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Abstract

Purpose of review: This opinion paper highlights the advancements in artificial intelligence (AI) technology for cardiovascular disease (CVD), presents best practices and transformative impacts, and addresses current concerns that must be resolved for broader adoption.

Recent findings: With the evolution of digitization in data collection, large amounts of data have become available, surpassing the human capacity for processing and analysis, thus enabling the application of AI. These models can learn complex spatial and temporal patterns from large amounts of data, providing patient-specific outputs. These advantages have resulted, at the moment, in more than 900 AI-based devices being approved, today, by regulatory entities, for clinical use, with similar to improved performance and efficiency compared to traditional technologies. However, issues such as model generalization, bias, transparency, interpretability, accountability, and data privacy remain significant barriers for broad adoption of these technologies.

Summary: AI shows great promise in enhancing CVD care through more accurate and efficient approaches. Yet, widespread adoption is hindered by unresolved concerns of interested stakeholders. Addressing these challenges is crucial for fully integrating AI into clinical practice and shaping the future of CVD prevention, diagnosis and treatment.

Keywords: Cardiovascular Disease; Artificial Intelligence; Machine Learning; Heart Disease

1 Introduction

According to the Center for Disease Control and Prevention (CDC) government agency, from 2018 to 2021, every 33 seconds someone died from a CVD in the United States of America (USA) (1). Globally, cardiovascular diseases (CVDs) represent 32% of global deaths, being the leading cause of mortality (1). The risk of CVD varies by sex, race, ethnicity, and demography, with, over three-quarters of the deaths taking place in low and middle-income countries (2).

These statistics highlight, among other factors, the bias and lack of generalization of the current methods for prevention, (3) diagnosis and treatment of CVDs (4). Current methods often rely on population averages to guide diagnosis and treatment protocols, overlooking the complexity and variability across humans (see Figure 1), possibly leading to ineffective or even harmful outcomes.

The use of artificial intelligence (AI) systems presents a powerful solution to this challenge. By leveraging vast amounts of data (5), AI can analyze and predict individual health patterns, enabling more accurate diagnoses and personalized decisions. This new paradigm can, for example, enable the identification of lifestyle changes that can help individuals reduce their risk of disease. Furthermore, AI can reduce unnecessary tests and procedures (often invasive) and provide timely interventions, making healthcare delivery more efficient, with lower burden on healthcare systems, towards overall, better patient outcomes.

With these advantages in mind, a substantial number of AI and machine learning models have been developed for CVDs, including coronary artery disease (CAD) (6), stroke (7), arrhythmias (8), digital stethoscopes (9), and heart failure (10), among others (11). Some of these AI models have shown to surpass the performance of traditional methods, and have been approved by regulatory entities, such as the U.S. Food and Drug Administration (FDA) and the European Conformity (CE), for use by clinicians, health systems, or patients (12).

However, besides encouraging results, the application of AI models to CVDs has yet to be adopted and deployed at a large scale (see **Table 1**). One concern regards the model's bias and lack of generalization resulting from performance evaluation on specific populations, without accounting for example, for demographic variations. In clinical practice, lack of generalizing capacity can lead to reduced model performance when applied to individuals of different hospitals with different data collection setups, different demographics, and subject-specific characteristics, exacerbating health disparities. Further concerns are related to the lack of the model's transparency, interpretability, and accountability, which can lead to a lack of trust in its predictions. Data privacy and cybersecurity are also important concerns, as the data used to train the models often contains sensitive personal information, which without the proper safeguards can be exposed to malicious actors. The combination of these concerns hinders the adoption of AI technology in clinical practice (4,13,14).

In this review, we aim to provide an overview of the current advancements in AI algorithms for CVDs. We highlight the transformative potential of these technologies within the field, addressing current challenges and outlining best practices to ensure their ongoing development and accessibility by all stakeholders.

2 AI Enabled Advances in Cardiovascular Care

Recent technological advances in data collection and storage have resulted in vast amount of multi-modal data being available for CVD-related disease prediction, diagnosis and treatment, i.e. in imaging, electronic health records (EHR), in-bed monitoring, wearable technologies and out-of-hospital monitoring, multi-omics, etc (4). This large and diverse cardiovascular health-related data have let to the development of new initiatives aiming to broaden access as well as take advantage of these resources, such that digital biomedical research can reach its full potential. One example is the NIH Big Data to Knowledge framework (15), which aims to provide guidelines under the FAIR principles of Findable, Accessible, Interoperable and Reusable digital biomedical data, promoting data access, tools and standardized methods. Besides open access and data interoperability, the program also focuses on enhancing training, development and dissemination of data science methods and establishing centers of excellence in data science. Similar initiatives include the UK Biobank (16), eMerge (17), and BigData@Heart (18). Leveraging these large datasets that include demographic, genetic, and lifestyle factors, has lead in the development of advanced cardiovascular risk prediction models with promising results in identifying high-risk or high-cost patients, i.e. those who are more likely to develop cardiovascular events, or which can result in more complex conditions requiring frequent hospital visits, interventions, and increased medical costs (19–21).

In each domain of CVD care, the amount of available multi-modal data far exceeds the capacity of a human to integrate and process them, enabling an opportunity for AI to accomplish just that. Initial studies (22) have shown that computer programs for interpreting ECGs are nearly as accurate, but not better, as cardiologists in diagnosing major cardiac disorders (91.3% versus 96%). With the introduction of deep learning and machine learning models, there is the potential of surpassing these earlier findings (23,24). One field where AI has had a predominant role is Medical Imaging, which demands years of expertise due to the complexity and time-consuming nature of the tasks, and where AI has been used for image segmentation, quantification and interpretation, patient scheduling, radiation dosing, among others (4). AI-based methods are distinct from traditional computer programs by requiring large amounts of data (often annotated) that are used to learn mathematical formulas that map the inputs to the outputs. Diverse models of AI have been developed, such as deep learning, machine learning, or reinforcement learning, depending on the structure of the model and the learning process (25,26).

The diversity within the field of AI contributes to its vast and continually evolving state of the art. Comprehensive reviews have been performed to summarize the literature (27–29). These have shown that CAD (namely atherosclerosis), arrhythmias, stroke, and heart failure are the most explored topics using AI methods, explored through convolutional neural networks (CNNs), support vector machines (SVMs), and ensemble or linear models. Many of these studies have shown promising results, surpassing the performance of traditional methods, and providing new tools that have been approved by regulation entities such as FDA and CE for the use of clinicians, health systems, and/or patients. Some of the most promising applications of AI in CVD are shown in the following sections.

Coronary Artery Disease The gold standard to assess CAD has been the use of invasive coronary angiography (ICA), a procedure that allows the visualization of the inside of the coronary arteries. In addition to being invasive, it has been reported (6) that 67% of ICA procedures has been followed by the absence of significant anatomical stenosis. Once a blockage is identified, fractional flow reserve (FFR) is the gold-standard measure to assess the hemodynamic significance of coronary stenosis (30). FFR determines the pressure differences across coronary artery stenosis to assess the physiologic significance of the blockage. The FFR is obtained through the use of a pressure wire, inserted through a catheter, and guided to the coronary arteries. This procedure is invasive, time-consuming, and requires radiation exposure. To improve the accuracy of the diagnosis and avoid invasive procedures an alternative has been to determine the FFR through non-invasive imaging techniques such as computed tomography (CT) Angiography (6). The FFR-CT is a model by Heart Flow that uses CT scans to create a 3D color-based model of the coronary arteries to return metrics such as percent of stenosis, plaque volumes, blood flow, pressure, and velocity (30). Heartflow uses AI models to segment the coronary arteries from the CT scan, then a 3d model is created of the patient's coronary anatomy. Then, the principles of fluid mechanics are used to simulate the blood flow and pressure in the arteries to determine the FFR (31). The model has been approved by the FDA and CE for clinical use.

In a study by Driessen et al. (32) involving 208 patients, CT-FFR demonstrated superior diagnostic accuracy for CAD at 87% per vessel, compared to 79% for standard CT Angiography (CTA), 82% for Single Photon Emission Computed Tomography (SPECT), and 80% for Positron Emission

Tomography (PET). Moreover, in a report by the National Institute for Health and Care Excellence (NICE) (6,33) the use of FFR-CT was reported to save up to £391 per patient, per year in the United Kingdom (UK)'s National Health Service (NHS) compared to other non-invasive imaging techniques, and a reduction of invasive procedures like ICA by 60%.

Overall, CT scans aided by AI systems can provide information on broad aspects of the patient's cardiovascular health, such as coronary artery stenosis, myocardial ischemia, myocardial perfusion, plaque burden, high-risk plaque, inflammation, wall motion analysis, myocardial scar and fibrosis, percent myocardium at risk, and risk scores such as the Leaman score (34), which assesses CAD by assigning weighted values based on key factors including percentage of arterial narrowing, the location of the affected arteries, and the type of identified plaque (6,35).

Stroke The build-up of plaques can lead to emergent large vessel occlusion (ELVO) (the blockage of a large vessel in the brain), which can cause a stroke. Upon the symptom's onset, the patient will require immediate treatment to restore blood flow to the brain. Current treatments require that they must be administered in a 24-hour window or less to avoid permanent brain damage or death (7,36). To reduce the time to treatment, the use of AI models has been proposed to identify patients with ELVO on CT scans. One example is the FDA-model-approved Viz AI (7). The algorithm involves identifying applicable CT Angiography series by inspecting Digital Imaging and Communications in Medicine (DICOM) metadata, verifying the presence of contrast, and extracting soft tissue using bone masks. Then, a 3D segmentation convolutional neural network analyzes the data to detect large vessel occlusions by comparing segment lengths (7). The system was evaluated in an 1167 patient cohort to validate ELVO detection, attaining an accuracy of 94%, sensitivity of 81%, and negative predictive value of 99% (36). In addition to its high accuracy, a study by Elijovish (36) evaluated the impact of integrating the Viz AI model into the clinical workflow. The authors found that using Viz AI on clinicians' mobile devices to automatically notify them of patients with ELVO reduced the time from the CT scan to treatment by 22 minutes, with a notification time of 7 minutes compared to 26 minutes when following the standard neurologist notification process. The delay in neurologist notification was attributed to staff expertise and required time availability for the manual interpretation and reporting of CT results.

Arrhythmias The ECG can be recorded through an insertable cardiac monitors (ICMs), which is put on patients to monitor syncope, and arrhythmias, or to help the diagnosis of unexplained symptoms (37). The use of AI systems has been shown to improve the accuracy of ICMs events. One example is the FDA-approved system AccuRhythm AI by Medtronic. The system, based on a deep CNN, was evaluated in a study of 5025 episodes of 147 patients and showed that it could reduce the false alerts of atrial fibrillation by 74% while maintaining the true alerts at 99.3% (38). Moreover, it contains a syncope algorithm, which reduced false alerts by 97.4% while maintaining 100% true alerts (8). Overall, the authors report that the assistance of AI in ICMs devices can lead to a 105-hour reviewing reduction time per clinic per year (38).

Additional FDA clearance for arrhythmia detection, includes Apple Watch (39), CardioLogs (40), KardiaAI (41), or Zio XT (42).

Heart Murmurs The inter-rater agreement for heart murmurs is low, ranging from 0.3 to 0.48. To improve the accuracy of heart murmurs detection, the use of AI models has been proposed (9). One example is the FDA-cleared model by Eko Health, Inc (9). The model used an electronic stethoscope to record heart sounds, which were then analyzed by a deep residual neural network (ResNet) with 34 layers, each with a 1D convolution, ReLu, batch normalization, dropout, and maximum pooling, and a final fully connected layer followed by a softmax. The model was trained on 34 hours of data collected by a commercial digital stethoscope, consisting of 5318 unique patients, and tested on separate 373 patients. The algorithm achieved a sensitivity of 76.3% and a specificity of 91.4%, using ground truth derived from patients' echocardiograms, which were annotated by three expert cardiologists to classify heart murmur, no heart murmur, or inadequate signal. Further devices have been cleared by the FDA for heart murmurs detection, such as the eMurmurID (43), Stethee Pro (44), Tyto Stethoscope (45), and Steth IO (46).

Further FDA-approved cardiovascular applications include risk of heart failure metrics through a hypotension index (10,47), left ventricular ejection fraction (48), or patient status index (11,49).

3 Emerging Concerns and Best Practices

To continue and increase the adoption of AI and machine learning models in cardiovascular medicine, models should be developed with consideration in equity, accuracy, transparency, interpretability, accountability, data privacy, and cybersecurity (4,13).

Bias Differences across geographic communities and racial and ethnic groups in access to healthcare (50) results in different treatments, outcomes, and consequently, mortality rates (50,51). Current methods to assess CVD either compare patient metrics to population-level empirical thresholds (52,53) or rely on the use of trained models on specific populations (53,54). Considering that cardiovascular risk depends on subject-specific factors including age, gender, ethnic variations, socioeconomic status, or patient-specific comorbidities, relying on population-level models (trained to represent the "mean" of the distribution of an entire populations rather than focusing on an individual) can result in exacerbating health care disparities (2). Therefore, AI algorithms should be developed with equity (absence of differences across social, economic, demographic, or geographic groups (51)) in mind. The equity objective is to enable equal access to healthcare for everyone. To improve the generalizability of AI models in CVDs, a diverse training set should be ensured, including a wide range of demographic and clinical characteristics in the training data. An alternative is for the model to include technical adaptations such as performing transfer learning for patient-specific adjustments (27), implement class reweighting (weights are assigned to each class inversely to its frequency), and provide information on whether it is adequate according to a patient's characteristics (4).

In addition, various forms of bias can persist during AI model deployment, such as algorithmic bias that develops during model deployment, human bias on collecting, annotation and data selection, and model calibration bias when the model is not correctly calibrated with the clinical data. Hidden biases, can be difficult to mitigate using methods like data augmentation or diverse datasets. Advanced fairness-aware algorithms, such as adversarial training, can help uncover and address these hidden biases. Adversarial training involves jointly predicting both the label and the bias attribute, which helps in identifying and negating bias during training. This approach allows to automate the process of detecting potential hidden biases without explicit specification.

Accuracy Despite the large number of models developed either for research or commercial purposes that exhibit satisfactory to good performances, few have been validated in prospective studies (55,56). Often they do not disclose their technical parameters openly, preventing reproducibility.

Many of these models have been tested on small datasets which are often not public, and the employed evaluation and validation metrics are often biased and therefore do not reflect the model's performance in the real world (29). One of the biggest problems in the deployment of AI algorithms in clinical practice is their bias towards the training data (57). This may occur, for example, when algorithms are trained to a single hospital's data, (including their patient populations, data collection devices or setup), and then show degradation of their performance when the testing data distribution differs from the training data. This is known as the problem of lack of generalization. This issue can be addressed by the use of large and representative amounts of training data in diverse settings. However, this is a complex and costly task, requiring additional resources for data labeling, data harmonization, interoperability across institutions, and data sharing agreements (58). These issues have been addressed by an extensive list of solutions, including the use of data augmentation techniques, domain adaptation, transfer learning, continual learning, or active learning (57). As new data is collected, models should be refined and updated. This will require close monitoring of the real-time accuracy as well as a pipeline for error detection and correction, which should be provided by the model's manufacturer (13). Balancing the bias and variance is key to improve the model generalization. While diverse sets can manage the variance, the model's complexity (the simpler the model, the low is the variance and higher can be the bias) and regularization techniques also play an important role in reducing the variance leading to improved model generalization.

Transparency and Interpretability According to the literature, the majority of AI models are "black-box" models, meaning that the model's decision-making process is not transparent to the user (13). This can be a concern in clinical practice, where the clinician needs to understand the model's predictions to know when to resort to the model's output and make informed decisions. To address this concern, the use of open-source software and datasets, interpretable models, such as decision trees, linear models, and rule-based models, or in the case of deep learning models, the use of model-agnostic interpretability techniques, such as LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations), to better provide insights into the model's decision-making process (59), has been recommended.

As with any other technology or product, it is expected that the more AI models demonstrate their ability to perform their intended tasks accurately, the less the interpretability of the negatively-biased "black-box" concept will be an issue, and the more prevailing their adoption will be, irrespective of whether or not a physician will eventually choose to adhere to their findings and/or recommendations.

It should be also noted, that if society expects clinical AI algorithms to be fully interpretable, it is possible that it would restrict the ability of AI developers to use state-of-the-art AI technologies that are not fully interpretable yet perform better than older AI technologies that are more interpretable. Hence, a balance between interpretability and performance is key for an optimal adoption of AI in cardiovascular medicine.

Accountability and Liability AI models are expected to be used similarly as the use of drugs or medical equipment, where the internal inner workings are outside of the clinician's knowledge and responsibility (13). For these to be integrated into clinical practice for patient care, clinicians should have proper training on the model's use, limitations, and potential biases. On the other hand, developers should monitor the model's accuracy, and regulation approval and after approval post-market accuracy and adverse-event monitoring. Upon these, clinicians are liable for using AI models as indicated by the manufacturer, and the manufacturer is liable for the product's safety and efficacy.

As new patient groups are studied, thereby reducing the sample bias, such descriptions should be entered into the AI algorithm label. Therefore, the critical issue of a physician's professional liability in case of an incorrect decision and a potentially harmful outcome, as with any other medical product, narrows down to a responsibility to use such algorithm as "labeled," which minimizes liability concerns

Data Privacy and Cybersecurity The data used to train the AI models often contain sensitive information, such as medical or mental health history, genetic information, or lifestyle habits and preferences. During the data collection, according to regulations such as the General Data Protection Regulation (60) established by the European Union, the patient should be given informed consent with information about the data collection, storage, and use, and the patient should have the right to access, correct, or delete the data.

Since, after data collection, without the proper safeguards, patient data can be exposed to malicious actors, leading to privacy breaches or manipulated predictions, the use of privacy-preserving techniques, such as the installation of anti-malware software, may ensure that the patient's data is protected from unauthorized access (13). Papernot et al (61) provide best practices to assure privacy and security during the development of machine learning systems.

4 Conclusion

CVDs remain the leading cause of death globally, with disparate outcomes across different populations and individuals. Traditional diagnostic and treatment methods often rely on population averages, neglecting the complexity and variability among individuals. Moreover, diagnosis remains heavily dependent on the doctor’s ability to analyze, interpret and synthesize complex readings of multimodal data, which may result in medical errors, potentially becoming a cause of death (62).

As large amounts of detailed personal data become available for every individual, AI models become more accurate and provide a path toward precision prevention, diagnosis, and treatment. These models have many technical advantages: they can learn complex patterns in the data with temporal and spatial dependencies, perform noise reduction, analyze multiple modalities concurrently, and provide a probability output of cardiac risk, among others.

Despite these advantages, there are remaining concerns pertaining to the assurance to the model’s performance generalization in unseen populations, fairness, transparency, interpretations, accountability and liability upon a medical decision , and cybersecurity (13).

Despite the concerns, large investments and resources by the industry, academic, non-profit, and governmental organizations, have led to significant scientific advancements in AI models for CVDs in recent years (4). Notable results are 98 AI-based devices which have been approved by the FDA and 40 by CE for cardiovascular applications (12,63). Although it is unclear whether these systems are being used in clinical practice, they have been shown to be attainable promises. These systems have been compared to traditional methods and have demonstrated to be more efficient and provide more accurate and timely interventions. Therefore, AI is expected to be revolutionary in cardiovascular healthcare delivery, offsetting existing problems. By addressing current gaps and challenges, AI technology has the potential to transform today’s medical practice. Through AI, cardiovascular medicine can become universally accessible and more equitable, facilitating and promoting significant improvement in health outcomes and quality of life.

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Figure Legends

Figure 1. Traditional statistical approach (**box on the left**) compared to using artificial intelligence (AI) (**box on the right**) for cardiovascular diseases (CVDs) diagnosis and treatment. **On top**, the biological continuum is shown, ranging from individuals with ideal health, and those with risk factors, to individuals with severe disease. From the continuum, samples representing individuals are extracted. **On the left**, the traditional approach predicts the subject's health based on sample averages ($\bar{x}$), while the AI approach approximates the population continuum, allowing for personalized decisions. Samples outside the population are beyond the model's knowledge, reiterating the need for representative data and unbiased models.

Table 1. Best Practices and Gaps and Challenges in AI for Cardiovascular Care.	
Best Practices	**Description**
1. Open Source & Collaboration	Open-source AI frameworks like TensorFlow and PyTorch have significantly improved AI development by providing comprehensive tools for building and training models, fostering global collaboration through community contributions, and enhancing reproducibility and accessibility with extensive documentation and shared pre-trained models.
2. Data Collection Devices	Modern data collection devices, such as mobile and wearable technologies, incorporate high-quality sensors, integrate multiple physiological measurements, undergo regulatory approval for accuracy, enable real-time and continuous data processing, store data digitally, and maintain user comfort and ease of use.
3. Public Datasets	Public datasets like PhysioNet and PhysioBank have driven significant advancements by enabling reproducibility, facilitating large-scale studies without the hurdles of data collection.
4. AI Algorithms	CNNs have advanced medical image analysis, aiding early detection of conditions like atherosclerosis and cardiomyopathy through segmentation of echocardiograms, MRIs, and CT scans. RNNs have exceled at analyzing time-series ECG or PCG data, improving detection of arrhythmias and atrial fibrillation. NLP have enhanced the extraction of relevant information from unstructured clinical notes and patient records, providing a comprehensive view of patient history.
5. Computing	The evolution of computing technology, including powerful CPUs and GPUs, has enhanced the training of complex AI models on large datasets, improving the accuracy and reliability of predictions for CVDs. Cloud-based AI services like Google Cloud, AWS SageMaker, and Microsoft Azure provide provides on-demand access to computational resources for AI model development and deployment.
6. Benchmarking	AI/ML-based algorithms receive regulatory approval from bodies like the FDA and EMA by benchmarking against current clinical standards to evaluate

Against Standards	performance and added value, facilitating their widespread adoption in clinical practice.
7. Multidisciplinary Teams	The creation of multidisciplinary teams and collaborations like Google DeepMind involving clinicians, data scientists, informatics specialists, and ethicists has ensured that developed AI algorithms address real clinical needs and are integrated seamlessly and safely into healthcare workflows with high accuracy.
Gaps & Challenges	**Background**
1. Bias & Generalization	AI models should achieve consistent performance across diverse and representative datasets to ensure equitable outcomes across all groups.
2. Transparency & Interpretability	AI decisions should be comprehensible to clinicians to promote trust and ease of use. Transparency, supported by comprehensive documentation of the training & inference—including data sources, preprocessing steps, levels of certainty, and identification of the most influential variables—allows for identifying optimal use and rectifying errors.
3. Accountability & Liability	Responsibilities should be distributed: the source organization must ensure continuous safety evaluations, rigorous regulatory approval, and provide adequate training for users, while clinicians should ensure their own training and proper use of the AI systems.
4. Data Privacy & Cybersecurity	AI systems can be vulnerable to hacking, leading to incorrect decisions or data leaks; thus, regular anti-malware updates, compliance with legal regulations, robust cloud security, and obtaining informed consent for data use while protecting privacy and using de-identified data are crucial. Prevention of unauthorized access/personnel would also help avoid data breaches and misuse.
5. Continuous Monitoring & Upgrading	AI models should be regularly updated and validated, ensuring a continued performance and obtaining necessary regulatory approvals for significant changes.
6. Financial Incentives	Financial motivations should not dictate the development of AI systems, as this can discourage the adoption of methods that, while potentially more costly or less profitable, ultimately lead to better patient outcomes.
7. Data	Lack of data standardization, harmonization, and quality assessment methodologies hinder

Harmonization & Interoperability	interoperability across all layers of a healthcare system and between different healthcare systems.
8. Environmental Sustainability	AI should focus on developing computationally efficient algorithms, utilizing energy-efficient hardware, and optimizing data centers with energy-saving measures such as advanced cooling systems and renewable energy sources.
9. Education & Training	Clinicians must receive ongoing education to understand AI decisions, determine their appropriate usage, and interpret results in the context of potential errors and biases.
RECOMMENDATIONS	
1. Prospective Studies	The algorithm should be validated through large-scale, prospective clinical studies that include a broad and diverse population, representing various demographics and groups.
2. Precision Prevention	AI systems should aim to shift from simply diagnosing and treating diseases to proactively preventing them before they develop. This involves taking action to prevent diseases from occurring or progressing, rather than waiting for symptoms to emerge.
3. Precision Medicine	The AI systems should adhere to a precision medicine approach, tailoring treatments to individual patients based on their genetic, environmental, and lifestyle factors, enabling personalized prevention plans and targeted interventions.
4. Implementation Science	Implementation science strategies should be applied to effectively integrate precision medicine into everyday clinical practice, ensuring barriers to adoption are overcome, integration is sustained over time, and long-term health benefits are achieved.

Key: MRIs: Magnetic Resonance Imaging; RNN: Recurrent Neural Network; PCG: Phonocardiogram; NLP: Natural Language Processing; CPU: Central Processing Unit; GPU: Graphics Processing Unit; AWS: Amazon Web Services; EMA: European Medical Agency.

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This paper comprehensively details the state of the art of AI for cardiovascular diseases as well as current challenges across uses and applications.

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This paper identifies current gaps in the implementation of AI in clinical practice and proposes a framework to support the effective integration and adoption of AI in medicine.

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