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Artificial Intelligence–Driven Multimodal Modeling for Personalized Cardiac Therapy Optimization

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ABSTRACT- Heart diseases have varying effects on people. The same treatment is not usually received equally by all patients. It is due to this that the standard treatment guidelines do not necessarily work well with everyone. Artificial intelligence (AI) has also been utilized in recent years to aid doctors in integrating various forms of health data, thereby enhancing patient care. This review describes how multimodal models based on AI can be the basis of individualized treatment in heart diseases.

We consider typical sources of data applied in cardiac care, such as electrocardiograms, heart images, wearables, electronic health records, and omics data, such as genetics. We explain how AI techniques, in particular, deep learning and multimodal data fusion, integrate such data to learn more about each patient. Contrary to previous works, which primarily concentrate on the diagnosis, the current review points to the opportunity of AI to assist in the selection of the appropriate treatment, dosing, predicting the treatment outcome, and providing long-term care through continuous monitoring. Another topic that we address is explainable AI approaches that enable physicians to comprehend model choices and have confidence in AI-based systems.

Besides, we address crucial issues, including discrepancies in the quality of data, risk-of-bias, absence of large clinical trials, and constraints of real-world application. We emphasize that safe and fair AI systems should be implemented that can be effective with various patient groups. Lastly, we map out the path of research in the future, including digital models of the heart, learning without privacy, and AI-directed clinical trials. On the whole, AI-based multimodal modeling can contribute to shifting heart care beyond general treatment principles to more adaptive, personalized, and effective therapy in clinical practice.

KEYWORDS- Artificial Intelligence, Multimodal Data, Personalized Cardiac Therapy, Cardiovascular Disease, Wearable Devices, Cardiac Imaging, Electronic Health Records, Omics Data, Precision Medicine

I. INTRODUCTION

Heart diseases are the major cause of death in individuals in the world. Approximately, millions of people suffer heart attacks, heart failure, and rhythm irregularities each year. The diseases are both expensive to the patients, families, and the healthcare system [1]. The results of the treatments are not always the most optimal ones, in spite of the fact that modern medicine exists. This is due to the fact that not everyone will be infected by heart disease in equal measures.

Most of the heart treatments are performed in line with the clinical guidelines. The findings on huge populations of patients are the basis for these recommendations. They are efficient on the labour of many, but not all. Patients are different in age, lifestyle, heredity, disease, and therapy response at this stage [2]. This is because of this reason one treatment that will be beneficial to one patient will not be beneficial to the other. It is even probable that there would be side effects or failure of the treatment for the patient [3]. This shows the failure of population-average care and the need to have more individualized care.

The field of cardiology is the most appropriate for personalized medicine to be used. This is so because heart care is generating landmark volumes of information. The electrical indicators of the electrocardiogram are collected by physicians. The imaging devices are echocardiography, MRI, and CT scan [4]. The wearable devices in use by the patients nowadays measure the heart rate, activity, and sleep. Electronic health records refer to long-term patient records that are kept in hospitals [5]. In addition, the new omics information that is being increasingly generated is genetic and molecular data. The combination of such data will result in a comprehensive and detailed image of the heart of each patient.

However, all this data can hardly be used concurrently. Each type of data is in different formats, scales, and quality. They do not readily mix with the conventional ways of analysis. It is here that artificial intelligence comes in. The quantity of complicated information that is capable of being processed by AI is enormous [6]. It can accept patterns that are barely observable by human beings. The AI is capable of putting together many sources of data that have been integrated to give it a better picture of the patient [7]. This will enable the transfer of general rules of treatments to the more specific but flexible treatment.

Artificial intelligence can also assist heart care in its development. Instead of making a single treatment choice, AIs have the option of updating their predictions as new information comes [8]. Using the real-life example, the wearables data can test the reaction of a patient to the

drug. The imaging can determine the structural changes of the heart. AI models can propose changes in therapy using this. This aids in long-term and patient-centered care.
Figure 1 gives the general picture of how AI is changing the upcoming age of cardiology. Integrating signals, images, and wearable data, AI is deployed in the cardiovascular practice to help in the diagnoses and prognoses [9]. The tools aid physicians in diagnosing the disease at an early stage, as well as monitoring the patients even when they are not attending the clinic. CVD AI is used to discover multiomic data, assist digital heart models, and design clinical trials [10]. These advancements have made the research on patient care processes faster. Other basic success requirements, including practicality, balanced performance among populations, and effective regulation, are also brought out in the Figure 1.

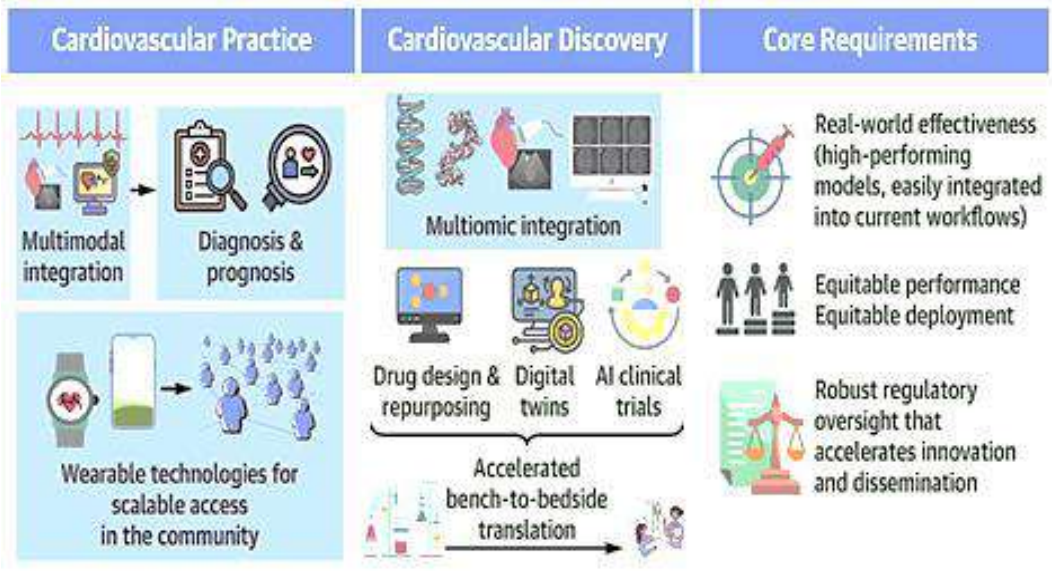

Figure 1: Next Era of AI in Cardiovascular Practice and Discovery [50]

It is my intention to review them to come up with these ideas. This is the only review that has united three areas. First, it provides an overview of the most important types of data applied in modern cardiac care. Second, it outlines the AI models, which can synthesize this data in a sensible way. Third, it is interested in the way the models will be able to facilitate the selection of therapy, its modification, and subsequent care. Unlike most of the past reviews, this is a review more on therapy optimization and practice application rather than diagnosis. The review will aid in coming up with personal, viable, and just cardiac service interlinking data, models, and clinical practice.

II. MULTIMODAL DATA ECOSYSTEM FOR CARDIAC THERAPY

The current state of heart care relies on a variety of patient data. Every type of data presents a varying aspect of heart health. There is no single source of data that will be able to explain the risks of a disease, response to treatment, or long-term outcome [11]. The combination of these data allows creating a more comprehensive and clearer view of the patient. This paragraph describes the primary data types applied in the field of cardiac care and ways they are used in the optimization of therapy.

A. Signal-Based Modalities

Electrical and physical activity of the heart are recorded by use of signal-based data. These data are highly favored because they do not require high expenditures to be collected and are easily collected.
The electrocardiograms (ECGs) are one of the cardiology tools that are used most often [12]. The 12-lead ECG is a normal ECG that records the electrical activity of the heart within a short interval. It helps in detecting problems with rhythm, heart attacks, and conduction disorders. The Holter monitors reach 24 hours or above. They document changes that may not be very clear when one visits the clinic temporarily [13]. The therapy may also make use of ECG information, such as the prescription of drugs for the treatment of arrhythmia or the decision of when the device therapy is required.
Wearable devices have been on the increase over the past few years. Fitbit and Smartwatch can monitor heart rate, physical activity, and sleep. Other widely used platforms for estimating the heart rhythm in many wearables include Photoplethysmography (PPG). Devices that check the variability of heart rates (HRV), which is a parameter of stress and autonomic activity, are available [14]. This is the reason why it is these data which show how the patients respond to therapy in their lives, not just in the hospital. Continuous monitoring can be utilized with the help of wearable data and can help to adjust the long-term treatment.

B. Imaging Modalities

Cardiac imaging is a graphical source of data that refers to the structure and functioning of the heart. In diagnosis and therapy planning, images are a major concern. Echocardiography is trendy because it is non-invasive, fast, and inexpensive. It shows the dimensions of the heart, the contractions of the heart walls, and the pumping [15]. Doctors use echocardiography to guide drug therapy and also to identify the placement of the device, such as cardiac resynchronization therapy.

Cardiac magnetic resonance imaging (MRI) is a method that provides detailed images of the heart tissue. It helps in identifying scar tissue, inflammation, and muscle trauma. Coronary arteries and accretion of calcium are often studied through the use of computed tomography (CT). Nuclear imaging can be used to establish blood flow and tissue viability [16]. These visual aids are useful in treatment planning as they show how severe the disease is and how well it responds to the treatment.

Coronary angiography refers to the act of direct visualization of blood vessels. It is necessary in Planning Interventions such as stent placement. Risk can be approximated, and individualized treatment options become possible using artificial intelligence models based on imaging.

C. Molecular and Omics Data

At the biological level, molecular information is provided. Such information can be handy when it comes to realizing why certain patients respond differently to similar treatment. Genomic data entails information about the genes of a patient. The pharmacogenomics field is concerned with the issue of gene effects on drug response [17]. Genetic variations might either cause some patients to take drugs slowly or rapidly. The information may be applied to influence the choice of the drug and its dosage.

Proteomics and metabolomics provide a quantification of proteins and metabolites in blood or tissue. Such measures are treatment and disease activity. Existing biomarkers that are used in heart care are troponin and natriuretic peptides [18]. Response to therapy and disease progression can be predicted using emerging biomarkers. The data of omics will be useful in precision medicine, relating biology to the results of treatment.

D. Clinical and Longitudinal Records

Long-term patient history is taken in clinical records. Electronic health records (EHRs) are records containing data from clinic visits, lab tests, and hospital stays [19]. These records contain diagnoses and medications as well as procedures.

The demographic information (age and sex) influences the risk of disease and drug response. Treatment choice is also affected by comorbid conditions, such as diabetes and kidney disease [20]. The history of treatment is where something has been tried before and has been found to be successful or not. Longitudinal data can assist AI models in learning the changes in patients over time. This assists in improved therapy planning and follow-up care.

E. Integrated Multimodal Framework

Figure 2 illustrates how the different kinds of data are integrated by a multimodal AI system. Wearables, EHRs, imaging, and signals, and wearables are first dealt with separately. Subsequently, AI models integrate them together in a way that integrates them [21]. The final product assists in accurate medication, including therapy selection, dose adjustments, and administration.

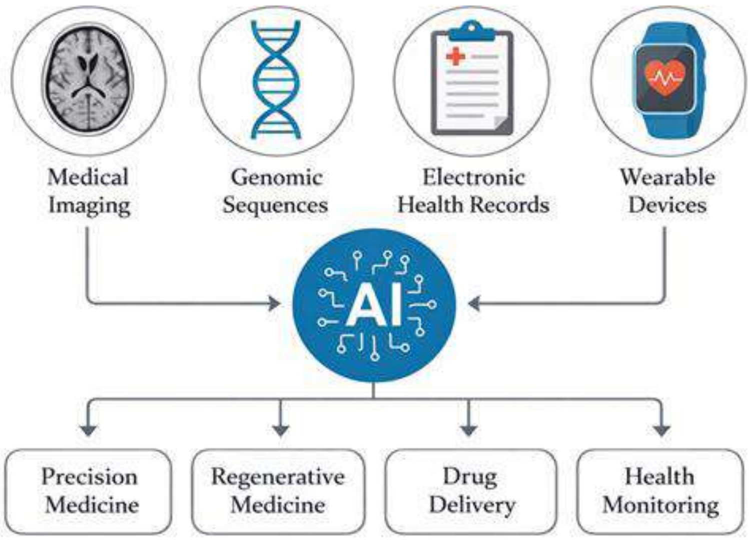

Figure 2: Multimodal AI Input

Single-modality models have definite limits. They do not save some of the vital information from other sources. The multimodal fusion allows AI to obtain more meaningful and credible patterns [22]. This increases the precision in forecasts and facilitates in decision making regarding individual therapy.

In cardiac care, the significant data captured can be summarized as presented in Table 1 below. It gives examples, AI practices, and clinical uses of the individual modality. Through this table, the reader can, within minutes, pick up how different data can be implemented in optimizing the therapy.

Table 1: Multimodal Data Types and Their Role in Cardiac Therapy Optimization

Data modality	Examples	AI techniques used	Clinical relevance
ECG signals	12-lead ECG, Holter monitoring	CNNs, LSTM, time-series models	Detects arrhythmias, guides drug therapy, supports device decisions
Wearable data	Heart rate, PPG, HRV, activity	Deep learning,	Monitors daily response to therapy, supports

	level	reinforcement learning	dose adjustment and long-term care
Cardiac imaging	Echocardiography, MRI, CT, nuclear imaging	CNNs, image segmentation models	Assesses heart structure and function, supports device and intervention planning
Coronary angiography	Vessel imaging, stenosis severity	CNNs, risk prediction models	Guides stent placement and interventional therapy
Genomic data	Genetic variants, pharmacogenomics	Machine learning, multimodal fusion	Predicts drug response and adverse effects
Proteomics & metabolomics	Blood proteins, metabolic markers	Feature-based ML, deep learning	Identifies disease activity and therapy response
Biomarkers	Troponin, BNP, inflammatory markers	Regression models, neural networks	Supports diagnosis, prognosis, and therapy monitoring
Electronic health records	Diagnoses, labs, medications	Transformers, ML classifiers	Provides long-term clinical history for personalized therapy
Demographic data	Age, sex, lifestyle factors	Risk models, ML classifiers	Improves risk assessment and treatment selection
Treatment history	Past drugs, devices, procedures	Sequential models, reinforcement learning	Helps adjust future therapy and avoid treatment failure

III. AI TECHNIQUES FOR MULTIMODAL CARDIAC MODELLING

Artificial intelligence is useful in the utilization of multimodal cardiac data. The AI approaches are applied differently based on the type of data and the aim of the clinic [23]. Certain approaches are built upon basic patterns, whereas other methods are taught complicated correlations among numerous sources of data. This paragraph describes the primary AI methods applied to cardiac modeling and the way they assist in optimizing the therapy.

A. Traditional Machine Learning

Traditional machine learning was one of the earliest AI tools, which was used in cardiology. These types of methods work well when the data is sorted, and the qualities are clear.

Some of the most common predictive outcomes that are used in regression models are the risk of disease or response to treatment. They are easy and understandable. Random forests are groups of decision trees that are utilized in an attempt to increase prediction accuracy [24]. They are also able to handle mixed data as well as reduce overfitting. The support vector machines are utilized to classify the groups of patients based on the risk or diagnosis. The models work well when the data sets involved are small and discrete.

The issue of feature engineering is one of the weaknesses of traditional machine learning. Specialists should select the features and be prepared to use them. It is a consuming process that may result in missing important trends. Raw signals, pictures, and massive unstructured data are also not coped with in conventional models [25]. Because of these limitations, they are more likely to be applied as benchmarking models or combined with another approach to a certain extent.

B. Deep Learning for Cardiology

Deep learning is currently becoming trendier in heart research. These models are directly acquired using data. They work with large and complex volumes of data.

CNNs, or convolutional neural networks, are highly used in cardiac imaging. They look at the images of echocardiography, MRI, CT, and angiography. CNNs can determine the changes in the heart structure and movement, and the tissue quality [26]. They assist in such tasks as predicting response to device therapy and leading the interventional planning.

The long short-term memory models are time-series-based recurrent neural networks. They may be transferred to ECG and wearable data. Among patterns learned by these models, there is a change of rhythm or pattern of therapy response. They can be applied as arrhythmia treatment tools and as a follow-up over a long period.

Deep learning models that are more recent are transformers. Long and complicated records also come in handy with them. In electronic health records, transformers can be used in cardiology [27]. They can handle years of patient history, diagnosis, medications, and lab results. This aids in capturing the effects of disease progression and treating the effects over a period of time.

Deep learning models are frequently very precise. They are, nevertheless, big data and massive computing ability. They are also harder to interpret than the traditional models.

C. Multimodal Fusion Strategies

Single-modality AI models are based on a single source of data. Other forms of information are not considered in such models. Multimodal fusion entails the integration of different data sets into a model.

Early fusion is done at incoming levels. The attributes of one modality are used together with the other and subsequently trained in a model [28]. This technique is simple and sensitive to the lack of sound. Late fusion is an outcome of combinations of models. All modalities are considered separately. The final forecast is based on aggregate outputs. It is a more workable strategy that can be handled easily.

Attention-based fusion is more advanced. These models familiarize themselves with the source of data that is important to every patient [29]. As an example, imaging might be significant to one patient, and wearable data might be significant to another one. The attention-based

method increases the personalization and the model performance.
Multimodal fusion is needed in the therapy. It allows AI models to consider the entire perspective of the patient instead of separate points.

D. *Explainable Artificial Intelligence*

The field of explainable AI, or XAI, is based on the explanation of AI decision-making models. This plays an important role in medical care, where the problem of trust and safety is critical [31]. The values of SHAP represent the influence of each feature on model prediction. They help the doctors with the rationale of a model prescribing a specific treatment. Grad-CAM detects regions in the image, and they define CNN responses. It can be used in the cardiac imaging models.

The explainable AI will increase clinical trust. Doctors like to use AI tools more in situations when they understand the rationale behind them. XAI is also necessary in regulation [31]. The health authorities should make medical AI systems transparent, safe, and fair.
Integrated Role of Figure 3.
Figure 3 gives a summary of the significant AI works in cardiac data modalities, including echocardiography, MRI and CT, ECG, and coronary angiography. The figure shows that there is a variation in the maturity of AI research in other modalities [32][52]. The majority of studies fall under ECG and echocardiography, although advanced imaging and interventional data are yet to be proven.

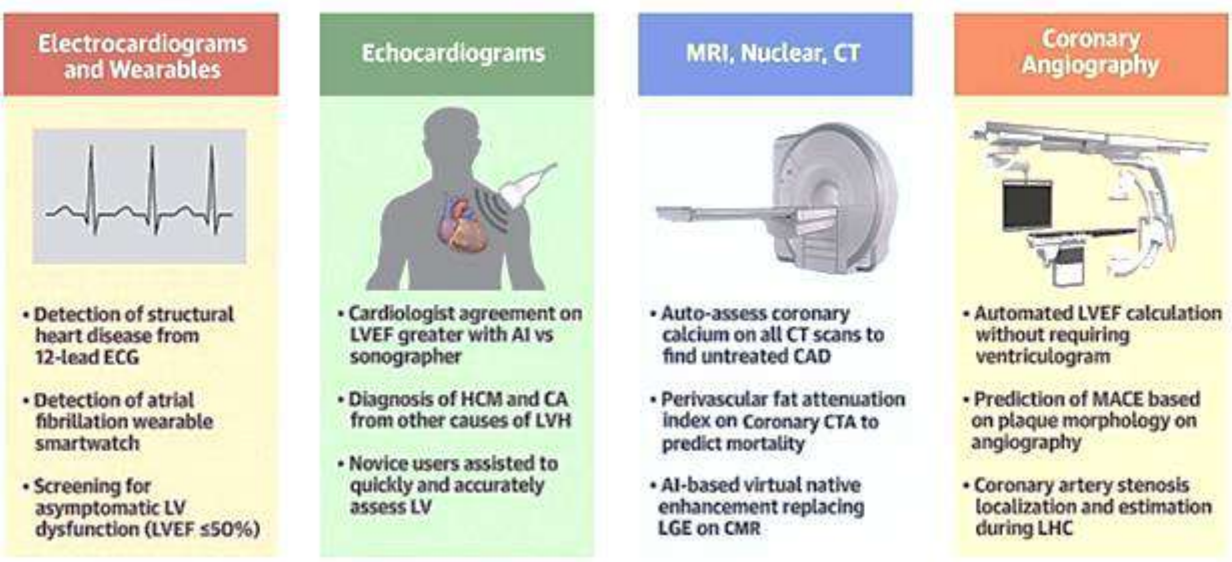

Figure 3: Key Studies in Cardiovascular AI by imagining Modality [52]

This figure indicates the most advanced and least investigated fields of therapy optimization. It also shows that there is a need to have multimodal models whereby the strengths are incorporated between the data types.

IV. AI-DRIVEN PERSONALIZED CARDIAC THERAPY OPTIMIZATION

Artificial intelligence in cardiology is primarily aimed at using AI to improve treatment choices as well as to diagnose disease [33]. All patients react to therapy in different ways. AI assists physicians in selecting the most appropriate treatment, modifying it during the course of time, and minimizing unwanted effects. Through multimodal data, AI assists in more accurate and individual patient cardiac care.

A. *Pharmacological Therapy*

Treatment of drugs is a major component of cardiac treatment. A large number of patients are on long-term blood pressure or heart failure medications or rhythm-controlling ones [34]. Nonetheless, the response of various patients to drugs is very different.
The AI models are used to assist in the selection of the drugs based on patient data, including ECG signals, imaging outcomes, biomarkers, and past medical history [35]. The models have the ability to determine the most probable drug to be effective on a particular patient. This minimises trial and error prescribing.
Another significant field is dose optimization. An insufficient dose may not be effective, and an excessive dose may result in harm. AI applications consider specific characteristics of a patient, kidney activity, and data on real-time monitoring to propose a more efficient and safer dosage [36]. Wearable data will also enable tracking of patient response to drugs in their everyday lives, and not necessarily when they are in the clinic.
Adverse drug events are also predicted with the help of AI. There are patients who are more susceptible to the side effects because of age, genes, or other illnesses [37]. Using genomic data, laboratory outcomes, and treatment history, AI models can determine patients at risk of increased risk. This will enable physicians to make therapy changes and enhance safety.

B. *Device-Based Therapy*

In case of sub-optimality in drug therapy, cardiac devices are used. These are machines that help in controlling the rate of the heart and improving heart function.
Pacemakers are used to decelerate or correct irregular heartbeats. The AI models will be able to process ECG and image data and decide when a pacemaker is required.

They can also help in setting the pacing to accommodate the patients.
ICDs are cardioverter-defibrillators, which are implanted as a measure of preventing sudden cardiac death. ICDs are not universally effective with patients [38]. Waste patients are patients most likely to get an outcome and avoid the unnecessary implantation of the devices with the help of AI models.
Cardiac resynchronization therapy is also referred to as CRT and is administered to heart failure patients. Many patients, however, do not like CRT [39]. The ECG, imaging, and clinical data combination in AI models has the potential to predict the CRT response before implantation. This improves the screening and treatment of patients.

C. Interventional and Surgical Planning

AI also helps in invasive cardiac treatments. They include the catheter-based procedures and heart surgery.
Use of stents is an important aspect of the coronary artery disease treatment. The AI models identify the size of the vessel, the extent of the blockage, and the blood flow based on the implied angiography images [40]. This will help the physicians to choose the right stent and positioning plan.
Valve replacement planning is also another area that is gaining popularity. The AI systems process the image information to measure the valve shape and functioning. This is useful in making a decision on whether to use surgical or transcatheter valve replacement. Reducing complications is also done by its use.
There is a need to risk-stratify before any intervention. Predicting the risk of procedures is achieved by means of imaging, clinical history, and lab data as the basis of AI models [41]. This will help the physician and the patient make decisions and prepare for the possible outcomes.
Table 2, at this level, is an overview of the implementation of different AI in specific cardiac therapies. The shift in AI-based diagnosis to real clinical treatment optimization is also mentioned in the table.

Table 2: AI Techniques and Personalized Cardiac Therapy Applications

AI approach	Data type used	Therapy domain	Key outcomes
Regression, ML models	Clinical data, labs	Drug selection	Improved treatment matching
Deep learning	ECG, wearables	Dose optimization	Safer and personalized dosing
CNNs	Cardiac imaging	CRT response prediction	Better patient selection
CNNs	Angiography images	Stent planning	Improved procedural accuracy
Transformers	EHRs	Risk stratification	Better outcome prediction
Reinforcement learning	Wearables, signals	Adaptive therapy	Real-time therapy adjustment
Multimodal AI	Signals + imaging + EHRs	Therapy optimization	Improved clinical outcomes

D. Adaptive and Closed-Loop Therapy

Customary cardiac treatment tends to be inactive. Clinic visits are used to make decisions that may not be altered for months. AI facilitates dynamic therapy that reacts to changes in the patient in real time.
Monitoring based on wearables is influential. Heart rate, rhythm, and activity are recorded continuously by the devices. These data are analyzed by AI systems in order to identify the signs of a deterioration of condition in the early stages [42]. It is then possible to make adjustments to the therapy before severe issues arise.
Reinforcement learning can be described as a form of AI that learns with feedback. In cardiology, it has the capability of testing minor therapy changes and monitoring the reaction of patients [43]. With time, the model gets to know the most appropriate approach toward every patient. This enhances individual and interactive care.
Digital cardiac twins remain a new concept. A digital twin is an artificial representation of the heart of a patient. It integrates pictures, messages, and medical information. Physicians have the opportunity to test the various types of therapies on the digital twin and see the outcomes before performing them on the patient [44]. Such a strategy can minimize risk and enhance results.
Altogether, AI-assisted therapy optimization brings cardiac care out of predetermined treatment principles. It promotes lifelong learning, decision-making in a patient-centered manner, and safer long-term management.

V. CLINICAL IMPLEMENTATION AND VALIDATION

To make AI improve cardiac care, it should be effective in the real-life clinical environment. It is not sufficient to have high accuracy in research studies. Doctors and patients should trust and safely apply AI systems [45]. This part will explain the process of AI model validation, implementation, and integration into the everyday heart care process.

A. External Validation and Bias

Most of the AI models work well when tested on the same data as the training data. Nonetheless, there is a tendency that the performance may decline when the models are used in new hospitals or patient groups. This is the reason why external validation is significant. External validation. AI models are tested by external data that may be across centers, regions, or populations. It assists in demonstrating that a model is capable of generalizing outside of the environment in which it was created.
One of the concerns of clinical AI is bias. Bias may arise whereby the training data do not represent all patient groups. As an illustration, models that are primarily trained on data of one gender or ethnicity can be very poor in other cases [46]. This may enhance health disparities.

Risk prediction, choice of therapy, and device choice in cardiology are vulnerable to bias.
Researchers will have to utilize a wide range of datasets to minimize bias, and place performance and show results in subgroups of patients. The AI systems should also be monitored regularly after implementation. Balanced and fair models are in support of equitable cardiac care.

B. Prospective Clinical Trials

The majority of AI research works in the field of cardiology are retrospective. They use the past to make predictions. Despite their usefulness, retrospective studies would not reveal the full picture of AI functioning in actual clinical practice. The AI systems require trials in real-time, which cannot be tested without prospective trials.
During prospective trials, AI tools are applied in collaboration with doctors in the process of treating patients. Measures are the outcomes of success, safety, and cost of treatment [47]. Such trials can contribute to the answer to the question of whether AI actually enhances care with respect to the standard practice. They also show practical problems, e.g., delay, data quality problems, or user error.
Clinical evidence is best represented by randomized controlled trials. In these trials, the patients are randomly selected to either AI-assisted care or conventional care. This would aid in minimizing bias and enhancing confidence in findings. AI systems have not yet reached the stage of routine cardiac care because of the lack of prospective trials.

C. Integration into Clinical Workflow

To be useful, AI must fit into the clinical workflows effectively. People cannot visit patients with complex devices, as physicians have no time. The artificial intelligence systems should be easy to use, fast, and adequately integrated into the existing hospital systems.
Most AI tools are being developed in the form of clinical decision support systems. They suggest but do not provide solutions [48]. There will still be care of patients under the responsibility of physicians. Due to visual displays and straightforward descriptions, clinicians are able to understand AI suggestions.
Training is also important. Nurses and doctors would need to possess some basic knowledge of how AI works and its limitations. Good system design, proper training, and reducing errors are some of the ways adoption improves. With an effective AI model, bad integration leads to low usage.

D. Human–AI Collaboration

Not to supersede clinicians, AI must assist them. Human-AI collaboration has the highest probability of success. Artificial intelligence is able to handle vast quantities of data in a short period. Clinicians have experience, judgment, and understanding of patients.
The partnership between humans and AI enhances safety. In case of necessity, doctors are able to challenge or counteract AI suggestions. This joint decision-making develops trust and mitigates the risk. Here, explainable AI is very important [49]. The clinicians will use an AI system better when they know the rationale behind a recommendation.
This participatory model coincides with the idea depicted in Figure 1, in which AI expands the practice and discovery, and addresses the real-life requirements.

E. Regulation and Real-World Readiness

AI systems can become massively used only once regulatory approval is provided. The health authorities are concerned with safety, effectiveness, and transparency. AI models will have to be verified to high standards [51]. It is also essential to monitor constantly after approval, particularly in the case of adaptive systems that evolve with time.
The privacy and security of data are essential. Patient information is to be ensured, and consent policies are to be observed. The developers and hospitals are required to provide proper data manipulation and transparency.
Going back to Figure 1, there are three fundamental requirements for successful clinical deployment. To start with, AI systems are supposed to demonstrate real-life performance. Second, they have to act fairly in all categories of patients. Third, they should be in compliance with regulatory and ethical requirements. These requirements are necessary to make AI-proposed personalized cardiac therapy a step towards research and clinical application.

VI. FUTURE DIRECTIONS

Artificial intelligence is a new area within cardiac care. The number of new ideas that can be used to improve personalized therapy is growing. Such guidelines in the future will aim at making the AI systems more correct, useful, and equitable in the real world.
One of the directions is the use of foundation models in cardiology. Foundation models are large AI models that are trained on very large datasets. They can learn the general patterns, and then be adapted to specific types of work. Wearable, EHRs, and images, ECGs, and images can be integrated into a single system in the field of heart care as foundation models. This would reduce the need for small models that have fewer tasks. It is also able to improve the performance of different hospitals and populations.
Federated learning is another possible strategy. The laws of privacy in most regions do not permit the sharing of patient information. Federated learning allows AIs to train on data that is kept in different hospitals without data transfer. The updates of models are shared only. This improves the security and confidentiality of information. It also allows cross-country and cross-health systems cooperation. Federated learning assists in attaining the equity provisions highlighted in Figure 1, especially when it comes to an underrepresented group.
The new technology is available that has tremendous potential and is known as digital cardiac twins. A digital twin is a simulated representation of the heart of a patient. It utilizes the images, signals, and clinical data to simulate the heart's behavior. Doctors can also have the capability to experiment with different treatments on the virtual twin before subjecting the patient to such treatments. This can help to mitigate risk as well as improve treatment planning. Digital twins also unite discovery and practice, as revealed in Figure 1.

The other critical goal is the ongoing therapy optimization. The current interventions are mostly altered during the clinic. Daily monitoring of patients can be done using wearables that have AI systems. The therapy can then be reworded as conditions of patients change. This practice embraces adaptive and long-term care. It is also reflective of the augmented role of wearable and signal-based data that is depicted in Figure 2 and Figure 3.

The health equity and Globality should be brought to the fore. The AI systems should be responsive to patients who are of different ages, genders, gender and backgrounds. They are also expected to be applicable in low-resource contexts. There exists the necessity to possess simple models, cheap devices, and sensible training data. Together, Figure 1 Figure 2 and Figure 3 can provide a roadmap to creating AI systems that are effective, inclusive, and scalable.

VII. CONCLUSION

The way heart disease is treated is evolving because of artificial intelligence. Multimodal AI allows for understanding every patient better by incorporating a wide variety of data. This has been demonstrated in this review that the signals, imaging, omics data, wearables, and clinical records can be integrated to facilitate personalized cardiac therapy.

Multimodal AI is a significant change in the care of the heart. Rather than diagnosing and providing general guidelines, AI allows for optimizing therapy. Therapy of choice, dosage, and outcome are chosen, modified, and assessed depending on patient-based information. This enhances safety, efficacy, and long-term outcome.

Nevertheless, technology itself is insufficient. The application of AI needs effective validation, equal performance, and proper regulation in order to be successful. Physicians need to be aware of AI systems and trust them. Patients should receive better care without risking or discriminating them.

There must be interdisciplinary cooperation. The collaboration of clinicians, data scientists, engineers, and policy makers is required. AI-based multimodal modeling can transform heart care by prioritizing innovation in line with clinical requirements to deliver a more personalized, adaptable, and fairer future of global heart care.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] E. J. Topol, "High-performance medicine: The convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, no. 1, pp. 44–56, Jan. 2019. Available from: https://www.nature.com/articles/s41591-018-0300-7

[2] K. W. Johnson *et al.*, "Artificial intelligence in cardiology," *Journal of the American College of Cardiology*, vol. 71, no. 23, pp. 2668–2679, Jun. 2018. Available from: https://www.sciencedirect.com/science/article/pii/S0735109718353056

[3] V. Tasouli-Drakou *et al.*, "Atherosclerosis: A comprehensive review of molecular factors and mechanisms," *International Journal of Molecular Sciences*, vol. 26, no. 3, p. 1364, Feb. 2025. Available from: https://www.mdpi.com/1422-0067/26/3/1364

[4] Y. Sethi *et al.*, "Precision medicine and the future of cardiovascular diseases: A clinically oriented comprehensive review," *Journal of Clinical Medicine*, vol. 12, no. 5, p. 1799, Jan. 2023. Available from: https://www.mdpi.com/2077-0383/12/5/1799

[5] Z. Qadrie *et al.*, "Wearable technology in healthcare: Opportunities, challenges, and future directions," *Smart Wearable Technology*, vol. 1, no. 17, 2025. Available from: https://bonviewpress.com/index.php/swt/article/view/578

[6] M. Michalczak *et al.*, "Artificial intelligence in medical education: A narrative review," *AI*, vol. 6, no. 12, p. 322, Dec. 2025. Available from: https://www.mdpi.com/2673-2688/6/12/322

[7] Z. Gao, "Artificial intelligence techniques for complex big data environments: Methods and perspectives," *Advances in Engineering Innovation*, vol. 16, no. 7, pp. 167–170, Jul. 2025. Available from: https://www.ewadirect.com/proceedings/aie/article/view/25599

[8] S. K. Devineni, "AI-enhanced data visualization: Transforming complex data into actionable insights," *Journal of Technology and Systems*, vol. 6, no. 3, pp. 52–77, May 2024. Available from: https://journals.jts.org/article/1911

[9] J. F. Hammadi *et al.*, "Artificial intelligence approaches for cardiovascular disease prediction: A systematic review," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 38, no. 2, pp. 1208–1218, May 2025. Available from: https://ijeecs.iaescore.com/index.php/IJEECS/article/view/30540

[10] F. Ekundayo and H. Nyavor, "AI-driven predictive analytics in cardiovascular diseases," *International Journal of Research Publication and Reviews*, vol. 5, no. 12, pp. 1240–1256, Dec. 2024. Available from: https://ijrpr.com/uploads/V5ISSUE12/IJRPR3437.pdf

[11] S. Amal *et al.*, "Use of multi-modal data and machine learning to improve cardiovascular disease care," *Frontiers in Cardiovascular Medicine*, vol. 9, Apr. 2022. Available from: https://www.frontiersin.org/articles/10.3389/fcvm.2022.840262

[12] Z. Ahmad and N. Khan, "A survey on physiological signal-based emotion recognition," *Bioengineering*, vol. 9, no. 11, p. 688, Nov. 2022. Available from: https://www.mdpi.com/2306-5354/9/11/688

[13] K. Sathya and G. Magesh, "Multimodal deep learning for cardiovascular risk stratification," *IEEE Access*, vol. 13, pp. 99672–99689, 2025. Available from: https://ieeexplore.ieee.org/document/10577064

[14] R. S. Chandel *et al.*, "Smart watches: A review of evolution in biomedical sector," *Materials Today: Proceedings*, vol. 50, no. 5, Aug. 2021. Available from: https://www.sciencedirect.com/science/article/pii/S2214785321057336

[15] D. Ginat and G. Lotfian, "Review of diagnostic radiology imaging modalities," *Medical Research Archives*, vol. 12, no. 10, 2024. Available from: https://esmed.org/MRA/mra/article/view/5763

[16] A.-C. Waldenström *et al.*, "Comparison of imaging modalities for detecting lymphatic nodal spread," *Physics and Imaging in Radiation Oncology*, vol. 8, pp. 33–37, Oct. 2018. Available from: https://www.sciencedirect.com/science/article/pii/S2405630818300576

[17] G. MNVP, "Multi-omics data integration: A modular approach," *Journal of Molecular and Genetic Medicine*, vol. 10, no. 4, 2016. Available from: https://www.researchgate.net/publication/311451294

[18] I. Subramanian *et al.*, "Multi-omics data integration, interpretation, and its application," *Bioinformatics and*

Biology Insights, vol. 14, Jan. 2020. Available from: https://journals.sagepub.com/doi/full/10.1177/1177932219899051

[19] Y. Jin *et al.*, "Impact of longitudinal data completeness of electronic health records," *Clinical Pharmacology & Therapeutics*, vol. 113, no. 6, pp. 1359–1367, May 2023. Available from: https://ascpt.onlinelibrary.wiley.com/doi/full/10.1002/cpt.2901

[20] S. Niu *et al.*, "Modelling patient longitudinal data for clinical decision support," *Information Systems Frontiers*, vol. 27, Jul. 2024. Available from: https://link.springer.com/article/10.1007/s10796-024-10513-x

[21] L. R. Soenksen *et al.*, "Integrated multimodal artificial intelligence framework," *npj Digital Medicine*, vol. 5, no. 1, Sep. 2022. Available from: https://www.nature.com/articles/s41746-022-00689-4

[22] Z. Zhang *et al.*, "Modality-enhanced multimodal fusion attention model," *Applied Sciences*, vol. 15, no. 19, p. 10825, Oct. 2025. Available from: https://www.mdpi.com/2076-3417/15/19/10825

[23] F. A. Ramos-Zaga, "Artificial intelligence and multimodal diagnostic approaches in cardiovascular disease," *Archivos Peruanos de Cardiología y Cirugía Cardiovascular*, vol. 6, no. 4, Nov. 2025. Available from: https://apcyccv.org/index.php/apcyccv/article/view/532

[24] A. Jiménez-Macías *et al.*, "Evaluation of traditional machine learning algorithms for featuring educational exercises," *Applied Intelligence*, vol. 55, no. 7, Mar. 2025. Available from: https://link.springer.com/article/10.1007/s10489-025-06386-5

[25] Y. Lai, "A comparison of traditional machine learning and deep learning in image recognition," *Journal of Physics: Conference Series*, vol. 1314, Oct. 2019. Available from: https://www.researchgate.net/publication/337053558

[26] T. Tsampras *et al.*, "Deep learning for cardiac imaging: Focus on myocardial diseases," *Hellenic Journal of Cardiology*, vol. 81, Dec. 2024. Available from: https://www.sciencedirect.com/science/article/pii/S1109966624002484

[27] C. Zhou *et al.*, "A comprehensive review of deep learning-based models for heart disease prediction," *Artificial Intelligence Review*, vol. 57, no. 9, Aug. 2024. Available from: https://link.springer.com/article/10.1007/s10462-024-10899-9

[28] A. Sucre *et al.*, "Multimodal fusion strategies for survival prediction in breast cancer," *Computational and Structural Biotechnology Journal*, vol. 27, pp. 4505–4516, 2025. Available from: https://www.sciencedirect.com/science/article/pii/S2001037025000385

[29] A. I. Khalil, "Multi-modal fusion techniques for improved diagnosis in medical imaging," *Journal of Information Systems Engineering and Management*, vol. 10, no. 1s, pp. 47–56, Dec. 2024. Available from: https://jisem-journal.com/article/100

[30] A. B. Arrieta *et al.*, "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges," *Information Fusion*, vol. 58, pp. 82–115, Jun. 2020. Available from: https://www.sciencedirect.com/science/article/pii/S1566253519308103

[31] R. R. Selvaraju *et al.*, "Grad-CAM: Visual explanations from deep networks via gradient-based localization," *International Journal of Computer Vision*, vol. 128, no. 2, pp. 336–359, Feb. 2020. Available from: https://link.springer.com/article/10.1007/s11263-019-01228-7

[32] J. Amann *et al.*, "Explainability for artificial intelligence in healthcare," *BMC Medical Informatics and Decision Making*, vol. 20, no. 1, Nov. 2020. Available from: https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-020-01332-6

[33] I.-U. Haq *et al.*, "Artificial intelligence in personalized cardiovascular medicine and cardiovascular imaging," *Cardiovascular Diagnosis and Therapy*, Apr. 2020. Available from: https://cdt.amegroups.org/article/view/38641

[34] F. Costa *et al.*, "Artificial intelligence in cardiovascular pharmacotherapy: Applications and perspectives," *European Heart Journal*, Jul. 2025. Available from: https://academic.oup.com/eurheartj/article/ehaf474

[35] T. Božina *et al.*, "Pharmacogenomics in the prediction of adverse effects of cardiovascular drugs," *Croatian Medical Journal*, vol. 66, no. 6, pp. 446–455, Dec. 2025. Available from: https://hrcak.srce.hr/320705

[36] S. Hedgire *et al.*, "Dose optimization in cardiac CT," *Physica Medica*, vol. 41, pp. 97–103, Sep. 2017. Available from: https://www.sciencedirect.com/science/article/pii/S1120179717301640

[37] M. K. Badawy *et al.*, "Radiation dose optimization in interventional cardiology," *Cardiology Research and Practice*, 2018. Available from: https://www.hindawi.com/journals/crp/2018/6912841

[38] Y. Hung *et al.*, "Artificial intelligence-enabled electrocardiography predicts future pacemaker implantation," *Journal of Medical Systems*, vol. 48, no. 1, Jul. 2024. Available from: https://link.springer.com/article/10.1007/s10916-024-02088-6

[39] J. Komp *et al.*, "Strategies and considerations for safe reinforcement learning in cardiac implantable electronic devices," *Medical Research Archives*, vol. 13, no. 3, Jan. 2025. Available from: https://esmed.org/MRA/mra/article/view/6363

[40] S. Samant *et al.*, "Artificial intelligence in coronary artery interventions," *Journal of the Society for Cardiovascular Angiography & Interventions*, vol. 4, no. 3, Mar. 2025. Available from: https://www.sciencedirect.com/science/article/pii/S2772963X24001105

[41] F. Tsakirian *et al.*, "Applications of artificial intelligence in transcatheter aortic valve replacement," *Life*, vol. 15, no. 11, p. 1724, Nov. 2025. Available from: https://www.mdpi.com/2075-1729/15/11/1724

[42] R. A. Ansari *et al.*, "Artificial intelligence-guided neuromodulation in heart failure," *Journal of Cardiovascular Development and Disease*, vol. 12, no. 8, p. 314, Aug. 2025. Available from: https://www.mdpi.com/2308-3425/12/8/314

[43] A. Deligiannis *et al.*, "The role of artificial intelligence in exercise-based cardiovascular health interventions," *Journal of Functional Morphology and Kinesiology*, vol. 10, no. 4, p. 409, Oct. 2025. Available from: https://www.mdpi.com/2411-5142/10/4/409

[44] A. Abedi *et al.*, "AI-driven real-time monitoring of cardiovascular conditions with wearable devices," *JMIR mHealth and uHealth*, vol. 13, Nov. 2025. Available from: https://mhealth.jmir.org/2025/11/e73846

[45] F. W. Asselbergs and T. F. Lüscher, "Trustworthy implementation of artificial intelligence in cardiology," *European Heart Journal*, Dec. 2024. Available from: https://academic.oup.com/eurheartj/article/ehae748

[46] B. S. Wessler *et al.*, "External validations of cardiovascular clinical prediction models," *Circulation: Cardiovascular Quality and Outcomes*, vol. 14, no. 8, Aug. 2021. Available from:

https://www.ahajournals.org/doi/10.1161/CIRCOUTCOMES.121.007858
[47] D. H. Barzilai *et al.*, "Randomized controlled trials evaluating artificial intelligence in cardiovascular care," *JACC Advances*, vol. 4, no. 11, Sep. 2025. Available from: https://www.sciencedirect.com/science/article/pii/S2772963X25002152
[48] F. Shaikh *et al.*, "Artificial intelligence-based clinical decision support systems using advanced medical imaging," *Current Problems in Diagnostic Radiology*, Jun. 2020. Available from: https://www.sciencedirect.com/science/article/pii/S0363018820300696
[49] T. F. Lüscher *et al.*, "Artificial intelligence in cardiovascular medicine: Clinical applications," *European Heart Journal*, Aug. 2024. Available from: https://academic.oup.com/eurheartj/article/ehae465
[50] R. Khera *et al.*, "Transforming cardiovascular care with artificial intelligence: From discovery to practice," *Journal of the American College of Cardiology*, vol. 84, no. 1, pp. 97–114, 2024. Available from: https://www.jacc.org/doi/10.1016/j.jacc.2024.05.003
[51] R. Cuocolo *et al.*, "AI medical device post-market surveillance regulations," *Insights into Imaging*, vol. 16, no. 1, p. 275, Dec. 2025. Available from: https://insightsimaging.springeropen.com/articles/10.1186/s13244-025-02146-8
[52] P. Elias *et al.*, "Artificial intelligence for cardiovascular care — Part 1: Advances," *Journal of the American College of Cardiology*, vol. 83, no. 24, pp. 2472–2486, Jun. 2024. Available from: https://www.jacc.org/doi/10.1016/j.jacc.2024.03.400