

Artificial Intelligence in Cardiomyopathy: Diagnosis and Personalized Care

Mahvish Mehdi¹, Susham Verma¹, Mohammad Abbas¹, Bashir Ahmad Mir², Aliya Abbas Rizvi¹, Farzana Mahdi¹

Received on: 13-07-2026

Published on: 30-08-2026

ABSTRACT

Background: Cardiomyopathies are a broad category of myocardial diseases and they belong to the most complex problems of cardiovascular medicine due to the clinical presentation, unexpected course of disease and varied response to therapy. Traditional diagnostic and prognostic models are important but limited in sensitivity and focused on linear connections. Objective: This review was undertaken to examine the role of artificial intelligence (AI), from machine learning (ML) to deep learning (DL) and multi-modal integration, to improve the accuracy of cardiomyopathy diagnosis and personalized treatment.

Methodology: A structured literature search was conducted across PubMed, Scopus, Web of Science, and Google Scholar for articles published between 2014 and 2025, using combinations of the keywords "artificial intelligence," "machine learning," "deep learning," "cardiomyopathy," "precision cardiology," "cardiac imaging," and "electrocardiography." Original research articles, systematic reviews, and narrative reviews describing the application of AI in the diagnosis, risk stratification, multi-omics characterization, and therapeutic guidance of cardiomyopathies were screened for relevance and eligibility, and the extracted evidence was synthesized narratively under the domains of imaging, electrocardiography, genomics/multi-omics, wearables, and electronic health records.

Key Findings: AI is increasing the understanding of disease heterogeneity, from imaging applications, where it enables automated measurement of chambers and identification of fibrosis with unprecedented consistency, to genomics and multi-omics, where it improves the interpretation of variants and polygenetic risk prediction. Also, integration of wearables, ECG and EHR systems further enhance the potential of artificial intelligence (AI) technologies for massive real-time monitoring and prediction of dangers. In addition to the current practices, new directions include explainable AI for trust of practitioners, digital twins for prediction of the illness course and federated learning for equity and worldwide applicability. There are certain regulatory milestones (FDA/EMA approval of some tools) that are indicative of the translational readiness of a product, but issues over algorithmic biases and generalizability persist.

Conclusion: In this paper we use existing information to present the blueprint for the future of precision cardiology when the approach to care will become more proactive instead of reactive to improve care for cardiomyopathy all across the world.

KEYWORDS: Artificial intelligence, Cardiomyopathy, Cardiac imaging, Electrocardiography, Precision cardiology.

Era's Journal of Medical Research. 13(2);2026 [doi: 10.24041/ejmr.2026.41]

INTRODUCTION

Cardiomyopathies are a group of myocardial illnesses that contribute significantly to the worldwide morbidity and mortality burden. Dilated cardiomyopathy (DCM), hypertrophic cardiomyopathy (HCM), restrictive cardiomyopathy (RCM), and arrhythmogenic cardiomyopathy (ACM) account for the vast majority of occurrences of heart failure, sudden arrhythmia death, and the need for heart transplants.¹ Cardiomyopathies affect more than one out of every 500 persons, and their frequency is increasing as diagnostics, genetic testing, and understanding of silent cases improve.² The clinical picture ranges from silent gene carriers to patients with fatal cardiac failure, highlighting the wide range of these disorders that make diagnosis and prognosis difficult. Despite advances in imaging and molecular cardiology, cardiomyopathies can only be detected and classified at late stages of development. Echocardiography cannot identify minor changes in DCM and HCM, whereas restrictive cardiomyopathies are often confused with other diastolic dysfunction-related diseases.³

¹Department of Personalized and Molecular Medicine, Era's Lucknow Medical College and Hospital, Era University, Lucknow, UP, India.

²Department of Cardiology, Era's Lucknow Medical College and Hospital, Era University, Lucknow, UP, India.

Corresponding Author: Mohammad Abbas

Email: rizvi.109@gmail.com

How to cite: Mehdi M, Verma S, Abbas M, Mir BA, Rizvi AA, Mahdi F. Artificial Intelligence in Cardiomyopathy: Diagnosis and Personalized Care. *Era J Med Res.* 2026;13(2):219-229.

The electrocardiogram is insufficiently sensitive for early stages of illness, and late gadolinium increase on CMR indicates late remodeling rather than early pathology.⁴ In fact, when comparing the clinical courses of individuals with the same sarcomeric mutation, one patient may have a lifelong asymptomatic and benign history, whilst another may die suddenly in early adulthood.⁵ Current models rely on family history, imaging, and functional

factors, which do not account for the complexity of genetic, molecular, and environmental modifiers and hence cannot anticipate unforeseen results. There is an urgent need for breakthrough approaches that will allow for earlier disease detection, personalized prognosis, and precise therapy recommendations. Artificial intelligence (AI), together with its numerous technologies such as machine learning (ML), deep learning (DL), and multimodal, is a game-changing solution to those difficulties. When applied to clinical data, AI has showed a greater ability than humans to make thorough diagnosis of cardiomyopathy. For example, automated chamber measurement and strain analysis on echocardiography using deep learning could aid in the early detection of DCM on a wide scale.⁶ AI CMR radiomics are more reproducible and accurate than standard procedures for quantifying diffuse fibrosis and myocardial disorganization in HCM.⁷ In addition to imaging, deep learning has been used to uncover hidden phenotypes of cardiomyopathy that are not visible to a trained reader and then detect them early on, using publicly available and low-cost data sources.⁸ Similarly, machine learning (ML) methods outperform current models for predicting arrhythmic events and sudden cardiac death (SCD) in ACM, opening up new avenues for better risk stratification.⁹ The most appealing application of artificial intelligence in cardiomyopathy is the combination of multimodal information. Genetic architecture, proteomic markers, and lifestyle variables all contribute to the development of these disorders, in addition to structural and functional abnormalities. When imaging, electrocardiography, genomes, and clinical data are combined in AI frameworks, they can provide more extensive prognostic information and potentially find previously unknown disease categories using unsupervised clustering algorithms.¹⁰ This holistic approach is congruent with the precision cardiology

paradigm, which states that patient care decisions should be based on individual risk trajectories and tailored therapies rather than big illness categories. While early detection and treatment of cardiomyopathies remain difficult, AI technologies have advanced to the point that they can supplement and enhance human skills in diagnosis, prognosis, and treatment. AI-enabled technologies for cardiovascular imaging and predictive analytics in clinical workflows are both translationally ready and clinically practical.¹¹ This study synthesizes increasing information on AI's involvement in diagnosis, risk stratification, and treatment decision-making, as well as future directions and obstacles. The main goal is to pave the way for precision cardiomyopathy care, in which artificial intelligence enables doctors to shift from reactive treatment to proactive, customized treatments that enhance outcomes for patients worldwide.

Foundations of AI in Cardiology

The application of artificial intelligence (AI) is rapidly growing in modern healthcare practice, which can be described as the ability of computing machines to undertake operations typically performed by humans, including such processes as pattern recognition, prediction, and decision-making.¹² Regarding cardiology, the increasing amount of multimodal data from cardiac imaging and electrocardiography (ECG), genomics, proteomics, wearables, and electronic health records (EHR) serves as an excellent basis for further development of AI technology. In the case of cardiovascular disorders, cardiomyopathies are particularly relevant due to their heterogeneity, complex molecular mechanisms, and high genetic penetrance. The use of AI allows for uncovering disease markers invisible to human analysis, data integration, and assisting doctors in early disease diagnosis and patient risk stratification and treatment.¹³



Figure 1: Core Applications of Artificial Intelligence (AI) in the Management of Cardiomyopathy.

Machine Learning and Deep Learning: The Core Engines

Underlying the application of artificial intelligence (AI) in cardiology are ML and DL techniques. The field of ML, as one branch of AI, concentrates on creating algorithms able to detect patterns in datasets through their own work without the need for coding. Logistic regression, random forest, and support vector machine are all examples of traditional ML algorithms used in cardiology to predict various outcomes, such as SCD risk, strain in echocardiograms, and myocyte fibrosis.¹⁴ However, these techniques require extensive expert feature engineering and cannot account for any latent disease mechanisms. On the other hand, DL takes advantage of multilayered neural networks capable of discovering hierarchical features in raw data. CNNs are known to work well with echocardiogram and cardiac magnetic resonance imaging analyses, and RNNs and transformers perform quite well in dealing with sequential data like ECG and output from wearable sensors.¹⁵ The applications of DL in the detection of structural changes, subclinical imaging findings, and arrhythmic predictors in cardiomyopathies are promising.

Learning Paradigms in Cardiovascular AI

The most prevalent type of machine learning is supervised learning, where models are trained using labelled datasets (for example, ECG classified into “normal” or “hypertrophic cardiomyopathy”). This method was used with success to predict arrhythmic events and diagnose cardiomyopathy earlier than traditional methods.¹⁶ Unsupervised learning uses unlabelled datasets to detect the underlying structure or identify new subtypes of diseases. Thus, clustering analysis of MRI radiomic signatures was able to identify different phenotypic groups of dilated cardiomyopathy with various outcomes.¹⁷ The least developed type in cardiology is reinforcement learning (RL). RL could be beneficial for creating an adaptive therapy by tuning the parameters of devices in real time during CRT or LVAD procedures.¹⁸ Recently, federated learning (FL) became available for machine learning. This algorithm uses texture analysis to identify microstructural changes. Texture analysis has revealed microstructural changes that are invisible to the human eye while also preserving patients' privacy and enabling the training of machine learning algorithms using datasets from multiple centers. Such an approach could be useful for rare diseases like cardiomyopathy when it is challenging to collect a sufficient number of patients in one center.¹⁹

Domains of Application in Cardiomyopathies

Imaging: Echocardiography: DL systems now provide full automation in terms of chamber quantification, strain imaging, and wall motion, which makes these tests less dependent on operators and decreases observer variability.²⁰ AI-based strain analysis has even been found capable of

identifying preclinical cardiomyopathy in patients who have a positive genotype but a negative phenotype, thus allowing for earlier intervention.²¹ Cardiac Magnetic Resonance (CMR), AI-powered radiomics, and DL techniques can help to identify myocardial fibrosis, scar load, and myocardial disarray, which are the characteristics of both hypertrophic and dilated cardiomyopathies.²² Segmentation models that, with the help of texture analysis, the microstructural changes that are invisible to the human eye have been found, which are automated speed up this technique because of not requiring manual annotation by radiologists, making it more reproducible among different centers. It is crucial that with the help of texture analysis, the microstructure changes have been found, which are invisible to human eyes and help in predicting arrhythmic complications.²³

Electrocardiography (ECG): AI-driven models when trained on conventional 12-lead ECGs can predict left ventricular systolic dysfunction, mutations leading to hypertrophic cardiomyopathy, and even genotype-positive phenotypes. One-lead wearable ECGs interpreted using DL models can predict atrial and ventricular arrhythmias even before their clinical occurrence months in advance. It is important that XAI techniques used in ECG models have helped discover different arrhythmia signatures associated with SCD risk in dilated and arrhythmogenic cardiomyopathies.²⁴

Genomics and Multi-Omics: Owing to the genetic nature of various cardiomyopathies, AI has been utilized in the classification of VUS, integration of multi-level omics data with imaging, and genotype-phenotype correlations. Variant Interpretation: AI-based approaches can enhance the classification of VUS and thereby reduce uncertainty in diagnosis.²⁵ Multi-Omics Integration: Modern multimodal AI approaches have combined the analysis of genomics, transcriptomics, and proteomics data along with imaging phenotypes to subtype diseases more accurately.²⁶ Predictive modeling, by associating rare mutations with various structural and functional traits, AI-based systems can stratify risks of arrhythmias, heart failure, and transplantation-free survival.

Wearables and Sensors: Continuous real-time physiological data collected through wearables and implantables using AI analytics helps in the detection of early decompensation, arrhythmias, and subtle disease progressions. Smartwatches and patches that use photoplethysmography sensors and ECG sensors can help monitor in real time. AI-enabled algorithms have been beneficial in the early diagnosis of LV dysfunction and silent arrhythmias.²⁷ Implanted devices, hemodynamic sensors, and implanted loop recorders, together with ML, can help predict acute decompensation days or even weeks in advance for making preemptive therapeutic changes.²⁸ This advancement in monitoring technology

can help bring monitoring out of hospitals and into homes, especially in resource-poor regions experiencing an increased incidence of cardiomyopathy.

Electronic Health Records (EHR): Applications of ML on longitudinal EHR data have been used to make predictions about patient risk and include predicting heart failure hospitalizations or finding patients with undiagnosed cardiomyopathy. **Risk Prediction:** Applications of ML on longitudinal EHR data have predicted hospitalizations for heart failure and remodeling in patients with dilated cardiomyopathy. **Phenotype Discovery:** The natural language processing tool has found patients with undiagnosed cardiomyopathies based on mining information from unstructured clinical notes. **Decision support and EHR-AI integration** will allow personalized treatment suggestions like recommending defibrillators or advanced treatment referrals.²⁹

Regulatory and Implementation Considerations

Regulatory supervision is essential to ensure safe use. AI is becoming more and more regulated as “Software as a Medical Device” (SaMD). AI-enabled echocardiography and arrhythmia detection systems have already been approved, but adaptive AI algorithms, which keep developing, present new challenges to regulators such as the FDA and EMA. Another challenge lies in implementation of the technology: bad design may cause alert fatigue while good implementation involves smooth integration into EHRs and clinical decision support.³³

AI in Diagnosis of Cardiomyopathies

The diagnosis of cardiomyopathies is among the major problems in clinical cardiology because of its diverse clinical presentation and unpredictable disease course. The use of such conventional diagnostic tools as echocardiography, CMR, CT, and ECG is essential but limited by the issues of subjective interpretation, low sensitivity to detect early or asymptomatic diseases, and inability to merge results of different tests. The use of artificial intelligence technologies, especially DL and radiomics approaches, can revolutionize the diagnostic process by increasing the accuracy, reproducibility, and effectiveness of the diagnostic process.³ The following section covers the application of AI in imaging diagnostics and ECG analysis of cardiomyopathies.

Echocardiography and Automated Interpretation

An echocardiogram is the initial step used in diagnosing cardiomyopathy because of the availability, affordability, and safety of this technique. However, the interpretation of the echocardiogram may vary depending on the individual performing it, which can lead to the possibility of missing subtle changes. However, the person performing the interpretation may influence the results, leading to the possibility of missing subtle changes. The AI echocardiogram analysis helps solve this problem and offers the possibility of quantitative analysis of the heart chambers, ejection fraction, and strain imaging. CNNs have been able to identify automatically the heart chambers' view, segmentation, and

Table 1: Comparative summary table for the domains of AI application in cardiomyopathies.

Domain	AI Technique	Clinical Application	Key Outcome/Benefit	References
Imaging	Deep Learning (CNN, Radiomics)	Automated chamber quantification, fibrosis detection, scar burden analysis	Higher reproducibility, early subclinical detection, and improved prognostic accuracy	22
Electrocardiography (ECG)	Deep Learning (CNN, RNN, Transformers)	Prediction of LV dysfunction, arrhythmic risk, and genotype-positive HCM detection	Non-invasive risk stratification, early arrhythmia detection, and explainable predictions	30
Genomics & multi-omics	Machine Learning, Multi-modal AI	Variant classification, genotype-phenotype correlation, disease subtyping	Improved accuracy in variant interpretation, precision in disease classification	31
Wearables & Sensors	Machine Learning, Deep Learning	Continuous monitoring, early decompensation detection, and arrhythmia prediction	Shifts monitoring from hospital to home, proactive interventions, and scalable screening	27
Electronic Health Records	Machine Learning, NLP	Risk prediction, phenotype discovery, individualized decision support	Identification of undiagnosed cases, personalized therapy guidance, and reduced hospitalizations	32

functional parameters' extraction with an accuracy that matches that of the best cardiologists.³⁴ Until now, manual strain imaging has been subject to variability, despite providing sensitive indicators of heart dysfunction. Until now, strain imaging has been performed manually, which has exposed it to variability. DL models enable automated strain calculation, which helps in the early diagnosis of diseases such as dilated cardiomyopathy (DCM) and hypertrophic cardiomyopathy (HCM) even before the development of function decline.³⁵ In addition, portable ultrasound machines combined with AI algorithms have shown promise in making echocardiograms accessible in underserved areas.

Cardiac MRI and CT scan

CMR continues to be the gold standard technique for characterization of myocardial tissue, which provides useful data on myocardial fibrosis, inflammation, and scar burden through LGE and T1/T2 mapping. AI improves diagnostic capabilities of CMR through automation of segmentation, quantification of fibrosis, and radiomics-based phenotyping. DL algorithms that learn from LGE imaging outperform manual methods in the detection and quantification of myocardial scars in terms of reproducibility.³⁶ Furthermore, radiomics analysis was able to identify textural biomarkers that are linked to poor clinical outcomes in DCM patients. CT AI's translation from bench to bedside in cardiology has become a tangible reality. CT imaging is routinely used as a diagnostic tool for cardiomyopathy, but it can still be useful in applications of AI technology. Automated quantification of heart chambers and texture analysis of myocardium can add structural information, whereas DL algorithms that utilize CT-based anatomy combined with functional imaging have potential for evaluation of arrhythmogenic cardiomyopathy.³⁷

ECG-Based AI Models

ECG is a cost-effective diagnostic method that is easily accessible; however, it has poor specificity in the diagnosis of cardiomyopathies. The development of AI-powered ECG interpretation has dramatically changed the use of this method, discovering latent markers of diseases. In one study, for example, an AI-ECG algorithm was able to detect left ventricular systolic dysfunction with high sensitivity, although human interpretation was negative.³⁸ Furthermore, DL algorithms were able to diagnose HCM through the interpretation of resting ECGs, which included subtle electrical abnormalities undetectable by humans. Moreover, AI-ECG was successfully used for hidden phenotyping, including identification of individuals prone to developing arrhythmias and sudden cardiac death (SCD) before the development of clinical disease. The combination of AI-ECG analysis with genetic testing can predict pathogenic mutations in HCM patients.³⁹

Multimodal Integration for Diagnosis

The true strength of AI is in the analysis of multimodal data sources. The combination of imaging modalities, ECG, and other clinical variables has been proven superior to single-modality techniques in distinguishing cardiomyopathies from other diseases leading to heart failure. For example, unsupervised clustering of multimodal data from CMR radiomics and ECG has identified new phenotypes of arrhythmogenic and restrictive cardiomyopathies. In addition, wearable devices also aid in the early detection of cardiomyopathies through continuous monitoring of rhythm abnormalities by AI-enabled ECG patches and smartwatches.³⁹

AI in Risk Stratification and Prognostication

Risk stratification and prognosis are essential components of cardiomyopathies, as they predispose patients to cardiomyopathies and put them at risk of developing heart failure, arrhythmias, and sudden cardiac death (SCD). While existing prediction algorithms using clinical characteristics, imaging biomarkers, and genomics have proved beneficial, they were constrained by their assumption of linear relationships, lack of sufficient precision, and inability to identify interplay within multiple data modalities. By applying artificial intelligence (AI), using sophisticated machine learning (ML) and deep learning (DL) tools, there is a possibility of improving the prognosis process by incorporating high-dimensional data and discovering unknown risks.⁴⁰

Predicting Sudden Cardiac Death (SCD)

Among the most important issues to be addressed in cardiomyopathies is the selection of candidates prone to sudden cardiac death (SCD) who may potentially benefit from the implantation of ICDs. At the moment, current guidelines use left ventricular ejection fraction (LVEF), which shows limited sensitivity and specificity. AI models trained on ECGs, cardiac magnetic resonance imaging (CMR), and genetic data have proved to be more accurate predictors than traditional markers. The use of DL algorithms, applied to CMR findings, such as the presence of fibrosis and strain abnormalities, is known to provide a better prediction of ventricular arrhythmias and SCD in hypertrophic cardiomyopathy (HCM) than LVEF-related criteria.⁴¹

Heart Failure Progression and Adverse Outcomes

However, the risk stratification goes further than the arrhythmias to predict the disease course. ML algorithms, based on longitudinal clinical records, biomarkers, and imaging markers, have revealed potential for predicting heart failure outcomes in dilated cardiomyopathy (DCM) patients.⁴² Such algorithms reflect complex relations like the interaction of the genetic mutations, myocardial fibrosis, and functional parameters, which Such algorithms capture complex relationships, such as the interactions between genetic mutations, myocardial fibrosis, and functional parameters, which regression algorithms

fail to detect. by regression algorithms. In the case of RCM and ARVC, the AI-derived imaging markers, in particular radiomics myocardial texture features, revealed the value of predicting disease course. Moreover, combining AI with wearables provides an opportunity for real-time monitoring of the patient for adaptive risk prediction.⁴³

Multimodal Prognostic Models

The most significant contributions in the field of risk prediction have come from AI models utilizing multimodal datasets. The combination of imaging, ECG, clinical, and genomics data provides a complete picture of the patient's trajectory. In HCM, ML models utilizing CMR radiomics combined with genomics data demonstrated excellent ability to predict adverse events and the requirement for advanced treatment.⁴⁴ Novel disease phenotypes with unique prognostic characteristics were discovered through unsupervised machine learning methods. The identification of different subgroups of patients in terms of their risk for arrhythmia using CMR and electrocardiographic parameters was described in ARVC.⁴⁵

AI in Guiding Personalized Therapeutics

In addition to risk stratification, AI techniques are now employed to personalize treatment according to predictive insights. Models have been developed to help in choosing the right time to implant an ICD, cardiac resynchronization therapy (CRT), and even heart transplantation. Most importantly, the predictive models created using AI are becoming explainable, meaning that they generate results that are interpretable enough for doctors to decide how to proceed with their patients. The clinical application is crucial as it connects algorithms with clinical practice.⁴⁶ AI transforms prognostic assessment in cardiomyopathies from using simple markers like LVEF to creating complicated and dynamic risk models. In this way, prediction of sudden cardiac death, heart failure progression, and response to treatments will enhance decision-making processes.

AI in Therapeutic Guidance

The treatment of cardiomyopathies is highly personalized, involving pharmacologic therapy, device-based treatment, surgery, and other forms of advanced support. However, the efficacy of treatment can be highly variable among patients because of genetics, co-morbid conditions, and the environment. Treatment paradigms used traditionally despite being evidence-based have failed to incorporate this variability. Artificial intelligence (AI) provides the chance to personalize treatment through data-driven predictions of the response to treatment.⁴⁷

Predicting Drug Response

Pharmacotherapy still represents the main approach in cardiomyopathy treatment that involves beta-blockers, ARNIs (angiotensin receptor neprilysin inhibitors), and mineralocorticoid receptor blockers. However, not all

patients demonstrate similar responses, and adverse drug reactions pose additional risks. Machine learning models capable of predicting response to a particular pharmacotherapy in terms of genetic, proteomic, imaging, and EHR data have been created for cardiomyopathy patients. For instance, machine learning models were used to predict DCM patients' responses to beta-blocker therapy, considering echocardiographic strain markers and ECG.⁴⁸ Moreover, machine learning models that allow predicting the response to ARNI therapy by combining the clinical and biomarker data have been designed.

Guiding Device Implantation

Implantable cardioverter-defibrillators (ICDs) and CRTs are critical devices in the treatment of SCD or advanced heart failure. Current guidelines mainly depend on ejection fraction thresholds and QRS complexes to select appropriate candidates for these devices, but these measures are not perfect and miss many patients who can benefit from them. Machine learning models have shown increased accuracy when predicting the suitability of these patients to undergo device insertion. Machine learning methods used in ECG and CMR images have provided more precise detection of conduction abnormalities in patients responding to CRT.⁴⁹ Likewise, risk stratification using machine learning based on fibrosis burden, ECG features, and genetics will help in the optimal implantation of ICDs.

AI-Driven Surgical and Interventional Planning

In some cases of cardiomyopathy, surgical or other forms of intervention treatment, such as septal myectomy in the case of HCM, LVADs, and even cardiac transplantation, are employed. These treatments are very risky and involve cautious patient selection. Currently, AI has been widely used for optimizing surgical procedures and predicting their outcome. In the case of HCM, deep-learning algorithms using CMR-based anatomic data help surgeons in planning septal myectomy through predicting surgical gradients and outcomes.⁵⁰ For advanced cases of DCM, models that predict survival from LVAD therapy and identify candidates for transplantation based on hemodynamic, imaging, and genomic information have been developed. Furthermore, reinforcement learning techniques are used to dynamically optimize LVAD pump speed.⁵¹

Personalized Therapeutic Pathways

Certainly, one of the most intriguing uses of AI in cardiology could be the generation of personalized therapeutic road maps. Using longitudinal data on patients, AI systems can forecast the time point when it becomes necessary to switch patients from pharmacotherapy to more invasive methods, such as the use of devices or surgery. For instance, there were developed machine learning models predicting heart failure hospitalizations and advanced therapies in DCM patients.¹³ In the future, AI could help

in developing the concept of a “digital therapeutic twin,” a virtual model of an individual patient that simulates the development of pathology and reaction to therapy in order to try different treatment scenarios prior to their implementation in clinical practice.⁵¹

Challenges in AI-Guided Therapeutics

Although there have been great strides, despite significant progress, some issues still persist, there are still some issues. Despite significant progress, implementing AI-based therapeutics in clinical practice still presents several challenges. Implementing AI-based therapeutics in clinical practice presents several challenges. Some of the key issues include variations in data quality, lack of access to big annotated data sets, and lack of standardization in imaging and monitoring tools.⁵² Another issue that needs to be considered is the ethical one, and this revolves around the possibility of introducing a biased algorithm in the decision-making process.⁵²

AI and Multi-Omics in Cardiomyopathy

AI integrates multi-omics data, including genomics, transcriptomics, proteomics, and metabolomics, to uncover complex molecular signatures underlying cardiomyopathies. This approach can improve early diagnosis, risk stratification, and identification of potential therapeutic targets, supporting more personalized patient care. This broader precision-medicine framework is relevant to AI-enabled cardiomyopathy care because multimodal molecular and clinical information can be incorporated into individualized assessment.⁵³

Genetic Testing and Variant Classification Using AI

Cardiomyopathies are usually genetically mediated conditions, but the application of genetic tests is constrained by the problem of interpretation of variants of unknown significance (VUS). Standard procedures use curated expertise and information on the population frequency of a given variant, which have drawbacks associated with underrepresentation of the annotations and possible biases. The advent of artificial intelligence and machine learning (ML) models in this area has allowed us to overcome these limitations by making possible data-driven analysis of genetic variants. ML models based on large genomic data repositories can classify the pathogenicity of VUS using information on the conservation of the given sequence, structure, and functional annotations.² The more advanced DL approach has revealed the existence of nonlinear associations between genetic variants and phenotypic traits that cannot be detected by standard methods. In the case of HCM, AI-based tools for prioritizing variants allow for faster detection of mutations and an improvement in the diagnostic yield.³⁹

Integration of Transcriptomics and Proteomics with Imaging

Whereas genomics can provide us an idea of genetic risks, it may not be able to describe complex states of diseases. In the case of cardiomyopathies, the integration of multiple omics data, including transcriptomics, proteomics, metabolomics, and imaging phenotypes, has turned out to be a strong tool. The use of AI helps integrate data from different modalities to discover unknown biological patterns. For example, some DL methods have helped in associating cardiac MRIs with transcriptomic data so that it is possible to identify markers for fibrosis, remodeling, and arrhythmogenic substrate.⁵⁴ Likewise, by integrating proteomic information with imaging phenotypes, some new biomarkers of disease progression in DCM patients have been found that are important predictors of hospitalization due to heart failure and survival without transplantation in DCM patients.⁵⁵ Besides discovering biomarkers, multimodal AI systems have been used for patient stratification. In the case of restrictive and arrhythmogenic cardiomyopathies, different phenotypic clusters have been identified based on omics imaging data using AI-based approaches.⁵⁶

Polygenic Risk Prediction

While mutations at a single locus have accounted for many familial cardiomyopathies, several cases are caused by a combination of genetic elements leading to idiopathic DCM and HCM. A Polygenic Risk Score (PRS), obtained by aggregation of the effect of many single nucleotide polymorphisms (SNPs), together with clinical and imaging data, is an approach that appears promising in predicting disease vulnerability among such patients. AI has improved PRS, together with clinical and imaging data, leading to a more accurate prediction by incorporating non-linear interactions between SNPs, the effects of rare variants, and environmental modifiers into the conventional regression-based approach. ML-based techniques are dynamic in weighting SNPs depending on their ancestry and context, thereby increasing prediction performance.² In HCM, the use of AI-PRS, together with clinical and imaging data, leads to an in-patient being able to stratify arrhythmia and adverse remodeling risks, even among genotype-negative patients with a familial history.⁵⁷ Furthermore, the use of PRS, together with clinical and imaging data, leads to an improvement in risk stratification. For instance, AI-PRS, together with echocardiographic strain parameters, has helped predict progression to cardiomyopathy in asymptomatic carriers.⁵⁷ Significantly, as population-scale biobanks continue growing, the use of federated learning techniques could help develop PRS in a privacy-preserving multi-center manner in light of rare variant distribution among single centers.

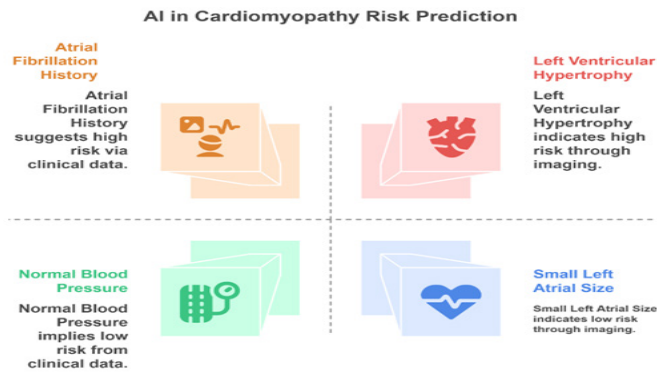


Figure 2: Artificial Intelligence (AI) in Cardiomyopathy Risk Prediction: Integrating Clinical and Imaging Data

Clinical Implementation and Real-World Evidence

The utilization of AI and multi-omics technology in clinical applications for cardiomyopathies has been transformed from a research field to a practical one as a result of the availability of big, multimodal data sets and the development of AI tools that can handle multidimensional data.⁵⁸

FDA/EMA-Approved Tools

Translation of AI in Cardiology from Bench to Bedside: AI's translation from bench to bedside in cardiology has become a tangible reality. It's just an abstract concept anymore. Various AI-enabled cardiovascular devices have both the US FDA and the European EMA cleared. Both the US FDA and the European EMA have cleared various AI-enabled cardiovascular devices. Most of them are related to imaging and arrhythmia recognition. Thus, FDA-cleared echocardiography systems now allow the automated calculation of left ventricular ejection fraction and volume measurements, minimizing the subjectivity of the process.⁵⁹ Similarly, FDA-cleared and CE-approved AI-based arrhythmia recognition algorithms included in wearable ECG monitors (such as smartwatches, patches, etc.) have already been designed for AF recognition, paving the way for more widespread applications in cardiomyopathies.⁶⁰

Integration into Clinical Workflow and EHR

AI needs to be embedded in the clinical workflow for it to become impactful. Incorporating AI components into the EHR system enables risk assessment, triage, and personalized treatment plans for the patient. For example, EHR system analysis that is based on machine learning technology has shown promise in identifying patients with undiagnosed dilated cardiomyopathy and in predicting hospitalization with higher accuracy than traditional risk scores.⁶¹ Clinical decision support systems based on AI are being tested to suggest imaging, device placement, or genetic testing in order to bring precision medicine into everyday clinical practice.

Barriers: Bias, Interpretability, and Generalizability

Although there have been some promising developments, obstacles abound. For instance, bias could be an issue, as AI models tend to learn based on data from rich nations that lack ethnic diversity, which raises doubts regarding their generalizability.⁶² Interpretability is another obstacle, since the predictions from the black box nature of deep learning may lead to distrust among clinicians when making life-changing decisions, such as the insertion of medical devices and referrals for transplantation. XAI will be key to overcoming this hurdle. Lastly, the generalizability of AI across different settings still needs to be verified.

Future Perspectives

Despite significant progress, the widespread adoption of AI in cardiomyopathy treatment still faces several challenges. One of the key issues is explainable AI or XAI. The majority of deep learning algorithms are "black box" models that provide a prediction without giving reasons. In situations where treatment requires the use of a device, such as treatment for multiple myeloma, clinicians are less inclined to use such a tool if it cannot demonstrate the value of its output. To garner trust and regulatory approval, it will be necessary to develop interpretable models, such as saliency maps for imaging or attention mechanisms for ECGs. A second frontier is digital twins, which will be virtual and patient-specific and will simulate the physiology of the heart under different conditions, using AI. Digital twins can be used in cardiomyopathies to combine genomic, imaging, and hemodynamic data to predict disease progression, evaluate therapeutic options, and tailor treatment strategies. While early proof-of-concept work has demonstrated feasibility in heart failure and arrhythmia modeling, further efforts and extensive validation and clinical workflow integration will be needed to make digital twins a routine tool in the clinical toolbox. Lastly, equity and applicability at the global level need to be addressed. There are concerns about the generalizability of many of the AI models, as they rely on data from high-income countries. based on data from high-income countries. If multi-ethnic cohorts are deliberately included, it is essential to prevent algorithmic biases from perpetuating health inequities and diminishing the global benefits of AI solutions; otherwise, algorithmic biases may contribute to sustaining health inequities and reduce the benefits of AI solutions for the world. Federated learning and collaborations across borders with other countries are potential avenues to create representative and privacy-preserving datasets.

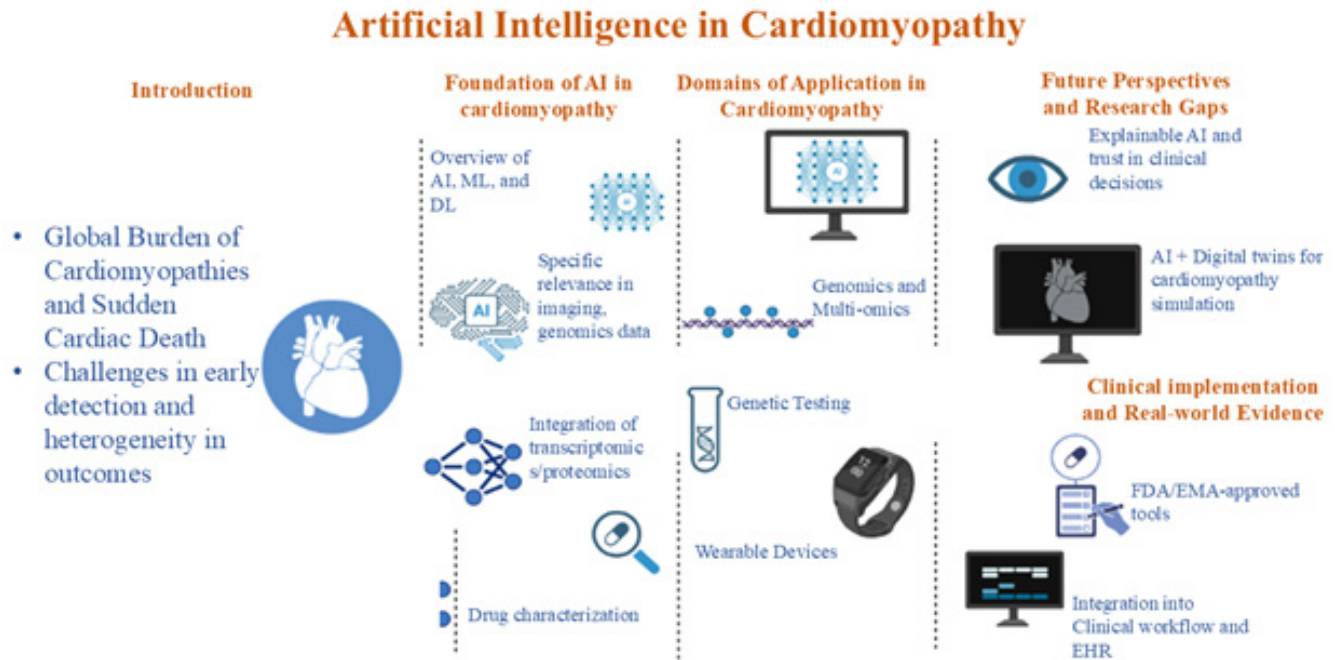


Figure 3: AI-driven cardiomyopathy care integrating multimodal data for early diagnosis, risk stratification, and personalized treatment, with future applications in explainable AI and digital twins.

CONCLUSION

Artificial intelligence (AI) is revolutionizing cardiomyopathy diagnosis, therapy, and management through better patient stratification. Utilization of cardiac imaging, clinical features, genetics, and multi-omics data in artificial intelligence allows for characterization of the disease not only in terms of diagnostic categories but also on the molecular and clinical level. Such deeper phenotyping is likely to be associated with better prediction of risk factors, discovery of new therapeutic targets, and earlier disease prevention. The key strength of AI is in the integration of multiple patient-level sources of information. Wearable devices, cloud computing platforms and federated learning enable continuous patient monitoring and more efficient analysis of large datasets. Future development of explainable AI may further help to increase clinician's confidence in predictions made by the algorithm. One of the potential ways in which AI might revolutionize medicine is the creation of digital twins and continuous remote monitoring which can help clinicians predict disease progression and patients' response to treatment before complications develop. At the same time, many challenges should be addressed including data biases, uneven distribution of technology access, and poor representation of patients from resource-poor regions. In summary, AI needs to be thought of not only as a diagnostic technology, but also as an extremely efficient acceleration mechanism for precision cardiology.

REFERENCES

- Lannou S, Mansencal N, Couchoud C, et al. The Public Health Burden of Cardiomyopathies: Insights from a Nationwide Inpatient Study. *J Clin Med*. 2020;29:7(4).
- Kim KH, Pereira NL. Genetics of Cardiomyopathy: Clinical and Mechanistic Implications for Heart Failure. *Korean Circ J* [Internet]. 2021 Oct;51(10):797–836.
- Jin Y, Che W, Yang J, et al. Classification, Diagnosis, and Prognosis of Cardiomyopathy: A Comprehensive Narrative Review. *Rev Cardiovasc Med*. 2025 Jun;26(6):36280.
- Asfour I, Karim S, Tabraiz SA, et al. Late Gadolinium Enhancement and Electrocardiographic Associations in Hypertrophic Cardiomyopathy. *Ann Noninvasive Electrocardiol* [Internet]. 2025 Jul;30(4):e70077.
- Sedaghat-Hamedani F, Kayvanpour E, Tugrul OF, et al. Clinical outcomes associated with sarcomere mutations in hypertrophic cardiomyopathy: a meta-analysis on 7675 individuals. *Clin Res Cardiol*. 2018 Jan;107(1):30–41.
- Salavati A, Van der Wilt CN, Calore M, et al. Artificial Intelligence Advancements in Cardiomyopathies: Implications for Diagnosis and Management of Arrhythmogenic Cardiomyopathy. *Curr Heart Fail Rep*. 2024;22(1):5.
- Polidori T, De Santis D, Rucci C, et al. Radiomics applications in cardiac imaging: a comprehensive review. *Radiol Med*. 2023;128(8):922–933.
- Nakayama M, Yagi R, Goto S. Deep Learning Applications in 12-lead Electrocardiogram and Echocardiogram. *JMA J*. 2025;8(1):102–112.

9. Chung CT, Bazoukis G, Lee S, et al. Machine learning techniques for arrhythmic risk stratification: a review of the literature. *Int J Arrhythmia*. 2022;23:10-15.
10. Yang XY, Li YM, Wang JY, et al. Utilizing multimodal artificial intelligence to advance cardiovascular diseases. *Precis Clin Med*. 2025;8(3):pbaf016.
11. Sethi Y, Patel N, Kaka N, et al. Precision Medicine and the future of Cardiovascular Diseases: A Clinically Oriented Comprehensive Review. *J Clin Med*. 2023;12(5):22-26.
12. Bhattad PB, Jain V. Artificial Intelligence in Modern Medicine - The Evolving Necessity of the Present and Role in Transforming the Future of Medical Care. *Cureus*. 2020;12(5):e8041.
13. Shuja MH, Shakil F, Shuja SH, et al. Harnessing Artificial Intelligence in Cardiology: Advancements in Diagnosis, Treatment, and Patient Care. *Heart Views [Internet]*. 2024;25(4):241-248.
14. Karatzia L, Aung N, Aksentijevic D. Artificial intelligence in cardiology: Hope for the future and power for the present. *Front Cardiovasc Med*. 2022;9:945726.
15. Patil D, Rane NL, Desai P, et al. Machine learning and deep learning: Methods, techniques, applications, challenges, and future research opportunities. In: *Trustworthy Artificial Intelligence in Industry and Society*. Deep Science Publishing; 2024. Available from: <https://deepscienceresearch.com/index.php/dsr/catalog/book/10/chapter/75>
16. Feeny AK, Chung MK, Madabhushi A, et al. Artificial Intelligence and Machine Learning in Arrhythmias and Cardiac Electrophysiology. *Circ Arrhythm Electrophysiol*. 2020;13(8):e007952.
17. Williams MC, Bednarski BP, Pieszko K, et al. Unsupervised learning to characterize patients with known coronary artery disease undergoing myocardial perfusion imaging. *Eur J Nucl Med Mol Imaging [Internet]*. 2023 Jul;50(9):2656-2668.
18. Komp J, Boggaram A, Kao DP, et al. Strategies and Considerations for Safe Reinforcement Learning in Programming Cardiac Implantable Electronic Devices. *Med Res Arch [Internet]*. 2025;13(3):67-71.
19. Nicola Rieke, Jonny Hancox, Wenqi Li, et al. The future of digital health with federated learning. *NPJ Digit Med [Internet]*. Available from: <https://pubmed.ncbi.nlm.nih.gov/33015372/>
20. Hirata Y, Kusunose K. AI in Echocardiography: State-of-the-art Automated Measurement Techniques and Clinical Applications. *JMA J [Internet]*. 2025;8(1):141-150.
21. Alahwany SH, Kamel O, Abdelghany A, et al. Leveraging artificial intelligence for risk stratification of inherited cardiomyopathies in under-resourced settings. *Hear Rhythm O2 [Internet]*. 2025 Aug; Available from: <https://linkinghub.elsevier.com/retrieve/pii/S2666501825002855>
22. Burrage MK, Ferreira VM. Cardiovascular Magnetic Resonance for the Differentiation of Left Ventricular Hypertrophy. *Curr Heart Fail Rep [Internet]*. 2020 Oct;17(5):192-204.
23. Li S, Kendrick J, Ebert MA, et al. Auto-segmentation, radiomic reproducibility, and comparison of radiomics between manual and AI-derived segmentations for coronary arteries in cardiac [18F]NaF PET/CT images. *EJNMMI Phys [Internet]*. 2025 Apr 27;12(1):42.
24. Siontis KC, Noseworthy PA, Attia ZI, et al. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nat Rev Cardiol [Internet]*. 2021;18(7):465-478.
25. Mohyeldin M, Mohamed FO, Molina M, et al. Artificial Intelligence in Hypertrophic Cardiomyopathy: Advances, Challenges, and Future Directions for Personalized Risk Prediction and Management. *Cureus*. 2025;17(7):e87907.
26. Subramanian I, Verma S, Kumar S, et al. Multi-omics Data Integration, Interpretation, and Its Application. *Bioinform Biol Insights*. 2020;14:1177932219899051.
27. Gaoudam N, Sakhamudi SK, Kamal B, et al. Wearable Devices and AI-Driven Remote Monitoring in Cardiovascular Medicine: A Narrative Review. *Cureus*. 2025;17(8):e90208.
28. Alyami AM, Kirimi MT, Neale SL, et al. Implantable Biosensors for Vascular Diseases: Directions for the Next Generation of Active Diagnostic and Therapeutic Medical Device Technologies. *Biosensors*. 2025;15(3):26-31.
29. Huda A, Castaño A, Niyogi A, et al. A machine learning model for identifying patients at risk for wild-type transthyretin amyloid cardiomyopathy. *Nat Commun*. 2021;12(1):2725.
30. Wu Z, Guo C. Deep learning and electrocardiography: systematic review of current techniques in cardiovascular disease diagnosis and management. *Biomed Eng Online [Internet]*. 2025;24(1):23.
31. Lin M, Guo J, Gu Z, et al. Machine learning and multi-omics integration: advancing cardiovascular translational research and clinical practice. *J Transl Med*. 2025;23(1):388.
32. Shen Y, Yu J, Zhou J, et al. Twenty-Five Years of Evolution and Hurdles in Electronic Health Records and Interoperability in Medical Research: Comprehensive Review. *J Med Internet Res*. 2025;27:e59024.
33. Liu Y, Yu W, Dillon T. Regulatory responses and approval status of artificial intelligence medical devices with a focus on China. *NPJ Digit Med [Internet]*. 2024;7(1):255.
34. Kapoor MC. Emerging Role of Artificial Intelligence in Echocardiography. *Ann Card Anaesth*. 2024;27(2):99-100.
35. Smiseth OA, Rider O, Cvijic M, et al. Myocardial Strain Imaging: Theory, Current Practice, and the Future. *JACC Cardiovasc Imaging*. 2025;18(3):340-381.
36. Meier C, Eisenblätter M, Gielen S. Myocardial Late Gadolinium Enhancement (LGE) in Cardiac Magnetic Resonance Imaging (CMR)-An Important Risk Marker for Cardiac Disease. *J Cardiovasc Dev Dis*. 2024;11(2): 31-41.
37. Lin A, Kolossváry M, Motwani M, et al. Artificial intelligence in cardiovascular CT: Current status and future implications. *J Cardiovasc Comput Tomogr*. 2021;15(6):462-469.
38. Kashou AH, Mulpuru SK, Deshmukh AJ, et al. An artificial intelligence-enabled ECG algorithm for comprehensive ECG interpretation: Can it pass the "Turing test"? *Cardiovasc Digit Heal J*. 2021;2(3):164-170.

39. Ordine L, Canciello G, Borrelli F, et al. Artificial intelligence-driven electrocardiography: Innovations in hypertrophic cardiomyopathy management. *Trends Cardiovasc Med*. 2025;35(2):126–134.
40. Wellens HJJ, Schwartz PJ, Lindemans FW, et al. Risk stratification for sudden cardiac death: current status and challenges for the future. *Eur Heart J*. 2014;35(25):1642–1651.
41. Srivats S, Zghyer F, Shahreri Z, et al. Sudden cardiac arrest: Limitations in risk-stratification and treatment, and the potential for digital technologies and artificial intelligence to improve prediction and outcomes. *Prog Cardiovasc Dis*. 2025;91:144–166.
42. Shu S, Hong Z, Peng Q, et al. A machine-learning-based method to predict adverse events in patients with dilated cardiomyopathy and severely reduced ejection fractions. *Br J Radiol*. 2021;94(1127):20210259.
43. Gerull B, Brodehl A. Insights Into Genetics and Pathophysiology of Arrhythmogenic Cardiomyopathy. *Curr Heart Fail Rep*. 2021;18(6):378–390.
44. Simon BD, Ozyoruk KB, Gelikman DG, et al. The future of multimodal artificial intelligence models for integrating imaging and clinical metadata: a narrative review. *Diagn Interv Radiol*. 2025 Jul 8;31(4):303–312.
45. Jentzer JC, Reddy YN V, Soussi S, et al. Unsupervised machine learning to identify subphenotypes among cardiac intensive care unit patients with heart failure. *ESC Hear Fail*. 2024 Dec;11(6):4242–4256.
46. Saeed I, Hashmi MU, Khalid M, et al. The Role of Artificial Intelligence in Heart Failure Diagnostics, Risk Prediction, and Therapeutic Strategies: A Comprehensive Review. *Cureu*. 2025;17(7):e87130.
47. Shitong Huang, Jiaxin Li, Qiuying Li, et al. Cardiomyopathy: pathogenesis and therapeutic interventions. *MedComm*. (2020). 2024 Oct 25;5(11):e772.
48. Kim AH, Jang JE, Han J. Current status on the therapeutic strategies for heart failure and diabetic cardiomyopathy. *Biomed Pharmacother*. 2022;145:112463.
49. Chia PL, Foo D. Overview of implantable cardioverter defibrillator and cardiac resynchronisation therapy in heart failure management. *Singapore Med J*. 2016;57(7):354–359.
50. Hang D, Nguyen A, Schaff H V. Surgical treatment for hypertrophic cardiomyopathy: a historical perspective. *Ann Cardiothorac Surg*. 2017;6(4):318–328.
51. Topkara VK, Elias P, Jain R, et al. Machine Learning-Based Prediction of Myocardial Recovery in Patients With Left Ventricular Assist Device Support. *Circ Heart Fail*. 2022;15(1):e008711.
52. Wubineh BZ, Deriba FG, Woldeyohannis MM. Exploring the opportunities and challenges of implementing artificial intelligence in healthcare: A systematic literature review. *Urol Oncol*. 2024;42(3):48–56.
53. Mehdi M, Verma S, Mir BA, et al. Precision Medicine in Cardiomyopathy: Advances and Future Directions. *Clin Genet*. 2025;108(6):641–53.
54. Babu M, Snyder M. Multi-Omics Profiling for Health. *Mol Cell Proteomics*. 2023;22(6):100561.
55. Cho SW. Clinical Implications of a Proteomics-Based Approach for Cardiomyopathy and Heart Failure. *Korean Circ J*. 2024;54(8):482–484.
56. Lteif C, Huang Y, Guerra LA, et al. Using Omics to Identify Novel Therapeutic Targets in Heart Failure. *Circ Genomic Precis Med*. 2024;17(3):e004398.
57. Hosseini K, Anaraki N, Dastjerdi P, et al. Bridging Genomics to Cardiology Clinical Practice: Artificial Intelligence in Optimizing Polygenic Risk Scores: A Systematic Review. *JACC Adv*. 2025;4(6 Pt 2):101803.
58. Zack M, Stupichev DN, Moore AJ, et al. Artificial Intelligence and Multi-Omics in Pharmacogenomics: A New Era of Precision Medicine. *Mayo Clin proceedings Digit Heal*. 2025;3(3):100246.
59. Jain SS, Elias P, Poterucha T, et al. Artificial Intelligence in Cardiovascular Care-Part 2: Applications: JACC Review Topic of the Week. *J Am Coll Cardiol*. 2024;83(24):2487–2496.
60. Antoun I, Abdelrazik A, Eldesouky M, et al. Artificial intelligence in atrial fibrillation: emerging applications, research directions and ethical considerations. *Front Cardiovasc Med*. 2025;12:1596574.
61. Ye J, Woods D, Jordan N, et al. The role of artificial intelligence for the application of integrating electronic health records and patient-generated data in clinical decision support. *AMIA Jt Summits Transl Sci proceedings AMIA Jt Summits Transl Sci*. 2024;2024:459–467.
62. Ueda D, Kakinuma T, Fujita S, et al. Fairness of artificial intelligence in healthcare: review and recommendations. *Jpn J Radiol*. 2024;42(1):3–15.

Orcid ID:Mahvish Mehdi - <https://orcid.org/0009-0000-8502-5722>Susham Verma - <https://orcid.org/0000-0001-6705-161X>Mohammad Abbas - <https://orcid.org/0000-0002-9810-8313>Bashir Ahmad Mir - <https://orcid.org/0009-0004-6773-4241>Aliya Abbas Rizvi - <https://orcid.org/0000-0002-8039-7081>Farzana Mahdi - <https://orcid.org/0000-0002-2188-2992>