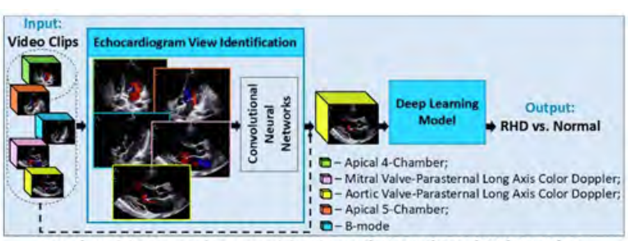
PC1-17

Machine Learning Detection of Rheumatic Heart Disease with Focus on Aortic Regurgitation by Echocardiography

Christina Yang[1], Pooneh Roshanitabrizi[1], Kelsey Brown[2], Joselyn Rwebembera[3], Emmy Okello[3], Andrea Beaton[4], Marius George Linguraru[1], Craig Sable[5]. [1]Children's National Hospital, Washington, DC; [2]Vanderbilt Children's Hospital, Nashville, TN; [3]Uganda Heart Institute, Kampala, Uganda; [4]Cincinnati Children's Hospital, Cincinnati, OH; [5]Oshner Children's Hospital, Jefferson, LA

Background: Detection of subclinical rheumatic heart disease (RHD) by echocardiography allows early intervention with secondary prophylaxis and prevents morbidity and mortality. Previous work by our team demonstrated high accuracy of 92% for artificial intelligence (AI) driven detection of RHD-related mitral regurgitation (MR), which represents 85% of subclinical RHD. We aim to further refine our algorithm for automated detection of RHD by adding detection of aortic regurgitation (AR). **Methods:** We developed a two-step deep learning model in Python , consisting of: (1) view identification and (2) AR-based RHD detection. In Step 1, the first frame of each cine-loop is analyzed to identify parasternal long axis color Doppler views focused on the aortic valve (AV-PLAX). In Step 2, we developed a deep learning model to simultaneously detect RHD based on the presence of AR during diastole. Independent testing was performed, and model performance was further evaluated using 5-fold cross-validation with an 80:20 train-validation split and assessed for accuracy, sensitivity, and specificity. **Results:** The model was trained and evaluated using 362 PLAX cine-loops from pediatric patients from Uganda obtained during RHD screening between 2018 and 2020, consisting of 181 AR cases and 181 control cases (302 from Standard portable device and 60 from hand-held portable machines). Independent testing was performed on 368 images, 45 from AR cases and 323 from control cases (354 from standard portable machine and 14 from hand-held machine). For view identification, we achieved 99% accuracy, sensitivity, and specificity on the test set and 98% accuracy, 97% sensitivity, and 99% specificity on the validation set. For RHD detection, we achieved an average accuracy of 94.8%, with a sensitivity of 82.2% and a specificity of 96.6%. The positive predictive value is 77% and negative predictive value is 97.5%. Across cross-validation folds, the model achieved a mean accuracy of 97.4% ± 0.7%, a mean sensitivity of 84.5% ± 2.9%, and mean specificity of 98.6% ± 0.9%. **Conclusions:** Our model achieved high accuracy for AR detection. Future work includes integrating AR detection with prior work on AI-driven MR detection to develop a complete automated RHD detection tool that can be applied to low-resource settings on hand-held echocardiograms.



Overview of the Proposed Framework for Rheumatic Heart Disease (RHD) Detection

PC1-18

Evaluation of False Negative AI Classification in ATTR Cardiac Amyloidosis

Syeda A. Hasan[1], Michael Randazzo[2], Matthew Maurer[3], Stephen Helmke[3], Marielle Scherrer-Crosbie[2], Azin Vakilpour[2], Karolina Zareba[4], Akash Goyal[4], Richard Cheng[5], Nicole Wakamatsu[5], Tetsuji Kitano[6], Masaaki Takeuchi[6], Viviane Tiemi Hotta[7], Marcelo Luiz Campos Vieira[7], Pablo Elissamburu[8], Ricardo Ronderos[8], Aldo Prado[9], Efstratios Koutroumpakis[10], Anita Deswal[10], Amit Pursnani[11], Nitasha Sarswat[1], Juan Cotella[12], Federico Asch[13], Jeremy Slivnick[1]. [1]University of Chicago, Chicago, IL; [2]Hospital of the University of Pennsylvania, Philadelphia, PA; [3]Columbia University Irving Medical Center, New York City, NY; [4]The Ohio State University Wexner Medical Center, Columbus, OH; [5]University of Washington, Seattle, WA; [6]Hospital of University of Occupational and Environmental Health, Kitakyushu, Japan; [7]Heart Institute (InCor), Sao Paolo, Brazil; [8]ICBA, Buenos Aires, Argentina; [9]Centro Privado de Cardiologôa, Tucuman, Argentina; [10]University of Texas MD Anderson Cancer Center, Houston, TX; [11]Endeavor NorthShore, Evanston, IL; [12]Cardiólogo en Altos de Salta Swiss Medical Group, Tucuman, Argentina; [13]MedStar Health Research Institute, Washington, DC

Background: Artificial intelligence (AI) assisted echocardiographic analysis is a novel and rapidly evolving approach being developed as a scalable, cost-effective screening tool for cardiac amyloidosis. However, AI performance across amyloid subtypes and diverse clinical cohorts, particularly factors contributing to false negative classification, remains poorly understood. **Methods:** In this multicenter, multinational study, developing AI software was applied to transthoracic echocardiograms from patients with confirmed transthyretin (ATTR) cardiac amyloidosis. Studies were categorized as true positive or false negative based on an AI-generated score threshold (>0.8 positive, <0.2 negative). Baseline demographic, clinical, biomarker, and comprehensive echocardiographic parameters were compared between groups. **Results:** Among 360 ATTR echocardiograms, 241 were correctly classified as true positive and 55 were false negative, and 64 were indeterminate which were excluded. Although multiple variables demonstrated nominal differences, no single demographic, clinical, biomarker, or echocardiographic parameter reliably distinguished true positive from false negative cases. Key echocardiographic features traditionally associated with cardiac amyloidosis, including wall thickness, global longitudinal strain, apical sparing ratios, and myocardial contraction indices, were not significantly different between groups. Clinical factors such as age and cardiac biomarkers did not explain AI misclassification. Baseline characteristics comparing true positive and false negative ATTR cases are shown in Table 1. **Conclusion:** In patients with ATTR cardiac amyloidosis, false negative AI classification could not be explained by echocardiographic features or basic clinical variables alone. These findings demonstrate potential areas for enhancing screening methods. Future research is needed to determine if integrating clinical red-flag indicators such as bilateral carpal tunnel syndrome, autonomic dysfunction, neuropathy, and spinal stenosis may improve detection and reduce false negatives in screening protocols.

Table 1. Baseline Characteristics for TTR Cardiac Amyloidosis Analyzed Echocardiograms

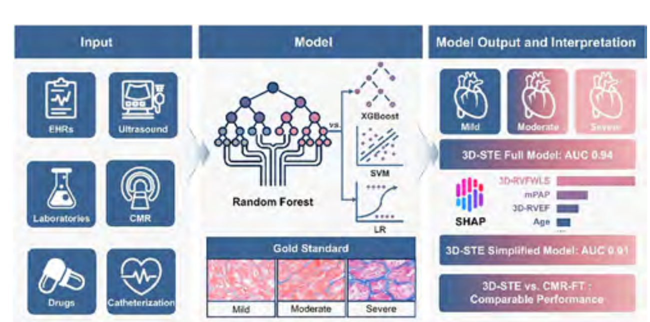
	True Positives	False Negatives	Total	p-value
	241 (81.4%)	55 (18.6%)	296 (100.0%)	
Age	75.653 (9.562)	76.142 (7.840)	75.744 (9.256)	0.724
Sex				
Male	101 (83.4%)	48 (87.3%)	249 (84.1%)	0.479
Female	40 (16.6%)	7 (12.7%)	47 (15.9%)	
Race				
White	80 (35.4%)	22 (44.9%)	102 (37.1%)	0.024
Black	75 (33.2%)	22 (44.9%)	97 (35.3%)	
Hispanic	28 (12.4%)	1 (2.0%)	29 (10.5%)	
Other	48 (19.0%)	4 (8.2%)	47 (17.1%)	
NT-proBNP (pg/mL)	2,899,099 ±4,915.708	3,925.240 ±8,724.610	3,088.249 ± 5,795.886	0.313
High Sensitivity Troponin (ng/L)	58.452 ±53.882	72.000 ±98.153	60.388 ± 60.885	0.591
LV posterior wall thickness (end-diastole) (mm)	14.519 ± 3.172	14.370 ± 2.630	14.492 ± 3.077	0.750
LV internal diameter (end-diastole) (mm)	40.385 ± 6.411	42.430 ± 7.095	40.758 ± 6.576	0.040
Interventricular septal thickness (end-diastole) (mm)	13.275± 2.441	13.679 ± 2.253	13.352 ± 2.407	0.328
Relative Wall Thickness	0.742± 0.229	0.705± 0.198	0.735 ± 0.224	0.285
LV mass index (g/m²)	114.108± 39.284	130.531± 51.782	116.378 ±41.303	0.153
LV ejection fraction biplane (%)	47.643± 13.095	45.491± 12.769	47.256 ± 13.041	0.287
LV global longitudinal strain (GLS) (%)	-13.643 ± 4.183	-12.875 ± 3.850	-13.509± 4.130	0.249
LV GLS (Bolndini method) (%)	-13.465 ± 4.707	-12.756± 3.915	-13.337 ± 4.576	0.313
Apical Sparing Ratio	2.383± 1.235	2.431 ± 1.223	2.392 ± 1.231	0.797
Strain apical-to-basal ratio (2-,3-,4-Chamber)	-0.729 ± 53.242	6.816 ± 26.569	0.645 ±49.515	0.317
Myocardial Contraction Fraction (MCF)	0.219 ± 0.099	0.201 ± 0.108	0.216 ± 0.101	0.321
Amyloid Longitudinal Strain Index (AMYLI)	13.513 ± 6.746	12.748 ± 6.400	13.379 ±6.679	0.517
RV basal diameter(mm)	39.881 ± 7.030	42.910 ± 7.130	40.484± 7.139	0.008
Tricuspid annular plane systolic excursion (mm)	16.442 ± 4.015	16.343 ± 3.888	16.425 ± 3.984	0.903
RV systolic tissue velocity (S') (cm/s)	8.801 ± 2.922	9.255 ± 3.348	8.888 ±3.006	0.364
Peak tricuspid regurgitation velocity (m/s)	28.617± 14.097	28.477 ± 14.754	28.592 ± 14.183	0.951
Mitral inflow E/A ratio	1.581± 0.605	1.740 ± 0.631	1.612 ± 0.610	0.264
Mean E/e' ratio	17.748± 6.044	17.873 ± 6.428	17.770 ± 6.099	0.907
Mean mitral annular e' velocity (cm/s)	5.252 ± 1.804	5.496 ± 1.638	5.293 ± 1.776	0.429
LA end-systolic volume biplane (ml)	77.839 ± 20.674	78.902 ± 27.571	78.034± 22.040	0.768
LA Reservoir strain A4C (%)	11.727 ± 7.590	12.670 ± 8.171	11.897 ± 7.693	0.433

PC1-19

An Explainable Machine Learning Model for Noninvasive Diagnosis of Right Ventricular Myocardial Fibrosis in End-Stage Heart Failure Patients

Zisang Zhang, Ye Zhu, Lang Gao, Qing He, Yukun Cao, Wei Sun, Jing Wang, Nianguo Dong, Mingxing Xie, Li Zhang, Yuman Li. Union Hospital, Tongji Medical College, Huazhong University of Science and Technology, Wuhan, China

Background: Right ventricular myocardial fibrosis (RVMF) is a prominent feature in end-stage heart failure, and its assessment depends on invasive endomyocardial biopsy. This study aims to develop an interpretable machine learning model based on three-dimensional speckle-tracking echocardiography (3D-STE) for the noninvasive assessment of RVMF, with histopathology as the gold standard. **Method:** This study prospectively included 149 end-stage heart failure patients who received heart transplantation as the development cohort, and 20 patients for prospective validation. Patients were divided into mild, moderate, and severe RVMF groups according to histopathology. We developed machine learning models by integrating clinical characteristics, conventional echocardiographic parameters, and 3D-STE parameter. The SHapley Additive exPlanations (SHAP) method was employed for model interpretability. A simplified model was developed using the top three noninvasive parameters to enhance clinical applicability. We further evaluated the agreement between 3D-STE and cardiac magnetic resonance feature tracking (CMR-FT) model. **Results:** The random forest model integrated 3D-STE parameter achieved superior performance on the test set, with an AUC of 0.94 (95% CI: 0.87, 0.99), sensitivity of 0.77 (95% CI: 0.60, 0.90), and specificity of 0.88 (95% CI: 0.80, 0.95). SHAP analysis revealed that 3D-RVFWLS was the most influential predictor, followed by mean pulmonary arterial pressure, three-dimensional right ventricular ejection fraction, and age. The simplified model using 3D-RVFWLS, three-dimensional right ventricular ejection fraction, and age maintained robust performance with an AUC of 0.91 (95% CI: 0.83, 0.98). The random forest model integrating 3D-STE parameter achieved comparable performance to that with CMR-FT in assessing mild, moderate, and severe RVMF (DeLong test, P = 0.801, 0.859, and 0.809). For prospective validation, the full and



PC1-26 - Oral

Artificial Intelligence-Assisted Automatic View Positioning (AutoVue) Significantly Improves Workflow Efficiency in Three-Dimensional Transesophageal Echocardiography Guidance of Structural Interventional Procedures

Martin Gruca[1], Teodora Szasz[2], Megan Yamat[1], Giancarlo Saldana[1], Jia Guo[1], Roydell Johnson[1], Kyle Hipke[1], Tatiana Radosavljevic[1], Irina Waechter-Stehle[3], Heinrich Schulz[3], Sebastian Wild[3], Jochen Peters[3], Frank M. Weber[3], Karima Addetia[1]. [1]University of Chicago, Chicago, IL; [2]Philips Healthcare, Cambridge, MA; [3]Philips Healthcare, Hamburg, Germany

Background: Transesophageal echocardiographic (TEE) guidance of structural interventional procedures necessitates repeated, time-consuming manual manipulation of three-dimensional multiplanar reformation views to obtain standard anatomical planes. This introduces operator-dependent variability and extends procedure time. We developed AutoVue, an artificial intelligence-assisted tool for automatic view positioning, and evaluated its impact on workflow efficiency and accuracy based on an expert-derived gold standard. **Methods:** Three structural echocardiographers analyzed 52 three-dimensional TEE datasets to obtain 6 standard views (aortic valve (AV), mitral valve (MV), tricuspid valve (TV), left atrial appendage (LAA)) (Figure, left panel). Each view was acquired using: (1) fully manual positioning, and (2) AutoVue -assisted positioning with optional refinement. Time-to-completion and number of user interactions were recorded. AutoVue accuracy was assessed by comparing automated positions to expert-defined reference standards using center distance (mm) and angular deviation (°). **Results:** AutoVue significantly reduced positioning time from 72.5±37.8s to 24.6±26.2s (66% reduction, p<0.001) and user interactions from 12.8±7.7 to 6.2±6.5 (51% reduction, p<0.001) (Figure top right). Benefits were consistent across all views, with greatest time savings for LAA (73%) and TV (72%). Individual analysis showed 95% of cases improved with AutoVue. AutoVue accuracy (center: 6.5±0.9mm; angle: 15.8±3.3°) was within manual inter-observer variability (11.0mm and 24.1°) (Figure bottom left). Inter-observer agreement improved 45-76% when using AutoVue versus manual positioning. For 78% of images AutoVue errors were below manual inter-observer variability. **Conclusion:** Artifical intelligence-based automatic view positioning reduces three-dimensional TEE workflow time by two-thirds while maintaining accuracy within inter-observer variability of manual manipulation. This technology has potential to improve clinical efficiency and standardization in image acquisition and structural procedure guidance.

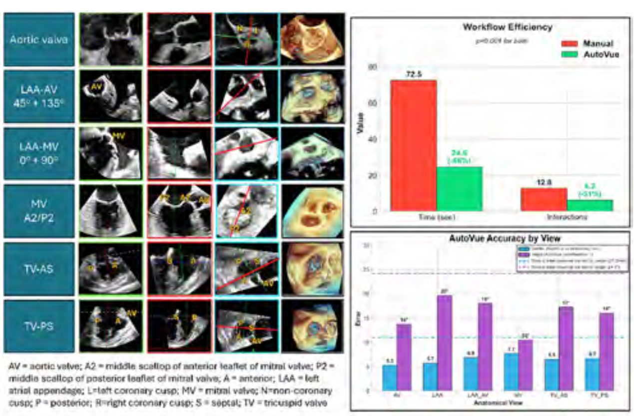


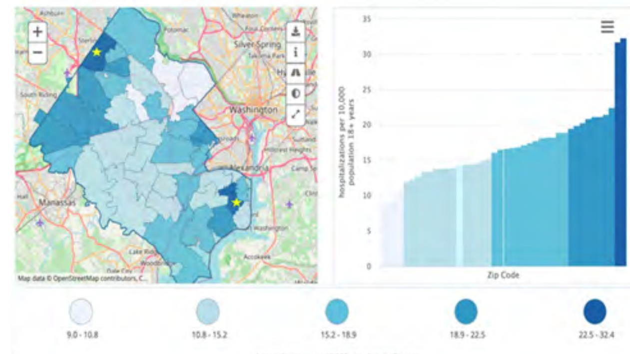
Figure. (Left panel) The 6 standard views being tested; (Right, top) Time and interaction comparison between manual and AutoVue -assisted positioning. (Right bottom) AutoVue positioning errors by anatomical view; dashed line indicates manual inter-observer variability threshold.

PC1-27 - Oral

Advancing Neighborhood Cardiovascular Health through Outreach and Risk Screening: The ANCHOR Trial

Jason Andrew Bonomo, Vanessa Vargas, Rupinder Bahniwal, Faith Metlock, Rosse Arisacain Ayala, Jacob McAuliffe, Muna Ayehu, Sabrina Bramson, Julie Heffernan, Alyssa Scott, Sharmaine McCoy, Karen Berube. Inova Health System, Falls Church, VA

Background: Valvular and structural heart disease (VHD/SHD) disproportionately affect racial and ethnic minorities and individuals of lower socioeconomic status in the United States (US). These individuals also experience reduced access to transcatheter valve therapies such as transcatheter aortic valve replacement (TAVR) and transcatheter edge-to-edge mitral repair (TEER), leading to delayed treatment and worse outcomes. Early identification of occult VHD and SHD in these communities may improve access to timely, life-saving care. Point-of-care echocardiography (POCE) enhances detection of VHD and SHD beyond auscultation and can be deployed in community settings; however, its role in screening for VHD/SHD and addressing health disparities in the US remains unexplored. Northern Virginia contains geographically defined communities with high social vulnerability and markedly lower age-adjusted rates of TAVR and TEER despite proximity to tertiary cardiac care, underscoring the need for innovative, community-based screening strategies. **Methods:** A regional needs assessment identified Northern Virginia communities with high 30-day heart failure readmission rates, low TAVR and TEER utilization, and elevated rates of critical limb amputation (Figure 1). An advanced cardiovascular (CV) screening clinic was established within a primary care site in a high-risk community. Asymptomatic adults with CV disease risk factors were referred. Patients underwent CV screening with artificial intelligence-enhanced POCE to assess for occult VHD and SHD. Ankle-brachial indices and electrocardiograms were obtained. In-person medical interpreters were available. **Results:** Forty-six patients were screened during fiscal year 2025; 43% were female, and 93% reported a primary language other than English. Clinically significant CV pathology was identified in 31% of patients, prompting cardiology referral. **Conclusion:** In communities with a disproportionate burden of cardiovascular disease, advanced CV screening using AI-enhanced POCE is a feasible and effective strategy for identifying occult cardiovascular disease and may bridge gaps in cardiovascular health equity. We have doubled our capacity at this clinic for fiscal year 2026 and are expanding these services to a second high-risk community.



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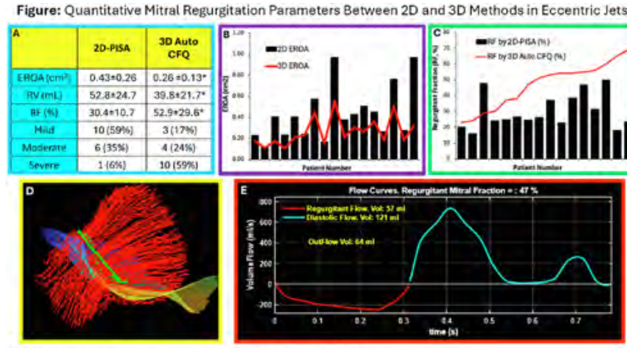
PC1-28

Exploring a Solution for the Quantification of Eccentric Mitral Regurgitation Jets Using Three-Dimensional Echocardiography

Jia Guo[1], Martin Gruca[1], Odile Bonnefous[2], Giancarlo Saldana[1], Theodora Sasz[3,1], Jimmy Su[3], Niklas Hitschrich[4], Michael Blankenhagen[4], Marcus Schreckenberg[4], Timothy Tan[5], Georg Schummers[4], Karima Addetia[1]. [1]University of Chicago, Chicago, IL; [2]Philips Healthcare, Suresnes, France; [3]Philips Healthcare, Cambridge, MA; [4]TOMTEC Imaging Systems, Unterschleiûheim, Germany; [5]Western Sydney University, Sydney, Australia

Background: The 2D proximal isovelocity surface area (2D-PISA) method for assessment of mitral regurgitation (MR) severity is known to be unreliable in the quantification of eccentric MR jets because of a hemispherical flow convergence assumption and poor alignment of Doppler and flow direction. A recently developed tool based on 3D color Doppler echocardiography quantifies regurgitant volume (RV), regurgitant fraction (RF), and effective regurgitant orifice area (EROA) throughout the cardiac cycle and was designed to eliminate these assumptions (Figure, bottom row). We hypothesize that this new method may better quantify eccentric MR than 2D-PISA. Accordingly, this study aims to compare RV, RF and EROA obtained from 2D-PISA to that obtained from 3D echocardiography in these patients. **Methods:** We conducted a pilot study in 17 patients with severe eccentric MR (age=69±13, 53% male) undergoing transesophageal echocardiography. Exams included 3D color acquisitions in which the color sector was optimized to capture the entire antegrade and retrograde flow past the mitral valve. RV, RF and EROA were calculated via 2D-PISA and mitral inflow stroke volume, as well as frame-by-frame across the cardiac cycle with a novel semiautomated 3D echocardiographic software (3D Auto-CFQ, Philips, Germany). **Results:** Within the cohort, 14/17 patients had flail posterior segments; the remaining 3 had malcoaptation, anterior segment prolapse, and posterior perforation. RV and EROA calculated by 2D-PISA was significantly larger than RV and EROA calculated by 3D echocardiography. RF was significantly larger when calculated by 3D echocardiography than by 2D-PISA. RF by 2D-PISA identified 12/17 as mild, 4/17 as moderate, and 1/17 as severe MR while 3D echocardiography

Figure: Quantitative Mitral Regurgitation Parameters Between 2D and 3D Methods in Eccentric Jets



	2D-PISA	3D Auto CFQ
EROA (cm²)	0.43±0.26	0.26±0.13*
RV (mL)	52.8±24.7	39.8±21.7*
RF (%)	30.4±10.7	52.9±29.6*
Mild	10 (59%)	3 (17%)
Moderate	6 (35%)	4 (24%)
Severe	1 (6%)	10 (59%)

A: Table of MR quantification parameters between 2D and 3D echocardiography
B: Comparison of estimated regurgitant orifice area between 2D-PISA and 3D methods
C: Comparison of regurgitant fraction between 2D-PISA and 3D methods
D: Example of a vector field used to derive estimated regurgitant orifice area via 3D
E: Graphing diastolic and regurgitant flow frame-by-frame using 3D to estimate regurgitant fraction
2D-PISA =two-dimensional proximal isovelocity surface area; 3D Auto CFQ=three-dimensional automated continuous flow quantification; EROA=estimated regurgitant orifice area; RV=regurgitant volume; RF=regurgitant fraction
*Statistically significant with two-sided P<0.05