The Use of Artificial Intelligence Guidance for Rheumatic Heart Disease Screening by Novices

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Introduction: A novel technology utilizing artificial intelligence (AI) to provide real-time image-acquisition guidance, enabling novices to obtain diagnostic echocardiographic images, holds promise to expand the reach of echo screening for rheumatic heart disease (RHD). We evaluated the ability of nonexperts to obtain diagnostic-quality images in patients with RHD using AI guidance with color Doppler.

Methods: Novice providers without prior ultrasound experience underwent a 1-day training curriculum to complete a 7-view screening protocol using AI guidance in Kampala, Uganda. All trainees then scanned 8 to 10 volunteer patients using AI guidance, half RHD and half normal. The same patients were scanned by 2 expert sonographers without the use of AI guidance. Images were evaluated by expert blinded cardiologists to assess (1) diagnostic quality to determine presence/absence of RHD and (2) valvular function and (3) to assign an American College of Emergency Physicians score of 1 to 5 for each view.

Results: Thirty-six novice participants scanned a total of 50 patients, resulting in a total of 462 echocardiogram studies, 362 obtained by nonexperts using AI guidance and 100 obtained by expert sonographers without AI guidance. Novice images enabled diagnostic interpretation in >90% of studies for presence/absence of RHD, abnormal MV morphology, and mitral regurgitation (vs 99% by experts, $P \leq .001$). Images were less diagnostic for aortic valve disease (79% for aortic regurgitation, 50% for aortic stenosis, vs 99% and 91% by experts, $P < .001$). The American College of Emergency Physicians scores of nonexpert images were highest in the parasternal long-axis images (mean, 3.45; 81% ≥ 3) compared with lower scores for apical 4-chamber (mean, 3.20; 74% ≥ 3) and apical 5-chamber images (mean, 2.43; 38% ≥ 3).

Conclusions: Artificial intelligence guidance with color Doppler is feasible to enable RHD screening by nonexperts, performing significantly better for assessment of the mitral than aortic valve. Further refinement is needed to optimize acquisition of color Doppler apical views. (J Am Soc Echocardiogr 2023;36:724-32.)

Keywords: Rheumatic heart disease, Artificial intelligence, Screening, Echocardiography

INTRODUCTION

Rheumatic heart disease (RHD) continues to cause significant morbidity and mortality in low- and middle-income countries, despite near elimination in high-income countries.[1] Rheumatic heart disease results from infection with streptococcus A (strep), which incites an immune response leading to the antibody-mediated damage of cardiac tissue, particularly the mitral and aortic valves.[2,3] Rheumatic

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Conflicts of Interest: David Adams, Randolph Martin, and Kilian Koepsell are employees of Caption Health. The remaining authors have no conflicts to declare.

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Abbreviations

ACEP = American College of Emergency Physicians

AP4 = Apical 4 chamber

AP5 = Apical 5 chamber

AV = Aortic valve

BW = Black and white

GLMER = Generalized linear mixed-effects regression

MV = Mitral valve

NS = Not significant

PLAX = Parasternal long axis

RHD = Rheumatic heart disease

UHI = Uganda Heart Institute

heart disease is a progressive disease, and patients often present late in the disease process with severe valvar dysfunction and heart failure.[4] However, before the development of clinical symptoms, there is a period of "latent" or subclinical disease marked by echocardiographic findings without clinical symptoms. Screening echocardiography has been shown to be superior to auscultation in identifying patients in this subclinical phase.[5,6] The World Heart Federation has developed evidence-based guidelines for the echocardiographic diagnosis of RHD.[7,8] Detection of disease during this latent period can enable early initiation of secondary antibiotic prophylaxis, which reduces the risk of disease progression.[9]

Implementation of large-scale echocardiographic screening in low- and middle-income countries, however, remains a challenge. Regions with the highest incidence of RHD often lack the infrastructure, equipment, or trained experts to make universal screening a reality. Numerous innovative strategies have been attempted to optimize screening; these efforts have primarily focused on the use of portable devices, task shifting of echocardiography performance to nonphysician health care workers, and the development of simplified screening protocols.[10-17] Artificial intelligence (AI), through aiding in image acquisition and automated diagnosis, holds promise to further expand the reach of echocardiography screening for latent RHD.[18]

Artificial intelligence guidance is a novel tool developed using deep-learning technology recently authorized by the U.S. Food and Drug Administration that provides real-time prescriptive guidance (live instructions on placement and fine manipulation of the transducer) that allows those health care personnel who are not experts in echocardiography to obtain diagnostic images. A recent study showed that these novice scanners can obtain diagnostic black and white (BW) images of left ventricular size and function, right ventricular size, and valvular anatomy as well as the presence of pericardial effusion after a short training session.[19] The use of color Doppler with AI guidance, which is essential for RHD screening, has not yet been studied. Therefore, the purpose of this study was to determine whether AI guidance with color Doppler could facilitate efficient, diagnostic-quality image acquisition by nonexpert users in a low-income RHD endemic setting.

METHODS

Design

This was a prospective, observational study to determine whether frontline providers could obtain diagnostic-quality images using AI guidance for patients with and without RHD in Uganda. Here, we examine the ability of trainees receiving either a standard or abbreviated training curriculum to obtain diagnostic-quality echocardiography images using BW (previously validated, Food and Drug Administration approved) and color Doppler (not yet validated) AI guidance in a tertiary care RHD center.

Technology

Navigational Guidance (Caption Health), integrated on the uSmart 3200t Ultrasound System (Terason), was modified for this study to allow guidance software to function with an experimental color Doppler modality in addition to in the currently available BW mode.[19] Artificial intelligence guidance software provides real-time instructions to enable the user to obtain optimal standard echocardiographic views. To do this, the software makes three dynamic interpretations during live scanning: (1) diagnostic quality of the imagery, (2) six-dimensional geometric distance (by position and orientation) between current probe location and the location anticipated to optimize the image, and (3) corrective probe manipulations to improve diagnostic quality, which are communicated to the scanner via textual probe manipulation suggestions as well as icons. From these interpretations, the AI provides a live quality assessment of the image, which is communicated via a quality meter on the screen and automatically records the image when a diagnostic threshold is reached (Figure 1, Supplemental Video 1).

Artificial intelligence guidance with color Doppler utilizes the same prescriptive guidance and quality meter as the BW mode. The technology analyzes the BW image to provide guidance while the color box is in place (Supplemental Video 2). The color box position is optimized for parasternal long-axis (PLAX) mitral valve assessment. The user is thus required to manually adjust the color box for other views. As a result, the end user chooses to manually record color Doppler images based on the BW quality meter and knowledge about position and quality of the color Doppler box relative to each view. This is the first study to assess the validity of color guidance.

Study Setting

The study was conducted in Kampala, Uganda, at the Uganda Heart Institute (UHI), a clinical and research institute located on the main campus of the Mulago National Referral Hospital. UHI is the coordinating center for the Ugandan National RHD Registry, which currently includes over 2,500 children and adults living with RHD.[20]

Two groups were included in the study: participants undergoing echocardiography and scanners performing echocardiograms (Figure 2). Volunteers, half with RHD and half with no known history of heart disease, underwent echocardiography. Novice trainees and experts (cardiologists working at UHI) performed the echocardiograms.

Patient Subjects

Patients between the ages of 5 and 40 years were recruited to participate in the study, with a goal enrollment of $n = 25$ patients with RHD and $n = 25$ normal subjects with no known history of heart disease. Patients with RHD were recruited from the Ugandan National RHD registry through invitation during regular clinic visits and by phone call. Subjects without RHD were recruited from friends or family members of patients seen at the UHI. Recruitment was designed to target balanced enrollment based on participant gender and a wide range of ages (target at least 3 patients per 5-year age bracket between 5 and 40 for those with RHD and otherwise healthy controls). Additionally, patients with RHD were recruited to encompass a variety of pathologies including individuals

HIGHLIGHTS

- Many cases of RHD remain undiagnosed worldwide.
- Navigational Guidance utilizes AI to provide live instructions to novice scanners.
- Novices can obtain diagnostic images for RHD after a short training program.
- Novice images do not match expert image quality but are adequate for RHD diagnosis.
- Navigational Guidance can enhance task-shifting to improve screening for RHD.

with latent RHD, as well as more severe disease affecting the mitral and aortic valves.

Scanners

Nurses from UHI and Mulago Hospital and nursing students from the Makerere School of Nursing, at least 18 years of age and without experience in ultrasound, were recruited to undergo training in the use of echocardiography with AI guidance and to perform screening echocardiograms on patient volunteers. Details of the training curricula are provided in the Supplementary Material. In brief, all trainees underwent a <5-hour training session including didactic material covering cardiac anatomy, RHD pathophysiology, and the basics of ultrasonography as well a hands-on training session with AI guidance. The hands-on training session covered a protocol of 7 standard transthoracic echocardiographic views: PLAX two-dimensional, PLAX color mitral valve (2 images), PLAX color aortic valve, apical 4-chamber (AP4), AP4 color mitral valve (2 images), apical 5-chamber (AP5), and AP5 color aortic valve. Trainees also completed a knowledge questionnaire and a training survey following training.

Over a 5-day period, each trainee, in groups of 7 or 8 trainees per day, and 2 experts, performed scans on 10 subjects (5 normal/5 RHD). The trainee scans were obtained independently, without any assistance other than AI guidance. Experts completed the identical scanning protocol (same ultrasound device, without the use of AI guidance) as the trainees on the same patient volunteers. Images were stored at 30 frames per second, with 2-second to 4-second clips recorded for each view and exported in DICOM format without any patient-identifying information onto USB drives for distribution to expert reviewers (see below).

Study Interpretation

A panel of 4 expert echocardiographers (C.S., J.K., D.A., and A.S.) independently (and blinded to whether the study was performed by a novice or expert) reviewed each study. Each diagnostic parameter (presence of RHD, mitral valve morphology, mitral regurgitation, mitral stenosis, aortic valve morphology, aortic regurgitation, aortic stenosis, left ventricular function) was assessed as being of diagnostic quality or not. After reviewing the study as a whole, the reviewers made a subjective assessment about whether or not the information was adequate to make a definitive overarching diagnosis (RHD positive/negative) and whether the study was adequate for diagnostic assessment of each parameter (yes or no). Reviewers were instructed to use their expertise and the minimal number of views needed to allow the study to be diagnostic. Reviewers also provided an overall diagnosis (normal, RHD, other) and diagnosis for each diagnostic parameter (when they thought the study was interpretable). Both the mitral and aortic valves were assessed in terms of morphology, regurgitation, and stenosis. The valve morphology was graded as normal or abnormal based on reviewer interpretation. Valve regurgitation was assessed as none, mild, or moderate/severe based on expert assessment of the regurgitant jet width and length in the parasternal and apical windows. Valve stenosis was assessed based on the presence and degree of flow acceleration on color Doppler in the parasternal and apical windows. Image quality for each view was assessed using the 1 to 5 American College of Emergency Physicians (ACEP) scale (Table 1).[21]

Statistical Methods

Participant demographic and clinical characteristics were described using means with SD and frequencies with percentages.

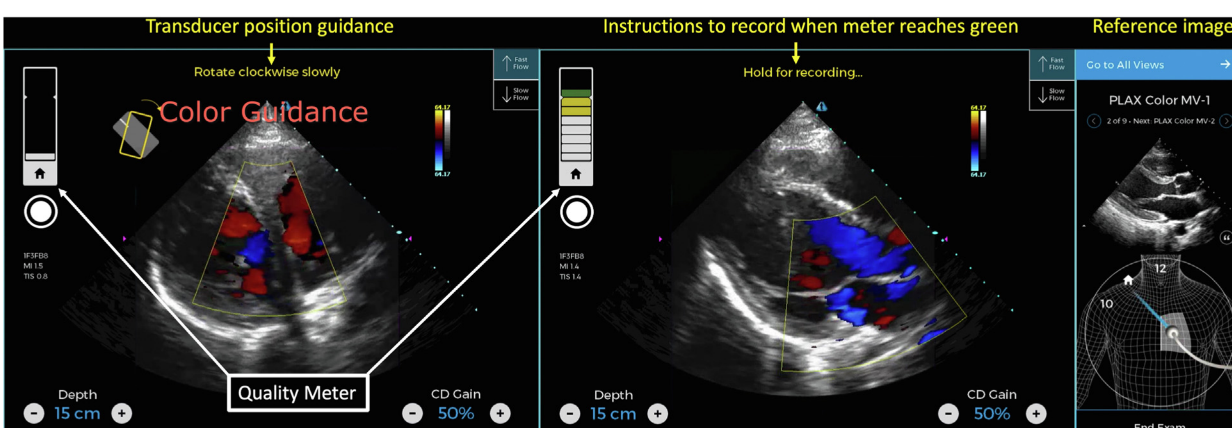

Figure 1 AI guidance user interface. Initial (*left*) and captured (*center*) PLAX color Doppler image of aortic outflow and mitral regurgitation using AI guidance. The reference image (*right*) instructs the novice where to place the transducer initially. Instructions on transducer movement result in an optimal image and increase in quality meter from white to yellow to green. While the color box position is optimized for PLAX mitral valve color Doppler, the scanner is required to use their own knowledge to optimally position the color box in the software version available during the study. Once the meter is in green, the scanner is instructed to manually acquire the image.

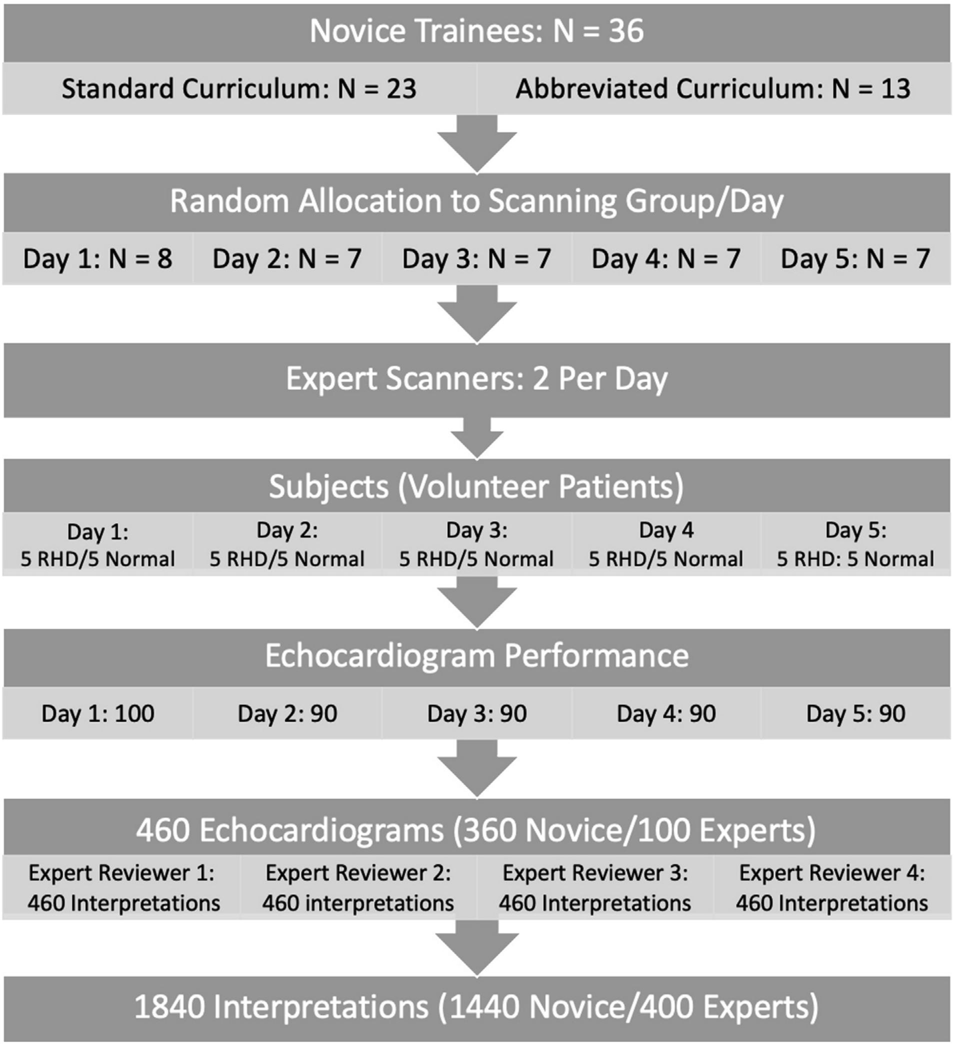

Figure 2 Study design diagram. Trainees received either the standard or abbreviated curriculum and then scanned 8-10 volunteer patients. Experts also scanned the volunteer patients. All studies were reviewed by expert cardiologists.

Independent-samples *t* tests for continuous variables and chi-squared tests for categorical variables were used to test for differences in characteristics of patient echocardiograms according to scanner status (e.g., expert vs novice). The primary end point was the ability of novices to acquire studies that were deemed to be interpretable (overall and subcategories) by expert reviewers. The goal performance was 80%.[22] The percentage of echocardiograms considered to be of high diagnostic quality were obtained using intercept-only generalized linear mixed-effects regression (GLMER). Models included a logit link function to model the binary responses and a random subject-specific intercept to account for the nesting of reads within expert echocardiographers. Inverse logit transformations were used to obtain estimates of the proportion of high diagnostic quality echocardiograms and the 95% CI on the probability scale. Secondary end points included assessing novice ACEP scores (goal of 80% of scores 3, 4, or 5) and impact of diagnosis (RHD vs normal) and curricula (standard vs short) on the percentage of interpretable studies and ACEP scores, as well as comparing the following between novices and experts: the percentage of studies deemed to be interpretable, percentage of interpretable studies resulting in correct diagnosis by expert reviewers, and ACEP scores. Separate models were fit to obtain estimates for each secondary end point of interest. Formal testing of group differences was performed via the inclusion of an indicator of group status as a fixed-effect term in the GLMER model.

Table 1 ACEP ultrasound scoring System

Score	Description
1	No recognizable structures, no objective data can be gathered.
2	Minimally recognizable structures but insufficient for diagnosis.
3	Minimal criteria met for diagnosis, recognizable structures but with some technical or other flaws.
4	Minimal criteria met for diagnosis, all structures imaged well and diagnosis easily supported.
5	Minimal criteria met for diagnosis, all structures imaged with excellent image quality and diagnosis completely supported.

The GLMER models were fit using the glmer function in the lme4 package (ver. 1.1.27).[23] All analyses were conducted using the R software environment for statistical computing and graphics (ver. 4.1.1).[24] Trainee surveys and knowledge questionnaires were analyzed to compare the mean score in the knowledge questionnaire between groups as well as the percentage of trainees self-reporting as ready to begin scanning.

RESULTS

A total of 36 novices and 10 experts participated in the study. This resulted in a total of 462 echocardiogram studies, 362 by novices (2 novices each scanned one patient twice) using AI guidance and 100 obtained by expert sonographers without AI guidance. As the study population scanned by experts and novices was the same (with 2 patients scanned twice in the novice group), there were no statistically significant differences in the characteristics of studies read between experts and novices. The average age of the patients screened was 22.5 years, 50% had a previous diagnosis of RHD, 28% had moderate/severe mitral regurgitation, and 8% had mitral stenosis.

Four expert readers interpreted 455, 432, 372, and 338 studies, respectively, resulting in 1,597 study interpretations available for analysis. There were no significant differences among the 4 experts in determination of primary or secondary end points. A total of 309 studies were interpreted by all 4 experts, 69 by 3 experts, 73 by 2 experts, and 8 by 1 expert. Three studies were not able to be interpreted. The difference between total potential interpretations (1,840) and actual impetrations were secondary to technical DICOM export issues.

Interpretable Studies

With the exception of left ventricular systolic function, the percentage of diagnostic parameters able to be interpreted was worse for novices (Figure 3). However, novice images still enabled diagnostic interpretation in >90% of studies with regards to the presence/absence of RHD, abnormal mitral valve morphology, and mitral regurgitation. Novices performed somewhat worse for mitral stenosis and aortic regurgitation and significantly worse for aortic valve morphology and aortic valve stenosis.

Novices performed better (higher percentage of interpretable studies) for overall diagnosis and mitral valve morphology in RHD patients than normal subjects, while they performed worse in RHD patients for aortic valve regurgitation and stenosis (Supplemental Figure 1). Experts (data not shown in figure) had similar performance in RHD patients and normal subjects for all diagnostic categories except aortic valve stenosis, for which they did worse in RHD subjects (86% vs 98%, $P = .05$).

Image Quality

The percentages of studies in ACEP categories 3, 4, or 5 were significantly higher for experts than for novices in all views (Figure 4). Novices reached the 80% threshold for PLAX BW and PLAX color mitral valve views, were close for AP4 BW views, and were less than 50% for AP5 views (Figure 5). Mean ACEP scores were significantly higher in expert studies for all views (data not shown). Novices scanning RHD patients had a lower percentage of studies (compared with novices scanning normal subjects) in ACEP categories 3, 4, and 5 in the PLAX color aortic valve view (77% vs 85%, $P = .03$) and AP5 color aortic valve view (30% vs 46%, $P = .001$).

Accuracy

The percentage of interpretable studies for which expert reviewers reached the same overall diagnosis as was found on the most recent echocardiogram report was not different between studies done by novices (89%) and those done by experts (86%) for overall diagnosis (Table 2). Surprisingly, for mild mitral regurgitation, studies performed by novices were more likely to have accurate diagnoses than those performed by experts (80 vs 69%, $P < .001$). There were no differences between novices and experts for moderate/severe mitral regurgitation or mitral stenosis.

DISCUSSION

This study represents the first analysis of the use of AI guidance with color Doppler for screening of RHD by nonexpert providers. The key finding is that although novices, with the use of AI guidance and limited training, performed worse than experts, they were able to

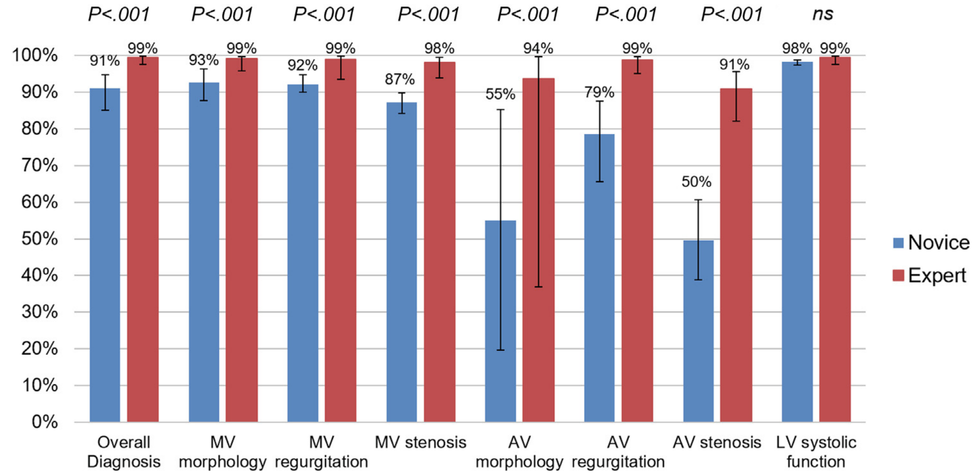

Figure 3 Interpretable studies, novices vs experts. The experts performed better than novices in all categories, but novice images enabled diagnostic interpretation in >90% of studies for the presence or absence of RHD, MV morphology, MV regurgitation, and stenosis. *AV*, Aortic valve; *LV*, left ventricle; *MV*, mitral valve; *NS*, not significant.

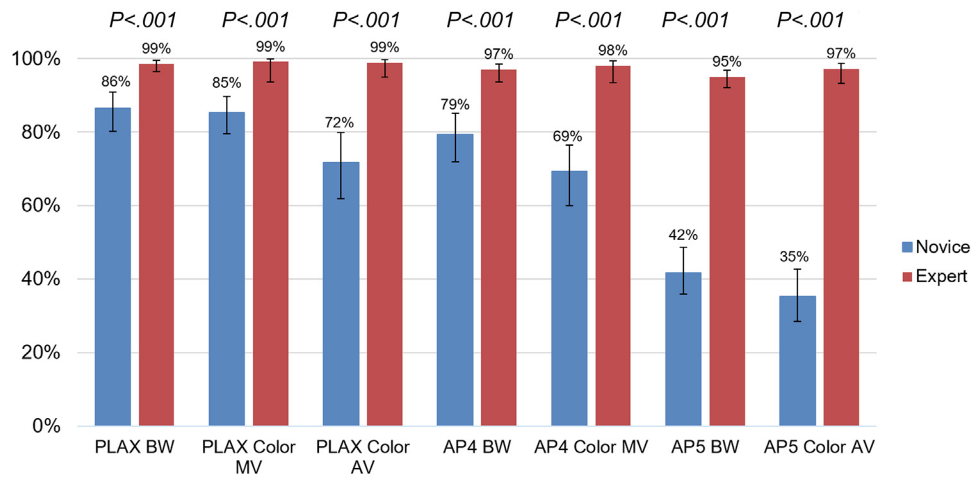

Figure 4 Diagnostic-quality studies by novices and experts. The expert studies were graded as higher quality than novice studies in all views. Over 80% of novice studies in the PLAX BW and PLAX color MV views were graded ACEP 3, 4 or 5, while a lower percentage of novice studies were high quality in other views. *AV*, Aortic valve; *MV*, mitral valve.

obtain diagnostic images in 91% of patients. Nonexpert images performed much better for overall diagnosis and assessment of the mitral valve than for assessment of the aortic valve. Novices attained images with the best quality in the PLAX window, with less optimal image acquisition in the AP4 and AP5 windows. Color Doppler image quality of the mitral valve was superior to those of the aortic valve.

There are numerous studies describing the value of AI for echocardiography including image view identification,[18,25] measurement,[22,25-28] and diagnosis.[28-30] Deep learning has also been used for image acquisition.[22,29,30] Narang *et al.*[19] demonstrated the use of AI guidance for screening by novices using the same technology and machines that we used in our study. Nurses with limited training obtained images of sufficient diagnostic quality to assess left ventricular size (98%), left ventricular function (98%), right ventricular size (92%), and pericardial effusion (98%). In our current study, we further adapted the AI guidance protocol and software to screening for RHD. Specifically, the screening protocol was limited to the PLAX apical 4 and apical 5 windows, and color Doppler was added to enable detection of aortic and mitral valve regurgitation and stenosis.

Using the RHD screening protocol, the novices demonstrated the ability to obtain images of diagnostic quality to assess the presence of RHD in 91% of studies, with 98% of studies sufficient for detection of left ventricular function. Novice performance in our study is comparable to that described in the Narang study *et al.* study in which 98% of studies were of sufficient quality to assess left ventricular size, left ventricular function, and pericardial effusion. The higher percentage of quality images in the adult studies likely reflects the added detail necessary for assessment of valve structure and function required for RHD detection in our study. Interestingly, our expert review panel was able to make correct diagnoses (compared with diagnoses in the patient's medical record) as or more frequently in interpretable studies acquired by novices (compared with those acquired by experts). We speculate that studies that were only interpretable when

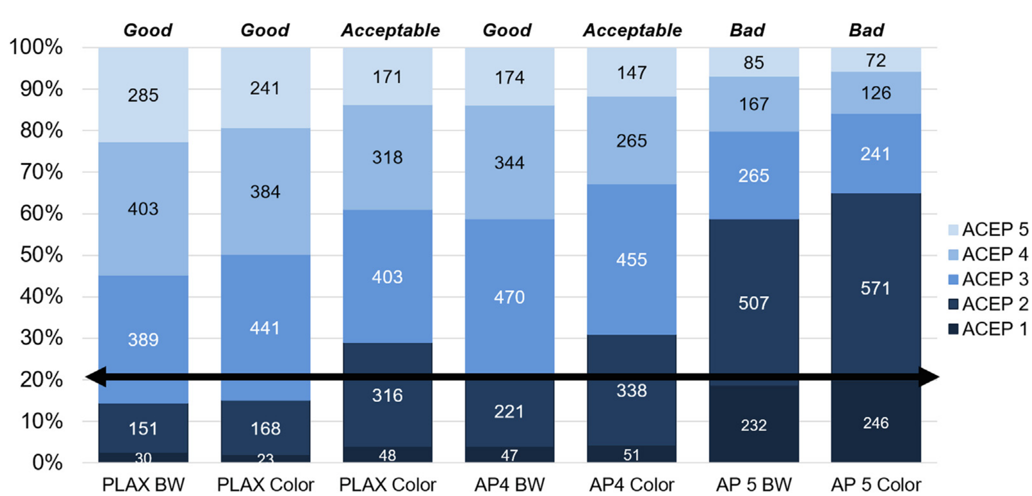

Figure 5 Novice ACEP scores. This shows raw data for novices. Ideally 80% or more of the views would be in the 3 lightest colors (ACEP 5, 4, or 3) and 20% or less (*below the bar*) would be in darkest colors (ACEP 2 or 1). Only PLAX BW, PLAX color MV, and AP4 BW are below (or at, in case of AP4 BW) this level. The PLAX color AV and AP4 color views are a little off from goal, and the AP5 views are far off from goal.

Table 2 Diagnostic accuracy for interpretable studies

	Novices (accuracy %, 95% CI)	Experts (accuracy %, 95% CI)	*P* value
RHD positive			
Overall	89.0 (85.5; 91.7)	86.0 (81.8; 89.4)	.160
RHD	80.1 (74.3; 84.8)	77.2 (70.3; 82.9)	.421
Normal	98.5 (96.9; 99.3)	95.6 (91.0; 97.9)	**.032**
Mild MV regurgitation			
Overall	79.5 (74.2; 84.0)	69.3 (59.0; 77.9)	**<.001**
RHD	77.2 (71.1; 82.3)	67.9 (60.4; 74.5)	**.025**
Normal	83.7 (70.0; 91.8)	70.2 (48.6; 85.4)	**<.001**
Moderate/severe MV regurgitation			
Overall	92.6 (90.4; 94.3)	89.1 (85.3; 92.1)	.054
RHD	85.5 (81.6; 88.7)	79.6 (71.3; 86.0)	.059
Normal	99.9 (86.2; 99.9)	99.4 (95.7; 99.9)	.621
MV stenosis			
Overall	85.3 (75.9; 91.5)	85.8 (76.9; 91.6)	.757
RHD	69.5 (52.6; 82.4)	72.1 (56.8; 83.6)	.481
Normal	99.8 (98.7; 99.9)	99.4 (95.6; 99.9)	.369

MV, Mitral valve.
Confidence intervals and *P*-values obtained from generalized linear mixed-effects regression.
Bolded values are significant ($P < .05$).

performed by experts may have more diagnostic ambiguity and/or have a higher percentage of incorrect diagnoses in the local medical record.

While >90% of studies, when taken as a whole, had enough views to allow them to be of diagnostic quality to assess RHD, some of the individual views (most commonly AP4 and AP5) themselves were of lower quality when objectively assessed by APEC scores. Significant degradation in apical views is likely due to a combination of apical views being more challenging, limited training, and technological limitations with AI guidance, especially with color Doppler. The AI guidance software itself may be more responsive to movement, with more optimal guidance in the parasternal window, and, relatedly, the guidance instructions provided in the parasternal window (often rotate, slide) are likely more easily understood and executed than those in the apical (often tail up/down) by novices performing the study. The version of color Doppler AI guidance used in this study did not allow for automated position of the color Doppler box; therefore, more manual manipulation was required for apical imaging and positioning the color box over the aortic valve. It would be expected that a 2- to 3-day training duration and more sophisticated color Doppler AI guidance would help to address these issues.

Despite these limitations, our study did show that image quality was still sufficient to obtain diagnostic-quality studies in most cases. This is consistent with other studies utilizing parasternal views alone. Diamantino *et al.*[12] demonstrated the viability of a focused single-view (PLAX) protocol for the diagnosis of RHD with a sensitivity of 81.1%, specificity of 75.5%, negative predictive value of 88.5%, and positive predictive value of 63.2%. Similarly, Remenyi *et al.*[31] evaluated the diagnostic utility of an abbreviated screening protocol involving a single PLAX sweep of the heart in two-dimensional and color Doppler. Compared with standard comprehensive echo, single PLAX sweep of the heart provided a sensitivity of 75% and specificity of 77% for detection of any definite RHD, and 91% and 76% (95% CI, 0.74–0.78), respectively, for detection of moderate or severe RHD. Unlike those studies that included more extensive novice training as well as novice image interpretation and diagnosis, our study only focused on whether or not novices with a very limited amount of training and access to diagnostic guidance could obtain diagnostic-quality images, without image interpretation. Taken together, these studies suggest a role for a limited screening protocol utilizing PLAX that would be scalable yet maintain adequate sensitivity.

Portable handheld devices provide cost and ease-of-use benefits over traditional echocardiogram machines, and studies have shown these devices to be effective screening tools for RHD, with high sensitivity and specificity.[10,14] Other strategies have focused on task shifting, which can be particularly beneficial in regions lacking specialty care, and multiple studies have shown that novices can be trained to effectively screen for RHD.[11,16,32] The application of AI guidance to RHD screening can help increase detection rates of RHD, complementing task shifting and handheld devices and leading to greater uptake of valuable secondary prophylaxis and reduction of RHD morbidity.

The concept of task shifting for RHD screening is not new. Colquhoun *et al.*[11] showed that following a 2-week-long workshop, nurses can screen for RHD using standard echocardiography definitions for definite and probable RHD, with a sensitivity of 100% and 83%, for definite and probable RHD, respectively, and a specificity of 67.4% and 79%. Engelman *et al.*[13] showed that after an 8-week training program, nurses in Fiji achieved a diagnostic accuracy of 89% when utilizing a focused echocardiogram using a portable ultrasound machine. Sims Sanyahumbi *et al.*[33] developed a short training course lasting 3.5 days for clinical officers who had substantial agreement with pediatric cardiologists on whether to refer screened patients, with a sensitivity of 91% and specificity of 65%. Further, other investigators have evaluated the use of handheld devices by novices. Mirabel *et al.*[32] investigated the use of handheld devices by

2 novices applying a simplified set of echocardiographic criteria, yielding sensitivities of 84% and 78% for disease detection. Similarly, Ploutz *et al.*[34] investigated handheld echo screening by nurses and found that the simplified approach had a sensitivity of 74% and a specificity of 79% for any RHD, which improved to 90.9% for definite RHD alone. Ultimately, the combination of using AI for enhanced image acquisition with machine learning and deep learning for automated diagnosis holds promise for RHD echocardiography screening at a much larger scale.[18,22,35]

This study contains important limitations. Even though the novices received a limited training curriculum lasting less than a full day, it is not possible from this study to assess the actual contribution of diagnostic guidance to our findings. This would require a larger study that compared the same training with and without access to this feature. This was a single-center experience performed at the UHI. The "testing" scans were completed within 1 week of training, some even within 1 to 2 days of the curriculum. We did not test long-term retention of scanning skills, which may deteriorate over time. Our study was not powered or long enough to measure whether novice performance increased with the number of scans. Our abbreviated protocol was most limited in the assessment of mitral stenosis due to lack of spectral Doppler and short-axis images. While the patients being scanned included both normal subjects and patients with RHD, this was a controlled research setting in which 50% of subjects had RHD. Our study used experts to train novices; a "train-the-trainer" model would be most appropriate for optimal scalability. A prospective study using a train-the-trainer methodology in an endemic clinical setting where the prevalence of RHD is 2% to 3% is needed to ultimately evaluate this technology and training process.

CONCLUSION

Screening for RHD by novices using AI guidance with color Doppler can be achieved. Novices obtained images with acceptable diagnostic quality for RHD and mitral valve disease. Image quality in PLAX window was very good, which is in line with other studies focusing on single-view RHD screening protocols. Future screening programs using AI guidance with technological improvements can enhance task shifting using handheld machines and holds promise for scaling up echocardiography screening for RHD.

SUPPLEMENTARY DATA

Supplementary data to this article can be found online at https://doi.org/10.1016/j.echo.2023.03.001.

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