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Review

Artificial Intelligence in Valvular Heart Disease: Current Applications and Future Perspectives

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ABSTRACT

Valvular heart disease (VHD) remains a major contributor to global cardiovascular morbidity and mortality, with diagnosis and management relying on complex multimodality imaging and expert interpretation. This narrative review aims to evaluate the current applications and future potential of artificial intelligence (AI) in VHD. A comprehensive literature search was conducted using major databases, including PubMed, Scopus, and Web of Science, focusing on studies published in English that examined AI applications in VHD diagnosis, procedural planning, intraprocedural guidance, and prognostic assessment. Relevant original studies, clinical trials, and review articles were included based on their methodological quality and clinical relevance. Current evidence indicates that AI enhances early detection through accessible modalities such as electrocardiography and chest radiography, while significantly improving the accuracy and reproducibility of echocardiographic assessment. AI also facilitates precise preprocedural planning for transcatheter interventions and offers real-time support during procedures through multimodal image integration. In addition, AI-driven models enable robust risk stratification and prediction of clinical outcomes. Emerging innovations, including in silico trials and robotic-assisted interventions, further highlight AI's transformative potential. Despite these advances, challenges related to data quality, bias, interpretability, and regulatory oversight remain. Continued validation and integration are essential to realize AI-driven precision medicine in VHD.

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Inteligencia artificial en la enfermedad valvular cardíaca: aplicaciones actuales y perspectivas futuras

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RESUMEN

La enfermedad valvular cardiaca (EVC) sigue siendo una de las principales causas de morbilidad y mortalidad cardiovascular a nivel mundial, y su diagnóstico y tratamiento dependen de técnicas de imagen multimodal complejas e interpretación experta. Esta revisión narrativa tiene como objetivo evaluar las aplicaciones actuales y el potencial futuro de la inteligencia artificial (IA) en la EVC. Se realizó una búsqueda bibliográfica exhaustiva en las principales bases de datos, como PubMed, Scopus y Web of Science, centrándose en estudios publicados en inglés que examinaran las aplicaciones de la IA en el diagnóstico, la planificación de procedimientos, la guía intraoperatoria y la evaluación pronóstica de la EVC. Se incluyeron estudios originales, ensayos clínicos y artículos de revisión relevantes en función de su calidad metodológica y relevancia clínica. La evidencia actual indica que la IA mejora la detección temprana mediante modalidades accesibles como la electrocardiografía y la radiografía de tórax, a la vez que mejora significativamente la precisión y la reproducibilidad de la evaluación ecocardiográfica. La IA también facilita la planificación preoperatoria precisa para las intervenciones transcatéter y ofrece asistencia en tiempo real durante los procedimientos mediante la integración de imágenes multimodales. Además, los modelos basados en IA permiten una estratificación de riesgo sólida y la predicción de resultados clínicos. Las innovaciones emergentes, como los ensayos in silico y las intervenciones robóticas, ponen de manifiesto el potencial transformador de la IA. A pesar de estos avances, persisten desafíos relacionados con la calidad de los datos, los sesgos, la interpretabilidad y la supervisión regulatoria. La validación e integración continuas son esenciales para lograr una medicina de precisión basada en la IA en las enfermedades hemolíticas virales.

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1. INTRODUCTION

Valvular heart disease (VHD) remains a significant contributor to heart failure (HF) worldwide. Approximately 21% of patients hospitalized for HF and 14% of those referred for echocardiographic evaluation of suspected HF have underlying VHD [1, 2]. Globally, the epidemiology of VHD varies; rheumatic heart disease predominates in low- and middle-income countries, whereas degenerative valvular disease is more prevalent in high-income regions [3]. Population aging has further amplified the burden of degenerative VHD, contributing to a 45% global increase in incidence over the past three decades [4, 5]. Consequently, HF secondary to VHD is expected to rise substantially [3].

Aortic and mitral valve diseases—particularly calcific aortic stenosis (AS) and degenerative mitral regurgitation (MR)—are the most common valvulopathies. Major advances in management have been driven by the rapid expansion of transcatheter valve replacement and repair technologies, with transcatheter aortic and mitral interventions increasing more than five- and ten-fold, respectively, in recent years [6, 7]. Novel therapies for tricuspid valve disease such as tricuspid transcatheter valve replacement and repair have also emerged [8, 9]. The creation and evaluation of artificial intelligence (AI) techniques is very appropriate for VHD. Despite this, the application of AI in VHD remains relatively underexplored, accounting for less than 3% of AI research in cardiovascular medicine [10]. AI is cantered on machine learning (ML) and deep learning (DL) techniques, with DL representing a subset of ML that employs neural networks modeled on human brain architecture (Figure 1). These systems identify hierarchical patterns within large datasets,

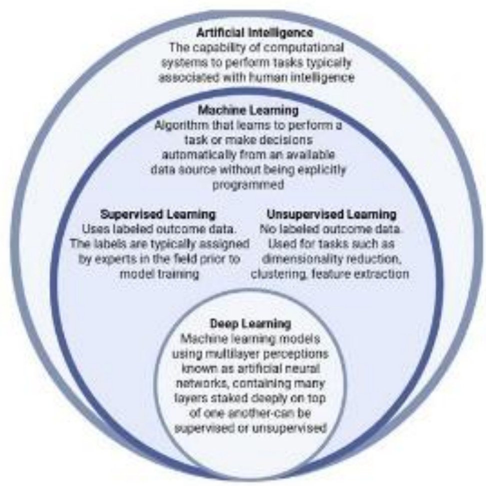

***Figure 1**: Overview of artificial intelligence and machine learning.*

enabling automated analysis and prediction.

The emergence of DL has raised interest in applying AI to the diagnosis and treatment of diseases across a wide spectrum of medical fields, including cardiology. Recent advances have demonstrated that AI can improve the detection of valvular abnormalities using echocardiography, electrocardiography (ECG), and even non-traditional imaging modalities [11]. Beyond diagnosis, AI shows promise in prognostic stratification and treatment guidance, including device selection for transcatheter interventions and prediction of procedure-related complications. This review discusses current and emerging AI applications in the diagnosis and management of VHD (Figure 2).

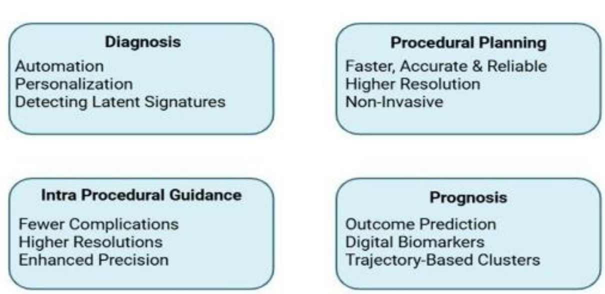

***Figure 2**: Artificial enhanced care in valvular heart disease.*

2. AI-GUIDED DIAGNOSIS

To diagnose VHD, a trained operator now needs to assess valve pressure gradients and velocities detected by transthoracic echocardiography (TTE), which requires access to advanced equipment and expertise.AI tools can improve VHD diagnosis using modalities that are more accessible like chest X-ray (CXR) and ECG, and they can expedite VHD diagnosis using TTE.

2.1. CHEST X-RAY

Recent studies have shown that AI models have utilized chest x-ray in identification and diagnosis of aortic stenosis (AS) and mitral regurgitation (MR). DL models applied to chest X-ray (CXR) imaging have demonstrated the ability to identify AS and MR with area under the receiver operating characteristic curve (AUROC) values of approximately 0.83 and 0.80, respectively [12, 13]. By analysing entire images rather than predefined regions of interest, these models can detect subtle radiographic signs of valvular pathology often missed by highly competent human observers. For example, the DL AS model's saliency maps showed hot spots in the left ventricle, left atrium, and aortic valve region, suggesting the model considered both aortic valve calcification and indications of increased pressures in the left cardiac system [12]. These findings suggest a potential role for AI-assisted

CXR screening in large healthcare systems with extensive imaging archives.

2.2. ELECTROCARDIOGRAPHY

AI-enhanced interpretation of both 12-lead and single-lead ECGs has enabled effective detection of clinically significant VHD, particularly when human recognition of the ECG elements is lacking [13-17]. Large-scale studies, including ADAPT-HEART and PRESENT-SHD, validated AI-ECG models in datasets exceeding 150,000 patients [18, 19]. The AUROC was around 0.8 in both the modalities from 12-lead ECG images and portable single-lead ECG respectively. Thus, they have proven that these models can identify a variety of structural cardiac abnormalities, including moderate or severe AS. Importantly, AI-ECG performance has shown reasonable concordance with echocardiography [15, 16], highlighting the potential of ubiquitous ECG-based screening to identify patients with actionable VHD across diverse clinical settings.

2.3. TRANSTHORACIC ECHOCARDIOGRAPHY

Transthoracic echocardiography (TTE) remains the cornerstone of VHD diagnosis but is resource-intensive process that requires a qualified cardiologist to evaluate the results and a trained cardiac sonographer to get numerous high-quality cardiac images and is subject to interobserver variability. AI integration can automate image acquisition, segmentation, and interpretation, improving efficiency and reproducibility [20, 21]. AI algorithms have demonstrated near-perfect accuracy in detecting and grading AS and MR from single echocardiographic views, even without color doppler imaging [22-24]. AI can distinguish between primary and secondary MR in addition to detecting and quantifying several factors that might be used to assess the severity of MR, such as the change in annular height and the separation between the mitral annulus and the inter-trigonal zone. These developments have improved our understanding of the pathogenesis of mitral valve disease. The difference between primary and secondary MR are now more evident, in primary MR, the mitral annulus enlarges while still functioning, whereas in secondary MR, the contractility of the mitral annulus decreases and undergoes flattening and dilatation losing its saddle shape [25]. As compared to the traditional image interpretation and analysis of echocardiogram images, AI has improved the diagnostic accuracy for VHD by using advanced algorithms. AI research on 3D full-volume color doppler echocardiography (CDE) was compared to conventional 2D-PISA CDE in terms of assessing the severity of AR in patients with at least moderate AR, using phase-contrast cardiac magnetic resonance (CMR) imaging as a reference [26]. AI was able to classify AR severity more reliably compared to 2D imaging, especially in patients with multiple regurgitant jets or eccentricity, where 90% of the graded AR severity was properly recognized by AI, compared to only 30% by traditional 2D imaging. Multicenter studies involving over 17,500 echocardiographic images have shown excellent external validation, with AUROC values reaching 0.98 for severe AS detection [23].

Combining these AI-powered features could expedite the diagnosis process by reducing the requirement for human interpretation abilities to analyze TTE images. Lastly, AI models may infer outcomes from a variety of imaging modalities. Cross-modality inference using AI further enables prediction of cardiac magnetic resonance–derived parameters or coronary artery calcium (CAC) scores from echocardiographic data, potentially streamlining diagnostic workflows and reducing the need for multiple imaging studies.

3. AI-GUIDED PROCEDURAL PLANNING

Precise anatomical assessment is critical for transcatheter valvular interventions such as transcatheter aortic valve replacement (TAVR) and transcatheter edge-to-edge repair (TEER). Similarly, precise preprocedural characterization of coronary plaque features and coronary vasculature anatomy is necessary for effective myocardial revascularization. These evaluations are time-consuming, and are prone to interobserver variability. AI solutions have been developed to ensure accuracy, reduce the workload of human resources, and expedite preprocedural planning. Similarly, precise preprocedural characterization of coronary plaque features and coronary vasculature anatomy is necessary for effective myocardial revascularization. These evaluations are time-consuming, and are prone to interobserver variability. AI solutions have been developed to ensure accuracy, reduce the workload of human resources, and expedite preprocedural planning.

In order to visualize structures in 3 D, TAVR planning and device selection make use of anatomical measurements (such as the aortic annulus diameter and aortic angle), landmarks, and cardiac imaging modalities. AI technologies have enhanced pre-procedural measurements for CT, CMR, and echocardiography, producing 3-D reconstructions that are more accurate than 2-D measurements [27, 28]. There was no clinically significant bias for anatomical measurements, and there were strong correlations between

AI-enhanced measures and manual annotations by skilled observers (average error <2 mm, correlation coefficient >0.91) [29-36]. Interestingly, the intraclass correlation coefficient of the AI model in a large study including 20 Chinese educational institutions was 0.998 [29]. indicating that experts in AI agree on the device selection. AI-automated measurements produce reliable data within shorter period and without human interference, attaining expert-level accuracy [30, 37].

While more current iterative reconstruction approaches involve physical modelling with complex math, traditional reconstruction techniques use filtered back projection to view anatomical valve structures using CT in a 3-D space [38]. Although iterative reconstruction approaches can improve image quality and reduce radiation exposure, they are computationally expensive. This challenge has been addressed by DL, which maintains superior contrast-to-noise and signal-to-noise ratios while generating images six times faster than iterative reconstruction methods [28, 39, 40]. Therefore, DL is a novel method that visualizes anatomical valve structures in 3-D space from high-quality images using fewer computer resources in less time.

In patients undergoing TAVR almost two thirds of them have concomitant coronary artery disease (CAD), indicating that AS and CAD frequently co-occur due to their shared pathophysiological pathways [41]. These patients should undergo CAD evaluation prior to aortic valve replacement prior to undergoing PCI and TAVR, or combined coronary artery bypass grafting (CABG) and surgical aortic valve replacement in the same setting. This preprocedural evaluation uses coronary computed tomography angiography (CCTA), and AI-automated interpretation can assist with it with accuracy comparable to that of seasoned readers [42]. Although CCTA's high sensitivity and significant negative predictive value enable the successful exclusion of CAD, its lack of specificity results in a high false positive rate. FFR is a modality to detect lesion specific significance obtained from invasive coronary angiography and assess the functional ischemia in order to further refine the false positive cases [43].

Of late, the US Food and Drug Administration (FDA), which may improve the specificity of CAD detection with CCTA [44-46], approved an AI algorithm, which evaluates FFR on CCTA noninvasively. There is a decrease in the burden invasive coronary angiography prior to TAVR due to AI enhanced FFR assessment of coronary lesions on CCTA in TAVR candidates, which has shown a sensitivity and negative predictive value of >95%, a specificity of 52% to 87%, and a positive predictive value of 40% to 88% [47-56].

A multiuser, multidevice mixed reality application for collaborative cardiac interventional planning was verified in a recent study [51]. This technique provides a precise 3D representation of the patient's anatomy using CT imaging data. The mixed reality program improves spatial understanding, improves procedural collaboration and allows clinicians to virtually manipulate anatomical structures and execute device simulations preoperatively. The system's dependability and potential for procedural planning optimization were confirmed by clinical validation, which showed that VR-derived data were equal to conventional CT-derived values [51].

4. INTRAPROCEDURAL GUIDANCE

AI offers real-time insights throughout the peri-procedure and facilitate cardiovascular interventions with better vision throughout the procedure can reduce the chance of adverse outcomes and improve accuracy. Intraprocedural transesophageal echocardiography (TEE) is crucial for real-time guidance of structural cardiac interventions such as TAVR and TEER [52]. Even while TEE uses safe ultrasound waves and can theoretically provide crucial hemodynamic and anatomical information throughout the procedure, the quality of TEE images is inferior than that of CT, which leads to less than ideal procedural guidance [52]. However, the utility of intraprocedural CT for real-time guidance is limited due to radiation exposure. Mathematical techniques have been proposed to integrate 2-D TEE images with preprocedural cardiac computed tomography (CT) scans to create a 3-D image utilizing temporal and spatial registration, which would enhance real-time guidance using TTE without requiring CT radiation exposure [52]. Better procedural outcomes and interventions that are more successful may arise from the employment of this strategy as a real-time guidance tool [53]. AI-assisted integration of real-time TEE with preprocedural CT imaging has the potential to improve intraprocedural visualization during structural heart interventions. Although clinical implementation remains limited, mathematical and AI-based registration techniques may enhance procedural accuracy while minimizing radiation exposure [52, 53]. Prospective studies are needed to assess the impact of such approaches on procedural success and long-term outcomes.

5. AI ASSISTED PROGNOSTIC PREDICTION

ML models leveraging structured clinical data demonstrated good discrimination capability in predicting in-hospital and

1-year mortality after TAVR [54-57]. Likewise ML models with its structure data have effectively predicted the need for post-TAVR permanent pacemaker implantation [58-60], and 6-month infective endocarditis with great accuracy [61]. Additionally, DL algorithms utilising cardiac CT images in addition to structured data, have been used to predict paravalvular leak [62], 2-year mortality [63], 30-day cerebrovascular events [64] and new-onset atrial fibrillation after TAVR [65] highlighting the incremental value of cardiac images over readily available clinical variables. A comparable effort has been made for TEER, albeit to a lower degree than TAVR. ML models used structured data to predict 30-day readmission after TEER, in-hospital mortality [66-67] and 1-year mortality [68-69]. It is interesting to note that the MITRALITY score accurately predicted 1-year mortality following TEER and outperformed current risk indicators in an external validation cohort [70].

The pre procedural data was utilised to obtain unsupervised and semisupervised AI providing a novel approach in predicting procedural outcomes by identifying phenotypic differences between patient groups. This technique has been applied to ML models for TAVR [71-73], and TEER [74]. The observed variations in survival outcomes among patient clusters according to clinical factors and echocardiograms allow for risk assessment and disease trajectory prediction. However, more accurate prognostication methods may result from the detection of human-invisible indicators of worse outcomes from more and more complex data streams, such cardiac imaging [75]. Recently developed and externally validated, DASSi (Digital AS Severity index) is a multimodal video-based AI biomarker for AS progression. Higher DASSi, was associated with increased peak aortic valve velocity portending increased risk of aortic valve replacement and was linked to faster AS progression, according to TTE or CMR videos [24].

6. AI GUIDED INNOVATIONS

Based on the concept of AI-guided treatment, "in silico clinical trials" (ISCT) will have greater role and have the potential to completely transform the way new treatments are assessed and selected for clinical practice [76]. Currently, any new product must be evaluated through pre-clinical and clinical trials that include both in vivo and ex vivo experiments on humans and animals. Although the goal of these studies is to demonstrate the safety and efficacy of a medication, they are costly, time-consuming, and have also been ethical concerns. Because ISCT makes it possible to test novel therapies through computational modelling instead of the conventional method, it may be possible to greatly streamline this procedure or possibly replace it completely.

ISCT may be most appropriate for transcatheter valvular heart intervention. Every patient undergoes pre-procedural CT scans. Combining intra-procedural data and post-procedural outcomes data sets, these can be constructed to create a substantial library of retrospective patient anatomy and physiology. AI can generate an almost infinite number of patient anatomy models using this database, and new device iterations can be digitally assessed for efficacy and safety. In addition to being more efficient than animal or bench-top testing, this method allows for the assessment of the device's long-term functionality, including potential failure modes. The concept of ISCTs as a strategy to accelerate the integration of new treatments into clinical practice holds considerable promise and is likely to attract strong interest from both healthcare professionals and medical device manufacturers. Since the models being tested must have stringent quality control and open data sharing, the primary challenge will probably be regulatory in nature [77].

7. ROBOTIC INTERVENTIONS

The concept of autonomous robots performing transcatheter or surgical procedures may be the ultimate use of AI in the treatment of VHD, even if this field has thus far primarily been restricted to in vivo animal research. Despite the fact that fully autonomous surgery is not currently feasible for clinical use, the field is developing quickly. Using recurrent neural networks with adaptive responses, the Endoscopic Partial-Autonomous Robot (EndoPAR) was shown to be able to tie knots in 2008 [78]. More recently, by observing operators suturing on video, an algorithm called Motion2Vec was able to learn how to do it [79].

Additional automation in the endovascular field has been thought to be feasible with the development of an automated robotic catheter that can identify paravalvular leaks (PVLs) and assist in their closure [79]. The robotic catheter examined by Fagogenis et al. employs "haptic vision," which combines image and contact sensors, to perceive, in contrast to standard PVL closure procedures, which are carried out by clinicians guided by fluoroscopic and echocardiographic images [79]. In a pig model with a beating heart, aortic PVL was identified by the automatic catheter as located from the left ventricular apex in 79 out of 83 trials (95% success rate). The operator then successfully sealed the leak with device.

8. CHALLENGES AND LIMITATIONS

Despite AI's potential to completely transform VHD management, there are still a lot of challenges to be addressed. In particular there is concern related to data privacy, algorithmic bias, the lack of standardized regulations, and the high cost of technology. Some of the above issues can be tackled with solutions like federated learning, encrypting the data enabling privacy protection, and several training dataset types that mitigate bias. International regulatory frameworks are required and financial aid for the research and development of these newer technologies will help remove barriers to their broader use. Furthermore, healthcare staff training is crucial to ensuring the smooth incorporation of new technologies into clinical practice. Eventually, these strategies will enhance patient outcomes by enabling the safe, efficient, and fair use of emerging technologies in healthcare.

9. FUTURE DIRECTIONS

Increased automation in the treatment of VHD has the potential to accelerate recovery, reduce complications, and shorten operative times. To effectively perform complex tasks, robotic systems must be capable of sensing, interpreting, and responding to their environment [80]. Robots can operate at varying levels of autonomy. At level 0, the robot functions solely under direct operator control, executing only the commands provided. At level 1, the robot offers limited assistance, including manual support and procedural options such as grasping with forceps. Currently, medical robotic systems can achieve up to level 3 autonomy, characterized by conditional autonomy. At this level, the robot can independently make decisions to achieve a defined goal—similar to a self-driving vehicle—while adapting to obstacles or unexpected events encountered during the procedure.

10. DISCUSSION

AI is poised to redefine the landscape of VHD by bridging gaps in diagnosis, decision-making, and procedural precision. One of the most compelling advantages of AI lies in its ability to democratize care by enabling early detection through widely available tools such as electrocardiography and chest X-ray, potentially reducing dependence on highly specialized imaging and expertise. This is particularly relevant in resource-limited settings where access to advanced cardiac imaging is limited [21]. Moreover, AI-driven automation enhances reproducibility and minimizes interobserver variability, a known limitation in conventional imaging interpretation. Its integration into preprocedural planning and intraprocedural guidance improves workflow efficiency and may translate into better procedural and clinical outcomes [29]. Importantly, AI-based predictive models support a shift toward personalized medicine by identifying high-risk phenotypes and enabling tailored therapeutic strategies. However, several barriers must be addressed before widespread clinical adoption, including data privacy concerns, algorithmic bias, limited interpretability, and the need for robust external validation across diverse populations. Future research should prioritize explainable AI, prospective clinical validation, and seamless integration into clinical workflows to ensure safe, equitable, and effective implementation in routine VHD care.

11. CONCLUSIONS

AI is emerging as a clinically meaningful adjunct in the management of VHD, with the strongest evidence supporting its role in imaging-based diagnosis, automated echocardiographic quantification, and CT-guided preprocedural planning for transcatheter interventions. AI-driven tools have demonstrated high accuracy in detecting and grading aortic stenosis and mitral regurgitation, while reducing interobserver variability and improving workflow efficiency. In the procedural domain, AI-enabled 3D reconstruction and automated measurements facilitate optimal device selection and procedural planning, particularly for TAVR, with near–expert-level reproducibility. Additionally, ML models integrating clinical and imaging data provide incremental value in predicting outcomes such as mortality, pacemaker implantation, and procedural complications, supporting a shift toward risk-adapted, personalized care. Despite these advances, current applications remain largely retrospective and require robust prospective validation across diverse populations. Key challenges include data standardization, algorithm transparency, and integration into routine clinical workflows. Future progress will depend on the development of explainable, generalizable models and their seamless incorporation into clinical decision-making pathways. Collectively, AI has the potential to move VHD management toward a more precise, efficient, and individualized paradigm.

12. CONFLICT OF INTERESTS

The authors have no conflict of interest to declare. The authors declared that this study has received no financial support.

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