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Review

Artificial intelligence in cardiovascular medicine: An exoskeleton for perception, reasoning and action

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ABSTRACT

Cardiovascular diseases are a leading cause of morbidity and death, necessitating advanced tools for early diagnosis and personalized care. Artificial intelligence could contribute to transform cardiology through a Perception, Reasoning and Action framework. In the Perception phase, artificial intelligence can improve data acquisition. The Reasoning stage involves artificial intelligence-driven data analysis, integrating large datasets to support clinical decision-making and personalized treatment plans. In the Action phase, artificial intelligence optimizes therapeutic interventions, automates clinical workflows and enhances patient engagement. Artificial intelligence might therefore free up time for cardiologists to focus more on direct patient care and less on data acquisition and analysis, although their supervision remains essential. This review also addresses the technical and ethical challenges of artificial intelligence, including quality of datasets, algorithmic bias, the need for explainable artificial intelligence and data privacy, while exploring future perspectives, such as quantum computing and interdisciplinary collaboration. By addressing these challenges, artificial intelligence has the potential to revolutionize cardiology by enhancing diagnostic precision, advancing risk prediction, optimizing healthcare delivery and improving therapeutic outcomes on a global scale.

1. Introduction

Cardiovascular diseases (CVDs) account for nearly one third of all global deaths, with increasing prevalence resulting from aging populations and lifestyle factors [1,2]. The complexity of CVDs requires advanced tools for early detection, precise diagnosis and prediction and personalized treatment. Artificial intelligence (AI), encompassing machine learning, deep learning and data analytics, has emerged as a technology that could improve these matters [3,4]. In cardiology, AI is improving the ability to detect cardiovascular events at an early stage [5] and to interpret large datasets, including medical imaging, to recognize features and patterns, aiding clinical decision-making and management.

This review aims to provide an overview of AI applications in cardiology, structured around the concepts of Perception, Reasoning and Action. This framework emerged in the 1980s to modelize autonomous robots' behaviour. By categorizing AI functions into these domains, we seek to elucidate how AI technologies are and will be further integrated into cardiology to improve patient outcomes.

The review is organized into these three main sections, each including case studies: Perception examines how AI is involved in the acquisition and interpretation of data, including advanced monitoring devices and data management systems; Reasoning discusses AI's role in data analysis, interpretation and decision-making support; and Action explores how AI actively executes tasks related to patient care through therapeutic applications and patient engagement tools. Finally, ethical considerations and future directions are addressed in dedicated sections.

Abbreviations: AI, artificial intelligence; CVD, cardiovascular disease; EHR, electronic health record; EU, European Union; GDPR, General Data Protection Regulation; NLP, natural language processing; SPCT, single-photon emission computed tomography.

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2. Perception

AI technologies are transforming the way in which cardiovascular data are received, collected and analysed, enabling unprecedented levels of accuracy and efficiency in clinical information acquisition. By integrating AI into various aspects of data collection, clinicians can obtain a more comprehensive understanding of a patient's cardiac health [6].

2.1. Electrocardiography

AI techniques, such as variational autoencoders, can improve the explainability and reliability of deep-learning models in electrocardiogram interpretation [7]. Moreover, AI algorithms can detect subtle changes in electrocardiogram patterns that may be overlooked by the human eye. An AI-enabled electrocardiography algorithm was able to identify patients with atrial fibrillation during normal sinus rhythm by recognizing latent patterns not discernible to clinicians [8]. Additionally, AI models have been developed to detect other conditions, such as hypertrophic cardiomyopathy [9] and cardiac amyloidosis [10], from electrocardiogram data. AI-enhanced electrocardiogram interpretation could also help clinicians in the early detection of electrolyte imbalances [11,12]. Finally, AI has been used to detect reduced ejection fraction from electrocardiogram data alone, providing a promising screening tool for assessing cardiac function [13].

2.2. Wearable technology and implantable sensors

Wearable technology, such as smartwatches and fitness trackers, has revolutionized cardiac monitoring by providing continuous remote real-time patient monitoring data, such as heart rate, rhythm, blood pressure and physical activity levels [14,15]. These devices use machine learning and deep-learning algorithms to detect arrhythmias, such as atrial fibrillation, often before symptoms manifest. For example, the Apple Heart Study demonstrated that wearable devices could identify undiagnosed atrial fibrillation in a large population sample [16], thus enabling earlier intervention. AI algorithms can filter out noise in electrocardiogram signals obtained from wearable devices, ensuring that the data used for analysis are accurate and reliable [17]. This is particularly important for data collected outside of clinical settings, where environmental factors can affect signal quality.

Moreover, AI-powered wearables can monitor other physiological variables, such as oxygen saturation and sleep patterns, contributing to a more holistic assessment of cardiovascular health [18]. These devices can help in the early detection of conditions such as sleep apnoea, which is a known risk marker for hypertension and heart failure [19]. AI algorithms analyse the collected data to predict episodes of hypotension or hypoxaemia before they occur, enhancing patient safety [20]. For instance, AI models can integrate data from wearable blood pressure monitors to predict the risk of hypertensive crises [21].

Implantable sensors offer even more detailed monitoring capabilities. Devices such as implantable loop recorders and haemodynamic monitors transmit data on intracardiac pressures and rhythms directly to healthcare providers; this facilitates proactive management of conditions such as heart failure by allowing clinicians to predict decompensation events before they become clinically apparent [22]. AI algorithms process the vast amounts of data from these devices to identify trends and predict adverse events [23]. The MONITOR-HF trial demonstrated that remote haemodynamic monitoring using implantable pulmonary artery pressure sensors improved quality of life and reduced hospitalizations in patients with heart failure [23].

2.3. Advanced imaging modalities

AI has also significantly improved medical imaging modalities. AI can assist in optimizing the acquisition of imaging data by guiding non-expert operators during echocardiography or magnetic resonance imaging procedures [24]. Real-time feedback provided by AI algorithms can improve image quality, optimize radiation exposure and contrast dose and reduce image acquisition and interpretation times [25].

In nuclear cardiology, AI now automatically quantifies myocardial blood flow from positron emission tomography polar maps, and flags perfusion defects on single-photon emission computed tomography (SPECT). Landmark studies have demonstrated that deep-learning analysis of SPECT polar maps improves per-patient coronary artery disease detection [26], and that quantitative positron emission tomography polar maps analysed by neural networks predict cardiovascular events beyond clinical variables [27]. Convolutional models can also track stents of catheters in fluoroscopic sequences in real time, allowing contrast-sparing roadmap guidance during percutaneous coronary intervention [28]. In echocardiography, deep-learning algorithms enhance image resolution and assist in the detection of CVDs [29]. AI algorithms can automate the quantification of cardiac structures and functions, reducing interobserver variability and improving diagnostic accuracy [30,31]. For instance, AI models can perform automated segmentation of cardiac chambers, facilitating rapid assessment of variables such as left ventricular ejection fraction [32]. AI algorithms can also help to detect CVDs (e.g. latent rheumatic disease) in endemic areas where trained medical staff are lacking [33,34].

In cardiac magnetic resonance imaging, AI helps to identify pathologies such as valvular diseases and cardiomyopathies with greater efficiency than traditional methods [35]. AI algorithms can detect subtle changes in tissue characteristics indicative of myocardial fibrosis or inflammation, and thus help to identify optimal infarct-related ventricular tachycardia ablation targets [36]. AI has been used to detect reduced ejection fraction from electrocardiogram data alone, providing a promising screening tool for assessing cardiac function [13].

On coronary computed tomography, AI can quantify the burden of atheromatous plaques, including at-risk plaques, whereas cardiologists and radiologists do not have sufficient time for these analyses in clinical practice [37]. Algorithms have also been developed to assess pericoronary fat attenuation [38], a marker of inflammation that plays a significant role in atherosclerotic disease [39]. AI-driven prediction of cardiovascular events based on coronary computed tomography analysis was more efficient than the usual variables in recent studies [40,41], including in patients without detected plaque. Thus a major field of investigation concerns "radiomics", which uses massive amounts of data from imaging, otherwise indistinguishable to the human eye [42].

2.4. Population-level data analysis

The integration of AI in managing large datasets has enabled the analysis of epidemiological trends and the identification of risk factors at a population level. Machine learning models process electronic health records (EHRs) to predict disease patterns and outcomes, which may contribute to public health planning and resource allocation [4]. By analysing data from thousands of patients, AI can identify previously unrecognized associations between risk factors and CVDs. For example, AI has been used to predict hospital readmission rates for patients with heart failure, aiding in the development of targeted interventions [43]. Additionally, AI can assist in stratifying patients based on their risk profiles, or in identifying clusters of patients, thereby enabling personalized treatment strategies [44].

AI facilitates the analysis of genomic data to identify genetic predispositions to CVDs. Processing vast amounts of genetic information, AI algorithms might help to detect mutations associated with conditions such as hypertrophic cardiomyopathy and long QT syndrome, aiding early diagnosis and family screening [45]. Furthermore, AI assists in analysing biomarkers from blood tests, enhancing the diagnosis and prognostication of conditions such as acute coronary syndromes [45]. AI models can integrate proteomic and metabolomic data to discover new biomarkers for CVDs [45].

Overall, AI technologies in the "Perception" category enhance the ability of clinicians to collect and interpret large amounts of cardiovascular data, leading to earlier detection of diseases, improved diagnostic accuracy and more efficient patient monitoring. These advances lay the foundation for subsequent analysis and intervention in patient care.

3. Reasoning

AI systems transform raw data into actionable insights, bridging the gap between complex datasets and clinical decision-making. Thanks to predictive modelling, risk stratification and real-time guidance, AI empowers clinicians to deliver personalized and precise cardiovascular care.

3.1. Predictive modelling and personalized risk scores

Machine learning algorithms enable the development of predictive models for cardiovascular events by analysing diverse datasets, including patient demographics, clinical history, imaging, laboratory results and genetic information. For instance, AI can predict the likelihood of heart failure hospitalization, sudden cardiac death or complications, allowing for early interventions or optimal discharge [4,43,46]. Personalized risk scores enhance preventive measures tailored to individual patient profiles [47].

The strength of AI lies in its ability to integrate data from various sources, offering a holistic perspective on cardiovascular health. Beyond clinical variables, AI analyses lifestyle factors, such as diet, exercise patterns and socioeconomic determinants, to enhance risk prediction [48,49]. This multidimensional approach facilitates personalized strategies, empowering clinicians to address risk factors comprehensively.

Natural language processing (NLP) algorithms further strengthen decision-making by extracting valuable insights from EHRs and unstructured clinical notes. These systems provide real-time alerts for potential drug interactions, recommend diagnostic tests and suggest evidence-based therapies [50,51]. Additionally, NLP identifies undocumented symptoms and risk factors, improving the completeness of patient records and supporting accurate diagnosis [52,53].

3.2. Pharmacotherapy and device-based optimization for personalized treatment

AI is transforming pharmacotherapy by predicting individual responses to medications, considering factors such as genetics (pharmacogenomics), co-morbidities and previous treatment outcomes [45,47,54]. Machine learning models suggest optimal dosing regimens, and identify patients most likely to benefit from specific therapies, thus personalizing treatment plans to improve outcomes in patients with complex cardiovascular conditions, reducing adverse drug reactions and intensifying therapeutic efficacy [45,53–55]. For instance, AI may successfully optimize anticoagulant therapy in patients with atrial fibrillation, balancing efficacy and safety in diverse populations [56].

The concept of "digital twins" – virtual models that replicate a patient's cardiac physiology – enables clinicians to simulate interventions such as valve replacements or arrhythmia ablations. These models predict outcomes and complications, allowing safer and more precise procedural planning [57–59]. Digital twins also facilitate personalized testing of therapeutic scenarios, improving the safety and effectiveness of real-life interventions [48,60].

In drug discovery, AI accelerates the identification of therapeutic targets by analysing molecular structures and biological pathways. By simulating interactions between drugs and cardiac tissues, AI reduces the time and cost associated with providing new treatments to clinical trials [50,51,53]. This approach has led to the development of promising compounds for heart failure and arrhythmias [45,54], while AI-driven drug repurposing has uncovered new applications for existing medications [47,61]. Furthermore, AI has been used in "in silico" modelling of clinical trials, simulating virtual patient populations to predict trial outcomes. This is particularly relevant for rare diseases, where targeted identification of responders can enhance trial efficiency [62].

To summarize, AI's analytical capabilities may profoundly impact cardiology by heightening predictive modelling, diagnostic accuracy, personalized treatment and workflow optimization. By integrating vast amounts of data and providing actionable insights, AI may support clinicians in delivering high-quality, patient-centred care.

4. Action

AI may actively contribute to patient care by boosting clinical interventions, automating routine processes and improving patient engagement. Whereas most AI developments in cardiology are currently at the research stage, the transition to validated tools is imminent. For certain clinical applications, AI is already being used effectively.

4.1. Help in clinical practice

AI-powered robotic systems have shown potential to enhance precision and standardize cardiac surgical procedures, such as coronary artery bypass grafting and valve repairs. Studies suggest that these technologies may reduce surgical trauma and improve outcomes through better intraoperative decision-making and automation. However, current evidence remains largely theoretical, with limited clinical data quantifying reductions in complication rates or hospital stays [63–65].

In interventional cardiology, AI enhances catheter-based procedures by improving imaging guidance, optimizing decision-making and increasing procedural precision (stent placement, electrophysiological ablations, etc.) [43,66]. Additionally, AI technologies contribute to the design and optimization of cardiovascular devices, including the development of stents aimed at improving long-term vessel patency and reducing complications [50,51].

Emerging pacemakers and implantable cardioverter-defibrillator platforms embed AI or adaptive algorithms chiefly to detect events and issue predictive alerts; fully autonomous physiological closed-loop therapy adjustment remains experimental, with only early proof-of-concept data available [67]. AI can develop personalized rehabilitation programmes, adjusting exercises and activities based on patient progress and feedback [3,51]. Remote monitoring allows clinicians to track recovery and intervene promptly if complications arise, enhancing patient outcomes.

AI-powered mobile applications and chatbots are emerging as tools to support patients in managing their cardiovascular conditions, by tracking symptoms, medication adherence and lifestyle changes [68,69]. These tools provide personalized alerts and educational materials aimed at empowering patients in self-care and reinforcing adherence to care plans. AI-driven chatbots also offer real-time assistance in addressing patient queries and facilitating patient-clinician communication through reminders and guidance. Although these innovations show promise in enhancing patient engagement and satisfaction, evidence of their impact on cardiovascular outcomes remains preliminary. Further clinical research is needed to validate their effectiveness in improving long-term health outcomes.

4.2. Help with healthcare system organization

AI is revolutionizing healthcare organization by optimizing workflows, improving operational efficiency and reducing administrative burdens. Predictive analytics enable hospitals to forecast admissions, optimize scheduling and allocate resources effectively, enhancing patient flow and minimizing delays [47,48,51,53]. In diagnostic imaging, AI prioritizes urgent cases, ensuring timely interpretation of critical findings [54,70].

NLP automates clinical report generation by extracting and summarizing data from consultation notes, reducing clinician workload and documentation errors [47,52]. These tools free up clinicians to focus on patient care, while ensuring resources are used efficiently to improve outcomes.

In summary, AI's active role in cardiology – ranging from enhancing therapeutic precision and streamlining hospital operations to facilitating personalized patient interactions – demonstrates its transformative potential to improve both clinical outcomes and patients' experiences, making care more efficient, accessible and patient-centred. Multiple future developments are awaited.

5. Challenges and ethical considerations

Although AI offers significant benefits in cardiology care, it raises ethical challenges and technical concerns that must be addressed to ensure safe, equitable and effective patient care.

5.1. Bias, model errors, hallucinations and the black-box effect

AI systems in cardiology face several technical challenges that can undermine their reliability and integration into clinical practice. One significant issue is algorithmic bias, where models trained on datasets that under-represent certain populations provide less accurate predictions for these groups. Such disparities risk exacerbating healthcare inequalities if not addressed through the development of diverse and representative training datasets [54,64]. Ensuring equitable care across all populations requires proactive efforts to mitigate these biases at every stage of AI development.

In addition to bias, a first set of technical limitations arises from prediction errors in traditional machine learning models. These may result from overfitting, sampling bias or poor generalization, and can lead to misclassification of imaging data or inaccurate clinical predictions [71]. In contrast, another critical limitation, specific to generative models, is the phenomenon of hallucinations, where AI systems produce outputs that are factually incorrect or entirely fabricated [72]. In cardiology, these hallucinations could manifest as false predictions or erroneous insights, such as misidentifying abnormalities in imaging data or providing inaccurate diagnostic recommendations. These errors can have significant consequences for patient safety if left unchecked. Mechanisms to detect and mitigate hallucinations are still evolving, and need to be tested robustly before AI systems are deployed in clinical settings [73].

The lack of interpretability in many AI models, often referred to as the "black-box" effect, further complicates their clinical application. Deep-learning algorithms, in particular, can obscure the reasoning behind their predictions, making it difficult for clinicians to validate or fully trust AI-driven recommendations [52,53]. This opacity may hinder patient consent and clinician confidence. Addressing this challenge involves advancing explainable AI technologies that provide insights into how predictions are generated. For instance, explainable electrocardiogram algorithms have been developed to elucidate the reasoning behind AI outputs, fostering greater trust in AI-assisted clinical workflows [7].

To navigate these challenges effectively, collaboration between clinicians and AI is essential to ensure that AI complements, rather than replaces, human judgment. By maintaining human oversight and integrating AI outputs into clinical workflows, healthcare providers can ensure accurate and context-aware application of AI recommendations [74].

5.2. Ethical, legal, security and environmental challenges

Cardiological data, including imaging, genetic profiles and EHRs, are inherently sensitive. The extensive collection, processing and analysis of the amount of personal data required to train AI models creates risks of data breaches and unauthorized access [52]. Compliance with regulations, such as the General Data Protection Regulation (GDPR), and adherence to cybersecurity best practices are essential to safeguard patient confidentiality.

The European Union (EU) AI Act introduces a regulatory framework specifically targeting AI technologies based on their risk level. In the context of cardiology, many AI applications – such as diagnostic tools, predictive algorithms and decision support systems – are classified as high risk because of their potential impact on patient health and safety. The EU AI Act requires high-risk AI systems to meet stringent standards, including transparency requirements, risk-management systems and human oversight. Regarding transparency requirements, AI systems must provide clear information about their capabilities and limitations; this is especially important in cardiology, where a misinterpretation of AI recommendations could lead to critical medical errors. In terms of risk management systems, developers must implement continuous risk management processes, focusing on the entire lifecycle of the AI system, from design to postmarket monitoring. Concerning human oversight, the regulation mandates that AI systems in healthcare should always allow for meaningful human intervention. In cardiology, this ensures that the final decision rests with the healthcare provider, reducing the risk of over-reliance on algorithmic outputs.

Cybersecurity concerns further complicate AI implementation. The impact of unauthorized access or data breaches can never be understated, as it not only affects patient security, but also undermines the integrity of AI systems dependent on vast datasets for training and validation. To protect against these threats, cybersecurity rules must be followed, including encrypting all patient data, conducting regular audits and vulnerability assessments, implementing continuous monitoring and using software that complies with security standards.

Determining responsibility for medical errors involving AI systems is another challenge. Clear legal guidelines and accountability frameworks are needed to address issues of malpractice and negligence involving AI. It is crucial to determine who is accountable for any given situation – the clinician, the institution or the AI developer – to guarantee legal clarity and patient safety.

By developing transparent, fair and secure AI systems, and by establishing clear legal and ethical frameworks, the cardiology community can harness the benefits of AI while minimizing risks, ultimately improving patient care and outcomes.

Finally, although AI tools in cardiology are promising for improving patient care, their environmental impact cannot be ignored. The sizeable energy footprint of large-scale model training and data storage calls for green AI strategies, such as model compression and renewable-powered data centres, to keep cardiovascular innovation environmentally sustainable [75].

6. Future perspectives

The integration of AI in cardiology promises transformative advances, but it also raises questions about the future of science and clinical practice, introducing both opportunities and challenges.

Emerging technologies, such as quantum computing, could significantly enhance AI capabilities, enabling the processing of complex medical data at unprecedented speeds [76]. This could lead to more sophisticated predictive models and faster analysis of large datasets, improving diagnostic accuracy and treatment planning. Similarly, emotional AI – designed to recognize and respond to human emotional cues – could enhance patient interactions by fostering more empathetic and personalized care. Although promising, these advances must be carefully assessed for their clinical relevance and ethical implications.

Widespread adoption of AI in cardiology hinges on addressing barriers and fostering enablers specific to each professional group, subspecialty and practice setting. Effective training of healthcare professionals is pivotal to ensure that AI is used optimally [64,74]. Updating medical curricula, providing continuous education and developing AI literacy among clinicians will be crucial. Organizational adjustments, including workflow redesign and investment in infrastructure, are also essential for seamless AI integration into clinical practice [53,77].

Collaboration among cardiologists, data scientists, engineers and ethicists will be indispensable in tackling complex healthcare challenges [53,54]. Interdisciplinary efforts can accelerate innovation, ensuring that AI solutions are not only technically advanced, but also clinically relevant, ethically sound and aligned with patient care objectives.

Over the coming decades, AI has the potential to revolutionize cardiology by enabling predictive preventive care and fully personalized treatment plans [1,43]. By leveraging big data and advanced analytics, AI can identify at-risk individuals and tailor interventions accordingly, potentially reducing the global burden of CVDs [2].

Human-machine collaboration will further enhance research efficiency, fostering discoveries that deepen our understanding of CVDs and lead to new treatments [54,78].

Embracing these emerging technologies and addressing the associated challenges will be pivotal in realizing the full potential of AI in cardiology. AI is already an integral part of our daily lives, whether we realize it or not. In the realm of cardiology, it holds immense promise for improving diagnosis and cardiovascular risk prediction, already demonstrating superior performance to clinicians in areas such as imaging. As a specialty grounded in patient interaction, clinical examination and the execution of invasive and non-invasive procedures, cardiology can greatly benefit from the ability of AI to save time by automating routine tasks; this enables cardiologists to focus more on research and personalized patient care, ultimately advancing the quality of care delivered.

Rather than viewing AI as a competitor, cardiologists should see it as a valuable supportive tool. However, sound clinical judgment and the ability to critically interpret AI-generated insights remain essential to ensure its safe and effective use. By fostering collaboration, investing in education and ensuring ethical integration, the cardiology community can maximize the benefits of AI to enhance patient outcomes, support clinical decision-making and reduce the global burden of CVDs.

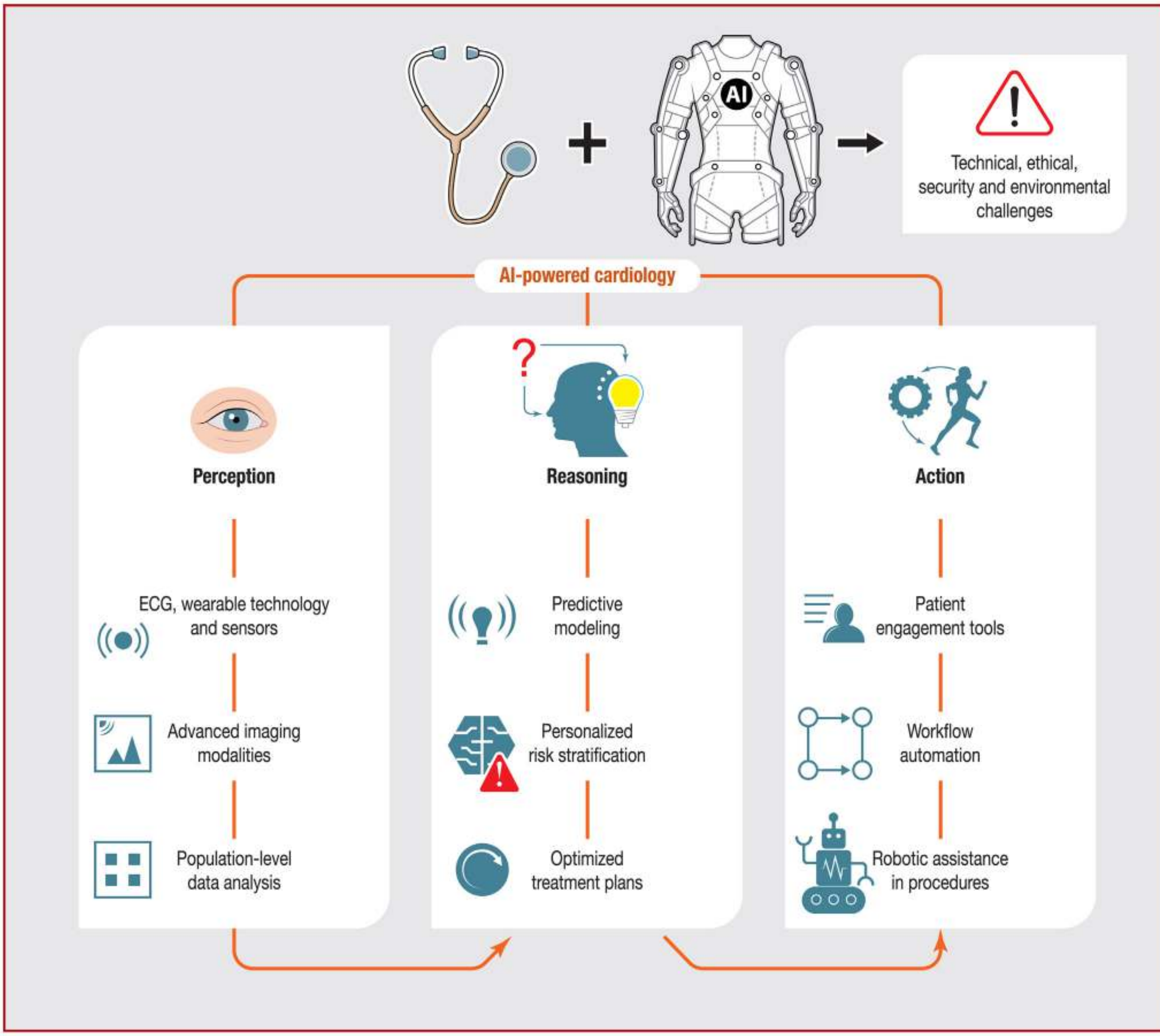
7. Conclusions

This review highlights the transformative potential of AI in cardiology through the Perception, Reasoning and Action framework. AI enhances data acquisition through advanced monitoring technologies, refines diagnostic precision with sophisticated analytics and actively improves therapeutic interventions and patient engagement. These capabilities collectively pave the way for a more efficient, patient-centred cardiovascular healthcare system.

AI holds the potential to revolutionize cardiology in a controlled and reasoned manner by enabling personalized medicine, improving diagnostic accuracy and optimizing treatment outcomes. However, realizing these benefits requires thoughtful integration, ethical vigilance and adherence to regulatory frameworks such as the GDPR, the EU AI Act and the *Commission Nationale de l'Informatique et des Libertés* (CNIL) guidelines. Only through such measures can these technologies be deployed safely, equitably and effectively.

Looking forward, emerging technologies, such as quantum computing and emotional AI, will further amplify AI capabilities, enabling advances from predictive preventive care to fully personalized treatment plans. Beyond clinical practice, AI's integration into medical education and research offers additional opportunities to streamline learning and accelerate scientific discovery, reinforcing its role as a cornerstone of progress in cardiovascular medicine.

By embracing innovation and proactively addressing challenges, the cardiology community can unlock AI's full potential to enhance patient outcomes, alleviate the global burden of cardiovascular diseases and reshape the future of cardiology.



Central illustration. Artificial intelligence (AI) in cardiovascular care: An exoskeleton for perception, reasoning and action. ECG: electrocardiogram.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI's ChatGPT, Perplexity, Research Rabbit and DeepL to assist in completing the bibliographic research and improving the formulation of sentences for enhanced clarity and readability. After using these tools, the authors carefully reviewed and edited the content as needed, and take full responsibility for the content of the publication.

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The authors declare that they have no competing interest.

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