Position Statement

Joint opinion document on echocardiography and artificial intelligence

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ABSTRACT

Echocardiography is a key tool in cardiac assessment but faces challenges such as subjectivity in interpretation and dependence on image quality. AI, through techniques like machine learning and deep learning, enables the automation of processes such as image acquisition, quantification of parameters (ejection fraction, ventricular volumes), and suspicion of pathologies (hypertrophic cardiomyopathy, cardiac amyloidosis). Additionally, AI facilitates medical education through simulations that provide real-time feedback. Despite its advantages, challenges remain, including the lack of transparency in algorithms ("black box"), the need for external validation, and dependence on image quality. In conclusion, AI will not replace echocardiographists but will become an indispensable tool for optimizing diagnosis and clinical decision-making.

ABBREVIATIONS

AI: artificial intelligence
ML: machine learning
DL: deep learning
EF: ejection fraction

INTRODUCTION

Day by day more data are generated in medical practice: telemetry monitoring, auxiliary imaging tests, clinical histories and electronic prescription. However, the capacity of the brain to interpret so much information is limited, leading to resorting to new technologies increasingly. In such scenario, artificial intelligence (AI) appears as an essential tool that, in spite of appearing to have an advanced development, it is in its first stages in terms of humans and AI interaction.[1]

Doppler echocardiogram is a fundamental tool in cardiovascular clinical practice, used for the structural and functional evaluation of the heart in real time. Its main limitations are inter and intraobserver variability, depending on the quality of the image obtained, as well as the time required to perform numerous measurements and calculations *(Table 1).* In this regard, AI enhances the capacity to process large volumes of information and it is positioning as a key tool to reduce variability in interpretation and to optimize the diagnostic accuracy of evaluation *(Figure 1).*

AI has different branches, with the main ones in echocardiography being the following:

- **Machine learning (ML):** it allows computers to learn from large volumes of data, where human experts de-

TABLE 1.
Current challenges. Reproduced and translated under authorization by Dr. Roberto Lang. University of Chicago Medicine.

CHALLENGES IN ECHOCARDIOGRAPHY
Large volume of patients
Clinical guidelines
Staff reduction
Manual examination
Interobserver variability
Time-consuming tasks
Differential diagnoses

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FIGURE 1.
Usefulness of AI in health care. Reproduced and translated under authorization by Dr. Roberto Lang. University of Chicago Medicine.

termine the set of characteristics to understand the differences between data input. Through mathematical algorithms, it identifies patterns, it identifies trends and improves its performance over time, facilitating the automation of complex processes; for example, the interpretation of images. Machine learning models are divided into three main categories: supervised learning (it uses sets of labeled data to train algorithms to classify data or predict results with accuracy) *(Figure 3);* unsupervised learning (it uses algorithms to analyze and group sets of unlabeled data, discovering hidden patterns or data grouping not requiring human intervention) *(Figure 4);* semi-supervised learning (it offers a middle ground between supervised and unsupervised learning).

- **Deep learning (DL):** it is a subcategory of ML. It is based on artificial neural networks with multiple layers imitating the operation of the human brain. These networks enable the analysis of data in a hierarchical manner and to extract complex characteristics. Its capacity to detect subtle changes or changes invisible to the human eye in structures has revolutionized diagnostic accuracy in echocardiography.

Use of AI in echocardiography may occur in different aspects:

1. **Automation of image acquisition:** AI helps operators, including those with little experience, to obtain echocardiographic images of high quality. In this regard, algorithms guide, in real time, the position and angle of transducers, ensuring optimal views. This reduces interobserver variability and it is particularly useful in environments with limited resources or where there are no specialists available.
2. **Acknowledgement and classification of echocardiographic views:** using different algorithms, the different echocardiographic views are identified and classified automatically, speeding up the work flow and minimizing human error.
3. **Automatic quantification:** AI enables the automatic measurement of parameters such as ventricular volumes, ejection fraction and transvalvular flows, among

FIGURE 2.
Model of supervised learning. Reproduced and translated under authorization by Dr. Roberto Lang. University of Chicago Medicine.

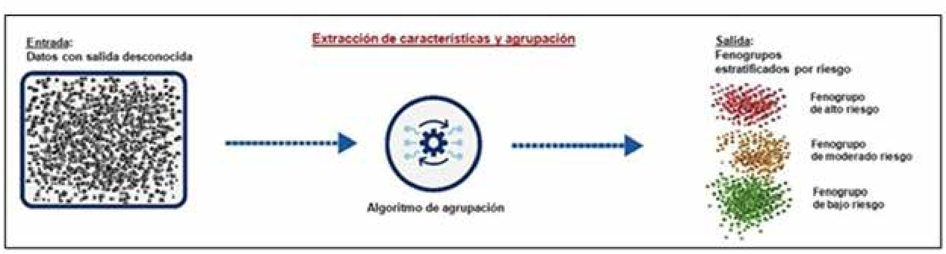

FIGURE 3.
Model of unsupervised learning. Reproduced and translated under authorization by Dr. Roberto Lang. University of Chicago Medicine.

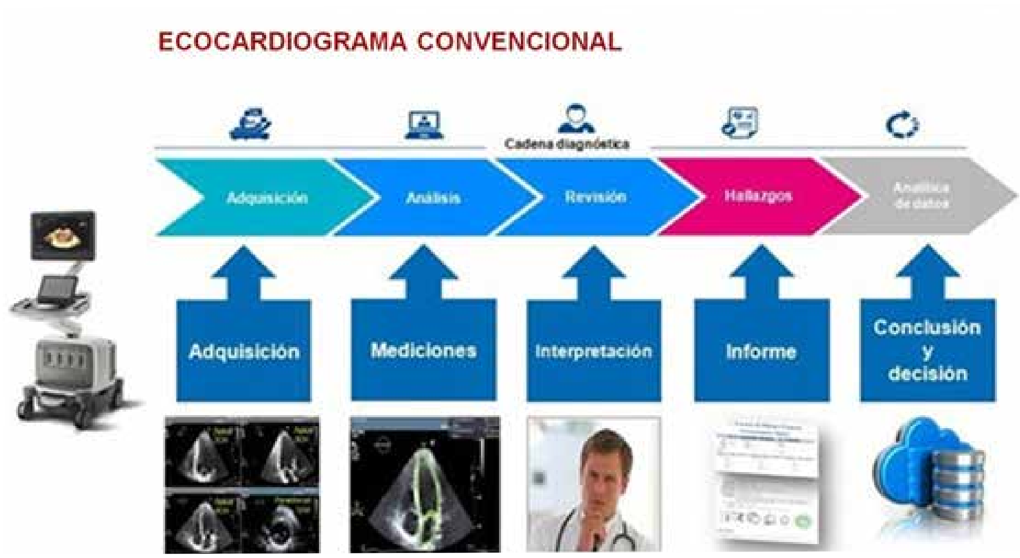

FIGURE 4.
Current era of echocardiography.
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FIGURE 5.
Future of echocardiography.
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others. This reduces the time of analysis and decreases inter and intraobserver variability. Thus, it is possible to assess, for instance, the systolic and diastolic function of the left ventricle or valve disease.

4. **Detection and diagnosis of pathologies:** AI allows to identify patterns associated with different heart diseases, such as hypertrophic cardiomyopathy, cardiac amyloidosis and pulmonary hypertension. These systems may alert clinicians about abnormal findings that could be overlooked in conventional evaluations.
5. **Education and training:** simulators have been developed based on AI that allow echocardiographers to be trained to practice with a wide variety of clinical cases. Algorithms offer feedback in real time on the quality of images and measurements made, improving the skills of image acquisition and interpretation.

Starting from the above items, it is possible to understand the mechanisms by which AI enables improving current practice, reaching an accuracy comparable to that of operators expert in the acquisition, interpretation and probability of etiological diagnoses of the different heart diseases *(Figure 4).* Recent studies suggest that AI also has a great potential to guide and predict results in transcatheter interventions.

Over the opinion article we will analyze how AI optimizes and will continue to optimize the performance of echocardiographic studies, improving diagnostic accuracy, minimizing mistakes and reducing interobserver variability, also called operator dependence, a key factor in this type of evaluation *(Figure 5).*

USE OF AI IN ECHOCARDIOGRAPHY

Measurement of diameters, volumes, ejection fraction and global longitudinal strain

Left ventricular systolic dysfunction is a frequent alteration originated by different pathologies. Its accurate evaluation is fundamental for the diagnosis, management and prognosis of cardiovascular diseases. Left ventricular ejection fraction (LVEF) is the most widely used parameter to assess systolic function and guide treatment. Echocardiographic evaluation presents limitations, such as visual analysis subjectivity and intra and interobserver variability, mainly influenced by the operator's experience.[2,3,4]

Current technology allows to automatize echocardiographic measurements, decreasing the variability between experts and beginners. This increases efficacy and optimizes the workflow in echocardiography laboratories.[5] Multicenter studies have evaluated independent software designed for an automatic detection of the endomyocardial edge, a technique that can be implemented not requiring AI. However, integrating AI-based algorithms has enabled optimizing this process, improving accuracy in the quantification of parameters such as 2D LVEF, left ventricular volumes and global longitudinal strain. These methods are particularly effective when image quality is moderate or good. However, in images with poorer quality, correlation with manual tracings reduces significantly.[6]

Besides the detection of the endomyocardial edge, the AI networks can precisely estimate global longitudinal strain, ventricular volumes, identify echocardiographic views and make accurate measurements in the ventricular mass and wall thickness.[7] This was proven in the work by Salte et al., whose model based on ML can automatically identify the three traditional apical views and estimate the global longitudinal strain in different heart conditions. This approach reduced the processing time to just 15 seconds, in comparison to the 3 to 5 minutes required with traditional methods.[8]

AI thus offers a powerful tool to analyze echocardiographic images with precision and efficacy, improving diagnostic capacities and reducing the time needed for these tasks.

EVALUATION OF ALTERATIONS OF SEGMENTAL WALL MOTION IN ISCHEMIC HEART DISEASE

Segmental wall motion alterations are early indicators of ischemic heart disease and independent predictors of major adverse cardiovascular events.[9,10,11] Although echocardiography is a key tool for diagnosis, a traditional evaluation based on visual interpretation presents significant limitations, including interobserver variability and dependency on operators experience.[12,13] AI may help to overcome these challenges by integrating convolutional neural networks and DL models that would allow evaluating them with accuracy.[9,10,11]

Several work groups have developed models with good results. Huang et al. developed a model based on convolutional neural networks in three dimensions, analyzing echocardiographic videos, achieving 81.1% sensitivity and 81.6% specificity, proving its capacity to detect segmental motion alterations using both time and space information.[9] Kusunose's work group proved that a DL model can have a precision comparable to experts in cardiology, with an area under the curve of 0.99 for segmental alterations.[14] Another group developed an AI solution in real time that guides unspecialized operators and facilitates access to quality echocardiograms in different clinical scenarios.[15] Lin et al. evaluated the performance of a model for automatic detection of anomalies in regional wall motion in patients suspected of myocardial infarction: they compared echocardiograms obtained with portable devices at the foot of the bed and standard devices. They developed an automated workflow that integrated the selection of views, ventricular segmentation, detection of wall motion alterations and quantification of cardiac function. The detection of motion anomalies showed an area under the curve of 0.88 and 0.91 in the studies obtained with portable and standard devices, respectively.[12] Other models are EC3D-Net and STGA-MS, which have displayed significant advancements in the automated detection of motion anomalies, exceeding conventional methods, improving diagnostic accuracy and reproducibility in the evaluation of ischemic myocardial dysfunction.[10,11]

Stress echocardiography allows evaluating the development of segmental contraction anomalies after applying physical or pharmacological stress. There should be quality control in the interpretation of regional wall motion anomalies, as there is a greater interobserver variability than in normal studies.[13] There are AI models showing a high diagnostic precision (84.4% sensitivity and 92.7% specificity) in an independent validation cohort, improving interobserver consistency and diagnostic confidence, increasing sensitivity by 10% and reaching an area under the ROC curve of 0.93.[16] Although technology does not substitute clinical evaluation, its integration can improve efficiency and accuracy for the diagnosis of myocardial ischemia. Additional studies are required to evaluate its applicability in wider populations, but automation of analysis by AI may optimize diagnostic accuracy and reproducibility in evaluation.[17]

EVALUATION OF DIASTOLIC DYSFUNCTION AND HEART FAILURE WITH PRESERVED EF

Left ventricular diastolic dysfunction is a key factor in the pathophysiology of heart failure. However, its echocardiographic evaluation is complex and requires a multiparameter approach. There is no single variable with enough diagnostic precision for its detection, so currently it is advised to use an algorithm that combines multiple measurements.[18]

In recent years, different investigations were developed with the goal of evaluating the usefulness of AI in this field. The initial stresses, with its strengths and limitations, have been previously analyzed in detail.[19] The heterogeneity in AI techniques used and the methodological differences in diagnostic reference (whether the final echocardiographic report, the opinion of experts and the algorithms of clinical guidelines) have prevented obtaining definitive conclusions in these first studies.

However, more recent research has included a higher number of studies and a more homogeneous methodology. In a paper published in 2021, Tromp et al. showed that a DL algorithm was not only able to identify and classify the necessary echocardiographic views to assess ventricular function (systolic and diastolic), but also to perform automated measurements of key variables in the diagnosis of diastolic dysfunction, such as ventricular volumes and Doppler velocities (both of blood flow and of tissue).[20] These measurements showed a high coincidence with those performed by expert operators and were validated in multiple patient cohorts.

That same year, Pandey et al. published a study where they evaluated another DL algorithm designed to identify subgroups in high and low risk of diastolic dysfunction.[21] Their findings were validated in external cohorts, including populations from the TOPCAT (Spironolactone for Heart Failure with Preserved Ejection Fraction) and the RELAX-HF (Effects of Serelaxin in Patients with Acute Heart Failure) trials: it was observed that patients classified as in high risk presented a higher rate of adverse events in follow-up (mortality and hospital admission due to decompensated heart failure), higher neurohormonal activation and less capacity for exercise. Furthermore, the neural network-based model predicted elevated filling pressures with higher accuracy (area under the ROC curve) in comparison with the algorithm of the American Society of Echocardiography from 2016.

In 2023, two large-scale studies were published. Chen et al. analyzed 1304 echocardiographic studies with the goal of developing an AI-based model, capable of identifying echocardiographic views, detecting the presence of diastolic dysfunction and establishing degree of severity. The model validation by comparison with human experts validation showed an excellent consistency.[22] On the other hand, Ackerman et al. analyzed more than 5000 patients exclusively using the apical four-chamber view. Its AI model showed an outstanding diagnostic performance, with an area under the curve (AUC) of more than 97% in the derivation cohort and 95% in the validation cohort for the identification of diastolic dysfunction.[23] Subsequently, in 2024, the same group from the Mayo Clinic published a follow-up study with a 3.4-year median, where it was proven that patients identified by the algorithm as patients with a probability of presenting diastolic dysfunction had a higher risk of mortality and hospitalization by heart failure over an observation period. These findings reinforce the prognostic usefulness of AI in risk stratification and early identification of patients with higher clinical vulnerability.[24]

In spite of advancements, there are still key challenges that should be solved before a routine implementation of AI in clinical practice. Among them, the following stand out: the need to define which of the multiple AI approaches is the most appropriate for this issue, validation in population groups that have not been studied yet, the management of "indeterminate" results, a lack of validation with more rigorous gold standards (such as invasive measurement of filling pressures and ventricular relaxation time, Tau), the evaluation of reproducibility, and last but not least, the financial impact entailed by the integration of these algorithms in echocardiography devices.

STUDIES FOR HEART VALVE DISEASES

Although echocardiography constitutes the method of choice for the diagnosis of heart valve diseases, there are still underdiagnosed cases, partly due to access limitations and variability in the acquisition and interpretation of images. The introduction of portable ultrasound devices has improved accessibility to this tool, although a proper training is still required to guarantee diagnostic quality studies. In this scenario, AI is transforming the evaluation and management of heart valve diseases, optimizing image acquisition and reducing operator dependence. In comparative studies, the diagnostic accuracy of nurses with no previous experience in echocardiography to assess aortic and mitral valve disease reached values of more than 92% in comparison to expert echocardiographers, showing the potential of these technologies to enhance echocardiography applicability in different clinical fields.[25]

In a scenario of assessment of valve diseases, AI can provide assistance with:

1. **Acquisition:** a proper visualization of chambers, valves, jets and Doppler signals requires training, so algorithms were developed to guide image acquisition. When comparing new nurses vs expert echocardiographers, the accuracy of the former to assess aortic or mitral valve diseases was more than 92%.[25]
2. **Identification:** just as with left ventricular images, AI not just allows reading data obtained from raw valve images, but also automatic measurements. This will be translated into shorter times in the management of valve diseases due a reduction in time to establish a diagnostic probability, thus decreasing interobserver variability to determine severity (currently, approximately 61% for mitral regurgitation). There are algorithms that can detect mitral and tricuspid valves with 98% and 90% accuracy, respectively; others are capable of identifying continuous-wave Doppler signal with 98% accuracy.[26,27] In a study with 256 patients, AI had an excellent diagnostic capacity compared with measurements made by humans in terms of maximum velocity of the aortic valve (r=0.97), mean gradient (r=0.94), aortic valve area (r=0.88), systolic volume (r=0.79), velocity time integral of the left ventricular outflow tract (r=0.89), aortic velocity time integral (r=0.96) and left ventricular outflow tract diameter (r=0.76).[27,28]

3. **Segmentation:** it refers to identifying a structure in an image, allowing automatizing the evaluation of diameters and annulus, valve or Doppler function. There are algorithms trained with mitral valve images, which obtained a variable accuracy, from modest to good (0.48-0.79) and an error rate close to 6% for perimeter measurement and 12% for the valve area.[29] In regard to Doppler, in a study, an algorithm was trained with 1132 patients with mitral regurgitation from mild to severe, and it was validated with 295 patients, achieving an accuracy close to 90% for each category of severity; another publication reported a correlation of 0.9 between an algorithm and an expert for the measurement of velocities, gradient and velocity time integral of Doppler signals.[30]
4. **Identification of severity:** it is based on identifying data exceeding human perception. In a cohort of 139 patients, it was possible to identify the severity of mitral regurgitation with an accuracy greater to 99%; another study could identify rheumatic diseases with 77% accuracy.[31,32] These algorithms also allow identifying mitral prosthetic valves with an area under the curve of 98%.

It not only allows to improve a current evaluation, but also add clinical, genetic and laboratory information, and data from auxiliary tests, achieving decision-making in a much shorter time.

There are models using ML developed for aortic valve disease: a study from the Cleveland Clinic identified phenotypes of aortic aneurysm in 656 patients with bicuspid valve, allowing associating them with predominant valve disease.[33,34,35,36] Another 3 studies were designed to identify groups in high risk within the range of aortic stenosis:

- Casaclang-Verzosa et al. described the progression of mild to severe stenosis in 346 patients using 79 clinical and echocardiographic variables. They showed 2 subgroups of moderate aortic stenosis (one male and with less EF; another with lower velocities, but greater left ventricular mass and atrial volumes) and their response after valve replacement.
- Sengupta et al. analyzed a cohort of 1052 patients with mild or moderate aortic stenosis and a group with severe low-flow low-gradient aortic stenosis. They found a group in higher risk with higher calcium score, elevated biomarkers, gadolinium uptake, incidence of valve replacement and pre- and post-surgical death. The validation model showed better discrimination and reclassification than current methods.
- Finally, Kwak et al. developed a model based on 398 patients with moderate to severe aortic stenosis, incorporating 11 clinical variables, of laboratory and echocardiographic, with the aim of identifying patients that may not benefit from an intervention. Through data analysis, they identified three differentiated subgroups, among which one presented high cardiovascular mortality, while another showed high total mortality. These findings suggest that the last subgroup may require an alternative therapeutic approach, highlighting the potential of AI in risk stratification and personalization of management strategies.

USEFULNESS IN TRANSCATHETER INTERVENTIONS IN STRUCTURAL HEART DISEASE

Transcatheter interventions in structural heart disease have exponentially increased due to population ageing and technological advancements, such as transcatheter aortic valve implant, left atrial appendage closure, atrial septal defect closure and procedures on atrioventricular valves. These interventions have turned into the first-line treatment for multiple pathologies, and AI has emerged as a key tool in the optimization of these procedures, improving selection of patients, preoperative planning, execution, post-implant monitoring and follow-up, contributing to optimizing clinical outcomes.[37,38]

In this scenario, AI, by supervised learning, predicts results and facilitates early diagnoses by reducing the time of image processing and inter and intraobserver variability through the analysis of large data volumes. By means of unsupervised learning, it identifies hidden patterns, classifies patients according to specific phenotypes and risks, and determines different outcomes and therapeutic responses.[37]

The selection of patients for heart valve interventions is based on symptoms and echocardiographic findings, while the indication of left atrial appendage closure is based on the risk of stroke or bleeding.[37] Through ML (with a technique called cluster analysis), hidden patterns can be discovered within data and patients can be classified into phenotypes with different clinical outcomes. In aortic stenosis, for instance, this technique helps to identify patients that may benefit from transcatheter treatment.[36,37,38] Furthermore, in atrial fibrillation, it allows to estimate the risk of stroke and evaluate specific anatomical variabilities of the left atrial appendage to facilitate the indication of percutaneous closure.

On the other hand, supervised ML is an alternative to conventional statistics to establish a prognostic probability and thus generate stronger models.[39] Nevertheless, AI algorithms are not free from biases, as they depend on data quality, relevance and integrity for their training.

In computed tomography (CT), DL is used to automatically segment and quantify aortic valve calcification; a key datum for diagnosis and mortality prediction.[40] In the cases of severe aortic stenosis with low flow and low gradient, where echocardiographic results can be misleading, calcium score by echocardiography based on AI has proven to be useful with clinical decision-making.

An algorithm based on more than 530,000 echocardiograms was developed, which improves the detection of severe aortic stenosis, exceeding the limitations of conventional measurements of the left ventricular outflow tract.[41] However, the complexity of DL algorithms requires a high capacity for computational processing, including graphic processing and computing units in the cloud.[42]

ML has also revolutionized the planning of transcatheter interventions by the generation of computational 3D models, which enable selecting devices in a more precise manner and predict performance.[43] This has been validated in procedures like transcatheter aortic valve implant, MitraClip, left atrial appendage (LAA) closure and transcatheter mitral valve replacement (TMVR). Particularly, a CT-based model has proved to accurately predict the deformation and apposition of the LAA closure device, improving the procedure's planning.[44]

During intervention, use of AI facilitates the automatic identification of anatomical structures by the fusion of fluoroscopic images with echocardiography or CT. This integration has been used in transcatheter aortic valve implant (TAVI) and LAA closure, reducing the time of the procedure and exposition to radiation.[45] Furthermore, AI-assisted planning with augmented reality enables the generation of 3D holograms in real time, optimizing visualization and the positioning of the device.[46]

In the follow-up in the short term, supervised ML has proven to predict in-hospital mortality with greater accuracy after TAVI and TMVR in comparison with traditional models.[47] Likewise, AI has exceeded the conventional score systems (EuroSCORE, STS) in the prediction of survival within 30 days after TAVI.[48] An efficient model was described, to predict the need for pacemaker implant after TAVI, a frequent complication, by the integration of clinical, electrocardiographic and echocardiographic data.[49]

AI-based automated quantification has also significantly reduced the time of analysis per patient.[50] As to the prediction of hospital stay after TAVI, an ML model has identified novel predictors, as the duration of the procedure, the need for physiotherapy and results according to the day of the week when the intervention is made.

IDENTIFICATION OF MYOCARDIAL DISEASES

The classification and diagnosis of myocardial diseases in early stages, when patients are still asymptomatic, represent a critical area where computational science may contribute great benefits. In clinical practice, these patients may remain undiagnosed for long periods, and only receive treatment when the disease has progressed to advanced stages. This has implications not just in the prognosis and quality of life of patients, but also in the reduction of future hospital costs.

Left ventricular hypertrophy is a frequent finding in clinical practice and is associated to adverse cardiovascular events such as arrhythmias, myocardial ischemia, heart failure and sudden cardiac death.[51,52] A study made by Zhang et al. proved that convolutional neural networks can identify echocardiographic windows and provide specific measures, such as wall thickness and left ventricular mass.[7]

From the point of view of etiological diagnosis, echocardiography is often not enough, and more complex studies are required for an accurate diagnosis. Between the main etiologies that present as ventricular hypertrophy, we find hypertension, hypertrophic cardiomyopathy, aortic stenosis, chronic kidney disease and cardiac amyloidosis. Other less frequent etiologies include myocarditis, sarcoidosis and storage diseases, such Fabry or Danon, besides mitochondrial cardiomyopathies.

Myocardial texture is difficult to evaluate and quantify by simple observation from a physician.[53] In this regard, AI has shown its capacity to differentiate myocardial hypertrophy secondary to hypertension from hypertrophic cardiomyopathy and uremic cardiomyopathy. It has been observed that hypertrophic cardiomyopathy presents a more homogeneous pattern of numerical values distribution in algorithmic analysis, which could be useful for etiological differentiation.[54]

In traditional echocardiographic in the evaluation of cardiac amyloidosis, although multiple suggestive findings can be identified, none has proven to be specific or sensitive enough to establish a definitive diagnosis. Besides, certain echocardiographic characteristics require advanced analysis with specialized software, which entails more processing time and it is usually applied in cases with an already confirmed diagnosis.[55]

A study in academic centers used a model based on echocardiographic videos with four-chamber views, achieving a high diagnostic accuracy (C-statistic of 0.96), superior to that of experts in detection of amyloidosis. They emphasized that the model had a better performance in the detection of cardiac amyloidosis by transthyretin than by light chains.[56] Another DL model could identify subtle changes in ventricular geometry, allowing the differentiation of cardiac amyloidosis from ventricular hypertrophy.[57] Even the FDA (Food and Drug Administration) approved the EchoGo® Amyloidosis AI software for the detection of cardiac amyloidosis by echocardiography. This system has shown a high diagnostic performance, with an area under the ROC curve of up to 0.93 and a negative predictive value of more than 85%. Its sensitivity is consistent between the different types of amyloidosis. Besides, it exceeded conventional analysis in patients older than 60 years with heart failure and increase in left ventricular wall thickness, with an area under the ROC curve of 0.93 in comparison to 0.73.

In patients with heart failure and preserved EF, with predominance of right congestion symptoms, the differential diagnosis includes restrictive cardiomyopathy and constrictive pericarditis. In this scenario, echocardiography is considered the first-line study for the diagnosis of constrictive pericarditis.[58,59] However, its accuracy depends on the quality of the study and the experience of the operator, and additional studies may be required, like CT, MRI or hemodynamic evaluation.[60,61,62]

In 2016, Sengupta et al. carried out a pilot study using speckle-tracking and AI by a classifier of associative memory to differentiate constrictive pericarditis of restrictive cardiomyopathy, obtaining an area under the curve of 0.89, above the conventional echocardiographic variables.[63] A more recent study used a DL model to differentiate constrictive pericarditis from restrictive cardiomyopathy secondary to amyloidosis, reaching an area under the curve of 0.97 with four-chamber view and external validation with area under the curve of 0.84.[64]

EDUCATION IN ECHOCARDIOGRAPHY

AI has become an invaluable tool to improve the acquisition and interpretation skills for echocardiographic images; particularly in training echocardiographers. AI-based simulators allow students to practice with a wide variety of clinical cases; from common scenarios up to complex and rare situations, which enriches their experience and training for real practice.

One of the most significant advancements in this field is the capacity of AI to offer feedback in real time. Algorithms may evaluate the quality of images acquired by the students, guiding them in the correct position and angulation of the transducer to obtain optimal views. Moreover, these systems can offer suggestions to improve the acquisition technique and point out common mistakes, accelerating the learning process and reducing dependency on the constant supervision by an instructor. This capacity is particularly useful in environments with limited resources, where access to experts in echocardiography can be scarce.

Another outstanding aspect is use of AI for image interpretation. DL models can analyze echocardiographic studies and compare the findings of students with those of experts, offering an objective evaluation of their performance. This not only improves the diagnostic accuracy of students, but also lets them get familiar with quality standards and best practices in the interpretation of studies. Moreover, AI can generate automated reports that work as study and reference material, facilitating reviews and continuous learning.

In brief, AI is revolutionizing education in echocardiography by providing interactive, personalized and accessible tools that improve the training of health care professionals. As these technologies continue evolving, they are expected to play an even more important role in preparing highly trained echocardiographers and in the reduction of variability for image acquisition and interpretation.

LIMITATIONS

The clinical application of AI in echocardiography faces multiple challenges that have to be approached before a widespread adoption. One of the main ones is the "black box" problem in algorithms; i.e. the lack of transparency in the internal operation of complex models, particularly those based on DL, which makes it difficult to interpret results and understand the criteria used for models to establish a diagnostic probability. This, evidently, can generate mistrust for a clinical use.

The quality of echocardiographic images is still a determinant factor in the performance of all these algorithms. Thus, image acquisition variability, influenced both by the experience of operators and by the technical features of the device, can affect model accuracy. This highlights the need for strategies to optimize data quality.

Another clinical aspect is the lack of standardization and external validation of many models, which raises questions about its applicability in clinical practice and in different populations of patients. Most studies that have evaluated AI in cardiology have been retrospective and require validation in multicenter studies in a large scale to demonstrate its usefulness in real clinical scenarios.

Finally, some models, mainly of ML, depend on data previously labeled by doctors, which may introduce inherent biases and systematic errors in the interpretation of findings. This dependency on human classification underscores the need to develop strategies to minimize the impact of these biases on algorithm training.

CONCLUSIONS

AI is revolutionizing the field of echocardiography, offering tools that improve diagnostic accuracy, reduce interobserver variability and optimize workflow in cardiac imaging laboratories. From the automatic quantification of parameters such as ejection fraction and global longitudinal strain, to the evaluation of heart valve diseases and the detection of segmental wall motion alterations in ischemic heart disease, AI has shown a significant potential to transform clinical practice. However, significant challenges persist, like the need for external validation of algorithms, the interpretability of AI models and the dependency on image quality.

The future of AI in echocardiography will depend on its effective integration in the clinical environment, combining automation with human supervision to guarantee accurate and reliable interpretations. As technical and methodological challenges are overcome, AI may transform echocardiography into an even more powerful tool, optimizing cardiovascular diagnosis and contributing to a more personalized and efficient medicine.

In conclusion, AI will not replace echocardiographers, but will turn into an indispensable ally for more accurate and personalized clinical decision-making.

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