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ARTIFICIAL INTELLIGENCE IN CARDIOVASCULAR SYSTEM: CURRENT TRENDS AND FUTURE PROSPECTS

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ABSTRACT: AI is a new technology that has been applied in the treatment of the heart since the time immemorial. It has facilitated easy diagnosis, risk assessment, treatment, and monitoring of patients in a cheaper way. The major cause of death in the world has remained cardiovascular diseases (CVDs). AI-based systems, such as machine learning (ML), deep learning (DL), and natural language processing (NLP) have enabled physicians to scan more complex data with accuracy and speed. The paper discusses some of the most widely used AI-based clinical technology that cardiologists are currently using. They are cardiac imaging, predictive analytics, wearable technologies, and physician-assisting systems. Some examples of the ways in which AI may be applied in the future are between groups of people, including in genomics, robotic interaction and digital twins, among others. This paper will attempt to provide a summary of past recorded achievements and demonstrate their significance to the development of research, assessment of evidence-based clinical care, and access to AI to achieve better patient outcomes in cardiovascular disease.

INTRODUCTION: Cardiovascular diseases (CVDs) are the worst morbidity and mortality cause on earth, an issue of significant concern in the developed and developing world. CVD has a significant percentage of mortality and disability worldwide, including its burden, which according to the World Health Organization and recent global burden studies is on the increase because of the aging of the population and the growing number of metabolic risks factors^{1, 2}. Over the decades, the cardiovascular risk stratification has been based on traditional clinical risk prediction frameworks, including the Framingham risk score, which combines a restricted amount of demographic and clinical risk factors to inform preventive interventions³.

Even though these tools have been of clinical benefit, they are limited in their ability to capture complex, nonlinearity interactions between risk factors and are limited by linear assumptions, which may lead to less accuracy in heterogeneous populations⁴. High-dimensional biomedical data accelerated development of electronic health records, high resolution medical imaging, wearable sensors, and other sources of high-dimensional biomedical data has introduced new possibilities of data-driven methods of medicine. Here, the field of artificial intelligence (AI) and machine learning has become more and more popular due to the possibility to detect rather complex patterns within massive sets of data that cannot be analysed through conventional statistical tools^{5, 6}.

These methods are actively investigated in most spheres of clinical medicine. The AI in cardiovascular practice has been promising in several areas, such as interpretation of images, prediction of risks, and clinical decision support. A number of authoritative-reviews and pioneering

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research grounded on the possibility of AI in enhancing diagnostic accuracy, efficiency and consistency in cardiovascular care have been noted^{7, 8}. On a larger scale, clinical decision-making and healthcare delivery models are increasingly becoming data-driven⁹. Although such a rapid technological advancement has occurred, there is a wide range of clinical maturity and strength of evidence regarding the application of various AI to cardiology. There are numerous systems that are still in their early development or even validation,

and significant issues in terms of generalizability, interpretability, bias, and the ability to integrate into regular clinical practices have still not been fully discussed^{10, 11}. Hence, it is necessary to have a systematic and critical review of the existing uses of artificial intelligence in cardiovascular medicine, its constraints, and prospects. The purpose of this review will be to generalize the key areas of AI implementation in cardiology, comment on the evidence level, and provide real-life opportunities of clinical implementation.

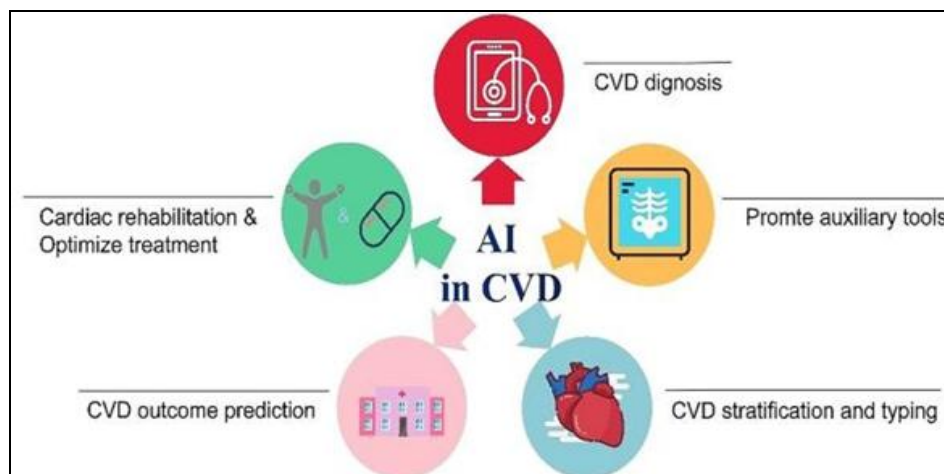


FIG. 1: AI IN CARDIOVASCULAR DISEASES

MATERIALS AND METHODS: This is a literature review that was done in the format of a narrative literature review and its target was up-to-date and emerging artificial intelligence (AI) applications in the context of cardiovascular medicine. The methodology and framework were generalized to follow the developed methodological frameworks of narrative reviews, integrative reviews, and the focus on transparent reporting and thematic synthesis over quantitative meta-analysis^{12, 13}. To find the peer-reviewed articles that were used, a thorough literature search was conducted with the use of the key scientific databases, such as PubMed, Scopus, and Web of science. The strengths and weaknesses of these databases in providing biomedical literature have been already outlined and used in the choice of search platforms¹⁴. Search strategy entailed searching using keywords and Medical Subject Headings (MeSH) that contained artificial intelligence, machine learning, deep learning, cardiovascular disease, cardiology, imaging, risk prediction, wearable devices, genomics, and clinical decision support systems.

Even though this was not a formal systematic review, the principles of the existing evidence synthesis methodologies were taken into account to enhance the ability to enhance the transparency and reproducibility of the literature selection process¹⁵. Further, the organization and presentation of the review were based on reporting concepts in accordance with the PRISMA 2020 statement¹⁶. The focus was put on original research articles, major reviews, consensus statements, and landmark clinical studies of high quality, preferably published in the past 10-15 years, and selective inclusion of older seminal works where needed due to conceptual and historical context. The articles were selected in the end according to their relevance to cardiovascular applications of AI, methodological rigor, and clinical significance.

RESULTS AND DISCUSSION:

Current Trends and Future Prospects in AI for Cardiovascular Medicine

AI in Cardiac Imaging: Artificial intelligence (AI) has become one of the most significant technologies in the cardiovascular imaging field

and has made it possible to interpret images automatically, enhance diagnostic accuracy, and improve the quality of work^{17, 18}. The adoption of deep learning methods in various imaging modalities including echocardiography, cardiac computed tomography (CT), cardiac magnetic resonance (CMR), and nuclear imaging has been noted to adopt rapidly based on a comprehensive state-of-the-art review^{17, 18}. Deep learning models have shown great accuracy in automated classification of views and functional assessment in echocardiography, which reduces the reliance of operators and decreases the inter-observer variability¹⁹. Systems based on convolutional neural networks have been demonstrated to classify standard echocardiographic views rapidly and accurately, to support downstream quantitative analysis and reporting^{19, 20}.

Moreover, beat-to-beat evaluation of cardiac activity through video-based AI methods has also made use of echocardiographic sequences as input

and provided a novel paradigm of real-time functional assessment²⁰. AI-based algorithms have been used in cardiac CT to automatically process images, segment them and characterize the plaque and stenosis. The performance of deep learning models has proven to be significantly good at analysing coronary CT angiography, and can lead towards the enhancement of diagnostic consistency and decreased reporting time²¹. On the same note, AI has been adopted in nuclear cardiology to assist with the interpretation of myocardial perfusion images, which has improved diagnostic accuracy and the risk assessment²².

Although these developments have been made, the majority of the AI applications in cardiovascular imaging are nowadays only assistive systems, not autonomous systems. Generalizability, external validation, and integration into clinical practice issues, as well as regulatory approval, are also critical issues that can hinder a wide-scale clinical adoption^{18, 22}.

TABLE 1: AI APPLICATIONS ACROSS CARDIAC IMAGING MODALITIES

Modality	AI Functionality	Clinical Benefit
Echocardiography	Chamber segmentation, EF estimation	Real-time analysis, reduced variability
CCT	Plaque analysis, vessel tracing	Early CAD detection
CMR	Tissue characterization, flow quantification	Accurate diagnosis of cardiomyopathies
PET/Nuclear	Perfusion mapping, tracer analysis	Improved ischemia detection

AI in Predictive Analytics and Risk Stratification: The key to cardiovascular prevention and management is proper risk stratification. Traditional risk models, including the Framingham risk score, have also been extensively applied in clinical practice, but have linear assumptions and few predictors, which can limit their effectiveness in a heterogeneous population. In addition, standard forms of statistics might fail to capture intricate non-linear interaction of risk factors²³.

The use of machine-learning models has been progressively considered to eliminate these constraints by incorporating a large number of clinical, demographic, and lab variables. A number of studies have shown that machine-learning methods can be better at cardiovascular risk prediction than traditional regression-based method. Such techniques are conducive especially to high dimensional data and are able to accommodate complex trends in large datasets²³.

²⁴. Besides clinical variables, genetic information has also been integrated into the contemporary risk prediction models.

Genome-wide polygenic risk scores have demonstrated potential to predict individuals with significantly elevated life-long risk of coronary artery disease, which could allow preventive interventions to be timelier and precisely target interventions. Nevertheless, some significant pitfalls can still be identified, such as the biases in population, insufficient representation of non-European descent, and doubts about the clinical utility and cost-efficiency²⁵.

Although the mentioned positive outcomes are encouraging, the majority of AI-based predictive risk models remain at the stage of development or validation. Before the widespread clinical implementation can be suggested, prospective evaluation, transparent reporting, and close evaluation of real-world impact are necessary^{23, 24}.

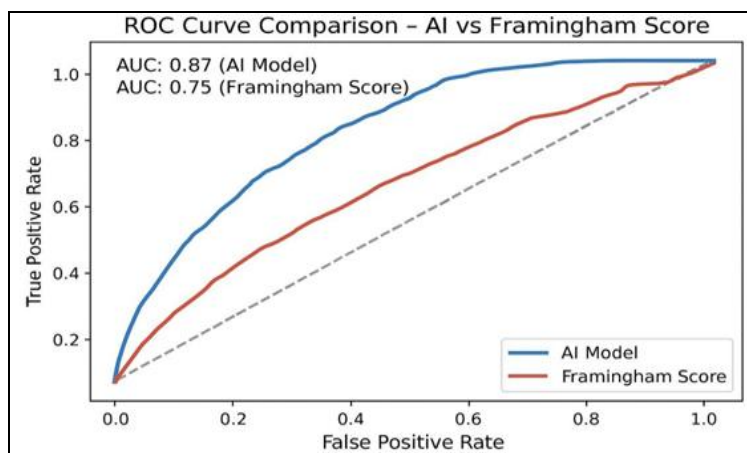


FIG. 2: ROC CURVE COMPARISON—AI VS. FRAMINGHAM SCORE (shows that AI models have a higher AUC for predicting heart events).

TABLE 2: COMPARISON OF TRADITIONAL VS AI-BASED RISK MODELS

Feature	Traditional Models	AI-Based Models
Variables used	Limited (5–10)	Extensive(100+)
Data types	Structured only	Structured+ unstructured
Population bias	High	Lower (with diverse training)
Accuracy	Moderate	High (AUC > 0.90 in some models)
Adaptability	Static	Dynamic and self- improving

Wearable Devices and Remote Health Monitoring Devices that use AI: Wearable and mobile health technologies have increased the possibilities of continuous monitoring of cardiovascular in non-clinical environments at a rapid pace. These devices can provide massive screening of cardiovascular diseases and longitudinal monitoring of cardiovascular disease (especially arrhythmias), coupled with mass screening and monitoring of the real world by employing miniaturized sensors and artificial intelligence (AI)-based signal processing ²⁶. Among the applications that have been studied the most is atrial fibrillation (AF) detection. Prospective and pragmatic studies have shown that smartwatch-based and smartphone-based systems can passively detect AF in wide populations, indicating the possibility of screening entire populations ^{26, 27}.

Besides that, photoplethysmography (PPG)-based methods embedded in cell phones have demonstrated good performance in AF detection,

extending access to rhythm monitoring even more ²⁷. In addition to the detection of arrhythmia, the AI-based analysis of electrocardiograms (ECGs) has been utilized to detect structural and functional cardiac abnormalities. Indicatively, deep learning models have been able to detect left ventricular systolic dysfunction even in the scenario where no clinical symptoms were observed using standard ECGs ²⁸. Wearable patch based continuous ECG monitoring has also been demonstrated to be more effective than intermittent strategies of monitoring paroxysmal arrhythmias ²⁹.

Regardless of such progress, there are still a number of challenges. Problems with data quality, false positives, patient compliance, data implementation in clinical processes, and absence of direct support on enhanced hard clinical outcomes need to be weighed. This also means that, as of today, the majority of wearable-based AI systems can be considered as screening and monitoring solutions and not solutions that can be regarded as diagnostic ^{26, 29}.

TABLE 3: AI-ENABLED WEARABLES IN CARDIOVASCULAR CARE

Device	AI Functionality	Clinical Utility
Apple Watch	ECG analysis, AF detection	Stroke prevention
Fitbit	Heart rate variability, activity tracking	Lifestyle modification
BioBeat	BP, HR, SpO ₂ monitoring	Hypertension and heart failure
Zio Patch	Long-term rhythm monitoring	Arrhythmia diagnosis

AI-assisted Stethoscopes: The element of cardiac auscultation has always been one of the inherent elements of cardiovascular examination, yet its diagnostic validity largely relies on the experience of the clinician and acoustical circumstances. Over the past few years, the use of digital stethoscopes in conjunction with artificial intelligence (AI)-based signal processing has been suggested to enhance the reliability and diagnostic worth of bedside auscultation³⁰.

The application of AI in the detection and classifications of heart murmurs has been created with the primary aim of developing AI-assisted systems in the field of auscultation. Papers that compare such methods with echocardiography have confirmed that deep learning models are capable of detecting clinically significant murmurs at very high accuracy, which implies that they can be used to screen and triage patients especially in primary care and resource constrained environments. They usually examine phonocardiogram signals to differentiate between the innocent and pathological

murmurs and rank patients with the need to further imaging^{30, 31}.

In addition to murmur detection, AI-based analysis of standard electrocardiograms has been demonstrated to detect left ventricular systolic dysfunction in addition to demonstrating the larger potential of machine-learning techniques to elicit latent diagnostic data in simple standard signals³². Nevertheless, the majority of the currently available AI-based assistance tools in both the form of an auscultation and ECG screening are adjunctive devices that are not designed to substitute conclusive diagnostic imaging^{30, 32}. Such limitations as variability in recording quality, environmental noise, paucity of external validation and lack of information about integration into clinical work and referral pathways are important. As a result, although AI-assisted auscultation is an exciting screening and decision-support tool, additional prospective research needs to be conducted to determine its legitimate clinical effect^{30, 31}.

TABLE 4: CAPABILITIES OF AI-SUPPORTED STETHOSCOPES

Device	AI Features	Clinical Use
Eko DUO	ECG + murmur detection	Valvular disease, AF
StethoMe	Sound classification	Pediatric screening
Think labs One	Amplified digital auscultation	Heart failure monitoring
ButterflyiQ+	AI-guided ultrasound	Cardiac imaging support

Clinical Decision Support Systems (CDSS)

Powered by AI: Clinical decision support systems (CDSS) are developed to support clinicians with the help of patient-specific guidance, signals, and hazard analysis at the point of care. Due to the incorporation of artificial intelligence (AI), CDSS have been transformed into data-driven systems that have the ability to learn using a large amount of clinical data and aid in complex diagnostic and therapeutic decisions³³. AI-based CDSS have been to date investigated in cardiovascular medicine, being applicable in arrhythmia identification, anticoagulation therapy optimization, identification of heart failure patients at high risk, and in imaging and diagnostic interpretation assistance^{33, 34}. Some systems have shown a reduction in diagnostic accuracy or a workflow process in controlled or retrospective studies although most of the systems currently in place are used as assistive systems and not autonomous decision-makers^{34, 35}. In spite of technical advances, real world implementation is

low. The key obstacles are insufficient integration with electronic health record, fatigue caused by alerts, transparency in the model reasoning, medical-legal issues, and inconsistent clinician trust. Moreover, numerous CDSS solutions are conditioned and tested on single-centre or retrospective datasets, which makes the issue of generalizability, dataset shift, and reproducibility in clinical practice concerning routine data particularly worrisome^{35, 36}. Notably, there is not yet enough strong evidence that AI-based CDSS can positively impact hard clinical outcomes (as opposed to process measures). Evaluation and explainability of the prospective will be necessary to be successful, as well as the lack of barriers to integration into clinical processes and active participation of clinicians in the development of the system and its implementation. Currently, AI-based CDSS are to be considered as systems that supplement clinical judgment and not substitute it^{33, 36}.

TABLE 5: AI-CDSS CAPABILITIES IN CARDIOVASCULAR CARE

Function	AI Capability	Clinical Impact
Diagnosis	Pattern recognition from EHRs and imaging	Early and accurate detection
Treatment	Personalized therapy recommendations	Improved outcomes
Prognosis	Risk prediction models	Preventive interventions
Workflow	Automation of documentation and alerts	Increased efficiency

AI in Genomics and Precision Medicine:

Artificial intelligence (AI) has been integrated with genomics and other high-dimensional data in the omics field, establishing new prospects of precision cardiovascular medicine in risk prediction, disease subtyping, and pharmacogenomics. These complicated datasets require machine-learning techniques to analyze them as they are not easy to process through standard statistical techniques^{37,38}.

The development of polygenic risk scores (PRS) of such diseases as coronary artery disease is probably one of the most developed so far in the field of cardiovascular medicine. There is extensive evidence of genome-wide PRS in large population studies demonstrating that individuals with significantly higher lifetime risk can be identified and thus earlier and more targeted preventive interventions may be implemented³⁹. In addition to risk prediction, AI has also been considered to subphenotype disease and interpret variants and discover biomarkers based on transcriptomic and proteomic data. Such methods can be used to

narrow down disease classification, reveal new mechanistic pathways, but most of them are at the research or early validation stage^{38,40}. Machine-learning has been suggested in the context of pharmacogenomics to predict drug response and adverse effects and improve therapeutic selection and safety. Nevertheless, still a large number of such applications are still in the preclinical research stage, and solid prospective data showing clinical utility in everyday cardiovascular practice is wanting⁴⁰.

Some of the key issues are population bias in genomic data, poor representation of non European origins, inability to interpret models effectively, and the lack of knowledge about the way that these models can be implemented in clinical environments^{37,39}. Thus, the existing application of AI-enabled genomics to cardiovascular care ought to be considered as supplementary and novel as opposed to being a typical part of clinical decision-making.

TABLE 6: AI APPLICATIONS IN GENOMICS FOR CARDIOVASCULAR MEDICINE

Application	AI Role	Clinical Impact
Polygenic Risk Scoring	Variant selection and weighting	Early disease prediction
Pharmacogenomics	Drugresponse modeling	Personalized therapy
Biomarker Discovery	Pattern recognition in omics data	Novel diagnostic tools
Gene Expression Profiling	Clustering and classification	Disease subtyping

Robotics and AI in Cardiac Surgery: Robotic-assisted cardiac surgery is one of the most technologically developed fields of application of artificial intelligence (AI) and computer-assisted systems in cardiovascular medicine. To achieve the minimally invasive approach and enhance the accuracy of the instruments, the selective procedures on which robotic platforms are applied today are mitral valve repair, coronary artery bypass grafting, and atrial septal defects repairs^{41,42}. This area has studied AI primarily regarding preoperative planning, intraoperative guidance, image-based navigation, and workflow optimization but not autonomous surgery. These are automatic segmentation of cardiac structures,

surgical path planning, motion stabilization, and real-time guidance on the basis of imaging and hemodynamic information^{43,44}. Robotic methods have been reported to reduce blood loss, short hospitalization, and quicker healing in well chosen centers and patients compared to traditional surgery^{42,45}.

Nevertheless, the use is not widespread. The significant obstacles are high cost of capital and maintenance, long learning curves, longer time to operation in the initial experience, and limited access to tertiary centers with huge volumes^{41,42}. Notably, the evidence of better long term clinical outcomes than traditional surgery is inconsistent,

and the majority of the studies lack randomness⁴⁵. Other issues are related to the complexity of the system, the reliance on the quality of imaging and medico-legal liability in AI-assisted intraoperative decision support. As a result, the existing robotic and AI-aided cardiac surgery systems can be considered auxiliary technologies that increase the

accuracy and ergonomics of the surgery, not the substitution of the experience of a surgeon. The next development will rely on the cost minimization, standardized training paths, clinical evidences, and close consideration of cost-effectiveness and patient-centered outcomes^{41,44}.

TABLE 7: AI AND ROBOTICS IN CARDIAC SURGERY

Phase	AI Contribution	Clinical Benefit
Preoperative	3D modelling, risk prediction	Personalized planning
Intraoperative	Tissue recognition, guidance	Precision and safety
Postoperative	Recovery tracking, complication alerts	Early intervention

Explainable AI and Digital Twins in Cardiology:

The transparency, trust, and clinical accountability of the rapidly growing use of costly machine-learning models in cardiovascular medicine have become significant concerns. The goal of explainable artificial intelligence (XAI) is to make predictions made by models understandable by defining the features were influenced, visualizing the decision pathways and explaining their decisions in a way that is comprehensible to humans. It becomes especially essential in cardiology, where the results of AI can have a direct effect on diagnostic and treatment⁴⁶. Such common XAI methods as SHAP and LIME have been used on cardiovascular imaging, electrocardiography and risk prediction models to assist clinicians in comprehending why a given model generates a particular output and to identify possible biases or spurious relationships. These methods enhance transparency, but they do not cover all the concerns of model robustness, dataset shift, or causal interpretation and their regular

clinical usefulness is yet to be systematically assessed⁴⁷. Simultaneously, the use of digital twins, computational representations of cardiovascular anatomy and physiology of a patient, has become an evident prospective practice of individual risk assessment, treatment planning, and procedural simulation. Digital twin models have been investigated in cardiology to be used in virtual testing of valve interventions, simulation of hemodynamics, and optimization of therapy plans⁴⁸. Nevertheless, the majority of digital twins are still research oriented. Among the key obstacles, there are high computational cost, reliance on high quality multimodal data, lack of prospective clinical validation, and inability to predict regulatory pathways. In turn, although both XAI and digital twins are valuable concepts in terms of conceptual development, their use in daily cardiovascular care must be considered as supplementary and early-stage but not full-fledged clinical technologies⁴⁹.

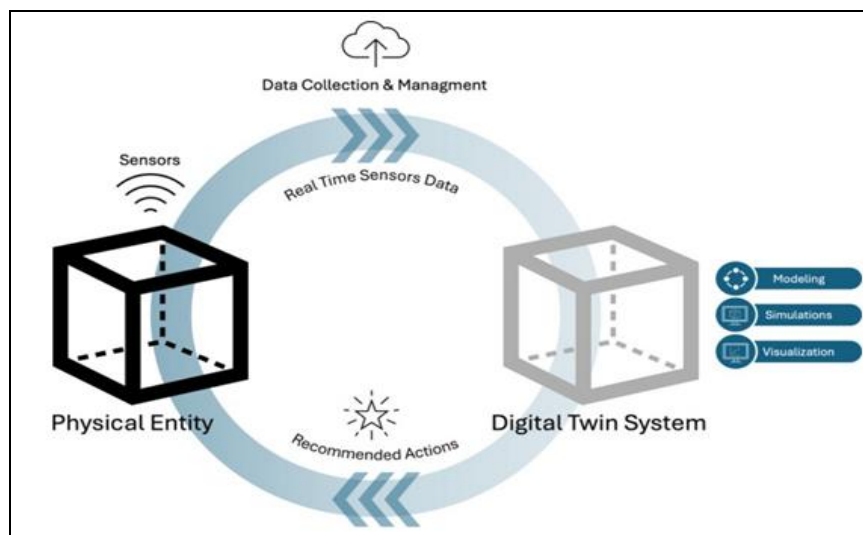


FIG. 3: ARCHITECTURE OF A DIGITAL TWIN SYSTEM

TABLE 8: EXPLAINABLE AI TECHNIQUES IN CARDIOVASCULAR APPLICATIONS

Technique	Function	Use Case
SHAP	Feature attribution	Risk prediction models
LIME	Local model approximation	Therapy recommendation
Attention Maps	Visual focus areas	Imaging interpretation

AI in Population Health and Epidemiology for Cardiovascular Disease:

The growing access to population-scale health data through electronic health records, registries, and administrative data bases has made it possible to use artificial intelligence (AI) to conduct population-level cardiovascular research. The machine-learning techniques are especially effective in modelling high-dimensional data which are extremely complex, and identifying patterns which could be hidden when working with the traditional methods of statistical analysis^{50, 51}. In population level, AI has been utilized to enhance risk stratification, outcome prediction and resource allocation. To illustrate this, machine-learning models have been trained to forecast mortality and severe outcomes based on large-scale health system data, which show that powerful prediction tools can be created even in the situation when individual-level data are either incomplete or heterogeneous⁵². These methods in epidemiology of the cardiovascular system provide the prospects of completing the classical risk modelling, as well as in health system planning^{51, 52}.

The idea of precision public health is set to apply data-driven approaches in order to provide appropriate intervention to the appropriate population at the appropriate time. The AI-based analytics can be useful to detect high-risk subgroups, streamline screening policies, and tailor cardiovascular disease prevention programs. Nonetheless, these methods are difficult to translate into policy and regular practice⁵³. Notably, ethical and equity issues also emerge when AI is applied in population health. Scaled application of predictive models has demonstrated the danger of algorithmic bias, especially when predictive models are being trained on non-representative or historically biased data. These biases can further worsen the prevailing health disparities unless properly managed by means of clear model formulation, external validation and ongoing monitoring⁵⁴. In general, as AI can greatly benefit cardiovascular population health research and policy planning, its application should be approached with a lot of care to guarantee the quality of the data, equitable use, governance, and real-world implications^{50, 54}.

TABLE 9: AI APPLICATIONS IN POPULATION-LEVEL CARDIOVASCULAR HEALTH

Application	AI Technique	Impact
Risk Mapping	Geospatial modelling	Identifies disease hotspots
Resource Allocation	Predictive analytics	Optimizes healthcare delivery
Equity Analysis	Clustering, NLP	Reveals disparities
Behavior Monitoring	Wearable data mining	Guides lifestyle interventions

Ethical and Regulatory Challenges of AI in Cardiovascular Medicine:

The use of artificial intelligence (AI) in cardiovascular medicine poses critical ethical, legal, and regulatory challenges on safety, accountability, transparency, and equity. With a growing role of AI systems in diagnostic and treatment choices, the lack of understanding of complex systems, the threat of automation bias, and accountability in the case of errors have become areas of concern⁵⁵. Algorithms bias is one of the most outstanding aspects of ethical issues. Trained predictive models based on historically-biased or non-representative data can directly or indirectly increase already existing disparities in access to care and clinical outcomes. Socioeconomic, racial,

and geographic factors have a strong impact on the disease burden and treatment trajectories in cardiovascular medicine, which is why it is particularly pertinent to this risk⁵⁶. Ethical and regulatory acceptance is also based on explainability and transparency. Clinicians and patients should be equipped with capabilities to comprehend at least on a high level how the AI systems will produce recommendations so that they will be able to be supportive of trust, informed consent, and appropriate clinical supervision. In the absence of meaningful interpretability, model failures, data drift, and unsafe behaviour occur in the real world are hard to detect^{55, 57}. Regulatorily, the majority of existing AI systems are assessed

with frameworks that were originally created to assess static medical instruments. Most AI models are however adaptive or in a continuous mode of learning thus making them difficult to validate, post-market surveillance, and version control. New strategies to the regulation of AI-based medical software have also started being pursued by regulatory agencies, yet standards that go global remain in their formative phase^{57, 58}. Lastly, data governance, privacy, and cyber security are the key enabling variables to the style of responsible AI

use. Massive aggregation of personalized health information covertly heightens the chances of breach and abuse of data and therefore, more stringent governance mechanisms, definite accountability frameworks, and continuous observation throughout the AI apparatus lifecycle^{56, 58}. In general, as vast cardiovascular care opportunities are provided by AI, it is essential to ethically and legally integrate AI with technology development to be sure that the innovation remains safe, fair, transparent, and patient-centred.

TABLE 10: SOURCES AND IMPACTS OF BIAS IN AI MODELS

Source of Bias	Impact	Mitigation Strategy
Skewed training data	Diagnostic errors	Diverse data collection
Labeling inconsistencies	Poor model generalization	Expert consensus labeling
Sensor limitations	Inaccurate readings	Inclusive hardware design

CONCLUSION: Artificial intelligence (AI) is fast changing various fields of cardiovascular medicine, such as imaging, risk forecasting, wearable devices, digital auscultation, clinical decision support systems, genomics, and robotic surgery. As emphasized in this review, AI-driven solutions can offer significant possibilities to enhance the accuracy of the diagnostic process, effectiveness of the workflow, and customized care throughout the cardiovascular continuum.

Nevertheless, the clinical adoption is currently in a heterogeneous state. Although a few applications like AI-assisted image analysis and wearable-based arrhythmia detection are on the verge of becoming routine clinical use, many other applications are still at early stages of development or validation. Critical issues remain, such as problems of the generalizability, data quality, bias, explainability, regulatory aspects and incorporation of it into the clinical workflows. The new ideas like explainable AI and digital twins are positive steps to achieve more transparent and trustful and patient-specific decision support but are still not developed enough to be used in clinical practice. Likewise, genomics, population health, and robotic surgery applications have significant potential but need more effective prospective evidence of how they can significantly improve patient outcomes and cost-effectiveness. In the end, the effective implementation of AI in cardiovascular practice will remain not only technically performed, but also clinically validated, ethically governed, aligned to regulations, and associated with clinicians. AI is to be regarded as

an effective way to enhance clinical expertise and not to substitute it. Artificial intelligence could be a transformative step in enhancing the quality, safety, and equity of cardiovascular care with careful and evidence-based execution and ongoing interdisciplinary cooperation.

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CONFLICTS OF INTEREST: Nil

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