multiple views achieved a concordance of 94% with guideline-based evaluations of diastolic dysfunction and demonstrated prognostic value, with an adjusted hazard ratio of 3.03 (95% confidence interval of 1.16 to 9.14) for the composite outcome of all-cause death and HF-related hospitalization[50].

Left atrial function

The quantification of left atrial strain using semiautomatic speckle-tracking software has provided valuable diagnostic and prognostic information across a broad range of cardiac pathologies[51,52]. However, AI-based measurements have been less explored. A multistep model trained on a dataset of 30,000 examinations and externally tested for automated diastolic assessment demonstrated a high correlation between AI-based and manual measurements of left atrial reservoir strain ($r = 0.87$, mean absolute error 3.1%)[50]. In a study assessing diastolic function, a good agreement was observed between AI-estimated and manual measurements of left atrial strain (bias <1%, limits of agreement from 7% to 8%)[49]. AI-based measurements of left atrial strain have also been shown to be a reliable predictor of pulmonary capillary wedge pressure in patients with HF, with a performance superior to that of E/e' and global longitudinal strain[53]. Specific challenges in applying AI to the left atrium that will need to be addressed include the anatomical complexity and thin walls of the left atrium, the susceptibility to image artefacts and the lack of standardized left atrial focus imaging views in available datasets.

Right ventricular function

Although the prognostic importance of right ventricular (RV) dysfunction is well established, few studies have focused on AI-based quantification of right ventricular function[54]. Two end-to-end models have been trained to predict right ventricular EF directly from 2D four-chamber images and achieved a mean absolute error of 5.54% and 7.67% points compared with right ventricular EF derived from 3D echocardiographic images and magnetic resonance imaging, respectively[55,56]. Furthermore, deep learning-based models have shown promising results for

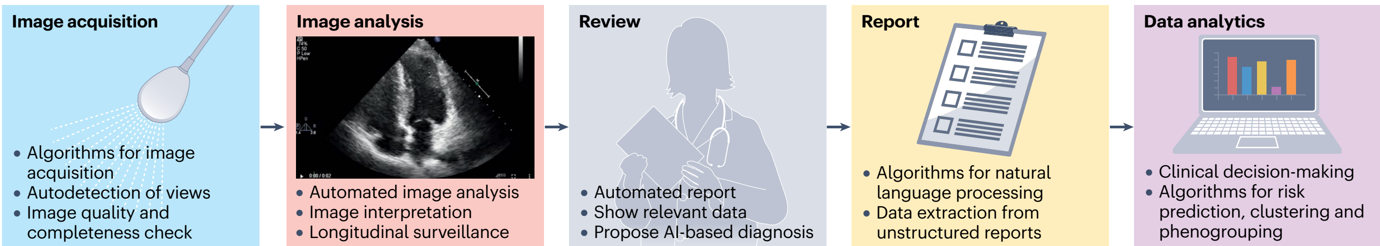


Fig. 2 | AI applied at different levels along the echocardiography workflow. Artificial intelligence (AI) approaches can be applied at multiple levels along the echocardiography workflow, from image acquisition and image analysis using 'raw' echocardiographic image data, to mathematical modelling of tabular data from structured reports and natural language processing to extract data from unstructured text.

quantification of right ventricular fractional area change, tricuspid annular plane systolic excursion and right ventricular free wall strain[18,57].

AI-enhanced echocardiography in disease detection

Deep learning-enhanced echocardiography offers transformative capabilities for cardiac disease detection (Table 2). By automatically encoding and integrating extensive information in image sequences, these systems can recognize complex features in data that evade human detection, such as subtle variations in cardiac echogenicity, wall motion and valve function, to identify patterns indicative of specific diseases. In this domain, end-to-end approaches and unsupervised learning can be exceptionally powerful.

Cardiomyopathies

Cardiomyopathies encompass a broad spectrum of diseases affecting the myocardium. Detecting cardiomyopathies can be challenging given their similarity in disease manifestations to more prevalent disorders. This challenge is particularly relevant in the early disease stages, when echocardiographic abnormalities might be minimal and, therefore, deployment of approved therapies is often delayed[58]. Furthermore, differentiating between various types of cardiomyopathies is crucial given that the therapeutic strategies vastly differ. Echocardiography typically serves as the primary tool for initially suspecting and identifying cardiomyopathies, and although multimodality imaging is recommended, its availability is often limited[59].

A landmark study from 2017 demonstrated the potential of a fully automated echocardiography algorithm to detect cardiomyopathy[11]. A deep learning-based method trained exclusively on 2D images identified hypertrophic cardiomyopathy with an AUC of 0.93 and cardiac amyloidosis with an AUC of 0.87 (ref. 11). Notably, the AI-predicted probability of disease showed a moderate correlation with key disease metrics such as LV mass (r = 0.23–0.36), indicating that the algorithm was capturing additional informative aspects of the images beyond standard measurements. Subsequent studies have corroborated these findings. For instance, a study reported an AUC of 0.90 for hypertrophic cardiomyopathy and 0.94 for cardiac amyloidosis, with near-perfect performance in detecting different forms of LV hypertrophy, achieving an AUC of 0.98 (ref. 60). A novel and clinically promising approach for detecting cardiomyopathies is to combine information from modalities that are inexpensive and readily available at hospitals worldwide. This approach is particularly relevant for patients with cardiac amyloidosis because advanced procedures, such as scintigraphy, cardiac magnetic resonance imaging, blood tests or cardiac biopsies, are required to establish the diagnosis[61]. Therefore, it is promising that a human-interpretation-free AI model has been shown to accurately detect cardiac amyloidosis, both transthyretin amyloidosis and light-chain amyloidosis, using a combination of electrocardiography and echocardiography[62,63]. Future studies using pattern recognition for rare diseases in the myocardium, in addition to the traditional quantification of cardiac structure and function, might lead to earlier diagnosis and better disease management.

Differentiating patients with cardiomyopathy from healthy volunteers represents a fundamental test for AI-assisted echocardiography. However, more clinically relevant comparisons are needed. For example, distinguishing between hypertrophic cardiomyopathy and physiological hypertrophy in the hearts of athletes can be challenging. A machine learning algorithm was shown to differentiate between physiological and pathological cardiac hypertrophic remodelling[64]. This algorithm achieved 87% sensitivity in identifying hypertrophic cardiomyopathy from athletic cardiac hypertrophy, which rose to 96% when accounting for age differences. Similarly, future research should also focus on distinguishing between conditions that can appear similar on echocardiography, such as conditions associated with thick cardiac walls, including cardiac amyloidosis, Fabry disease and hypertensive heart disease.

Valvular heart disease

Valvular heart disease demands precise diagnostic and grading tools to inform treatment strategies. Doppler imaging, including colour Doppler, continuous wave and pulsed wave, is essential for assessing valve function, whereas 2D echocardiography videos are needed to assess valve structure and motion. An ideal clinical decision support tool should integrate these diverse data streams for comprehensive analysis. This tool should not only identify the presence of valvular heart disease but also assess its severity. In case of discordant measurements, for example, when one measurement suggests severe valve disease whereas another only moderate disease, the software should present the relevant images and tracings used in each measurement to assist in decision-making. Advances in deep learning have led to the development of algorithms capable of diagnosing and quantifying common valvular diseases. AI-based analysis of aortic valve Doppler signals has shown high accuracy in matching human measurements of velocities (r = 0.97) and pressure gradients (r = 0.94), enabling accurate detection and quantification of aortic stenosis[65]. A well-designed study using self-supervised contrastive pretraining demonstrated that by only analysing 2D parasternal long-axis videos without Doppler imaging, a deep learning algorithm could accurately detect severe aortic stenosis with an AUC of 0.94–0.98 across internal and external

Table 1 | Major studies describing the development of AI algorithms for the echocardiographic quantification of cardiac structure and function

Study design and algorithm	Number of studies or samples	Performance	Ref.
LV structure and systolic function			
2D A4C, A2C. Training, internal and external validation; multistep	1,145 studies (training), 406 studies (internal), 1,029 studies + 31,241 studies + 10,030 images (external)	LVEF: MAE 6% to 10%, R 0.75–0.89	13
		LVESV: MAE 10 to 17 ml, R 0.83–0.95	
2D A4C, A2C. External validation; multistep	602 studies	LVEF: MAD 6.7%, LOA −1.2 ± 16, R 0.79	18
		LVESV: MAD 16 ml, LOA −1.5 ± 16 ml, R 0.89	
2D A4C, A2C. Internal and external validation, repeated echocardiography cohort and real-time echocardiography cohort; multistep	1,881 studies + 849 studies for validation, 40 patients with repeat echocardiography and 50 patients with real-time echocardiography	LVEF: MAE −5.5% to 0.3%, R 0.19–0.72	15
		LVESV: MAE −4 to 2.7 ml, R 0.67–0.92, 77% reduced measurement time	
2D A4C, A2C. Blinded, randomized trial of AI versus sonography assessment of LVEF; multistep	3,769 studies	LVEF: MAD 6.3% in AI group versus 7.2% in manual group (difference −0.96%, 95% CI −1.34% to −0.54%, P < 0.001)	21
Training, internal and external validation; multistep	212 images (training and internal validation), 148 images + 2,565 images + 450 images (external validation)	LVEF: MAE 3.7% to 5.6%, R 0.83–0.91	20
		LVESV: MAE 4.7 to 6.8 ml, R 0.96–0.97	
Training, internal and external validation; multistep	64,028 studies (training and internal validation), 9,248 studies + 10,030 studies (external validation)	LVEF: MAE 4.2% to 5.3%, R2 0.60–0.74	43
		LVESD: MAE 2.0 to 3.3 mm, R2 0.77–0.83	
2D A4C, A2C, A3C. Compared with 3D echocardiography; external validation; multistep	109 patients	LVEF: MAE −5.2% (−4.4% for 3D echocardiography), LOA 11.2% (11.4% for 3D echocardiography), R 0.70	27
		GLS: MAE 4%, LOA 6.3%, R 0.55	
		LVESV: MAE 5.7 ml, LOA 20.8 ml, R 0.84	
2D A4C, A2C. Internal and external validation; end-to-end	10,030 patients + 2,895 images	LVEF: MAE 4% to 6%, R2 0.77–0.81	23
2D A4C, A2C plus A3C, PLAX, PSAX for five-view model; end-to-end	340 patients + 189 patients	LVEF: MAE 0.9% (0.8% for five views), R 0.88 (0.92 for five views)	24
2D A4C, A2C. Estimate degree of contraction instead of border detection or volume assessment; end-to-end	>50,000 studies	LVEF: MAD 2.9%, R 0.95, LOA 11.8%	25
2D with either one of A4C, A2C or A3C, plus POCUS; end-to-end	166 patients + 67 patients	LVEF: MAE −0.6% to 0.8%, ICC −0.86 to 0.95	26
		LVEF: POCUS: ICC 0.84, MAE 2.5%	
Derivation and internal validation; end-to-end	6,417 studies (LVEF), 526 studies (GLS) and 8,427 studies (LVESV)	LVEF: MAD 6%, LOA 20%	11
		GLS: MAD 1.4%, LOA 5.8%	
		LVESV: MAD 9 ml, LOA 39 ml	
A4C, A2C, A3C. Fully automated measurements by motion estimation; multistep	200 patients with a wide range of LV function	GLS: MAD 1.4%, R 0.93	33
A4C, A2C, A3C. Test–retest reproducibility of the fully automated measurements by motion estimation; multistep	40 patients + 32 patients	GLS: MAD 1.4% to 1.6%, MDC 3.7% to 3.9%	34
A4C, A2C, A3C. External validation cohorts; multistep	3,741 real-world images + 176 echocardiography core laboratory images	GLS: MAE −0.7% to 0.7%, R 0.76–0.84	19
A4C, A2C, A3C. Internal and external validation; multistep	6,819 apical images + 300 apical images	GLS: MAE 2%, R 0.91	36
A4C view only. Internal and external validation; multistep	894 general studies, 68 studies of athletes, 2,782 studies of hypertrophic cardiomyopathy, 2,696 studies of hypertensive heart disease, 1,150 + 185 studies of cardiac amyloidosis	GLS: MAE −3.3%, ICC 0.56	37
PLAX. Internal and external validation; multistep	23,756 patients	IWT/PWT: MAE 1.2 to 1.7 mm/1.4 to 1.8 mm	45
		LV diameter: MAE 2.4 to 3.8 mm	
PLAX. Internal and external validation; multistep	1,265 studies + 100 studies	LV diameter: MAE 0 to −0.2, LOA 5.2 to 8.8 mm	44

Table 1 (continued) | Major studies describing the development of AI algorithms for the echocardiographic quantification of cardiac structure and function

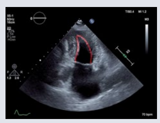
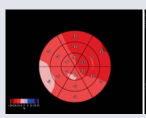
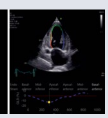
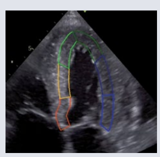
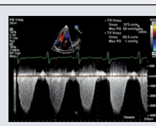
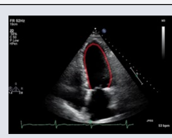
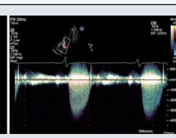
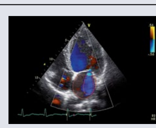
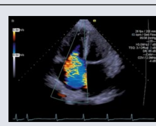
Study design and algorithm	Number of studies or samples	Performance	Ref.
LV diastolic function			
Doppler and tissue Doppler. Training, internal and external validation; multistep	1,145 studies (training), 406 studies (internal), 1,029 studies + 31,241 studies + 10,030 images (external)	*E*/*e*′: MAE 1.7 to 1.8, R 0.79–0.90	13
		e′: MAE 1.4 to 1.9, R 0.67–0.78	
Doppler and tissue Doppler. External validation; multistep	602 studies	*E*/*e*′: LOA 0.28 ± 4.31, R 0.95	18
		e′: LOA −0.02 ± 1.78 to −0.05 ± 2.33, R 0.94–0.95	
Doppler and tissue Doppler. Training, internal validation and external validation; multistep	862 studies + 239 studies (training and internal validation), 154 patients + 10,030 images + 450 images (external validation)	*E*/*e*′: bias 1.1 to 1.2, R 0.97–0.98	20
		e′: bias 0.7 to 1.1, R 0.93–0.98	
Doppler and tissue Doppler. Training, internal and external validation; multistep	1,304 studies + 2,238 studies (training and internal validation) + 388 studies (external validation)	*E*/*e*′: MAE −0.05 to 0.19	49
		TRV peak: MAE −3.5 to 1.7	
LA structure and function			
2D A4C, A2C. Training, internal and external validation; multistep	1,145 studies (training), 406 studies (internal), 1,029 studies + 31,241 studies + 10,030 images (external)	LA volume: MAE 5 to 11 ml, R 0.62–0.93	13
2D A4C, A2C. External validation; multistep	602 studies	LA volume: MAD 9.3 ml, LOA −0.7 ± 25 ml, R 0.88	18
2D PLAX. Training, internal and external validation; multistep	64,028 studies (training and internal validation), 9,248 + 10,030 studies (external validation)	LA dimension: MAE 2.5 mm, R2 0.75	43
2D A4C; multistep	339 studies	LA strain: MAE 3.2%, ICC 0.63	53
Doppler and tissue Doppler. Training, internal validation and external validation; multistep	1,304 studies + 2,238 studies (training and internal validation) + 388 studies (external validation)	LA volume: MAE −0.2 to −1.3 ml	49
		LA strain: MAE 0.07% to 0.71%	
Right-side heart structure and function			
2D A4C to predict 3D-derived RVEF. Training, internal and external validation; end-to-end	944 studies (training and internal validation), 365 studies (external validation)	RVEF: bias 4.6 to 5.5, R 0.67–0.75	55
2D A4C to predict cardiac MRI-derived RVEF; end-to-end	85 patients with pulmonary hypertension	RVEF: MAE 7.67%, R 0.65	56
2D, M-mode, strain. Training and internal validation; multistep	250 patients	FAC: MAE 0.8 ± 10.8%	57
		TAPSE: MAE −0.04 ± 0.54 cm	
		RVFW strain: MAE 0.2 ± 6.6%	
2D A4C and Doppler. External validation; multistep	602 studies	RA area: MAD 1.8 cm2, LOA −1.0 ± 4.4 cm2, R 0.91	18
		RV diameter: MAD 4.9 mm, LOA −2.1 ± 11.5 mm, R 0.64	
		TRV max: MAD 0.13 m/s, LOA −0.05 ± 0.39 m/s, R 0.93	

E/*e*′, ratio of early diastolic transmitral inflow velocity (*E*) to early diastolic mitral annular velocity (*e*′); A4C, apical four-chamber view; A2C, apical two-chamber view; A3C, apical three-chamber view; AI, artificial intelligence; CI, confidence interval; FAC, fractional area change; GLS, global longitudinal strain; ICC, intraclass correlation; IWT, intraventricular wall thickness; LOA, limit of agreement; LA, left atrial; LV, left ventricular, LVEF, left ventricular ejection fraction; LVESV, left ventricular end-systolic volume; MAD, median absolute deviation; MAE, mean absolute error; MDC, minimal detectable change; PLAX, parasternal long axis; POCUS, point-of-care ultrasonography; PWT, posterior wall thickness; RA, right atrial; RV, right ventricular; RVEF, right ventricular ejection fraction; RVFW, right ventricular free wall; TAPSE, tricuspid annular plane systolic excursion; TRV, tricuspid regurgitant velocity.

datasets representative of a general screening population[66,67]. This Doppler-free approach has also been proven to be feasible for aortic stenosis screening in 2D imaging datasets without Doppler, accurately distinguishing between no, mild or mild-to-moderate aortic stenosis and more advanced (moderate or severe) disease with an AUC of 0.75 (ref. 68). This approach shows promise for point-of-care screening of valvular heart disease using deep learning-based echocardiographic technologies.

Mitral regurgitation can generally be visually detected using colour Doppler imaging, but quantification proves challenging owing to the need to integrate multiple echocardiographic modalities. Consequently, interobserver variability in mitral regurgitation assessment often occurs, leading to inconsistent classification of severe mitral regurgitation and decreased accuracy in determining the optimal timing of intervention. Deep learning algorithms designed for apical view assessment of colour Doppler images across the mitral valve have been developed for quantifying mitral regurgitation severity. Such algorithms have demonstrated accurate classification of mitral regurgitation severity across a large number of studies and cohorts, with AUCs >0.90 for the identification of moderate or severe mitral regurgitation[69,70]. This simple approach of only using colour Doppler assessment has considerable potential for automated screening of mitral regurgitation. In addition, AI-automated assessment of proximal isovelocity surface area has been shown to be feasible, with a deep learning-based model demonstrating strong agreement with reference measurements (intraclass correlation of 0.83) for fully automated

Table 2 | Artificial intelligence-assisted echocardiography for disease detection

Conditions	Echocardiography examples	Scientific evidence
Cardiomyopathies		
Cardiac amyloidosis	 	Accurate detection from 2D images Distinction from physiological hypertrophy Combination with electrocardiography to further improve detection Pattern recognition
Hypertrophic cardiomyopathy		
Heart failure		
Heart failure with preserved ejection fraction		Accurate detection of heart failure from a single apical four-chamber view Accurate detection of heart failure from automated global longitudinal strain images Black box models for detecting left ventricular pressures
Heart failure with reduced ejection fraction		
Ischaemic heart disease		
Regional wall motion abnormalities	 	Regional strain of accurately detects regional wall motion abnormalities Differentiates Takotsubo syndrome from acute myocardial infarction
Myocardial infarction		
Pulmonary hypertension		
Precapillary, post-capillary		Accurate measurement of tricuspid regurgitation velocity Detection from 2D images only Distinguish precapillary versus post-capillary pulmonary hypertension
Valvular heart disease		
Aortic stenosis and regurgitation	 	Near-perfect accuracy in measuring Doppler signals Accurate detection of aortic stenosis from 2D images Quantification of mitral regurgitation severity by integrating multiple measures Surveillance of disease progression using 3D echocardiography
Mitral stenosis and regurgitation		
Tricuspid regurgitation		

The figures for cardiac amyloidosis, heart failure with preserved ejection fraction, heart failure with reduced ejection fraction, ischaemic heart disease, aortic stenosis, mitral regurgitation and tricuspid regurgitation are adapted from ref. 142.

integrated proximal isovelocity surface area measurements, while accounting for both non-hemispherical convergence and flow rate variations over time[71]. An alternative approach might even integrate multiple measures of mitral regurgitation severity. A deep learning model was trained to measure 16 mitral regurgitation-related parameters in a cohort of individuals with any degree of mitral regurgitation selected from the general population[72]. The preferred model used nine of these parameters to achieve an AUC of 0.97 for moderate or severe mitral regurgitation versus no or mild mitral regurgitation. Phenotyping of mitral regurgitation by AI-based echocardiography analysis has also been shown to improve prediction of event-free survival after mitral valve surgery[73]. Finally, algorithms have also been developed for automated assessment of valves by 3D echocardiography, enabling automated measurements of the aortic, mitral and tricuspid valves[74].

HF

HF is a clinical syndrome characterized by specific signs and symptoms, corroborated by evidence of cardiac abnormalities detected through imaging, and the gold standard diagnostic test remains invasive measurement of elevated LV filling pressures[75]. Echocardiographic detection of LV dysfunction, which has been demonstrated to be performed accurately by AI in several studies[13,15,19,21,23,33] (Table 1), is a prerequisite but not sufficient on its own for diagnosing clinical HF. For example, systolic dysfunction defined by LVEF <40% and diastolic function defined by E/e' >13 can reliably be detected among all-comers with an AUC of 0.90–0.92 with the use of multistep AI models[13]. By using end-to-end methods trained to identify HF with preserved EF (HFpEF), algorithms analysing only a single apical four-chamber video clip can diagnose HFpEF with AUCs of 0.95–0.97 (ref. 76). This AI model was able to correctly reclassify 74% of participants who were previously stratified as having intermediate risk of HFpEF according to the HFA-PEFF and H2FPEF clinical scores. Moreover, a second version of this HFpEF AI model successfully predicted the risk of HF-related hospitalizations, with incremental prognostic value beyond that of the clinical scores[77]. Deep learning-based strain analysis alone has shown promising results in identifying patients with clinical HF, with greater accuracy for HF with reduced EF (HFrEF) (AUC of 0.98) than for HFpEF (AUC of 0.82)[19]. However, additional data are needed to detect HF as defined by invasive measurements[53].

Ischaemic heart disease

Echocardiography is the most commonly used non-invasive imaging tool for detecting regional LV wall motion abnormalities in the diagnostic assessment of suspected myocardial infarction. The accurate recognition of wall motion abnormalities by echocardiography requires trained and experienced physicians because the abnormalities can be subtle. However, deep learning-based algorithms have shown promise in detecting regional wall motion abnormalities from the standard apical views in patients with suspected acute myocardial infarction. Compared with expert readers, an algorithm detected regional wall motion abnormalities with an AUC of 0.85 for bedside echocardiography and 0.90 for standard echocardiography[78]. Other studies of deep learning-based detection of regional wall motion abnormalities from apical views have yielded similar results[19,24,79]. AI models have also been applied to stress echocardiography to assess ischaemia in patients with suspected coronary artery disease. In the PROTEUS trial[80], participants undergoing a stress echocardiogram were randomly assigned to undergo AI-augmented image interpretation or standard of care, but the AI-assisted decision-making did not demonstrate non-inferiority. However, AI stress echocardiography was found to be beneficial for less-experienced clinicians and in subgroups of patients in whom images are known to be difficult to interpret. The ability of AI models to discriminate myocardial infarction from mimicking conditions such as Takotsubo syndrome has also been investigated. In a study using a real-time AI method for the fully automated interpretation of echocardiograms, the system differentiated these two conditions with an AUC of 0.79, which was more accurate than the classification performed by cardiologists[81].

Pulmonary hypertension

Dyspnoea is a common indication for echocardiography, whereby the accurate assessment of pulmonary artery pressure is required. The pulmonary arterial pressure is typically estimated using Doppler imaging of the tricuspid regurgitation velocity, which can be accurately quantified by AI echocardiography[13]. However, a reliable measurement is not always available owing to insufficient tricuspid regurgitation jet or poor image quality. Elevated pulmonary pressures can also result in right ventricular enlargement and dysfunction, which can be detected on 2D echocardiography images. By training an AI model on apical four-chamber view images only, pulmonary hypertension was accurately detected with an AUC of 0.85 (ref. 11). Other AI algorithms have also been developed to classify pulmonary hypertension, and even distinguish precapillary versus post-capillary hypertension, with significantly better predictive accuracy than guideline-based echocardiographic assessment[82,83].

AI in image acquisition

Image quality and standardized imaging views are crucial for accurate measurements and diagnostic interpretations in echocardiography. The processing speed of deep learning-based systems enables real-time user feedback during scanning, thereby guiding operators to optimize acquisitions. This capability has numerous potential applications.

AI-guided acquisitions to assist novice staff and reduce variability

AI-guided acquisitions can be particularly beneficial for less-experienced operators and in high-pressure environments such as emergency departments, as well as in pre-hospital settings and when portable or hand-held point-of-care ultrasonography (POCUS) are used. A multicentre study demonstrated that nurses with limited echocardiographic experience who used a vendor-independent AI-based guidance application trained on >5 million observations acquired interpretable images for LV size and function in 98.8% of cases and for right ventricular size in 92.5% of cases[40]. The same application enabled medical students to acquire diagnostic-quality images in 58%, 86% and 68% of patients for the apical long-axis, four-chamber and two-chamber views, respectively[38]. Similarly, another study found that nurses and medical residents with minimal training on echocardiographic examination acquired images using an AI-based guidance application of sufficient quality to assess LV size and function, right ventricular size and pericardial effusion in 99.2%, 99.6%, 92.9% and 100% of patients, respectively, with concordant diagnostic interpretations between novice staff and expert sonographers[84].

By alerting operators to errors such as foreshortening or rotational misalignment, AI-guided acquisitions can improve standardization and reduce variability across experience levels, which is crucial for consistent diagnostic accuracy. This aspect is particularly important for serial echocardiography examinations, such as in cardio-oncology, where precise and reproducible image acquisition and measurements

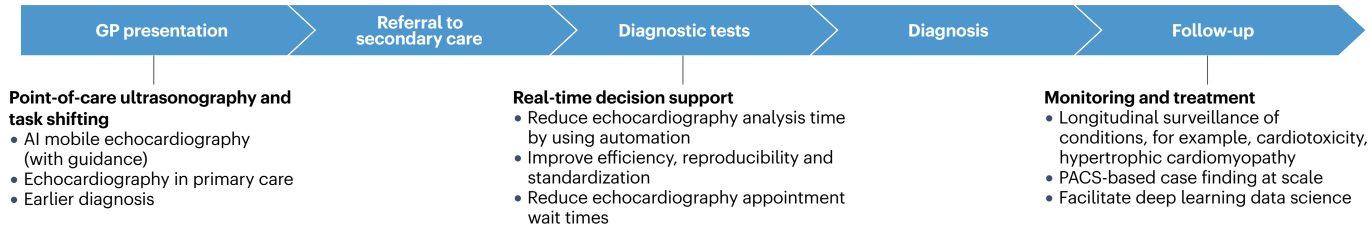


Fig. 3 | Potential clinical applications of AI-assisted echocardiography. The potential applications of artificial intelligence (AI) echocardiography in cardiovascular disease management span from real-time decision support in specialized echocardiography laboratories to screening and early disease detection in non-specialized settings, and advanced monitoring of disease progression and clinical trials. GP, general practitioner; PACS, picture archiving and communication system.

are essential to guide treatment. A deep learning model was trained by slicing 3D echocardiography volumes to simulate the movements of a 2D probe, calculate the probe orientation and provide real-time scan assistance[85]. By visualizing the view plane and suggesting adjustments of the probe posture (such as position on the chest wall, rotation, tilting or sliding), the application reduced foreshortening, rotation and tilt errors even among experienced sonographers[86,87]. Additionally, AI applications are being developed to provide automatically estimated quality scores during scanning, which can help to reduce the subjectivity and variability that are traditionally associated with image quality assessment[30,88–90].

Training and education
AI offers new training opportunities, potentially helping sonographers, cardiology trainees and other health-care providers to acquire diagnostic-quality images more quickly. AI-guided simulations and feedback during practice sessions can accelerate learning and build confidence. For example, an AI model that accurately identified and labelled central anatomical structures in echocardiograms has been developed[91]. In another study, internal medicine trainees were randomly assigned to use POCUS devices either with or without AI assistance[92]. After the training period, both groups were tested using the same non-AI device. Students in the AI group had faster scan times, superior image quality and better detection of reduced LV systolic function compared with students who did not use AI. However, both groups reported limited trust in the AI system, highlighting the need for further development before clinical implementation.

TEE
AI-guided acquisition has primarily been applied to transthoracic echocardiography, but also has potential for application to TEE. TEE is performed in various settings, including perioperative and intensive care units, which necessitate focused, fast and precise examinations. A method for AI-guided probe movement to acquire standard TEE views holds promise for novice staff and might potentially be integrated with robotic systems[93]. The development of a deep learning model that accurately classified standardized TEE views represents a crucial step towards further image analyses and intraprocedural guidance[94].

Clinical applications of AI in echocardiography
The potential applications of AI-enhanced echocardiography are vast, spanning from simple screenings by general practitioners to advanced monitoring of cardiac diseases and outcome measures in clinical trials (Fig. 3).

Increased efficiency and standardization
In the immediate future, perhaps the most transformative impact of AI echocardiography will be the automation of time-consuming and error-prone manual tasks and improvement of measurement standardization. These aspects can increase diagnostic efficiency and accuracy, ensure consistency across institutions and operators, lead to more timely and precise treatment interventions, and ultimately improve patient outcomes[13–15]. A randomized trial evaluated the integration of AI-based automated analysis into clinical echocardiography workflows by alternating manual and AI-assisted days for sonographers[95]. The AI system increased daily examinations from 14.1 to 16.7, reduced examination time and tripled the number of parameters analysed per study. Despite increased workload, sonographers reported lower fatigue on AI-assisted days, probably due to automation of repetitive tasks. High accuracy of AI-generated data was observed, with strong concordance between AI outputs and expert-approved results, such as LVEF measurements (intraclass correlation of 0.92). Nonrandomized studies also demonstrated substantial reductions in time for measuring stored images[14].

Real-time AI decision support systems
One of the key strengths of AI-enabled echocardiography is the ability to perform measurements concurrent with image acquisition. When integrated into the workflow of echocardiography laboratories, this capacity can improve efficiency and help to standardize measurements. For instance, an abnormal LVEF detected during scanning could prompt the sonographer to take a series of images (such as strain, to identify amyloid or regional strain for LV dyssynchrony), creating 'living' or 'adaptive' protocols to ensure adequate imaging for diagnosis without over-imaging. A complete report can be generated while the patient is present in the echocardiography laboratory. This capability extends beyond standard quantifications, such as volumes and Doppler signals, and might also improve disease surveillance, monitoring and prognostication. By analysing previous echocardiographic examinations, the AI algorithm can quickly detect changes and provide real-time alerts to clinicians. Furthermore, retrospective analyses of stored images can be used to provide quality feedback and objective quality comparisons, which might be especially helpful for larger health-care systems with multiple sites, for core laboratories and for accreditation agencies.

Screening for cardiovascular disease
Screening for heart disease remains a challenging field in preventive health care. Although screening holds great potential for early

detection and intervention that can drastically change patient outcomes, it also introduces risks related to false-positive findings and overtreatment. AI-assisted echocardiography might refine this facet of cardiology by improving the precision and reliability of image analysis, and by providing tools for identifying subtle signs of risk that are not detectable by the human eye. Ongoing research, such as the SYMPHONY trial[96], is investigating the efficacy of AI-assisted echocardiography in screening for HF among high-risk populations. This trial, among others, are exploring the boundaries of AI in identifying early disease markers that could inform timely management strategies.

AI-assisted POCUS

AI-assisted POCUS has been shown to be feasibly performed by novice health-care staff for bedside LVEF determination[97], with both good correlation and low bias when comparing automatic LVEF measurements using POCUS and the reference biplane volumetric method of disks using high-end scanners[98]. More recent work demonstrated the potential of novel deep learning models to leverage POCUS images for screening and subphenotyping a broad range of cardiomyopathies[99]. These advances introduce new avenues to POCUS, such as remote monitoring by home-based echocardiography and a hospital-at-home setting, but more research is needed.

Democratization of echocardiography

With the advent of AI-driven software, health-care staff with limited experience in imaging, including general practitioners and nurses, can perform basic screening echocardiography in non-traditional settings[39,40]. In a study of patients with suspected HF, a digital diagnostic pathway incorporating AI-automated hand-held echocardiography performed by non-specialists was designed to expedite access to key diagnostic tests[100]. The study demonstrated that AI-automated analyses of hand-held and standard cart-based echocardiograms were interchangeable with expert human analysis. Notably, the digital pathway reduced the wait times for diagnostic investigations, allowing for earlier treatment initiation and a reduction in hospitalizations.

In low-income and middle-income countries, where health-care resources and specialty training are often limited, AI-augmented echocardiography could be especially transformative. Task shifting – where certain medical tasks are delegated to less specialized health-care workers – and the development of portable devices can substantially improve diagnostics, even bringing these technologies not just to the bedside, but even to people's homes in the community. For instance, a study demonstrated that nurses in Tunisia equipped with a deep learning-driven electronic decision support tool for acquiring and interpreting cardiac ultrasonography images were able to diagnose patients with HFrEF in their own homes, with similar accuracy to trained cardiologists in the clinic[101]. In Kampala and Uganda, AI-guided echocardiography with colour Doppler was proven feasible in screening for rheumatic heart disease by non-experts, particularly for assessing the mitral valve[102]. These findings suggests that deep learning-assisted decision support tools can democratize the practice and availability of echocardiography by enabling task shifting in remote and low-resource settings, reducing costs, improving service availability and ultimately strengthening universal health-care coverage. However, owing to the initial costs and technological infrastructure required for AI implementation, most research on AI in health care has been performed in high-income countries. Therefore, future studies should evaluate the effects on quality and health economics of implementing AI in low-income and middle-income regions.

Monitoring for disease progression and treatment response

AI-enhanced echocardiography offers considerable promise for improving the monitoring and management of slowly progressing cardiac diseases, including the detection of cardiotoxicity from oncology treatments. Targeted cancer therapies can induce cardiotoxic effects, often manifesting as subtle cardiac dysfunction long before symptomatic HF develops. Guidelines advocate for the incorporation of echocardiography for baseline risk assessment and ongoing surveillance, positioning echocardiography as a primary tool for identifying chemotherapy-related cardiotoxicity[103]. By improving precision and reducing operator-related variability in measurements, AI methods could enable clinicians to detect subtle abnormalities that might otherwise be overlooked. This capability supports more nuanced and timely treatment plan adjustments. AI-enabled global longitudinal strain measurement was accurate for monitoring cardiac function of patients with breast cancer who received trastuzumab or pertuzumab for adjuvant or metastatic disease[11]. A feasibility study of patients with cancer receiving chemotherapy showed that oncologists and nurses could accurately detect LVEF of <50% with a hand-held AI-assisted ultrasonography device, illustrating its potential to expedite the clinical workflow for patients with cancer and streamline patient care[104]. Similarly, AI echocardiography holds potential to transform the management of conditions such as hypertrophic cardiomyopathy through the optimization of longitudinal surveillance. This technology improves the accessibility and reproducibility of echocardiographic evaluations, potentially providing imaging end points for therapeutic dosing of cardiac myosin inhibitors and for monitoring treatment response and toxicity. Moreover, emerging applications of AI in echocardiography might potentially have key roles in the precision care of patients with valve disease, such as the surveillance of aortic stenosis, not only with respect to early detection but also monitoring, risk prediction and tailored interventions[105].

Clinical research

Echocardiography is used to assess eligibility criteria and outcome measures in clinical trials. Given the need for a high degree of accuracy and repeatability, this setting is carefully controlled. Even under these stringent conditions, AI-enhanced echocardiography has demonstrated reliability and efficiency, primarily owing to its high degree of standardization and low variability[18]. Thus, AI-supported echocardiography has already been successfully integrated into echocardiography core laboratory workflows.

Another potential application in clinical trials is AI-based analysis and interpretation of stored echocardiography images and reports, which can accelerate eligibility assessment and screening procedures. For example, in a population-based cohort study, a keyword search of medical records combined with an AI-automated reading of stored Digital Imaging and Communications in Medicine (DICOM) echocardiographic images successfully identified patients with HFpEF and HFrEF, as well as controls without HF, yielding clusters of patients that shared diseases, had elevated plasma natriuretic peptide levels and poor outcomes[106]. In another example that was based purely on echocardiographic reports, an AI model that integrated multidimensional echocardiographic data identified specific subgroups of patients with HFpEF with greater accuracy than current echocardiography guidelines for predicting LV filling pressures (AUC of 0.88 versus 0.67)[107].

In summary, AI applied to echocardiography in clinical trials offer an opportunity to improve efficiency at reduced costs. Such AI-assisted electronic surveillance might have application in the automated monitoring of clinical records for early disease detection, treatment quality improvement initiatives and screening processes for clinical trials.

Finally, AI echocardiography holds great potential to improve cardiovascular disease phenotyping and risk stratification by providing imaging end points at unparalleled scale. For instance, measurement-based AI classifications of aortic stenosis severity has demonstrated greater accuracy in the prediction of aortic valve replacement within a 5-year period compared with conventional classification[108]. Follow-up of aortic stenosis progression using a similar strategy has also been proven to be accurate. In addition, a deep learning-based algorithm was shown to reduce unnecessary echocardiographic examinations by 49% for following up aortic stenosis progression compared with follow-up recommendations by European guidelines[109].

Challenges in applied AI echocardiography

Developing trustworthy AI in echocardiography

The potential benefits of AI in echocardiography are immense, but developing and implementing these technologies present substantial challenges[110]. Developers should prioritize creating 'trustworthy AI' that is lawful, ethical, robust and transparent, while addressing the specific needs in echocardiography, such as reducing variability, decreasing operator dependence in image acquisitions and measurements, and improving workflow efficiency[22,110–113]. To promote the development of trustworthy AI in echocardiography, we propose seven guiding principles tailored to the unique challenges within echocardiography (Box 2).

Compared with other imaging modalities, echocardiographic data are highly diverse and more prone to suboptimal image quality[114]. These characteristics present challenges for AI models, which rely on large volumes of high-quality, curated datasets for accurate training.

Box 2 | Seven guiding principles for trustworthy AI in echocardiography

This box outlines seven key principles designed to guide researchers, clinicians, journal editors and health-care system providers in developing and applying artificial intelligence (AI)-based solutions in echocardiography. Adhering to these principles in AI technology will help to markedly improve patient outcomes while ensuring patient safety, ethical standards, transparency, reproducibility and robust clinical integration.

1. Trust and human oversight

AI systems in echocardiography should be designed to facilitate human oversight, allowing clinicians to review, correct and override decisions when necessary, ensuring patient safety and fostering trust. Clinicians retain full control over critical diagnostic decisions and have the ability to validate AI-based predictions during the echocardiographic assessments.

2. Data diversity, fairness and ethical decision-making

To promote fairness, avoid discrimination, minimize biases and ensure equitable care, AI models in echocardiography should ideally be trained and validated using diverse datasets that represent varied demographics, age groups, disease stages and imaging qualities across different populations and equipment. AI models should also ideally be continuously audited to identify and address biases that arise in real-world usage, particularly for under-represented patient populations.

3. Transparency, explainability, robustness and reproducibility

Transparent reporting of the development of AI systems in echocardiography should provide clear documentation of how the models were developed, how results are generated and how the models were, or need to be, stress-tested for robustness in rare, atypical or edge-case conditions.

4. Clinical validation, generalizability and monitoring

AI models in echocardiography must undergo rigorous validation and testing using both internal and external datasets, ideally including implementation studies in diverse populations to ensure generalizability across diverse populations and settings. The use of checklists such as TRIPOD[154], CONSORT-AI[155] and PRIME[156] is encouraged for post-deployment monitoring to track accuracy and performance over time. Establishing robust, technique-specific reference values is essential to ensure accurate clinical interpretation, given that measurements can differ between systems and vendors, and require tailored cut-off values for clinical reporting.

5. Regulatory governance, compliance, accountability and risk management systems

For the clinical implementation of AI systems in echocardiography, compliance with relevant regulations, clear lines of responsibility, risk management systems and post-market surveillance are needed to ensure ongoing regulatory compliance and to manage risks associated with ongoing clinical use. To ensure environmentally responsible implementation, AI systems should also align with sustainability goals, incorporating energy-efficient designs and minimizing environmental impact through regulatory frameworks and accountability mechanisms.

6. Continuous learning and adaptation

AI models in echocardiography should incorporate mechanisms for continuous learning, enabling periodic retraining and adaptation as new clinical data become available, technologies advance or when echocardiographic practices evolve.

7. Workflow integration, usability and societal impacts

The development of AI systems should consider the specific clinical needs within echocardiography and seamless integration into existing clinical workflows, enhancing efficiency without disrupting clinical practice. Broader societal impacts, such as reducing health-care inequalities and promoting sustainable practices in cardiac care, should also be considered.

Box 3 | Real-world implementation of AI-assisted echocardiography

This case study outlines how artificial intelligence (AI) was integrated into the echocardiography department of the University Hospital of Bordeaux, France, where >21,000 echocardiography examinations are conducted each year[157]. The integration occurred in two phases:

Phase 1: technical integration and set up

An AI processing station (Us2.ai) was integrated into the hospital's Department of Information Technology. The Next Unit of Computing (NUC) server, installed with AI software, was connected to the hospital's internal network as a web IP server with a unique IP address and port, thereby negating the need for a virtual private network. The NUC was linked to two separate Vivid E95 echocardiography machines (GE HealthCare). The set up enabled dual data transmission, allowing each echocardiographic exam to be simultaneously sent to both the Picture Archiving and Communication System (PACS), including the reporting software (ComPACS, MediMatic) and the NUC for real-time monitoring and data comparison.

Phase 2: data collection and comparative analysis

To compare echocardiographer-measured results with measurement produced by the AI system, examinations from two specific rooms were routed to both the PACS and NUC over 2 months. Routine transthoracic echocardiography procedures were conducted in rooms scheduled between 2 and 6 months ahead of time. Scheduling followed a department protocol, unaltered for research purposes. Examinations were conducted by nurse sonographers, residents with <1 year experience and expert echocardiographers with >5 years of experience, adhering to the established protocol. Each examination included recordings of 20–30 electrocardiogram-synchronized loops and 10–20 images, mainly Doppler recordings, which were labelled and sent to both the PACS and the NUC. Reports and measurements were generated by echocardiographers in the PACS software, and the NUC processed the images autonomously without human supervision, identifying views and conducting all possible measurements dependent on image quality.

The AI system was successfully integrated into the hospital's infrastructure within 6 weeks. In 894 echocardiograms performed by operators (nurses, residents and experts), there was good to excellent alignment between AI and human measurements, notably for parameters such as left ventricular ejection fraction (intraclass correlation of 0.81) and mitral E-wave velocity (intraclass correlation of 0.97). The average bias was −4 ± 15% across all parameters. Subgroup analysis highlighted higher concordance among expert echocardiographers and residents than with nurses.

In conclusion, this case study illustrates that AI can be successfully incorporated into clinical echocardiography practice, with high concordance between AI and human measurements.

Transforming raw echocardiographic data into usable AI models requires meticulous preparation to ensure that the data are accurate and representative. Improving data annotation strategies with standardized, high-quality labels is crucial for optimizing AI in echocardiography, enabling model training that aligns with the specific and complex requirements of echocardiography, and improving applicability in clinical practice. Furthermore, AI models in echocardiography can also inherit biases from training data, which can result in incorrect predictions, disease misclassification and discriminatory outcomes[115,116]. Such biases can arise from under-representation of certain demographics, age groups or disease stages in training datasets, limiting the generalizability and potentially affecting diagnostic accuracy in diverse patient populations[117,118]. For example, studies have shown that AI models can rely on 'shortcut learning' (that is, generating predictions on the basis of improper correlations in the training data) for disease classification that relies on demographic factors[119,120]. Although this homogeneity might address fairness within the training data, the model often is not generalizable across new testing environments[121]. Addressing these biases is crucial because they can have far-reaching consequences for diagnostic precision and fairness. Additionally, proprietary algorithms for data processing and analysis pose challenges to interoperability, limiting the broader application of AI technologies across diverse clinical settings. Standardization efforts are needed to ensure compatibility with various echocardiographic platforms and facilitate widespread adoption.

The inherent variability in echocardiographic data presents additional challenges for validating AI models. External testing in independent, real-world datasets is essential to ensure safe and equitable AI implementation. Furthermore, current medical data structures are not always well suited to support large-scale models, such as large language models, which depend on efficient data processing and structural annotation. As algorithms become increasingly complex, greater technical expertise is required to ensure reliability and trustworthiness. Several studies have highlighted potential concerns, such as AI models taking demographic shortcuts in disease classification, and the limitations of traditional deep learning methods in sustaining performance improvements over time[121,122].

A phased roadmap for the AI transition in echocardiography

Research until now has focused on developing and validating AI models, and limited evidence exists on their integration into clinical practice, with a few exceptions[123,124] (Box 3). Unlike previous technologies in cardiology, implementing AI in echocardiography is complex, involving multiple stakeholders and presenting unique challenges. For example, AI can augment or constrain the work of health-care professionals by enabling the close interaction between humans and AI systems. Advances such as generative AI blur the boundaries between human and machine capabilities[123]. Barriers to implementation include uncertainties related to patient harm, bias and privacy concerns[125]. Building trust in AI is therefore paramount.

To ensure safe and ethical integration, there is a pressing need to educate our cardiovascular workforce on the specific challenges of applying AI to echocardiography. Users should be vigilant of automation bias (the tendency to rely on AI output over clinical judgement), especially when the quality of image acquisition or other factors might adversely influence model performance and pose harm to patients[126].

A structured, phased approach can guide echocardiography laboratories in adopting AI safely and effectively, addressing its challenges while exploiting its potential[123,127]. In Box 4, we propose a roadmap consisting of five phases: phase 1 involves the preparation of the laboratory, phase 2 addresses clinical workflow requirements, phase 3 is a pilot of a low-risk AI strategy, phase 4 entails the adoption of a more advanced AI system and phase 5 is the stage in which access to this AI system is expanded. Throughout all phases, continuous monitoring of AI systems is vital to ensure their sustained performance, safety and adaptability. Establishing regular feedback loops among clinicians, developers and regulators helps to address real-world challenges and refine workflows. The periodic retraining of AI models will be necessary to adapt to the advances in echocardiographic technologies and evolving clinical data. Beyond the individual medical institutions, the regional health-care ecosystem and government-level policies can have crucial roles in the successful implementation of AI in echocardiography. New AI-specific legislation, reimbursement pathways or national policy changes can facilitate AI adoption in echocardiography, just as regional policy changes aided the adoption of electronic medical records in many nations in the past decade.

Future directions and innovations

The implementation of AI in echocardiography represents a paradigm shift in both research and clinical cardiology. AI-assisted enhancements in echocardiographic image acquisition and the automation of measurements, interpretation and reporting have the potential to streamline the workflow, improve precision and contribute to better patient care[5,128]. With rapid technical advances, representative validation and testing procedures, and randomized clinical trials, AI systems are likely to become more trustworthy and integrated into clinical practice, both as auxiliary tools and to support diagnostic decisions. We expect to see AI algorithms capable of interpreting echocardiographic datasets enriched by clinical data and complementary diagnostic modalities[62]. Such integration will require seamless user interfaces and strong interoperability with existing health-care technologies. Addressing the interoperability of AI systems across different vendors is crucial for streamlining operations in multisite, multivendor echocardiography laboratories while minimizing training requirements for personnel. Future research and development should prioritize creating standardized frameworks that increase the compatibility of AI algorithms, thereby reducing the financial and operational burden on health-care

Box 4 | A roadmap for the integration of AI-assisted echocardiography into clinical practice

This roadmap illustrates a structured approach for the safe and effective integration of artificial intelligence (AI) into clinical echocardiography, emphasizing the importance of preparation, addressing barriers, piloting, validation and equitable access. Continuous monitoring and improvements are central throughout all phases to ensure safety, performance and alignment with clinical and sustainability goals.

Phase 1: prepare the laboratory
- Establish a strategic foundation by aligning leadership teams, including clinicians, administrators and IT staff, on clear AI goals and communicating its clinical value.
- Build trust among staff through education, transparent communication and training to understand AI tools and validate outputs.
- Invest in infrastructure, including data storage systems and comparable equipment.

Phase 2: address clinical workflow requirements
- Identify and address clinical, technical and regulatory barriers early.
- Ensure seamless workflow integration without disrupting clinical practice and adapt tools to diverse clinical environments.
- Prioritize compliance with standards such as General Data Protection Regulation and the EU AI Act.
- Foster staff trust through transparency and user-centric design.

Phase 3: pilot low-risk AI
- Introduce AU tools in controlled settings with low-risk applications, such as acquisition guidance or automating left ventricular ejection fraction and global longitudinal strain measurements.
- Validate AI outputs against human interpretations to build confidence and identify limitations before broader adoption.
- Pilot studies should include diverse patient populations to ensure generalizability.

Phase 4: adopt advances AI
- As applications for disease classification and phenogroup clustering become available, their adoption will require extensive validation across diverse populations and clinical scenarios to ensure safety, efficacy and generalizability.
- Protocols for integrating these tools into clinical workflows should focus on trustworthiness, human oversight, transparency and cost–effectiveness.

Phase 5: expand access
- Promote equitable access to AI-enhanced echocardiography by addressing disparities in adoption.
- Prioritize cost-effective workflows, ensure compatibility with diverse equipment and train clinicians in underserved regions.
- Validate real-world performance across varied populations, including resource-constrained environments, to ensure fairness and reliability.

Continuous monitoring and innovation
- Ensure AI performance, safety and adaptability through ongoing feedback, real-time evaluation and periodic retraining to address evolving clinical data and patient demographics.
- Establish robust systems for detecting and mitigating biases, ensuring consistent performance across diverse populations and imaging scenarios.
- Incorporate advances in echocardiography technologies, such as transducers with higher temporal and spatial resolution, 3D and high-frame-rate imaging, to enable more comprehensive assessments.
- Foster collaboration between clinicians and AI developers and regulators to continuously refine tools and workflows, ensuring the seamless integration of cutting-edge innovations into clinical practice.

institutions. Furthermore, as AI systems learn from ever-greater volumes of data, they might provide insights into subtle patterns in population health, provide opportunities of interpreting images in novel ways beyond our current knowledge, and contribute to refining disease taxonomy and risk stratification across diverse patient groups.

Some technical areas of innovation in AI echocardiography are particularly promising. Foundation models for echocardiography have emerged that can apply what they have learned to a wide range of tasks, rather than being limited to a narrow set of predefined ones[129]. These models enable images and text to be encoded into compact representations that can then be applied in multiple separate prediction tasks for which the model was never specifically trained. One such vision–language foundation model was trained on data from nearly 100,000 patients, including >1 million echocardiographic videos and corresponding expert text[129]. The model predicted EF with a mean absolute error of 7.1% and identified dilated chambers, LV hypertrophy, tamponade and intracardiac devices with reasonable accuracy. Moreover, the model tracked individual patients across multiple studies with an AUC of 0.86 and identified clinical changes over time, such as cardiac surgery with an AUC of 0.77. Although promising, substantial technical improvements and validation are needed.

Other promising AI developments go beyond traditional image acquisition and analysis. Autonomous echocardiography using robotic arms and navigation systems could reduce the reliance on technical expertise, reduce work-related musculoskeletal injury[130] and improve efficiency[131–133]. Whether such systems would improve availability, be cost-effective and allow equitable patient care will need careful considerations in well-designed randomized trials.

AI is being explored in novel ways for analysing more nuanced characteristics of the heart. For example, ultrafast echocardiography (high frame rate, typically >1,000 frames per second) is a promising technology that could provide mechanistic characterization of myocardial tissue properties by capturing naturally occurring or externally applied mechanical waves[134,135]. The capabilities of deep learning could be invaluable for the analyses and identification of subtle patterns in these waves. Another promising approach for the characterization of myocardial tissue uses AI to analyse 'radiomics-derived' texture-based features in echocardiographic images ('ultrasomics')[136,137]. These features can capture subtle information about the texture, shape and intensity of myocardial structure that might not be evident to the human eye. A pilot study demonstrated the potential of ultrasonics to distinguish between healthy and infarcted myocardium[138].

Wearable ultrasound devices that integrate compact microelectronics with flexible patches are being explored for their potential to enable continuous, real-time cardiac monitoring[139–141]. By utilizing AI to autonomously optimize settings and analyse data, these devices could provide novel insights into the cardiovascular system.

Conclusions

AI-supported echocardiography has already made substantial advances and is being integrated into clinical practice at leading centres worldwide. The future success of AI-supported echocardiography will depend on sustained collaboration among clinicians, data scientists, engineers, industry partners, regulators, health-care systems, professional societies and patients. This multidisciplinary effort is essential to ensure that AI-driven tools are ethically developed and equitably deployed while focusing carefully on data and model safety. As large datasets continue to grow, computational power expands and AI models become more sophisticated, the role of AI in echocardiography will expand, making trustworthy, high-quality cardiac care accessible to a broader patient population worldwide.

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References

1. Lang, R. M. 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.* **28**, 1–39.e14 (2015).
2. Thorstensen, A., Dalen, H., Amundsen, B. H., Aase, S. A. & Stoylen, A. Reproducibility in echocardiographic assessment of the left ventricular global and regional function, the HUNT study. *Eur. J. Echocardiogr.* **11**, 149–156 (2010).
3. Nagueh, S. F. et al. Interobserver variability in applying American Society of Echocardiography/European Association of Cardiovascular Imaging 2016 guidelines for estimation of left ventricular filling pressure. *Circ. Cardiovasc. Imaging* **12**, e008122 (2019).
4. Won, D. et al. Sound the alarm: the sonographer shortage is echoing across healthcare. *J. Ultrasound Med.* **43**, 1289–1301 (2024).
5. Hanneman, K. et al. Value creation through artificial intelligence and cardiovascular imaging: a scientific statement from the American Heart Association. *Circulation* **149**, e296–e311 (2024).
6. Jordan, M. I. & Mitchell, T. M. Machine learning: trends, perspectives, and prospects. *Science* **349**, 255–260 (2015).
7. Carneiro, G., Nascimento, J. C. & Freitas, A. The segmentation of the left ventricle of the heart from ultrasound data using deep learning architectures and derivative-based search methods. *IEEE Trans. Image Process.* **21**, 968–982 (2012).
8. Abdi, A. H. et al. Automatic quality assessment of echocardiograms using convolutional neural networks: feasibility on the apical four-chamber view. *IEEE Trans. Med. Imaging* **36**, 1221–1230 (2017).
9. Madani, A., Arnaout, R., Mofrad, M. & Arnaout, R. Fast and accurate view classification of echocardiograms using deep learning. *npj Digit. Med.* **1**, 6 (2018).
10. Østvik, A., Smistad, E., Aase, S. A., Haugen, B. O. & Lovstakken, L. Real-time standard view classification in transthoracic echocardiography using convolutional neural networks. *Ultrasound Med. Biol.* **45**, 374–384 (2019).
11. Zhang, J. et al. Fully automated echocardiogram interpretation in clinical practice. *Circulation* **138**, 1623–1635 (2018).
12. Siontis, K. C., Noseworthy, P. A., Attia, Z. I. & Friedman, P. A. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nat. Rev. Cardiol.* **18**, 465–478 (2021).
13. Tromp, J. et al. Automated interpretation of systolic and diastolic function on the echocardiogram: a multicohort study. *Lancet Digit. Health* **4**, e46–e54 (2022).
14. Hirata, Y., Nomura, Y., Saijo, Y., Sata, M. & Kusunose, K. Reducing echocardiographic examination time through routine use of fully automated software: a comparative study of measurement and report creation time. *J. Echocardiogr.* **22**, 162–170 (2024).
15. Olaisen, S. et al. Automatic measurements of left ventricular volumes and ejection fraction by artificial intelligence: clinical validation in real time and large databases. *Eur. Heart J. Cardiovasc. Imaging* **25**, 383–395 (2024).
16. Krittanawong, C. et al. Deep learning for echocardiography: introduction for clinicians and future vision: state-of-the-art review. *Life* **13**, 1029 (2023).
17. Ostvik, A. et al. Myocardial function imaging in echocardiography using deep learning. *IEEE Trans. Med. Imaging* **40**, 1340–1351 (2021).
18. Tromp, J. et al. A formal validation of a deep learning-based automated workflow for the interpretation of the echocardiogram. *Nat. Commun.* **13**, 6776 (2022).
19. Myhre, P. L. et al. External validation of a deep learning algorithm for automated echocardiographic strain measurements. *Eur. Heart J. Digit. Health* **5**, 60–68 (2024).
20. Cai, Q. et al. Automated echocardiographic diastolic function grading: a hybrid multi-task deep learning and machine learning approach. *Int. J. Cardiol.* **416**, 132504 (2024).
21. He, B. et al. Blinded, randomized trial of sonographer versus AI cardiac function assessment. *Nature* **616**, 520–524 (2023).
22. Balagopalan, A. et al. Machine learning for healthcare that matters: reorienting from technical novelty to equitable impact. *PLoS Digit. Health* **3**, e0000474 (2024).
23. Ouyang, D. et al. Video-based AI for beat-to-beat assessment of cardiac function. *Nature* **580**, 252–256 (2020).
24. Kusunose, K. et al. A deep learning approach for assessment of regional wall motion abnormality from echocardiographic images. *JACC Cardiovasc. Imaging* **13**, 374–381 (2020).
25. Asch, F. 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* **12**, e009303 (2019).
26. Asch, F. M. et al. Deep learning-based automated echocardiographic quantification of left ventricular ejection fraction: a point-of-care solution. *Circ. Cardiovasc. Imaging* **14**, e012293 (2021).
27. Myhre, P. L. et al. Concordance of left ventricular volumes and function measurements between two human readers, a fully automated AI algorithm, and the 3D heart model. *Front. Cardiovasc. Med.* **11**, 1400333 (2024).
28. Lang, R. M. et al. Use of machine learning to improve echocardiographic image interpretation workflow: a disruptive paradigm change? *J. Am. Soc. Echocardiogr.* **34**, 443–445 (2021).

29. Leclerc, S. et al. Deep learning for segmentation using an open large-scale dataset in 2D echocardiography. *IEEE Trans. Med. Imaging* **38**, 2198–2210 (2019).
30. Smistad, E. et al. Real-time automatic ejection fraction and foreshortening detection using deep learning. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **67**, 2595–2604 (2020).
31. Ghorbani, A. et al. Deep learning interpretation of echocardiograms. *npj Digit. Med.* **3**, 10 (2020).
32. Alvén, J., Hagberg, E., Hagerman, D., Petersen, R. & Hjelmgren, O. A deep multi-stream model for robust prediction of left ventricular ejection fraction in 2D echocardiography. *Sci. Rep.* **14**, 2104 (2024).
33. Salte, I. M. et al. Artificial intelligence for automatic measurement of left ventricular strain in echocardiography. *JACC Cardiovasc. Imaging* **14**, 1918–1928 (2021).
34. Salte, I. M. et al. Deep learning for improved precision and reproducibility of left ventricular strain in echocardiography: a test–retest study. *J. Am. Soc. Echocardiogr.* **36**, 788–799 (2023).
35. Nyberg, J. et al. Deep learning improves test-retest reproducibility of regional strain in echocardiography. *Eur. Heart J. Imaging Methods Pract.* **2**, qyae092 (2024).
36. Stowell, C. C. et al. 2-dimensional echocardiographic global longitudinal strain with artificial intelligence using open data from a UK-wide collaborative. *JACC Cardiovasc. Imaging* **17**, 865–876 (2024).
37. Kwan, A. C. et al. Deep learning-derived myocardial strain. *JACC Cardiovasc. Imaging* **17**, 715–725 (2024).
38. Schneider, M. et al. A machine learning algorithm supports ultrasound-naïve novices in the acquisition of diagnostic echocardiography loops and provides accurate estimation of LVEF. *Int. J. Cardiovasc. Imaging* **37**, 577–586 (2021).
39. Huang, W. et al. Point-of-care AI-enhanced novice echocardiography for screening heart failure (PANES-HF). *Sci. Rep.* **14**, 13503 (2024).
40. Narang, A. et al. Utility of a deep-learning algorithm to guide novices to acquire echocardiograms for limited diagnostic use. *JAMA Cardiol.* **6**, 624–632 (2021).
41. Berg, E. A. R. et al. Fully automatic estimation of global left ventricular systolic function using deep learning in transoesophageal echocardiography. *Eur. Heart J. Imaging Methods Pract.* **1**, qyad007 (2023).
42. Yu, J. et al. Automatic assessment of left ventricular function for hemodynamic monitoring using artificial intelligence and transesophageal echocardiography. *J. Clin. Monit. Comput.* https://doi.org/10.1007/s10877-023-01118-x (2024).
43. Lau, E. S. et al. Deep learning-enabled assessment of left heart structure and function predicts cardiovascular outcomes. *J. Am. Coll. Cardiol.* **82**, 1936–1948 (2023).
44. Howard, J. P. et al. Automated left ventricular dimension assessment using artificial intelligence developed and validated by a UK-wide collaborative. *Circ.: Cardiovasc. Imaging* **14**, e011951 (2021).
45. Duffy, G. et al. High-throughput precision phenotyping of left ventricular hypertrophy with cardiovascular deep learning. *JAMA Cardiol.* **7**, 386–395 (2022).
46. Gilbert, A. et al. User-intended doppler measurement type prediction combining CNNs with smart post-processing. *IEEE J. Biomed. Health Inform.* **25**, 2113–2124 (2021).
47. Jeon, J. et al. A unified approach for comprehensive analysis of various spectral and tissue doppler echocardiography. in *2024 IEEE International Symposium on Biomedical Imaging (ISBI)* https://doi.org/10.1109/ISBI56570.2024.10635387 (IEEE, 2024).
48. Jevsikov, J. et al. Automated mitral inflow Doppler peak velocity measurement using deep learning. *Comput. Biol. Med.* **171**, 108192 (2024).
49. Chen, X. et al. Artificial intelligence-assisted left ventricular diastolic function assessment and grading: multiview versus single view. *J. Am. Soc. Echocardiogr.* **36**, 1064–1078 (2023).
50. Park, J. et al. Artificial intelligence-enhanced automation of left ventricular diastolic assessment: a pilot study for feasibility, diagnostic validation, and outcome prediction. *Cardiovasc. Diagn. Ther.* **14**, 352–366 (2024).
51. O'Neill, T., Kang, P., Hagendorff, A. & Tayal, B. The clinical applications of left atrial strain: a comprehensive review. *Medicina* **60**, 693 (2024).
52. Ferkh, A., Clark, A. & Thomas, L. Left atrial phasic function: physiology, clinical assessment and prognostic value. *Heart* **109**, 1661–1669 (2023).
53. Yaku, H., Komtebedde, J., Silvestry, F. E. & Shah, S. J. Deep learning-based automated measurements of echocardiographic estimators of invasive pulmonary capillary wedge pressure perform equally to core lab measurements: results from reduce LAP-HF II. *J. Am. Coll. Cardiol.* https://doi.org/10.1016/S0735-1097%2824%2902306-4 (2024).
54. Konstam, M. A. et al. Evaluation and management of right-sided heart failure: a scientific statement from the American Heart Association. *Circulation* **137**, e578–e622 (2018).
55. Tokodi, M. et al. Deep learning-based prediction of right ventricular ejection fraction using 2D echocardiograms. *JACC Cardiovasc. Imaging* **16**, 1005–1018 (2023).
56. Murayama, M. et al. Deep learning to assess right ventricular ejection fraction from two-dimensional echocardiograms in precapillary pulmonary hypertension. *Echocardiography* **41**, e15812 (2024).
57. Chernyshov, A. et al. Automated segmentation and quantification of the right ventricle in 2-D echocardiography. *Ultrasound Med. Biol.* **50**, 540–548 (2024).
58. Arbelo, E. et al. 2023 ESC guidelines for the management of cardiomyopathies. *Eur. Heart J.* **44**, 3503–3626 (2023).
59. Alwan, L. et al. Current and evolving multimodality cardiac imaging in managing transthyretin amyloid cardiomyopathy. *JACC Cardiovasc. Imaging* **17**, 195–211 (2024).
60. Yu, X. et al. Using deep learning method to identify left ventricular hypertrophy on echocardiography. *Int. J. Cardiovasc. Imaging* **38**, 759–769 (2022).
61. Kamel, M. A. et al. How artificial intelligence can enhance the diagnosis of cardiac amyloidosis: a review of recent advances and challenges. *J. Cardiovasc. Dev. Dis.* **11**, 118 (2024).
62. Goto, S. et al. Artificial intelligence-enabled fully automated detection of cardiac amyloidosis using electrocardiograms and echocardiograms. *Nat. Commun.* **12**, 2726 (2021).
63. Oikonomou, E. K. et al. Artificial intelligence-enabled electrocardiography and echocardiography to track preclinical progression of transthyretin amyloid cardiomyopathy. *Eur. Heart J.* https://doi.org/10.1093/eurheartj/ehaf450 (2025).
64. Narula, S., Shameer, K., Salem Omar, A. M., Dudley, J. T. & Sengupta, P. P. Machine-learning algorithms to automate morphological and functional assessments in 2D echocardiography. *J. Am. Coll. Cardiol.* **68**, 2287–2295 (2016).
65. Krishna, H. et al. Fully automated artificial intelligence assessment of aortic stenosis by echocardiography. *J. Am. Soc. Echocardiogr.* **36**, 769–777 (2023).
66. Holste, G., Oikonomou, E. K., Mortazavi, B. J., Wang, Z. & Khera, R. Efficient deep learning-based automated diagnosis from echocardiography with contrastive self-supervised learning. *Commun. Med.* **4**, 1–10 (2024).
67. Holste, G. et al. Severe aortic stenosis detection by deep learning applied to echocardiography. *Eur. Heart J.* **44**, 4592–4604 (2023).
68. Wessler, B. S. et al. Automated detection of aortic stenosis using machine learning. *J. Am. Soc. Echocardiogr.* **36**, 411–420 (2023).
69. Long, A. et al. Deep learning for echo analysis, tracking, and evaluation of mitral regurgitation (DELINEATE-MR). *Circulation* https://doi.org/10.1161/CIRCULATIONAHA.124.068996 (2024).
70. Vrudhula, A. et al. High-throughput deep learning detection of mitral regurgitation. *Circulation* **150**, 923–933 (2024).
71. Wifstad, S. V. et al. EasyPISA: automatic integrated PISA measurements of mitral regurgitation from 2-D color-doppler using deep learning. *Ultrasound Med. Biol.* https://doi.org/10.1016/j.ultrasmedbio.2024.06.008 (2024).
72. Sadeghpour, A. et al. An automated machine learning-based quantitative multiparametric approach for mitral regurgitation severity grading. *JACC Cardiovasc. Imaging* https://doi.org/10.1016/j.jcmg.2024.06.011 (2024).
73. Bernard, J. et al. Integrating echocardiography parameters with explainable artificial intelligence for data-driven clustering of primary mitral regurgitation phenotypes. *JACC Cardiovasc. Imaging* **16**, 1253–1267 (2023).
74. Nedadur, R., Wang, B. & Tsang, W. Artificial intelligence for the echocardiographic assessment of valvular heart disease. *Heart* **108**, 1592–1599 (2022).
75. Bozkurt, B. et al. Universal definition and classification of heart failure: a report of the Heart Failure Society of America, Heart Failure Association of the European Society of Cardiology, Japanese Heart Failure Society and Writing Committee of the Universal Definition of Heart Failure. *J. Card. Fail.* https://doi.org/10.1016/j.cardfail.2021.01.022 (2021).
76. Akerman, A. P. et al. Automated echocardiographic detection of heart failure with preserved ejection fraction using artificial intelligence. *JACC Adv.* https://doi.org/10.1016/j.jacadv.2023.100452 (2023).
77. Cassianni, C. et al. Automated echocardiographic detection of heart failure with preserved ejection fraction using artificial intelligence is associated with cardiac mortality and heart failure hospitalization. *J. Am. Soc. Echocardiogr.* **37**, 914–916 (2024).
78. Lin, X. et al. Echocardiography-based AI detection of regional wall motion abnormalities and quantification of cardiac function in myocardial infarction. *Front. Cardiovasc. Med.* **9**, 903660 (2022).
79. Slivnick, J. A. et al. Echocardiographic detection of regional wall motion abnormalities using artificial intelligence compared to human readers. *J. Am. Soc. Echocardiogr.* **37**, 655–663 (2024).
80. European Society of Cardiology. PROTEUS trial suggests AI for heart scans may benefit decision making for less-experienced clinicians (ESC, 2024); https://www.escardio.org/The-ESC/Press-Office/Press-releases/PROTEUS-Trial-suggests-AI-for-heart-scans-may-benefit-decision-making-for-less-experienced-clinicians.
81. Laumer, F. et al. Assessment of artificial intelligence in echocardiography diagnostics in differentiating Takotsubo syndrome from myocardial infarction. *JAMA Cardiol.* **7**, 494–503 (2022).
82. Liao, Z. et al. Automatic echocardiographic evaluation of the probability of pulmonary hypertension using machine learning. *Pulm. Circ.* **13**, e12272 (2023).
83. Hirata, Y., Tsuji, T., Kotoku, J., Sata, M. & Kusunose, K. Echocardiographic artificial intelligence for pulmonary hypertension classification. *Heart* **110**, 586–593 (2024).
84. Mor-Avi, V. et al. Real-time artificial intelligence–based guidance of echocardiographic imaging by novices: image quality and suitability for diagnostic interpretation and quantitative analysis. *Circ. Cardiovasc. Imaging* **16**, e015569 (2023).
85. Pasdeloup, D. et al. Real-time echocardiography guidance for optimized apical standard views. *Ultrasound Med. Biol.* **49**, 333–346 (2023).
86. Sabo, S. et al. Real-time guidance by deep learning of experienced operators to improve the standardization of echocardiographic acquisitions. *Eur. Heart J. Imaging Methods Pract.* **1**, qyad040 (2023).
87. Sabo, S. et al. Real-time guiding by deep learning during echocardiography to reduce left ventricular foreshortening and measurement variability. *Eur. Heart J. Imaging Methods Pract.* **1**, qyad012 (2023).
88. Luong, C. et al. Automated estimation of echocardiogram image quality in hospitalized patients. *Int. J. Cardiovasc. Imaging* **37**, 229–239 (2021).

89. Huang, K.-C. et al. Artificial intelligence aids cardiac image quality assessment for improving precision in strain measurements. *JACC Cardiovasc. Imaging* **14**, 335–345 (2021).
90. Van De Vyver, G. et al. Regional image quality scoring for 2-D echocardiography using deep learning. *Ultrasound Med. Biol.* **51**, 638–649 (2025).
91. Liu, Z. et al. Automated deep neural network-based identification, localization, and tracking of cardiac structures for ultrasound-guided interventional surgery. *J. Thorac. Dis.* **15**, 2129–2140 (2023).
92. Baum, E. et al. Acquisition of cardiac point-of-care ultrasound images with deep learning: a randomized trial for educational outcomes with novices. *CHEST Pulm.* **1**, 100023 (2023).
93. Li, K., Li, A., Xu, Y., Xiong, H. & Meng, M. Q.-H. RL-TEE: autonomous probe guidance for transesophageal echocardiography based on attention-augmented deep reinforcement learning. *IEEE Trans. Autom. Sci. Eng.* **21**, 1526–1538 (2024).
94. Steffner, K. R. et al. Deep learning for transesophageal echocardiography view classification. *Sci. Rep.* **14**, 11 (2024).
95. Kagiyama, N. Artificial intelligence-based automated echocardiographic measurements and the workflow of sonographers: randomized crossover trial (AI-Echo RCT) (American Heart Association, 2024).
96. US National Library of Medicine. *ClinicalTrials.gov* https://clinicaltrials.gov/study/NCT05919342 (2023).
97. Motazedian, P. et al. Diagnostic accuracy of point-of-care ultrasound with artificial intelligence-assisted assessment of left ventricular ejection fraction. *npj Digit. Med.* **6**, 201 (2023).
98. Kagiyama, N. et al. Multicenter validation study for automated left ventricular ejection fraction assessment using a handheld ultrasound with artificial intelligence. *Sci. Rep.* **14**, 15359 (2024).
99. Oikonomou, E. K. et al. Artificial intelligence-guided detection of under-recognised cardiomyopathies on point-of-care cardiac ultrasonography: a multicentre study. *Lancet Digit. Health* **7**, e113–e123 (2025).
100. Campell, R. OPERA - AI — reporting of handheld echocardiography in suspected heart failure (European Society of Cardiology Congress, 2023).
101. Tromp, J. et al. Nurse-led home-based detection of cardiac dysfunction by ultrasound: results of the CUMIN pilot study. *Eur. Heart J. Digit. Health* **5**, 163–169 (2024).
102. Peck, D. et al. The use of artificial intelligence guidance for rheumatic heart disease screening by novices. *J. Am. Soc. Echocardiogr.* **36**, 724–732 (2023).
103. Lyon, A. R. et al. 2022 ESC guidelines on cardio-oncology developed in collaboration with the European hematology association (EHA), the European society for therapeutic radiology and oncology (ESTRO) and the international cardio-oncology society (IC-OS). *Eur. Heart J. Cardiovasc. Imaging* **23**, e333–e465 (2022).
104. Papadopoulou, S.-L. et al. Artificial intelligence-assisted evaluation of cardiac function by oncology staff in chemotherapy patients. *Eur. Heart J. Digit. Health* **5**, 278–287 (2024).
105. Oikonomou, E. K. et al. A multimodal video-based AI biomarker for aortic stenosis development and progression. *JAMA Cardiol.* **9**, 534–544 (2024).
106. Oo, M. M. et al. Artificial intelligence-assisted automated heart failure detection and classification from electronic health records. *ESC Heart Fail.* **11**, 2769–2777 (2024).
107. Pandey, A. et al. Deep-learning models for the echocardiographic assessment of diastolic dysfunction. *JACC Cardiovasc. Imaging* **14**, 1887–1900 (2021).
108. Sengupta, P. P. et al. A machine-learning framework to identify distinct phenotypes of aortic stenosis severity. *JACC Cardiovasc. Imaging* **14**, 1707–1720 (2021).
109. Sánchez-Puente, A. et al. Machine learning to optimize the echocardiographic follow-up of aortic stenosis. *JACC Cardiovasc. Imaging* **16**, 733–744 (2023).
110. Sengupta, P. P., Dey, D., Davies, R. H., Duchateau, N. & Yanamala, N. Challenges for augmenting intelligence in cardiac imaging. *Lancet Digit. Health* **6**, e739–e748 (2024).
111. Díaz-Rodríguez, N. et al. Connecting the dots in trustworthy artificial intelligence: from AI principles, ethics, and key requirements to responsible AI systems and regulation. *Inf. Fusion* **99**, 101896 (2023).
112. Lüscher, T. F., Wenzl, F. A., D'Ascenzo, F., Friedman, P. A. & Antoniades, C. Artificial intelligence in cardiovascular medicine: clinical applications. *Eur. Heart J.* https://doi.org/10.1093/eurheartj/ehae465 (2024).
113. Khera, R. et al. Transforming cardiovascular care with artificial intelligence: from discovery to practice: JACC state-of-the-art review. *J. Am. Coll. Cardiol.* **84**, 97–114 (2024).
114. Tseng, A. S., Lopez-Jimenez, F. & Pellikka, P. A. Future guidelines for artificial intelligence in echocardiography. *J. Am. Soc. Echocardiogr.* **35**, 878–882 (2022).
115. Vrudhula, A., Kwan, A. C., Ouyang, D. & Cheng, S. Machine learning and bias in medical imaging: opportunities and challenges. *Circ. Cardiovasc. Imaging* **17**, e015495 (2024).
116. Mihan, A., Pandey, A. & Spall, H. G. V. Mitigating the risk of artificial intelligence bias in cardiovascular care. *Lancet Digit. Health* **6**, e749–e754 (2024).
117. Seyyed-Kalantari, L., Zhang, H., McDermott, M. B. A., Chen, I. Y. & Ghassemi, M. Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. *Nat. Med.* **27**, 2176–2182 (2021).
118. Duffy, G. et al. Confounders mediate AI prediction of demographics in medical imaging. *npj Digit. Med.* **5**, 188 (2022).
119. Brown, A. et al. Detecting shortcut learning for fair medical AI using shortcut testing. *Nat. Commun.* **14**, 4314 (2023).
120. Banerjee, I. et al. "Shortcuts" causing bias in radiology artificial intelligence: causes, evaluation, and mitigation. *J. Am. Coll. Radiol.* **20**, 842–851 (2023).
121. Yang, Y., Zhang, H., Gichoya, J. W., Katabi, D. & Ghassemi, M. The limits of fair medical imaging AI in real-world generalization. *Nat. Med.* https://doi.org/10.1038/s41591-024-03113-4 (2024).
122. Dohare, S. et al. Loss of plasticity in deep continual learning. *Nature* **632**, 768–774 (2024).
123. Gama, F. et al. Implementation frameworks for artificial intelligence translation into health care practice: scoping review. *J. Med. Internet Res.* **24**, e32215 (2022).
124. Rajpurkar, P., Chen, E., Banerjee, O. & Topol, E. J. AI in health and medicine. *Nat. Med.* **28**, 31–38 (2022).
125. European Parliament. Directorate general for parliamentary research services. artificial intelligence in healthcare: applications, risks, and ethical and societal impacts (2022); https://data.europa.eu/doi/10.2861/568473.
126. Khera, R., Simon, M. A. & Ross, J. S. Automation bias and assistive AI: risk of harm from AI-driven clinical decision support. *JAMA* **330**, 2255–2257 (2023).
127. Wang, F. & Beecy, A. Implementing AI models in clinical workflows: a roadmap. *BMJ Evid. Based Med.* https://doi.org/10.1136/bmjebm-2023-112727 (2024).
128. Gill, S. K. et al. Artificial intelligence to enhance clinical value across the spectrum of cardiovascular healthcare. *Eur. Heart J.* **44**, 713–725 (2023).
129. Christensen, M., Vukadinovic, M., Yuan, N. & Ouyang, D. Vision–language foundation model for echocardiogram interpretation. *Nat. Med.* **30**, 1481–1488 (2024).
130. Barros-Gomes, S. et al. Characteristics and consequences of work-related musculoskeletal pain among cardiac sonographers compared with peer employees: a multisite cross-sectional study. *J. Am. Soc. Echocardiogr.* **32**, 1138–1146 (2019).
131. Li, K. et al. Autonomous navigation of an ultrasound probe towards standard scan planes with deep reinforcement learning. in *2021 IEEE International Conference on Robotics and Automation (ICRA)* https://doi.org/10.1109/ICRA48506.2021.9561295 (IEEE, 2021).
132. Soemantoro, R., Kardos, A., Tang, G. & Zhao, Y. An AI-powered navigation framework to achieve an automated acquisition of cardiac ultrasound images. *Sci. Rep.* **13**, 15008 (2023).
133. Amezcua, K.-L. et al. Design and testing of ultrasound probe adapters for a robotic imaging platform. *Sci. Rep.* **14**, 5102 (2024).
134. Villalobos Lizardi, J. C. et al. A guide for assessment of myocardial stiffness in health and disease. *Nat. Cardiovasc. Res.* **1**, 8–22 (2022).
135. Caenen, A. et al. Ultrasound shear wave elastography in cardiology. *JACC Cardiovasc. Imaging* **17**, 314–329 (2024).
136. Hathaway, Q. A. et al. Ultrasonic texture features for assessing cardiac remodeling and dysfunction. *J. Am. Coll. Cardiol.* **80**, 2187–2201 (2022).
137. Sengupta, P. P. & Chandrashekhar, Y. Advancing myocardial tissue analysis using echocardiography. *JACC Cardiovasc. Imaging* **17**, 228–231 (2024).
138. Jamthikar, A. D. et al. Cardiac ultrasonic tissue characterization in myocardial infarction based on deep transfer learning and radiomics features. Preprint at *medRxiv* https://doi.org/10.1101/2024.03.29.24305067 (2024).
139. Amado-Rey, A., GonçalvesSeabra, A. & Stieglitz, T. Towards ultrasound wearable technology for cardiovascular monitoring: from device development to clinical validation. *IEEE Rev. Biomed. Eng.* https://doi.org/10.1109/RBME.2024.3410399 (2024).
140. Moisello, E. et al. PMUT and CMUT devices for biomedical applications: a review. *IEEE Access* **12**, 18640–18657 (2024).
141. Hu, H. et al. A wearable cardiac ultrasound imager. *Nature* **613**, 667–675 (2023).
142. Democratizing echocardiography with AI. *Us2.ai* https://us2.ai/publications/ai-echo-white-paper/ (2023).
143. Turing, A. M. On computable numbers, with an application to the entscheidungsproblem. *Proc. Lond. Math. Soc.* **s2-42**, 230–265 (1937).
144. Hunter, D. J. & Holmes, C. Where medical statistics meets artificial intelligence. *N. Engl. J. Med.* **389**, 1211–1219 (2023).
145. Haug, C. J. & Drazen, J. M. Artificial intelligence and machine learning in clinical medicine. *N. Engl. J. Med.* **388**, 1201–1208 (2023).
146. Shehab, M. et al. Machine learning in medical applications: a review of state-of-the-art methods. *Comput. Biol. Med.* **145**, 105458 (2022).
147. LeCun, Y., Bengio, Y. & Hinton, G. Deep learning. *Nature* **521**, 436–444 (2015).
148. Sidey-Gibbons, J. A. M. & Sidey-Gibbons, C. J. Machine learning in medicine: a practical introduction. *BMC Med. Res. Methodol.* **19**, 64 (2019).
149. Reading Turchioe, M. et al. Systematic review of current natural language processing methods and applications in cardiology. *Heart* **108**, 909–916 (2022).
150. Will ChatGPT transform healthcare? *Nat. Med.* **29**, 505–506 (2023).
151. Boonstra, M. J., Weissenbacher, D., Moore, J. H., Gonzalez-Hernandez, G. & Asselbergs, F. W. Artificial intelligence: revolutionizing cardiology with large language models. *Eur. Heart J.* **45**, 332–345 (2024).
152. Amadou, A. A. et al. EchoApex: a general-purpose vision foundation model for echocardiography. Preprint at https://doi.org/10.48550/arXiv.2410.11092 (2024).
153. Zhang, Z., Wu, Q., Ding, S., Wang, X. & Ye, J. Echo-vision-FM: a pre-training and fine-tuning framework for echocardiogram videos vision foundation model. Preprint at *medRxiv* https://doi.org/10.1101/2024.10.09.24315195 (2024).
154. Collins, G. S., Reitsma, J. B., Altman, D. G. & Moons, K. G. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD Statement. *BMC Med.* **13**, 1 (2015).
155. Liu, X., Cruz Rivera, S., Moher, D., Calvert, M. J. & Denniston, A. K. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension. *Nat. Med.* **26**, 1364–1374 (2020).
156. Sengupta, P. P. et al. Proposed requirements for cardiovascular imaging-related machine learning evaluation (PRIME): a checklist. *JACC Cardiovasc. Imaging* **13**, 2017–2035 (2020).
157. Lafitte, S. et al. Integrating artificial intelligence into an echocardiography department: feasibility and comparative study of automated versus human measurements in a high-volume clinical setting. *Arch. Cardiovasc. Dis.* https://doi.org/10.1016/j.acvd.2025.04.051 (2025).

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P.L.M., B.G. and C.S.P.L. researched data for the article. All authors contributed substantially to discussion of content, wrote the article, and reviewed and/or edited the manuscript before submission.

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