

Review Article

Exploring ‘algo-rhythms’ in cardiovascular diseases: a narrative review of the efficacy of using artificial intelligence in coronary artery disease and atrial fibrillation

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Received: 20 June 2024

Accepted: 03 August 2024

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ABSTRACT

Recent strides in cardiology have introduced a transformative era by integrating artificial intelligence (AI) into coronary artery disease (CAD) management. This comprehensive review comprehensively explores AI applications in CAD, including diagnosis, screening, risk stratification, treatment assistance, and prognosis. Acknowledging AI's potential to revolutionize CAD care, the review emphasizes understanding current integration and limitations for clinicians and researchers. The manuscript explores the current and potential applications of AI in managing cardiovascular disorders underscoring the developments in cardiovascular care for CAD and atrial fibrillation (AF). The manuscript has been drafted based on scale for the assessment of narrative review articles (SANRA) guidelines to search, compile, contemplate, and extract data. Investigators independently searched PubMed, and Google Scholar following the protocol mentioned in the literature. This manuscript illuminates the evolving landscape of AI in CAD and AF management. While showcasing AI's promise in diagnostic accuracy and treatment strategies, the review emphasizes a cautious yet optimistic approach. The comparison with conventional methods reveals AI's efficacy, signalling a paradigm shift in cardiovascular care. Acknowledging limitations, researchers and clinicians are urged to navigate the integration of AI with discernment. The synthesis of optimism and caution guides the harnessing of AI's transformative potential in advancing cardiovascular healthcare.

Keywords: Cardiology, Artificial intelligence, Coronary artery disease, Atrial fibrillation, Deep neural networks

INTRODUCTION

Coronary artery disease (CAD) remains a leading cause of mortality and morbidity worldwide. The complex interplay of genetic predisposition, lifestyle factors, and environmental influences underscores the multifactorial nature of CAD. Over the years, advancements in medical technology, particularly the integration of artificial intelligence (AI), have revolutionized the approach to CAD management. AI, with its capacity to analyze vast datasets and identify intricate patterns, holds immense

promise in enhancing the prevention, diagnosis, and treatment of CAD. Integrating AI in CAD management marks a significant shift in clinical practice. This manuscript delves into the various applications of AI across the continuum of CAD care, from early diagnosis and risk prediction to treatment optimization and long-term outcomes assessment. The role of AI in diagnosis and screening is paramount. Traditional modalities like stress echocardiography (SE) have been augmented by AI algorithms, leading to improved accuracy and inter-reader agreement in detecting CAD-related abnormalities.¹

Additionally, AI-driven risk prediction models based on novel biomarkers offer a proactive approach to identifying individuals at higher risk of CAD, enabling timely interventions and personalized care strategies.² Moreover, AI-assisted treatment planning and clinical decision-making have streamlined procedures such as intravascular ultrasound (IVUS)-guided percutaneous coronary intervention (PCI), ensuring precise lesion characterization and optimal therapeutic outcomes.³ AI's predictive capabilities extend to monitoring treatment efficacy and anticipating complications, facilitating early intervention and tailored management strategies.⁴

Furthermore, AI-based risk stratification tools have redefined prognostication in CAD, enabling clinicians to anticipate adverse outcomes and tailor interventions accordingly.⁵ These advancements underscore the transformative potential of AI in optimizing patient care and clinical outcomes in CAD management. In addition to improving clinical decision-making, AI has the potential to enhance patient education and engagement. AI-driven platforms can provide personalized risk assessments, treatment plans, and lifestyle recommendations, empowering patients to take an active role in their cardiac health. This manuscript critically evaluates the comparative efficacy of AI-based methodologies against conventional approaches, highlighting the enhanced diagnostic accuracy, predictive power, and clinical utility offered by AI-driven solutions.⁶ Additionally, it addresses the limitations and challenges associated with AI implementation in CAD management, providing insights into future directions and opportunities for refinement and innovation in this rapidly evolving field.⁷

Through a comprehensive literature review and analysis, this manuscript aims to contribute to the growing body of evidence supporting the integration of AI in CAD management, paving the way for more effective, personalized, and data-driven approaches to combating this prevalent cardiovascular disease.

METHODS

Literature search and study selection

A research question was created using the PICO framework. The population in discussion includes individuals affected by CAD and AF. The focus is on the application of AI in managing these cardiovascular conditions. The population includes individuals with CAD who have undergone percutaneous coronary interventions (PCI), as well as those with AF who require risk prediction, diagnosis, stroke prediction, anticoagulation management, electrical cardioversion, and catheter ablation. The manuscript delves in deep to cover a broad spectrum within the cardiovascular patient population, emphasizing the potential impact of AI across different aspects of care.

A search was conducted on the database PubMed using: [(ai artificial intelligence)MeSH] AND cardiovascular disease AND echocardiography, [(ai: artificial intelligence)MeSH] AND cardiovascular disease AND electrocardiography, [(ai artificial intelligence)MeSH] AND cardiovascular disease AND cardiac imaging, ((Artificial intelligence) AND (Deep neural network)) AND (Electrocardiography), ((Artificial intelligence) AND (Deep neural network)) AND (Echocardiography), ((artificial intelligence) OR (machine learning)) AND (cardiovascular)) AND (management), (((((artificial intelligence) OR (machine learning)) OR (deep learning)) AND (cardiovascular disease)) AND (patient outcome))))), (((((ai artificial intelligence) OR (deep neural network)) AND (cardiovascular disease)) AND (patient outcome))))), (((((ai artificial intelligence) OR (machine learning)) OR (deep learning)) AND (cardiovascular disease)) AND (cost-effectiveness))))), (((((ai artificial intelligence) OR (machine learning)) OR (deep learning)) AND (cardiovascular disease)) AND (cost analysis))))), (((((artificial intelligence) OR (machine learning)) OR (deep learning)) AND (cardiovascular disease)) AND (allocation of resources))))), "Cardiovascular Diseases"[Mesh] OR "Cardiovascular Disease*"[tiab] OR "Cardiovascular Problem*"[tiab] OR "Cardiovascular Event*"[tiab], and ai artificial intelligence[MeSH Terms] OR AI[tiab] OR "Artificial Intelligence"[tiab] OR "Machine Learning"[tiab] OR "Deep Learning"[tiab].

Filters used were: free full text, classical article, clinical study, clinical trial, clinical trial protocol, clinical trial, phase I, clinical trial, phase II, clinical trial, phase III, clinical trial, phase IV, comparative study, controlled clinical trial, English abstract, multicenter study, pragmatic clinical trial, randomized controlled trial, twin study, clinical trial, veterinary, humans, observational studies, English, and recent 5 years from 2019.

Study selection

The selected studies were imported into Rayyan.ai (software) after shortlisting, and duplicates were eliminated. The remaining duplicates were manually checked and removed. Authors individually assessed papers using titles, keywords, and abstracts in three teams of two. Articles passing the initial screening underwent a thorough review by each author to decide their suitability for the review.

Discrepancies in study selection between the primary reviewers were resolved with input from a third reviewer. Preference was given to higher-quality or larger-sample studies in cases of overlap.

Inclusion and exclusion criteria

The studies identified through systematic search were comprehensively read to assess their appropriateness for incorporation into the review (Table 1).

Table 1: Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
Population	
Individuals diagnosed with CAD or AF	Studies that did not focus on individuals with CAD or AF
Study design	
Studies that investigate the application of AI in the management of CAD or AF. Systematic reviews, randomized controlled trials (RCTs), observational studies, and case-control studies, clinical trials	Case reports, editorials, letters, and conference abstracts without sufficient detail. Studies with a sample size below a predefined threshold (e.g., fewer than 10 participants).
Intervention	
Studies that assess the use of AI in various aspects of CAD and AF management, including but not limited to diagnosis, screening, risk stratification, treatment assistance, monitoring treatment efficacy, prediction of complications, and prognosis.	Studies that do not involve the use of AI in the context of CAD or AF.
Comparison	
Studies that compare AI-based methods with conventional approaches in the context of CAD or AF management.	Studies that do not include a comparison between AI-based methods and conventional approaches.
Outcome measures	
Studies report outcomes related to diagnostic accuracy, screening effectiveness, treatment precision, risk stratification, and long-term prognosis.	Studies lacking relevant outcome measures related to CAD or AF management.

Over 1200 articles were screened and checked for duplicates, and 15 articles were screened to meet the inclusion criteria. Two articles were added via hand searches.

RESULTS

Management of CAD using AI

In recent years, there has been a shift in the way CAD is approached, with the integration of AI into the field of cardiology. AI has emerged as a powerful tool that can go through large amounts of data and detect patterns to reliably predict outcomes, which offers the potential to revolutionize the prevention, diagnosis, and treatment of CAD. However, many of its practical applications are still in development and have their limitations. The following

studies detail how AI can be used in the diagnosis, screening, risk stratification, prevention, and prognosis of CAD.

Diagnosis and screening

Stress echocardiography (SE) is one of the most widely used modalities for non-invasive assessment of CAD. It has a low cost, low radiation exposure, and high patient tolerability. Typically, it involves a clinician detecting regional wall motion abnormality ‘by eye’, which leads to high interobserver and intraobserver bias. Upton et al developed an AI system to automate stress echocardiography to support clinician diagnosis. When clinicians were provided with an AI interpretation and asked to make a clinical decision, they were more accurate and confident in their decision, resulting in increased accuracy and inter-reader agreement.¹ AI can also be employed for risk prediction and early diagnosis by analysis of multiple novel risk factors. A study by Cheng et al used logistic regression and ANN models to provide a new method for the early diagnosis of CHD by analyzing serum interferon-gamma and MIG for the prediction of CAD.²

A study by Venkatesh et al to test the random survival forests (RF), a machine learning technique was aimed at predicting cardiovascular risk and outcomes accurately by negating numerous variables seen in other predictive models. When this was followed by Cox regression methods, it improved the prediction accuracy by avoiding overfitting and non-convergence. It also emphasized the importance of deep phenotyping with the help of subclinical biomarkers including blood biochemistry and imaging in cardiovascular event prediction especially in the asymptomatic population.⁶

Assisting treatment and clinical decision-making

AI-assisted diagnostic techniques have enhanced the ability to arrive at appropriate clinical decision-making on further management. For instance, intravascular ultrasound (IVUS) is one of the modalities useful for planning percutaneous coronary intervention (PCI) procedures. It provides information on the morphology of vessel walls and lumen as well as characteristics of plaques. Cho et al proposed an IVUS-based deep learning algorithm model that performed a rapid and accurate assessment of the extent of calcified plaques and attenuated plaques in whole vessels. This provided an idea regarding the anatomical location of the lesion as well as the accurate degree of vessel occlusion to be treated with the help of PCI.⁷

Monitoring treatment efficacy and predicting complications in patients with disease

AI has applications in predicting long-term complications and hence preventing them. PCI with stenting is now routine practice for revascularization after cardiac events.

However, the long-term success of PCI has the possibility of developing stent restenosis (SR), caused by excessive neointimal hyperplasia, leading to recurrent lumen narrowing at the site of initial PCI, which may manifest clinically as stable angina, acute coronary syndrome, or myocardial infarction (MI). Identifying such patients with SR is a major challenge. Sampredo-Gómez et al developed an ML model to predict 12-month follow-up stent restenosis (SR) in patients with STEMI undergoing PCI using ML. Applied immediately after stent implantation, their ML model was found to differentiate better those patients who will present with SR over current discriminators. This information can be used to provide personalized care to patients undergoing PCI.³

IVUS-based deep learning method not only guides the indications for PCI but predicts specific possible complications about plaque characteristics. The calcified plaques were found to be more prone to in-stent restenosis and thrombosis. In contrast, the attenuated plaques were found to progress to distal embolization resulting in likely fatal arrhythmias. These complications can likely be predicted early on with such advanced modalities during interventional procedures and prevented accordingly.⁷

Coronary computed tomography angiography (CCTA) is one of the other modalities that gives an in-depth view of atherosclerotic plaque features aiding the prediction of cardiovascular outcomes. Andrew Lin et al aimed to devise a machine learning (ML) score integrating CCTA-derived quantitative plaque features to accurately predict vessel-specific ischemia by invasive fractional flow reserve (FFR) and impaired hyperemic myocardial blood flow (MBF) by positron emission tomography (PET). It was found to perform superior to the standard CCTA stenosis evaluation and enabled precise identification of plaque features contributing to ischemia risk and complications.⁸

Prediction of adverse outcomes

Risk stratification is a cornerstone in clinical practice to evaluate adequate treatment strategies in CAD, especially acute myocardial infarction. Cardiovascular magnetic resonance (CMR) imaging enables precise myocardial deformation assessments including dedicated sequences, useful for risk assessment. It is non-invasive and functional, however, clinical implementation has been complicated by cost, complexity, and time needed for quantitation. This limits large-scale analysis.^{4,5}

Backhaus et al aimed to assess the reproducibility of automated deformation imaging compared to the reference standard of manual analyses and to evaluate its value for major adverse cardiac event (MACE) prediction using CMR imaging. During the 12-month follow-up period, AI-based automated GLS assessment showed similarly high diagnostic accuracy and excellent agreement compared to the reference standard of manually derived GLS.⁴

Another study by Knott et al aimed to investigate whether, in a multicenter setting quantitative myocardial perfusion (global mean stress MBF and MPR) by CMR perfusion mapping would be independently associated with adverse outcomes. Their AI model performed automatic segmentation of the left ventricle cavity and myocardium, using a convolution neural net approach to delineate the left ventricle cavity and myocardium. On follow-up, AI quantification of cardiovascular magnetic resonance perfusion mapping provided a strong, independent predictor of adverse cardiovascular outcomes.⁵

ML has been used to predict all-cause mortality in patients with suspected CAD undergoing coronary CT angiography by integrating clinical and visually assessed CT angiography parameters. However, Frederic Commandeur et al objectively combined clinical data and quantitative CT measures such as coronary artery calcium (CAC) and epicardial adipose tissue (EAT) comprehensively to predict the long-term risk of MI and subsequent cardiac death in asymptomatic individuals. This ML provided significant cardiovascular outcome prediction superiority to atherosclerotic cardiovascular disease (ASCVD) risk score or CAC score.⁹

Comparing AI-based methods with conventional methods

After discussing the potential AI has in managing CAD, it is important to assess how AI methods compare with conventional methods. Overall, the above studies report improved or better results after using AI models.

Upton et al showed that visual inspection of the myocardial regions by AI, from which features were used for classification were broadly similar to those regions identified by clinicians as having regional wall motion abnormalities during the clinical reading of the SE.¹

In the study by Backhaus et al, manual strain analyses were performed by an experienced investigator using feature tracking post-processing software and compared with the automated strain analyses. AI-based automated GLS assessment shows similarly high diagnostic accuracy and excellent agreement compared to the reference standard of manually derived GLS.⁴

The study by Venkatesh et al showed that the RF technique performed better than established risk scores with increased prediction accuracy (decreased Brier score by 10–25%). Imaging, electrocardiography, and serum biomarkers applied in the machine learning technique strongly predicted cardiovascular events in asymptomatic individuals compared to traditional cardiovascular risk factors.⁶

In the study by Cho et al, there were no significant differences in per-vessel measurements between the IVUS-based model and humans. In the per-vessel analysis, the ROI's attenuation and calcification burden indices significantly correlated with the human measurements.⁷

Commandeur et al devised an ML model that comprehensively integrated clinical data with CAC and EAT values and obtained a significantly higher AUC than atherosclerotic cardiovascular disease (ASCVD) risk and CAC score for predicting cardiovascular events.⁹

Limitations of AI

Although IVUS gives an elaborate picture of vessel plaque characteristics, the depth and thickness of plaque might affect the exact prediction of in-stent restenosis and thrombosis as it might have variable stent under-expansion. The usage of multiple frames per vessel in an attempt to improve the accuracy of detecting the extent of lesion might have also led to the clustering effect. These suggest a possible effect of over-prediction of certain features and thus over-prediction of outcomes.⁷

The ML score integrating CCTA for predicting FFR and PET scan for MBF had certain limitations. CCTA-based plaque findings were not confirmed by intracoronary imaging and the quantitative PET was performed with the less frequently used [15O] H₂O tracer due to which the subsequent findings may not be generalizable to more commonly used PET tracers such as [13N] NH₃ and Rubidium-82. Also, though the ML model was trained on the multicenter NXT trial which incorporated several different CT scanners and acquisition protocols, the PACIFIC trial test set comprised a single center and CT scanner.⁸

The ML integrating clinical data with CAC and EAT had less number of subjects and the small rate of observed events (<4%) over a long-term follow-up may have led to overfitting.

Also, the EISNER trial included only asymptomatic subjects with no prior history of CAD or significant comorbidity.⁹

Management of AF using AI

Risk prediction diagnosis

High-risk patients can be identified with the help of various risk predictor scores like cohorts for heart and aging research in genomic epidemiology (CHARGE-AF) Bundy et al used machine learning to identify novel variables for 5-year AF risk prediction and developed CHARGE-AF Enriched model and parsimonious model that include the clinical risk factors age, weight, current smoking, NT-proBNP, coronary artery calcium score, and cardiac troponin-T. These models performed similarly to each other (c-statistic, 0.804 and c-statistic of 0.806 respectively) but were better than the CHARGE-AF Simple model (c-statistic 0.795).¹⁰

There is a challenge in diagnosing AF patients because it remains asymptomatic till it presents with complications. A PULsE-AI trial was conducted using a machine learning

algorithm for AF risk prediction along with diagnosing testing using 12 lead ECG and KardiaMobile device was compared with routine care for diagnosis of AF and related arrhythmia and was found to be effective with a diagnosis of 9.41% participants with AF and related arrhythmia compared with 4.93% with only routine care.¹¹

Stroke prediction

Han et al evaluated the AF burden signature using machine learning models and compared it with the CHA₂DS₂-VASc score for stroke prediction. Three machine learning models were tested: convolutional neural networks (CNN), random forest (RF), and L1 regularized logistic regression (LASSO). These models performed better than the CHA₂DS₂-VASc score alone. When these models were combined with the CHA₂DS₂-VASc score both sensitivity and specificity improved.¹²

Anticoagulation management

Ru et al compared clinical decision support systems (CDSS), assisted by artificial intelligence and usual care for AF patients. According to this study using CDSS improved the proportion of patients receiving guideline-directed antithrombotic therapy which was 8.071 times higher than that in the usual care group.¹³

Electrical cardioversion success

In patients with persistent AF electrical cardioversion is frequently performed and there is a high recurrence rate after electrical cardioversion. Prediction of successful cardioversion is difficult. Vinter et al compared the random forest model with the traditional logistic regression model for sex-specific prediction of successful electrical cardioversion. According to this study, the random forest model and logistic regression model showed only moderate discriminative performance for the benefit of electrical cardioversion among both genders.¹⁴

Recurrence after catheter ablation

AF is commonly treated with catheter ablation but there is an increase in several AF asymptomatic recurrences after ablation. Huang et al compared the recurrence detection rate between handheld AI-based single-lead ECG monitor (big thumb) (BT group) and traditional follow-up group. According to this study follow-up after AF ablation therapy in the BT group led to more detection of AF recurrence than the TF group. Adherence to anticoagulation in patients in the BT group (51%) was also higher than in the TF group (25.4%). The big thumb is an affordable AI-based device that can be used in clinical practice for AF follow-up after ablation therapy.¹⁵

Cost-effectiveness of AI and its impact on healthcare

The quality of life of patients with coronary heart disease following PCI is investigated in this work by utilizing

artificial intelligence processors in conjunction with continuous care. In addition to offering a network care continuum with AI handlers to enhance the healthcare system and offer novel ideas on enhancing the recovery of CHD patients following surgery, we also examine the effects of PCI on the postoperative quality of life of patients with coronary heart disease. The SF-36 is an intuitive and uncomplicated health questionnaire that provides a thorough overview of body pain, intelligence, energy, and social function. A total of 19 items overall with a 100-point score. The higher the score, the better the quality of the patient's life. Role function, cognitive function, social function, and health level are all greater in the experimental group than in the control group, suggesting that this nursing approach can enhance the patient's range of physical functions. Heart rate, blood pressure, blood lipids, and fasting blood glucose were all significantly different ($p < 0.05$) between the experimental and control groups. The laboratory group's and the control group's pre-treatment blood pressure, blood lipids, fasting glucose, and heart rate are comparable and do not differ significantly ($p > 0.05$). Following the PCI processes. The experimental group's heart rate decreased from 91.39 ± 9.14 to 78.82 ± 7.31 , and their blood pressure dropped from 137.32 ± 11.82 to 118.32 ± 11.82 . The control group's index change range was narrow; heart rate decreased from 91.02 ± 8.45 to 84.23 ± 8.18 , and blood pressure barely changed, going from 137.30 ± 14.07 to 129.91 ± 14.07 . The Hamilton depression inventory (HAMD) and the Hamilton anxiety inventory (HAMA) were assessed during this study. During therapy, patients' unpleasant emotions such as anxiety, depression, and uneasiness are apparent in both scores.

The experimental group's HAMD value was 9.18 ± 1.20 and the HAMA value was 9.06 ± 0.77 , both of which were considerably lower than the control group's values, $p < 0.05$. Following the PCI procedure, there are notable variations in the two patient groups' adherence to various facets of their postoperative recovery. In comparison to the control group, the experimental group had a significantly higher number of patients identified in various recovery items. The implementation of web-based continuity of care has a more pronounced monitoring impact on these patients, helping them and their families understand the importance of medication, a healthy diet, frequent rest, and follow-up appointments. It also fully mobilizes the patient's initiative and supports them in building the habit of recovering more following the surgery, ultimately improving the patient's quality of life. The experimental group's level of dependence dropped sharply from 32% to 14% three months after they were released from the hospital, suggesting that postoperative care can effectively assist patients in gradually weaning themselves off of treatment and placing more of an emphasis on their activities and review for recovery.¹⁶

The PULsE-AI trial aimed to assess the efficacy of a screening strategy that includes a machine learning risk prediction algorithm in conjunction with diagnostic tests

for detecting undiagnosed AF in primary care. The purpose of this study was to assess the screening strategy's cost-effectiveness in a practical scenario. Approximately 14,004 additional lifetime diagnoses compared with regular treatment alone, and 45,493 new diagnoses of AF across the UK's high-risk population (3.3 million) were predicted as a result of the screening strategy. The anticipated per-patient expenditures for patients with elevated risks who underwent the screening method was £1,985 (compared to £1,888 for patients solely receiving routine treatment). The screening method was linked to a population-level rise in costs of almost £322 million and an increase of 81,000 QALYs. With an ICER of £3,994/QALY, the screening method only proved to be cost-effective when compared to normal treatment at an acceptable ICER threshold of £20,000 per QALY gained. Through the use of an AF risk prediction algorithm, it is more cost-effective to identify individuals who are at a high risk of going undiagnosed with AF and to refer them for diagnostic testing instead of just providing regular treatment.¹⁷

DISCUSSION

The comprehensive exploration of AI applications in the management of CAD and AF yields profound insights into the evolving landscape of cardiovascular care. The robustness of AI in enhancing diagnostic accuracy and screening processes is evident in studies encompassing stress echocardiography, novel biomarkers, and machine learning techniques such as random survival forests. These applications showcase promising outcomes in the early detection and characterization of CAD, affirming the potential of AI to revolutionize clinical practice.

The transition to AI-assisted treatment strategies, particularly in intravascular ultrasound (IVUS) for percutaneous coronary interventions (PCI), demonstrates how AI augments precision in therapeutic approaches. Moreover, the predictive capabilities of AI harnessed through advanced imaging modalities like cardiovascular magnetic resonance (CMR) and coronary computed tomography angiography (CCTA), emerge as invaluable tools for risk stratification and long-term outcome prediction in CAD patients. The comparison between AI-based methods and conventional approaches consistently reveals the efficacy of AI in CAD management, underscoring its potential to reshape traditional paradigms.

Limitations

However, a prudent approach must acknowledge the limitations inherent in AI applications. The variability in plaque characteristics affecting prediction accuracy, data confirmation constraints, and the challenge of overfitting in smaller datasets illuminate areas that demand meticulous consideration. This nuanced understanding of AI's strengths and limitations serves as a foundation for the judicious interpretation of its findings in clinical settings.

CONCLUSION

The comprehensive exploration of AI applications in the management of CAD and AF yields profound insights into the evolving landscape of cardiovascular care. The robustness of AI in enhancing diagnostic accuracy and screening processes is evident in studies encompassing stress echocardiography, novel biomarkers, and machine learning techniques such as random survival forests. These applications showcase promising outcomes in the early detection and characterization of CAD, affirming the potential of AI to revolutionize clinical practice.

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Funding: No funding sources

Conflict of interest: None declared

Ethical approval: Not required

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Cite this article as: Sharma S, Bhatia S, Dixit A, Kumar AJ, Singla H. Exploring ‘algo-rhythms’ in cardiovascular diseases: a narrative review of the efficacy of using artificial intelligence in coronary artery disease and atrial fibrillation. Int J Res Med Sci 2024;12:3554-61.