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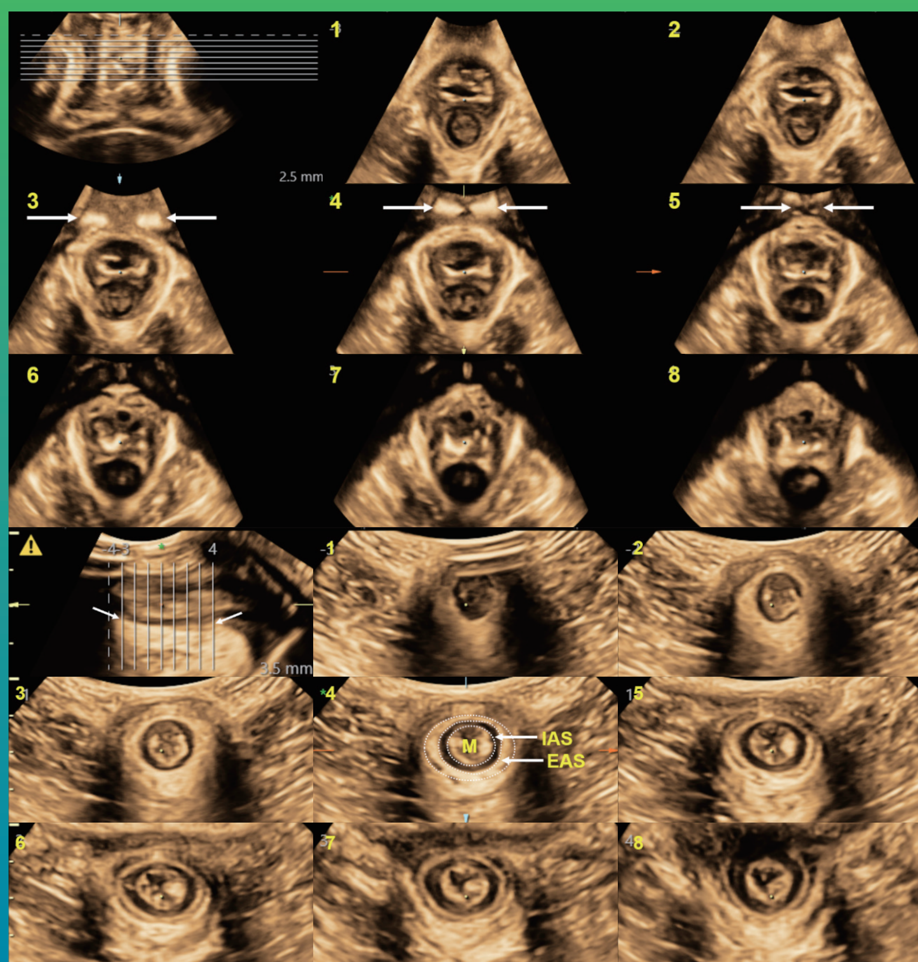

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ORIGINAL RESEARCH

Artificial Intelligence-assisted Medical Imaging in Interventional Management of Valvular Heart Disease

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Abstract: The integration of medical imaging and artificial intelligence (AI) has revolutionized interventional therapy of valvular heart diseases (VHD), owing to rapid development in multimodality imaging and healthcare big data. Medical imaging techniques, such as echocardiography, cardiovascular magnetic resonance (CMR) and computed tomography (CT), play an irreplaceable role in the whole process of pre-, intra- and post-procedural intervention of VHD. Different imaging techniques have unique advantages in different stages of interventional therapy. Therefore, single imaging technique can't fully meet the requirements of complicated clinical scenarios. More importantly, a single intraoperative image provides only limited vision of the surgical field, which could be a potential source for unsatisfactory prognosis. Besides, the non-negligible inter- and intra-observer variability limits the precise quantification of heart valve structure and function in daily clinical practice. With the help of analysis clustered and regressed by big data and exponential growth in computing power, AI broken grounds in the interventional therapy of VHD, including preoperative planning, intraoperative navigation, and postoperative follow-up. This article reviews the state-of-the-art progress and directions in the application of AI for medical imaging in the interventional therapy of VHD.

Key words: VHD; AI; Machine learning; Medical imaging; Interventional therapy

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The incidence rate of VHD correlates nonlinearly with the growth of age. In population younger than 65 years old, the incidence rate is less than 2%, whereas in population aged between 65 to 75, the incidence rate has risen to 8.5%. The incidence rate has spiked to 13.2% in population older than 75 years [1]. Focusing on the treatment of VHD for elders with high surgery risk, and contraindications for traditional open-heart surgery, the area of transcatheter interventional therapy has made remarkable achievements with advantages such as minimal invasiveness, lowered risk, and quick post-operative recovery. This is largely due to the important role medical imaging plays in the process of preoperative planning, intraoperative guidance, and postoperative follow-up of the intervention therapy. However, observer variability in imaging evaluation of cardiac structure and function still exists. In the meantime, the surgeon's need for more accurate imaging continuously grows with the updating and innovating of interventional devices and the desire to expand

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indications for interventional procedures, especially when individual clinical case gets complicated. AI, with its strong capability to process massive data and to self-correct, has already shown great promise in improving efficiency and reproducibility in cardiac function assessment [2,3]. With the continuous development of deep learning (DL) algorithm, AI is becoming increasingly stronger and will serve as a powerful tool in the field of medical imaging in the future. Here we review the current status of AI in the management of VHD, especially focusing on the accurate diagnosis and prediction that medical imaging provides in surgical intervention (Fig. 1).

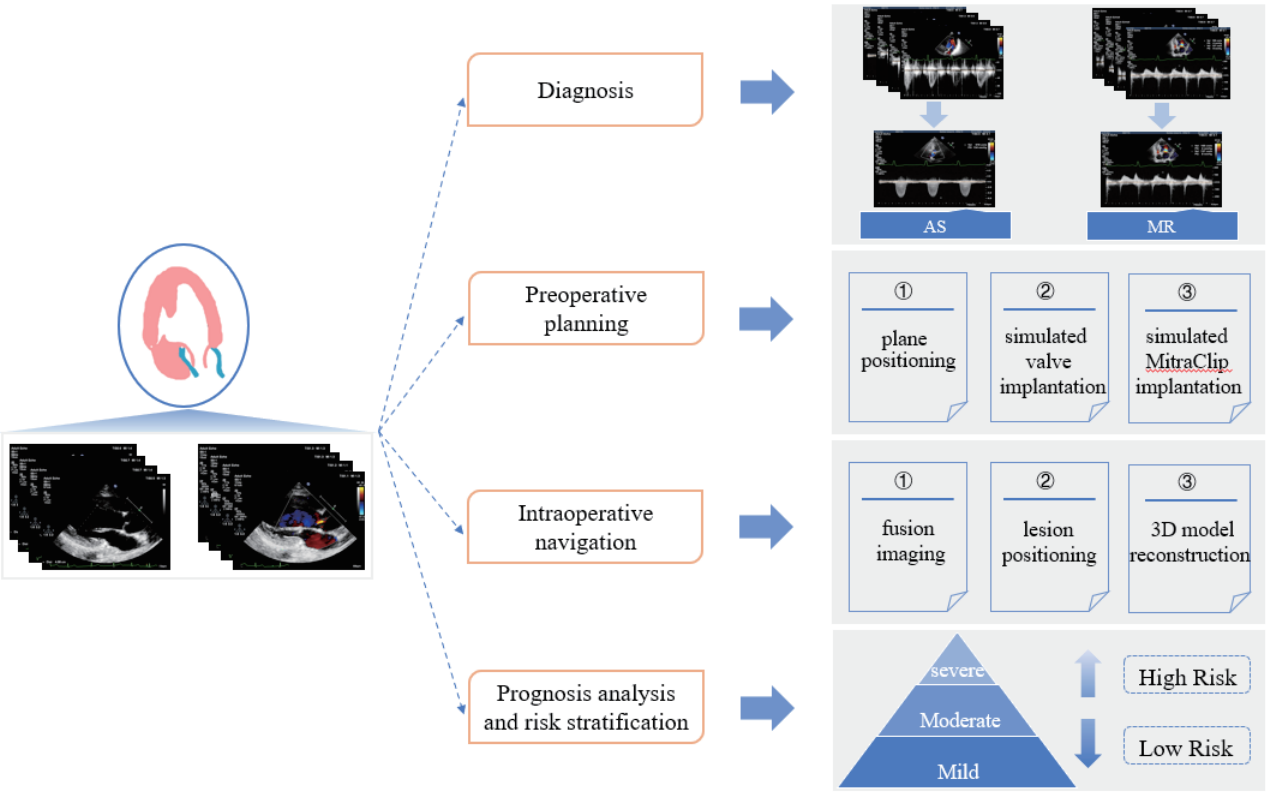

Figure 1 Overview of AI-assisted medical imaging in interventional management of VHD. Current AI-assisted medical imaging in interventional management of VHD mainly focuses on disease diagnosis, pre-operative planning, intra-operative navigation, prognosis analysis and risk stratification. Diseases diagnoses are mainly based on aortic stenosis and mitral regurgitation. Pre-operative planning mainly includes plane positioning, simulating valve implantation, and simulating MC implantation. Intra-operative navigation focuses on image fusion, lesion localization, and three-dimensional model reconstruction.

AI-assisted Medical Imaging for VHD Interventional Management

Diagnosis

Accurate diagnosis of VHD is essential to clinical decision-making. At present, the commonly used imaging diagnosis methods for VHD include echocardiography, CMR, CT, etc. Many operation steps in the imaging process are laborious and repetitive. This situation can be changed with advances in AI, which can automatically segment the anatomical structure of the heart, extract important phenotypic features related to interventional diagnosis and treatment, and visualize the disease process. The incorporation of AI into medical imaging will greatly improve the efficiency of the measurement process.

Aortic Stenosis Accurate diagnosis of aortic stenosis (AS) is crucial to the clinical decision of valve replacement. Different machine learning (ML) algorithms have been developed for the diagnosis of specific VHD, including least absolute shrinkage and selection operator (LASSO), random forests (RFs), eXtreme Gradient Boosting (XGBoost), etc. Kang et al. [4] developed a prediction model to diagnose severe aortic stenosis with three different ML algorithms based on the radiometry characteristics of 408 patients undergoing cardiac CT scans and finally realized the accurate recognition of severe AS. The results showed that the radiomic prediction model derived from LASSO, RFs and XGBoost had excellent performance. The combined model composed of LASSO with feature selection and XGBoost with model classification showed the highest c index of 0.921 in the validation set. Compared to prediction models based on traditional aortic valve calcium volumes and scores, radiomics prediction models seemed to present higher discrimination abilities for severe aortic stenosis, although statistical significance of the difference was lacking. What's more, the phenotype of aortic stenosis could also be accurately identified through topological data analysis (TDA). Sengupta et al. [5] conducted similarity analysis on patients and used the AS phenotype obtained from unsupervised clustering learning as labels to develop an ML classifier, which was used to identify AS of different severity levels. Its diagnostic performance was validated by independent markers of disease severity obtained from the gold standard. The study showed that compared with the traditional nursing classification standard, the ML-based approach showed higher discrimination ability for AS with different severity, and its values of corresponding pathophysiology markers were consistent with that of the gold standard. Yang et al. [6] developed a DL framework to automatically analyze Doppler information obtained from echocardiography videos for the first time, achieving the diagnosis of VHD and quantifying its disease severity. The results showed that the diagnostic accuracy of this method for VHD was high, equivalent to the performance of experienced experts. It's worth mentioning that the area under the curve of AS obtained in the prospective validation set was 0.97. Meanwhile, in assessing the severity of VHD, the consistency between the DL algorithm and a doctor is comparable to that between two experienced doctors.

Mitral Regurgitation For patients with mitral regurgitation (MR), accurate evaluation of regurgitation severity and correct identification of etiology by multimodal imaging is also very important. Recent progress in ML methods brings the hope of AI-assisted automated medical imaging in evaluating MR. Moghaddasi et al. [7] used the texture analysis method to extract image features from video echocardiograms of 102 patients, and accurately identified MR severity through support vector machine(SVM), linear discriminant analysis, and template matching technology classifiers. The results showed that the accuracy of the ML method in identifying patients with normal, mild, moderate, and severe MR was 99.52%, 99.38%, 99.31%, and 99.59%, respectively. Pimor et al. [8] used a hierarchical clustering algorithm based on echocardiography videos and clinical information from 122 patients to divide MR patients into three phenotypic groups with different characteristics and prognoses, helping clinical doctors identify high-risk patients in the early stage and achieve personalized and refined disease management. By means of principal component analysis and unsupervised clustering algorithm, Bartko et al. [9] divided 383 patients with stable chronic heart failure and reduced ejection fraction into four main phenotypic groups according to the 32 morphological variables recommended by the guidelines. The morphological and functional characteristics of secondary MR and its impact on prognosis were explored. The results indicated that MR in HFrEF is not only related to changes in LV morphology, but also to LA and mitral annulus structure, and there is a strong correlation between significant reduction in left ventricular volume and increased mortality.

The power of non-invasive imaging, a traditional visual tool for disease diagnosis, can be increased exponentially when organically combined with AI, which can improve accuracy and efficiency, and is expected to achieve individualized, accurate and efficient intelligent medical treatment of VHD.

Preoperative planning

When developing treatment strategies for patients with VHD, the medical team often faces the dilemma of risk aversion versus therapeutic gain. When traditional open-heart surgery is deemed unfavorable for patients, transcatheter may be the only choice of plan. To ensure optimal outcomes for patients, pre-operative planning is of vital importance, in which AI-assisted medical imaging may serve as a powerful tool.

Transcatheter Aortic Valve Replacement Accurate locating the aortic valve ring plane is a crucial step in determining the valve size before transcatheter aortic valve replacement (TAVR). Contrast-enhanced coronary computed tomography angiography (CCTA) is a key imaging technique for quantifying valve structure in preoperative planning. Due to the complexity of aortic valve anatomy and the presence of artifacts in CCTA, locating critical sections is a time-consuming and challenging task. Theriault-Lauzier et al. [10] first applied the recursive convolutional neural network algorithm to the aortic valve plane locating task based on 1007 ECG-gated CT volume data from 94 patients with degenerative severe AS with an aim to accurately infer the position of the annular aortic valve plane and the direction of the valve. The results showed that the proposed method, enabled automatic location of the aortic valve plane with accuracy comparable to that of experts. Besides, this approach was independent of the unique anatomical characteristics of the aortic valve and could be extended to other anatomical structures. Al et al. [11] adopted regression tree ML algorithm to train the CCTA images from 31 cases of transcatheter aortic valve implantation (TAVI) and 40 patients without TAVI with an aim to automatically locate 8 important anatomic markers of aortic valve. The results showed that this method can facilitate preoperative surgical planning for TAVI and guide physicians to quickly obtain aortic valve images for clinical analysis.

Table 1 AI-assisted medical imaging in diagnosis of VHD

Study	VHD	Task	AI methods	Samples	Performance metrics
Kang, N. G. et al. [4](2021)	AS	Diagnosed severe AS	LASSO; RFs; XGBoost	Training: 312 subjects Testing: 96 subjects	AUC: 0.921 (LASSO & XGBoost)
Sengupta, P. P. et al. [5](2021)	AS	Distinguished AS phenotypes	TDA; ML	1964 subjects	AUC: 0.988 Accuracy (%): 94.3 Precision (%): 91.3 Recall (%): 95.5
Yang, F. et al. [6](2014)	AS	Differential diagnosis with other diseases	ML	Training: 1335 subjects Validation: 311 subjects Testing: 434 subjects	AUC: 0.97 Accuracy (%): 94 Sensitivity (%): 90 Specificity (%): 94
Moghaddasi, H. et al. [7](2016)	MR	Detected normal, mild, moderate and severe MR subjects	Textural analysis; SVM; LDA; TM	5004 images	Accuracy (%): 99.45 (SVM) Accuracy (%): 95.72 (LDA,NN) Accuracy (%): 95 (TM) Sensitivity (%): 99.38 Specificity (%): 99.63
Pimor, A. et al. [8](2019)	MR	Distinguished MR phenotypes	DL	122 subjects	HR: 3.57 (1.72-7.44)
Bartko, P. E. et al. [9](2021)	MR	Explored the morphological and Functional characteristics of secondary MR	PC; cluster analysis	383 subjects	HR: 2.18 (clusters3)

AS, aortic stenosis; MR, mitral regurgitation; LASSO, least absolute shrinkage and selection operator; RFs, random forest; XGBoost, extreme gradient boosting; TDA, topological data analysis; ML, machine learning; SVM, support vector machine; LDA, linear discriminant analysis; TM, template matching techniques; DL, deep learning; PC, principal component; AUC, area under curve; NN, neural network; HR, hazard ratio.

A number of studies have adopted the finite element (FE) modeling technology based on the anatomical structure of lesions to achieve simulated implantation of interventional valves, which has important clinical value in determining the size and location of implanted valves, improving the rationality and efficiency of preoperative planning. However, in patients with unclear aortic root dimensions, the selection and positioning of implanted valves are challenging. To address this clinical problem, Rocatello et al. [12] used FE modeling technology to predict the maximum aortic valve contact pressure and contact pressure index based on the CT images of 62 patients with severe AS. They further verified it by using the data of postoperative echocardiography, angiography and electrocardiogram to determine optimal valve size and implantation position. The results showed that the method had good consistency. At the same time, the method could help estimate the optimal implant size and location for patients with unclear aortic root dimensions, providing effective technical support for personalized surgical decisions. De Jaegere et al. [13] and Auricchio et al. [14] relied on FE modeling technology to simulate the TAVR surgical process, conduct preoperative planning and evaluate the severity of postoperative aortic valve regurgitation, which helped them determine the appropriate implant size and the optimal implantation depth. Astudillo et al. [15] used deep convolutional neural network (DCNN) and image post-processing techniques to automatically predict the circumference and area of the aortic ring and calculate the size of the prosthesis to be implanted based on the preoperative CT images of 473 patients with TAVI. The results showed that the difference between AI prediction results and manual measurements was similar to the difference between human observers, and the analysis time was less than 1 s. Therefore, this method can help practitioners automatically and accurately select the size of TAVI implants with negligible time, improving surgical efficiency, and achieving repeatability in the analysis of results.

Transcatheter Mitral Valve Replacement Quantitative analysis of the valve structures is critical to transcatheter mitral valve replacement (TMVR), but manual analysis is time-consuming and labor-intensive. To tackle this clinical issue, Astudillo et al. [16] used the multi-detector row computed tomography (MDCT) images of 71 MR patients to develop an algorithm for automatic detection of the mitral valve (MV) annulus, successfully realizing the measurement of multiple biological parameters. Compared with manual analysis (25 minutes), the analysis time of a single patient was only 1 s, which greatly sped up the process. Oguz et al. [17] analyzed the volume data set based on three-dimensional transesophageal echocardiography (3D TEE) examination in 59 patients undergoing TMVR with the aid of 3D modeling software (MV Navigator), and then they explored the correlation between 3D TEE parameters and MR reduction. The results showed that a second operation only occurred in patients with poor 3D TEE anatomical display, confirming a good correlation between 3D TEE parameters and MR reduction, which is helpful for early screening of patients suitable for TMVR surgery. Assessing the valve's interaction with the primary mitral annulus and surrounding cardiac cavity structures, as well as selecting the appropriate valve size and implantation depth, is critical to improving TMVR outcomes and reducing complications. Guerrero et al. [18] generated three-dimension (3D) heart models based on preoperative CT images of patients with severe MV and used FE modeling to perform virtual implantation of the valves at different depths, which can quantify left ventricular outflow tract (LVOT) size and predict whether LVOT obstruction would occur. The study demonstrated that the models can be used to predict the risk of TMVR-induced LVOT obstruction, confirming the dynamic interaction between the implanted device and the surrounding tissues. At the same time, this study compared and analyzed the effect of valve implantation with different valve sizes, different mitral ring implantation depths, different angles and different contraction periods, and verified the reliability of AI in evaluating the risk of LVOT obstruction [19,20].

Transcatheter Edge-to-edge Repair Patients with severe MR are at high risk of surgical treatment, and transcatheter edge-to-edge repair (TEER) is the preferred treatment option.

The MitraClip (MC) device is the most commonly used therapeutic instrument in the TEER field, and the FE modeling technique is often used to quantify its biomechanical effects. Kong et al. [21] used FE modeling technology to simulate MC device for TEER treatment, and evaluated its biomechanical interaction by quantifying the morphological changes between MV device and MC device in real MR patients. The results indicated that the biomechanical results obtained by this method were consistent with the actual values. Sturla et al. [22] adopted a similar method to establish a FE model that simulated the biomechanical effects of valves before and after MC implantation, which could evaluate the biomechanical effects of important anatomical structures during the surgical process. The results showed that MC implantation significantly alleviated the clinical symptoms of severe MR patients for all simulated valves. The research showed that this method has important clinical value for MC implantation and can help optimize preoperative treatment plans. Caballero et al. [23] evaluated the biomechanical interaction between MC device and specific anatomical structures by quantifying the dynamic changes between the valve and surrounding tissues based on the fluid structure interaction (FSI) modeling framework. The study showed that computer simulation can reveal the biomechanical interactions between complex implant devices and specific anatomical structures, with the potential to guide device positioning and improve surgical outcomes.

FE modeling of MV physiology has been proposed to study the biomechanical impact of MV repair, but their translation into the clinics remains challenging. In response to this challenge, Mansi et al. [24] evaluated the biomechanical impact of mitral valve repair by establishing a FE model to achieve quantitative analysis of valve structure and function, and verified the reliability of the system with 3D TEE in 120 patients. At the same time, the system was used to simulate MC in performing TEER treatment, and the results showed that the predicted MV closure effect after surgical intervention was consistent with the actual surgical outcome, indicating that the system has clinical potential. Although FM modeling can simulate different surgical procedures, it is time-consuming. To tackle this challenge, Dabiri et al. [25] used the XGBoost decision tree model and DL model to predict the effect of TEER therapy with MC. The DL model showed an prediction accuracy comparable to that of the FE model, but its running time is less than 1 second, an astonishing increase in efficiency as compared to 6 h by the FE model, thereby effectively facilitating the process of TEER by providing real-time intraoperative information.

Intraoperative navigation

The image fusion technology in VHD is vital for the safety, precision and efficiency of intraoperative navigation. It has shown unique clinical value in interventional therapy by integrating space and time information and superimposing echocardiographic images with perspective.

Transcatheter Aortic Valve Replacement Biaggi, P. et al. [26] developed fusion software (FS) with 3D TEE and perspective images of 138 patients with severe AS who received TAVR treatment. This study is the first to investigate the efficacy of the novel FS in the perioperative period of TAVR. The results showed that FS can be used to visually represent and accurately analyze the individual anatomy of patients, quickly and automatically adjust the optimal C-arm angle, as well as accurately locate the aortic root and determine the artificial valve size. However, image fusion has problems such as single image positioning and image quality differences. Echo Navigator (EN) can effectively solve these problems by virtue of its multi-directional imaging. Biaggi, P. et al. [26] applied EN in TAVR surgery. They superimposed 3D TEE and perspective images in real time, automatically generating heart models with key anatomical markers, and realizing accurate locating of the optimal flap ring plane and pacemaker lead position.

Based on the ionizing radiation of fluoroscopy, Luo et al. [27] developed a magnetic navigation system for TAVI with preoperative four-dimensional CT images and intraoperative two-dimensional ultrasound images, reconstructed dynamic 3D aortic valve models combined with real-time ECG signals, and determined the target location for aortic valve prosthesis implantation. At the same time, the system could automatically extract the contour of the aortic valve root from the intraoperative short-axis ultrasound image and register it with the dynamic aortic valve model, guiding the interventional physician to accurately position the aortic valve prosthesis. Reliable system performance is crucial to the safety of patients. In order to objectively evaluate its performance, Mazomenos et al. [28] evaluated surgical skills by analyzing the motion patterns of the catheter/guide wire in fluoroscopy video sequences with or without robot assistance, confirming that robot-assisted TAVR surgery can reduce complications and improve surgical efficiency.

As 3D TEE provides real-time imaging and is radiation-free, it plays an important role in the intraoperative navigation of TAVR. Prihadi et al. [29] applied aortic valve navigator (AVN) in 3D TEE image reconstruction of aortic valve structure to quantify aortic ring and root size. This method has good correlation and consistency with existing clinical diagnostic criteria, and is expected to be a potential alternative method for TAVR intraoperative navigation. In order to improve the interpretability of ultrasonic images, Lang et al. [30] developed an algorithm for automatic contour extraction by combining 3D TEE images with the static heart model obtained from preoperative CT. They then verified it on human body image data, thus successfully building an enhanced image guidance system for TAVI. The results showed that real-time image guidance is expected to improve the accuracy of TAVI and optimize intraoperative navigation.

Transcatheter Mitral Valve Replacement The application of intraoperative 3D TEE in the treatment of TMVR has been well proved. Coisne et al. [31] evaluated the measurement differences between 3D TEE and CT, the gold standard measurement, in intraoperative navigation based on 57 patients who received MV prosthesis treatment, and defined the optimal 3D TEE parameters for TMVR. The results showed that 3D TEE imaging was feasible for most patients and there was little difference between the two modes. 3D TEE showed great potential to replace CT imaging for intraoperative guidance. Although 3D TEE can improve the visualization of MV, image analysis relies on the sonographer's experience, and manual labeling of local MV anatomical structures is time-consuming and labor-intensive. Jin et al. [32] used anatomical intelligence in ultrasound (AIUS) technology to locate mitral valve prolapse (MVP) based on 3D TEE images of 90 patients with degenerative MVP, and validated its performance in assisting operators in MVP localization. The results show that the AIUS algorithm not only effectively improved the accuracy of MVP area localization, but also significantly reduced the image analysis time of complex lesions. The semi-automatic algorithm of AIUS can be used to help junior doctors quickly and accurately locate MVP, which has important clinical value in planning surgical paths.

Transcatheter Edge-to-edge Repair TEE is essential for intraoperative guidance of TEER therapy with MC. Altiok et al. [33] used two-dimensional transesophageal echocardiography and real-time three-dimensional transesophageal echocardiography (RT 3D TEE) to guide the TEER treatment with MC of 28 patients with severe MR. A structured analysis of the information provided by the two imaging methods was conducted to evaluate the value of RT 3D TEE for this complex interventional surgery. The results showed that RT 3D TEE could help identify optimal surgical anatomical sites and achieve real-time accurate detection of MV anatomical location, which no doubt could improve MC implantation strategy and help the surgical operator build confidence. The incremental value of fluorography-echocardiographic fusion imaging (FI) in the provision of intraoperative guidance for TEER is unclear. To delve into this clinical problem, Melillo et al. [34] compared the TEER treatment effect after MC implantation in 80 patients with severe MR before and after FI guidance and evaluated their clinical value. The results showed that intraoperative navigation using FI protocol significantly reduced fluoroscopy time and improved the success rate of surgery. Sündermann et al. [35] applied EN software to the treatment of 21 patients, evaluating the feasibility and safety of using MC for TEER treatment through real-time fusion of echocardiography and fluoroscopy images. The results showed that EN software is feasible and safe, which can be used to guide the surgical process in real time.

Table 2 AI-assisted medical imaging in pre-operative planning of VHD interventional therapy

Study	Operation	Task	Technology	Samples	Performance metrics
Theriault-Lauzier, P. et al. [10] (2021)	TAVR	Plane positioning	CNN	94 subjects	Localization error (mm): 0.9 ± 0.8 (testing)
Al, W.A. et al. [11] (2018)	TAVR	Located important anatomic markers	ML	71 subjects	Localization error (mm): 2.04 ± 1.11
Rocatello, G. et al. [12] (2019)	TAVR	Determined the optimal valve size and implantation position	FE	62 subjects	Accuracy (%): 71 Maximum contact pressure (%): 75 Contact pressure index (%): 71
De Jaegere, P. et al. [13] (2016)	TAVR	Simulated the TAVR surgical process	FE	60 subjects	Accuracy (%): 80 Cutoff value (ml/s): 16.0 Sensitivity: 0.72 Specificity: 0.78
Auricchio, F. et al. [14] (2014)	TAVR	Simulated valve implantation	FE	2 subjects	Stress state has consistency (between 2 subjects)
Astudillo, P. et al. [15] (2019)	TAVR	Calculated the size of the implanted prosthesis	CNN	Training: 355subjects Testing: 118 subjects	Total analysis time(s): < 1 Device size has consistency (between the manual and automatic selection)
Astudillo, P. et al. [16] (2019)	TMVR	Measured multiple biological parameters	DL	71 subjects	Total analysis time (s): < 1
Oguz, D. et al. [17] (2019)	TMVR	Explored the correlation between 3D-TEE parameters and MR reduction	3D TEE; Mitral Valve Navigator.	59 subjects	Optimal MR reduction: 68%
Guerrero, M. et al. [18] (2018)	TMVR	Simulated valve implantation	FE	/	Total analysis time: < 3 h
Wang, D.D. et al. [19,20] (2018)	TMVR	Simulated valve implantation	CAD	38 subjects	R2: 0.8169 (neo-LVOT surface area) Sensitivity: 100% Specificity: 96.8%
Kong, F. et al. [21] (2020)	TEER	simulated the biomechanics of MC implantation	FE; MC.	1 subject	Antero-posterior distance: ↓26% Annulus area: ↓19% Valve opening orifice area: ↓48% Regurgitant orifice area: ↓63% Anterior leaflet peak stresses: ↑ 64% Posterior leaflet peak stresses: ↑62% Anterior leaflet peak strains: ↑ 20% Posterior leaflet peak strains: ↑10%
Sturla, F. et al. [22] (2015)	TEER	Simulated the biomechanics of MC implantation	FE; MC.	3 subjects	Systolic CoA: ↑11-40% Systolic leaflet stresses (Kpa): 100-500 Diastolic leaflet stresses (Kpa): 250 (subject 3) Diastolic orifice area (%): ↓58.9%
Caballero, A. et al. [23] (2020)	TEER	Evaluated the biomechanics of MC implantation	FE; FSI; MC.	1 subject	Antero-posterior distance: ↓28% Mitral annulus spherecity index: ↓39% Anatomic regurgitant orifice area: ↓52% Anatomic opening orifice area: ↓71% Diastolic anterior leaflet stress: ↑210% Diastolic posterior leaflet stress: ↑145%
Mansi, T. et al. [24] (2012)	TEER	Evaluated the biomechanical impact of mitral valve repair	FE; ML.	25 subjects	Mean error (mm):1.49 ± 0.62 (ground truth) Mean error (mm):2.75 ± 0.86 (automatic detection) Total analysis time (min): < 14
Dabiri, Y. et al. [25] (2023)	TEER	Predicted the effect of TEER therapy with MC	DL; XGBoost.	1267 FE models	MAPE: 54 and 0.310 (DL) MAPE: 0.115 and 0.231 (XGBoost) Total analysis time (s): < 1

TAVR, transcatheter aortic valve replacement; TMVR, transcatheter mitral valve replacement; TEER, transcatheter mitral valve edge-to-edge repair; 3D TEE, three-dimensional transesophageal echocardiography; MR, mitral regurgitation; MC, mitraclip; CNN, convolutional neural network; ML, machine learning; FE, finite element; DL, deep learning; CAD, computer aided design; FSI, fluid-structure interaction; XGBoost, extreme gradient boosting; LVOT, left ventricular outflow tract; CoA, coaptation area; MAPE, mean absolute percentage error.

AI and image fusion technologies have effectively improved visual field clarity and operational accuracy in valve interventional surgery, but there are still many challenges. First, the heterogeneity of valve structure and the complexity of movement lead to the deviation of echocardiography and perspective fusion, which limits its clinical application and promotion. Second, real-time image analysis is needed in valve interventional surgery, and the algorithm performance needs to be improved. Therefore, efficient and real-time visualization of intraoperative images combined with image interpretation to assist diagnosis is an important research direction at present.

Prognosis analysis and risk stratification

TAVR provides a new treatment strategy for patients

Table 3 AI-assisted medical imaging in intra-operative navigation of VHD interventional therapy

Study	Operation	Task	Technology	Samples	Performance metrics
Biaggi, P. et al. [26] (2020)	TAVR	Investigated the efficacy of FS in the perioperative period of TAVR	FI; EN; 3D TEE.	Total: 138subjects FS+: 69subjects FS-: 69subjects	Procedure time (min): 42.1 ± 15.2 (FS+) Procedure time (min): 49.2 ± 20.7 (FS-) Contrast agent use (ml): 34.3 ± 22.0 (FS+) Contrast agent use (ml): 39.0 ± 23.3 (FS-) Fluoroscopy time (min): 11.4 ± 4.7 (FS+) Fluoroscopy time (min): 10.9 ± 5.5 (FS-) Pearson correlation *r*: 0.63-0.78 Interclass correlation coefficient: 0.95-0.99
Luo, Z. et al. [27] (2013)	TAVR	Reconstructed aortic valve models and determined the target location for aortic valve prosthesis implantation	MTS; 2D US; 4D CT.	ECG signal	Aortic root segmentation algorithm error (mm): 0.92 ± 0.85 Computational time (ms): 36.13 ± 6.26 Yielding fiducial localization errors (mm): 3.02 ± 0.39 Target registration errors(mm): 3.31 ± 1.55 Deployment distance(mm): 3.23 ± 0.94 Tilting errors (°): 5.85 ± 3.06
Mazomenos, E. B. et al. [28] (2016)	TAVR	Evaluated surgical skills and verified the role of robot assisted TAVR surgery	FE; k-means clustering; EM.	12 subjects (novice group: 6 subjects)	The median value of the procedure time (s): 34.9 (stage 1) The median value of the procedure time (s): 111.2 (stage 2) Maximum accuracy (%): 83 (k-means) Maximum accuracy (%): 91 (EM) Average speed (px/s): 22.3 (stage1) Average speed (px/s): 22 (stage2) P = 0.031(conventional equipment vs robotic system)
Prihadi, E. A. et al. [29] (2018)	TAVR	Quantified aortic ring and root size	3D TEE; AVN.	150 subjects	Mean analysis time (min): 4.2 ± 1.0 $r \geqslant 0.90$ (inter- and intra-observer variability)
Lang, P. et al. [30] (2012)	TAVR	Build TAVI's enhanced image guidance system	3D TEE	/	Mean contour boundary distance error (mm): 1.3 (short-axis views) Mean contour boundary distance error (mm): 2.8 (long-axis views) Mean target registration error (mm): 5.9
Coisne, A. et al. [31] (2020)	TMVR	Defined the optimal 3D TEE parameters for TMVR	3D TEE	57 subjects	AUC: 0.88-0.91 (mitral annular area) AUC: 0.85-0.91 (mitral annular perimeter)
Jin, C. N. et al. [32] (2016)	TMVR	Located MVP	AIUS	90 subjects	Accuracy (%): 89 (nonexperts) Image analysis time (min): 1.9 ± 0.7 (experts) Image analysis time (min): 5.0 ± 0.5 (nonexperts)
Altiok, E. et al. [33] (2011)	TEER	Evaluated the value of RT 3D TEE	RT 3D TEE; 2D TEE.	28 subjects	Advantages: 9/11 (RT 3D TEE)
Melillo, F. et al. [34] (2021)	TEER	Explored the TEER treatment effect after MC implantation	FI; MC.	80 subjects	Fluoroscopy time (min): 37.3 ± 14.6 Procedural time (min): 92.2 ± 36.1
Sündermann, S.H. et al. [35] (2014)	TEER	Evaluated the feasibility and safety of using MC	EN Software; MC.	21 subjects	Radiation dose (Gy/cm2): 146.5 ± 123.6 Total procedure time (min): 136.2 ± 50.2

TAVR, transcatheter aortic valve replacement; TMVR, transcatheter mitral valve replacement; TEER, transcatheter mitral valve edge-to-edge repair; FS, fusion software; TAVI, transcatheter aortic valve implantation; 3D TEE, three-dimensional transesophageal echocardiography; MVP, mitral valve prolapse; RT 3D TEE, real-time three-dimensional transesophageal echocardiography; MC, mitraclip; FI, fusion imaging; EN, echo navigator; MTS, magnetic tracking system; 2D US, two-dimensional ultrasound; 4D CT, four-dimensional computer tomography; FE, finite element; EM, expectation maximization; AVN, aortic valve navigator; AIUS, anatomical intelligence in ultrasound; 2D TEE, two-dimensional transesophageal echocardiography; AUC, area under curve.

with severe AS who cannot receive conventional surgery, but there are risks such as higher postoperative blood events and higher in-hospital mortality. In response to this challenge, Navarese et al. [36] conducted a large-scale, multicenter study to construct a model based on the clinical information database of 5,185 severe AS patients undergoing TAVR treatment, and verified its clinical value in predicting the intraoperative and postoperative bleeding risk of TAVR patients. This model showed great promise in preoperative patient screening and personalized treatment plan formulation. Jia et al. [37] developed a BLeNet model based on DL to achieve accurate prediction of postoperative bleeding complications after TAVR. The study showed that the model had good predictive performance in the stratification of patients at high and low risk of bleeding, which is expected to optimize clinical decision-making. CMR is widely used in AS risk stratification. Kwak et al. [38] used the random survival forest model to identify important CMR predictors associated with mortality after TAVR based on the clinical, echocardiographic, CMR, and other multi-modal parameters of 799 patients with AS. The results showed that extracellular volume fraction, late gadolinium enhancement, right ventricular ejection fraction, and left ventricular end-diastolic index volume were the most predictive markers of CMR.

Patients with severe MR tend to have a poor prognosis, but currently effective risk stratification methods for MR patients are lacking. To address this clinical problem, Zweck et al. [39] adopted ML algorithm to evaluate the preoperative clinical parameters of 1,009 patients undergoing TMVR surgery. After developing MITRALITY scores and conducted external verification, they applied the score to risk stratification of patients undergoing TMVR surgery. The results showed that the MITRALITY score only requires 6 easily accessible preoperative clinical parameters to accurately predict 1-year mortality rate after TMVR surgery, superior to current clinical risk stratification methods. This model can be used to provide support for screening patients of TMVR treatment and determining the timing of surgery [40]. Hernandez-Suarez et al. [41] used multiple ML algorithms such as random forest, logistic regression, SVM, naive Bayes and artificial neural network to predict the in-hospital mortality of TMVR patients based on the clinical data of 849 patients with TMVR. The results showed that the logistic regression model has the best predictive performance and acute kidney injury is the main influencing factor of in-hospital mortality. However, the above studies only included clinical data obtained when constructing prediction models, lacking echocardiography, CT, and other imaging information. To this end, Tse et al. [42] developed a multi-tasking ML model to improve the risk stratification of MR based on clinical information, echocardiogram, and laboratory indicators from 706 patients with MR. The results showed that it can accurately predict the postoperative mortality of TMVR and improve the overall risk stratification performance. Based on multi-modal imaging data, AI can improve individualized and precise prediction capabilities, promoting the development of surgical decision-making towards rationalization, personalization, and efficiency.

AI-assisted Learning and Training of VHD Imaging

Interventional therapy of VHD involves multiple complex scenarios and is extremely challenging, requiring operators to acquire necessary skills and accumulate clinical experience. However, this operation is not an item in the standard database of surgical skills [43]. Most hospitals each year usually conduct only a few operations of this sort, and thus most doctors lack technical training and clinical experience. With its strong learning ability, AI has shown unique clinical value in the teaching and training of interventional therapy of VHD.

Liu et al. [44] used augmented reality (AR) technology to develop a new AR three-dimensional visualization system for image-guided transcatheter intervention surgery, which they expect to be used to assist doctors in the treatment of structural heart disease. This system can segment the 3D model of the patient's heart by means of CT images. With the spinal column used as a general benchmark marker to register the intraoperative perspective image with the 3D heart model, AR-guided cardiac intervention can be successfully carried out. Combined with 3D printing models, this system can enhance visualization, assisting doctors in analyzing complex cardiac anatomical structures. The results showed that the automatic registration method based on AR had a high success rate (100%) and a low registration error (0.42 mm), which could play an important role in training interventional doctors.

Minimally invasive MV repair is extremely challenging, requiring years of training for the necessary skills. Engelhardt et al. [43] used 3D printing technology to prepare novel silicone replicas of patient-specific MV to assist surgeons in learning and mastering the operation skills. Twelve surgeons (5 experts and 7 beginners) were included in the study to perform a comparative experiment of single MV reconstruction on silicone replicas. The results showed that preoperative-specific simulation surgery could quantitatively assess the valve geometry and improve the safety and effectiveness of MV repair. The system is expected to guide beginners to complete basic training on a more concrete basis, and shorten the learning curve of doctors.

Challenges and Prospects

Interventional therapy of VHD is a frontier research direction of AI in the medical field. With its strength in accuracy and efficiency, AI provides new perspectives for preoperative planning, intraoperative navigation, and postoperative risk assessment of interventional therapy of VHD. However, AI in clinical practice still faces many challenges.

First, model training relies on massive amounts of data. Most of the existing studies have relied on a single-center dataset to develop AI models, and they lack high-quality external validation sets. Second, model evaluation and application require human supervision to avoid wrong decisions. Finally, model decisions lack interpretability. As a "black box" algorithm, the prediction process of AI is not transparent, which affects the clinical translation of the model.

Several steps need to be taken for the future development in this field. First, medical privacy protection standards need to be formulated to ensure data security. Second, based on the actual clinical diagnosis and treatment processes, high-quality and standardized multimodal databases are to be established. Third, high-performance AI models are to be developed for multiple diseases. Finally, multidisciplinary communication needs to be strengthened for the personalization, standardization and intelligence of interventional therapy of VHD.

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Conflict of Interest

The authors have no conflict of interest to declare.

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