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Review

An Update on the Use of Artificial Intelligence in Cardiovascular Medicine

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Abstract: Artificial intelligence, specifically advanced language models such as ChatGPT, have the potential to revolutionize various aspects of healthcare, medical education, and research. In this review, we evaluate the myriad applications of artificial intelligence in diverse healthcare domains. We discuss its potential role in clinical decision-making, exploring how it can assist physicians by providing rapid, data-driven insights for diagnosis and treatment. We review the benefits of artificial intelligence such as ChatGPT in personalized patient care, particularly in geriatric care, medication management, weight loss and nutrition, and physical activity guidance. We further delve into its potential to enhance medical research, through the analysis of large datasets, and the development of novel methodologies. In the realm of medical education, we investigate the utility of artificial intelligence as an information retrieval tool and personalized learning resource for medical students and professionals.

Keywords: artificial intelligence; cardiovascular medicine

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1. Introduction

In recent years, artificial intelligence (AI) has made significant advancements and is applicable in numerous fields including medicine. By combining linguistics and computer science, AI enables performance of tasks such as understanding abstract concepts, reasoning, learning, adapting, and reacting, which typically requires human intelligence [1–3].

In November 2022, OpenAI L.L.C. (based in San Francisco, CA, USA) introduced ChatGPT—an AI driven large language model (LLM) chat-bot built on generative pre-trained transformer (GPT) architecture and trained using datasets in various languages [4,5]. GPT models in general are artificial neural networks based on deep learning architecture, pre-trained on large data sets of unlabeled text, to enable generation of human-like response outputs [5]. The model's advanced language understanding and generation capabilities make it suitable for utilization in content creation, customer service, and program assistance among other applications [5,6].

AI advancements in medicine have led to numerous applications from encompassing precise disease stratification, remote cardiac monitoring, integration of multimodality imaging, and AI-aided diagnosis and therapy selection [7]. These are particularly applicable to preventive cardiology, electrophysiology, heart failure, and interventional cardiology.

ChatGPT has recently gained significant attention for its numerous potential applications in various fields of medicine, including precision medicine, medical education, clinical decision-making, and research. In this review, we further explore the current discourse on the use of artificial intelligence and ChatGPT in cardiovascular medicine and its major subspecialities and explore its potential applications.

2. Artificial Intelligence: A Brief Overview

While a broad term, AI encompasses various techniques from machine learning to deep learning to complete complex tasks similar to human intelligence. Machine learning involves strategies to self-learn from experience through exposure of data [8]. These strategies can be split either into supervised learning or unsupervised learning. Supervised learning uses a labeled dataset to predict a known outcome by selection and weighing features. Examples of supervised learning algorithms include linear regression, support vector machines, and random forest which can all be used for classification and regression analysis. Unsupervised learning uses unlabeled data to predict unknown associations. Examples of unsupervised learning algorithms include clustering and principal component analysis which are used for clustering, association, and dimensionality reduction. These machine learning models are used to create an artificial neural network (ANN) inspired by the organization of the human brain [9]. Deep learning involves a multilayered artificial neural network to produce abstract, nonlinear representations of data [9]. The most common forms are deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). The difference is based on how the layers of nodes are designed [8,9]. Deep learning neural networks require many layers stacked sequentially to create a feature map summarizing the presence of detected features in the input [9]. For instance, raw image data are typically transformed into features prior to input into CNNs [9]. A transformer model is a neural network that generates new text based on input attributes with parallel processing through an attention mechanism. ChatGPT (GPT-4) uses a transformer model trained on large language modeling data in an unsupervised manner. This model is then trained on smaller supervised datasets to solve specific tasks, in particular commonsense reasoning and reading comprehension. This method builds on the use of a specific type of RNN called long short-term memory (LSTM). AI technology differs in its applications and limitations for different data types. This requires the appropriate intelligent mathematical model for the dataset in question [8].

Materials and Methods

To identify relevant studies and retrieve the articles, a comprehensive search of the PubMed database was conducted. A combination of Medical Subject Heading (MeSH) terms and search words related to artificial intelligence and cardiovascular disease were used. MeSH and search terms included “artificial intelligence”, “AI”, “ChatGPT”, “cardiology”, and “cardiovascular disease”. Only English-language literature was included. Animal studies and review articles were excluded. A flow diagram outlining the search strategy, screening, and data extraction is highlighted in Figure 1.

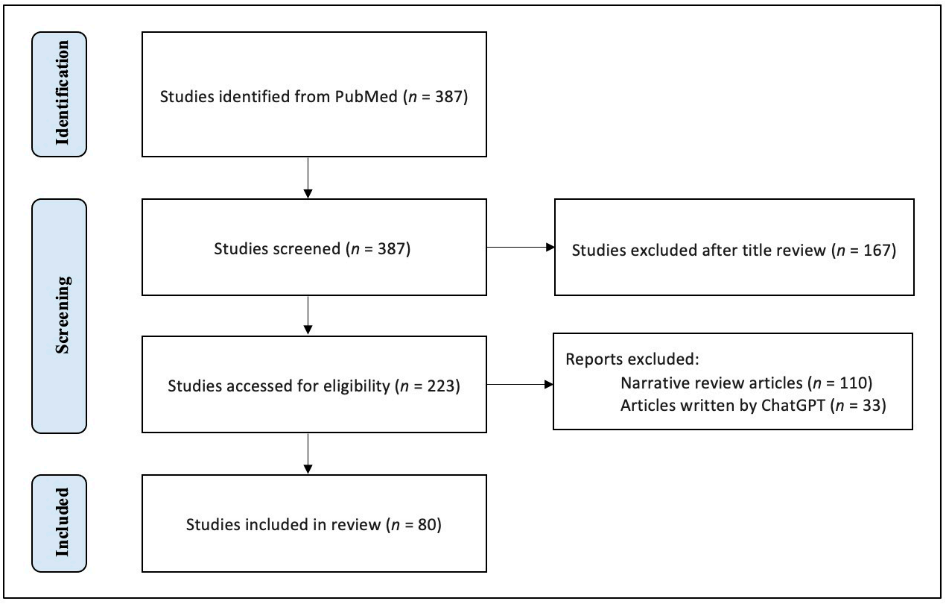

Figure 1. A flow diagram of study selection.

3. Applications and Utility of Artificial Intelligence in Cardiovascular Medicine Major Subspecialties (Figure 2)

3.1. Preventive Cardiology

With the expanse of AI in other fields of medicine, the preventive cardiologist may incorporate this growing information in their practice. Preventive cardiology focuses on the practice of primordial, primary, and secondary prevention of adult cardiovascular disease. Preventive cardiologists are typically well equipped with the necessary knowledge and skill set to focus on reducing death related to the growing global burden of cardiovascular disease [10]. Major cardiovascular disease risk factors include diabetes/cardiometabolic disease, hypertension, hyperlipidemia, chronic kidney disease (CKD), thrombosis, and inflammatory state [11–15].

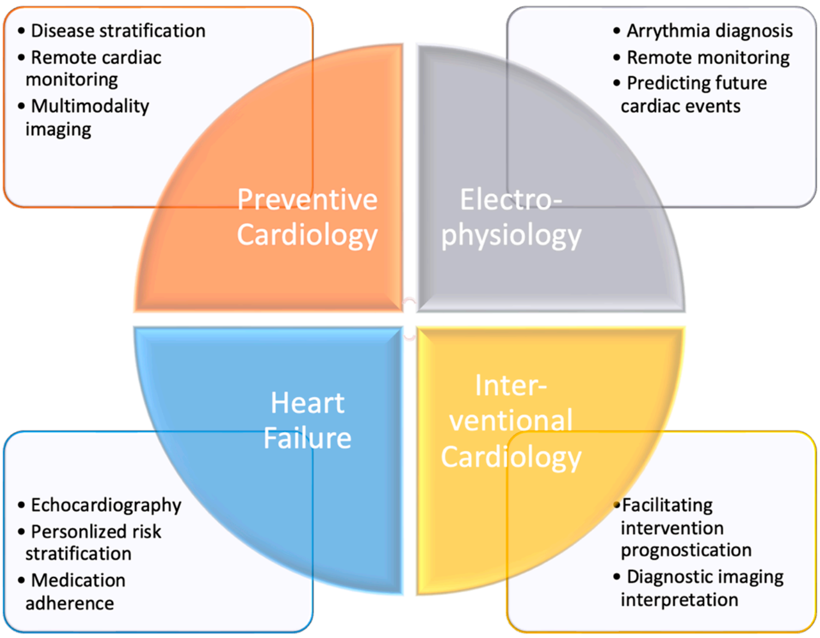

Figure 2. Applications and utility of artificial intelligence in cardiovascular medicine and its major subspecialties.

The increasing accessibility of AI language models make it a novel source for patients to seek information regarding their medical health issues. ChatGPT has shown potential in medical education to common patient questions, such as in diabetes self-management and education. ChatGPT performed well in understanding and providing accurate responses to patients' questions concerning their diabetes care, demonstrating strong patient-facing utility. It is important to note that language models like ChatGPT are limited by their data sets and are trained on general information databases. These models are not trained on specific medication information [16]. As such, these models do not have immediate access to external information and can only provide responses to the information that they were trained on. Furthermore, they may not be able to provide the most up-to-date information. This would impact the recommendation to patients for use of this technology. AI models are also enhancing prediction and diagnosis of complications of diabetes which can lead to adverse cardiovascular events [17]. Other AI models like machine learning algorithms have been used to predict factors contributing to hypertension and hyperlipidemia, which is particularly geared toward clinician use. Liao et al. created a pre-processing model to allow for electronic medical record (EMR) data to be used in machine learning processing to assess for trends and identify patients with known risk factors for hypertension and hyperlipidemia [18]. The use of machine learning to improve prediction performance of the so called "double-hyper disease" (hypertension and hyperlipidemia) has important practical and clinical significance. Machine learning has also demonstrated high sensitivity for predicting new-onset hypertension [17]. Another promising use of machine learning is photoplethysmography for blood pressure estimation [19], useful from both a patient-use and clinician standpoint, leading to more accurate continuous blood pressure monitoring. This is particularly useful from a preventive cardiology standpoint, given the increased global burden of hypertension and the associated morbidity and mortality. Integration of single sensor photoplethysmography into regular wearable devices would allow for development of a novel non-invasive, continuous way of monitoring—a technology that is not yet routinely available or approved for ambulatory outpatient use. Navdeep et al. highlight the novel AI algorithms, pulseData and Renalytix AI, to determine progression of CKD based on biomarkers from electronic health records [20]. Deep learning has even been shown to help detect acute kidney injury and renal failure progression requiring hemodialysis with a lead time up to 48 h [21]. As AI grows in other domains of medicine, it allows for better cardiovascular risk assessment for clinicians.

Preventive cardiologists use their clinical knowledge along with diagnostic investigations to minimize these risk factors and optimize patient outcomes [10]. The current direct applications of AI and ChatGPT are limited based on the limited publications listed on PubMed. However, based on the growing applications of AI in other fields of medicine, the preventive cardiologist will have an enhanced toolkit for effective patient care. As the field progresses, primary as well as secondary prevention models for disease management will require more integration of genetic, molecular, demographic, clinical, and environmental data. This provides an opportunity for a robust multidisciplinary team of basic scientists, clinicians, epidemiologists, computer scientists, and regulators for developing accessible platforms for further personalized medicine [21]. The use of machine learning and language learning models is promising in interpreting trends in patients' electronic health records, reducing administrative tasks such as note taking and appeal letters, and generating responses to common medical questions by patients. The limitations of AI and ChatGPT are based on the training dataset and have limited comprehension in medicine owing to no explicit training in healthcare or medical applications [22]. Another important implication with the use of language learning models is the reproducibility of its responses to avoid medical errors and patient harm [23]. As transformers move forward, physicians will be limited on their input due to the possibilities of "hallucinations" created by these models and the need for output verification [22]. The concept of AI hallucinations refers to the phenomenon whereby the model generates output and/or creates text that may be incorrect, nonsensical, or simply not real. The goal of most AI models is artificial general intelligence where training regimens allow models to attain general-purpose cognitive capability [22]. As the field of AI expands, the preventive cardiologist will have more tools to aid in diagnostic assessment of patients' overall risk and progression of cardiovascular disease and a more personalized approach with incorporation of their electronic health records.

3.2. Cardiac Electrophysiology

In the field of cardiology, one of the first applications of artificial intelligence was applied in electrocardiography (ECG). This was first performed by an ANN designed by Danssen et al. in 1990 to identify wide complex QRS as either SVT or VT. The ANN was able to correctly identify SVT in 93% of cases (86/92) and VT in 84% of cases (125/148) [24]. Some of the earliest work from the 1990s involves ANNs analyzing ECGs to localize the atrioventricular accessory pathway in patients with Wolff-Parkinson-White syndrome and achieving a 92% success rate [25]. AI can have several important applications in the field of cardiac electrophysiology, primarily enhancing the interpretation of electrolyte derangements, as well as diagnosis of structural cardiac disease, and arrhythmias [7], which can be particularly useful from a clinical standpoint with such applications geared toward clinician use. Abnormal atrial or ventricular rhythms are classified as cardiac arrhythmias and are estimated to affect anywhere from 1.5% to 5% of the general population [26]. Of these, atrial fibrillation remains the most prevalent arrhythmia in the aging population, and is a common illness encountered by cardiac electrophysiologists [26].

ECGs remain a key diagnostic tool for arrhythmias, and AI has been increasingly applied to ECG technology, aiding clinicians in establishing timely and accurate electrocardiographic diagnoses. The clinician-facing application of AI to ECG is twofold: to perform human-like tasks (i.e., ECG interpretation), and to extend human capability (i.e., extending ECG interpretation to disease screening and risk stratification) [21]. The ability of AI to perform the first task of ECG interpretation has been previously demonstrated on single lead and 12 lead ECG interpretations [27–32]. With regards to the second task, AI models have been able to detect diseases that may not have a pathognomonic ECG signature, including but not limited to pulmonary hypertension, hypertrophic cardiomyopathy, cardiac amyloidosis, neurotic stenosis, concealed long QT syndrome, atrial fibrillation, and COVID-19 [33–39].

AI such as ChatGPT also has considerable scope in arrhythmia detection and/or arrhythmia prediction with the advent of wearable smart devices, which have created opportunities for both patients and clinicians to measure physiologic data relevant to heart health [7]. These data can then be classified into clinically interpretable information, which can aid the clinician with identification of disease states and clinical decision support [7]. For example, AI has the capability to analyze pulse waveform data from optical sensor derived signals which can suggest the presence of an arrythmia such as atrial fibrillation [40,41]. The AliveCor Kardia (ACK) lead 1 ECG wearable devices have demonstrated sensitivity of 100% detecting atrial fibrillation and specificity of 94% detecting sinus rhythm. Wegner et al. demonstrated that a novel parasternal approach using the ACK device for atrial fibrillation detection can achieve similar high sensitivity and specificity, 96% and 97%, respectively [42]. Abdou and Krishnan summarize the current wearable ECG remote monitoring devices on the market [42]. These algorithms can also be applied to ECG data for similar detection purposes [28,43]. Overall, the algorithms to date only examine a small fraction of all available clinical data. With time and development of broader AI models, aggregation from multiple sensors with the potential of linkage of individuals to the healthcare enterprise through software operating on such devices, may be possible in the future [7].

Similar clinician-facing applications exist in management of cardiac implantable devices such as implantable cardioverter-defibrillators (ICDs) and cardiac resynchronization therapy (CRT) devices, as well as ablation and mapping. Westphal et al. demonstrated the feasibility of using machine learning to estimate left ventricular pressure (LVP) and maximal raise of LVP using a piezoelectric microphone embedded in a pulse generator to guide CRT optimization in AV delay. While this study had its limitations, it highlighted the novel approaches of AI models to improve CRT response [44]. Due to the significant interobserver variation and interpretation and significance of electrograms during ablation procedures, application of AI models can potentially be used for detection and mapping of cardiac arrhythmias, and to predict outcomes of implantable electronic device therapies [45–49]. Furthermore, novel intracardiac mapping modules incorporating machine learning have also been recently reported to accurately reconstruct left atrial and pulmonary vein anatomy during ablation procedures [7,50].

Future potential applications of AI in electrophysiology can be applied to improve our understanding of the genetic basis for cardiovascular and arrhythmia disorders. This can be applied to data from medical history, lifestyle, and mobile health data through wearables, rhythm monitoring, genomics, proteomics, and metabolomics. This can expand on work by Juhola et al. [51] in identifying abnormal calcium transient profiles in cardiomyocytes that may harbor mutations in genes associated with catecholaminergic polymorphic VT, long QT syndrome, and hypertrophic cardiomyopathy. AI has the potential for significant impact on patient care; however, it will need to demonstrate training and validation of data sources that represent the US population, cover the intended patient population, independent training and validation sources, and prespecified analysis and endpoints if it will be accepted by the FDA to interact with devices. An important concern for AI in the field of electrophysiology is the concept of "overfitting", where computational algorithms have poor generalizability when applied to an actual test or untrained data [21]. Such algorithms typically perform well during the training period yet demonstrate poor generalizability during actual practical testing. The problem can be addressed by providing high-quality data for training, along with close monitoring during the training period.

3.3. Advanced Heart Failure and Circulatory Support

The natural history of heart failure is characterized by periods of clinical stability, alternating with phases of exacerbation, eventually resulting in a progressive decline in a patient's functional capacity [17,52]. Artificial intelligence and machine learning has attempted to simplify several aspects of heart failure care from a clinician standpoint, including diagnosis, classification, estimation of severity, and prediction of rehospitalization [17].

Echocardiography plays a pivotal role in evaluating underlying cardiac structure and function in patients with heart failure, but this technique remains highly dependent on the individual sonographer's experience for acquisition of images, as well as subjective interpretation by an expert reader, typically a cardiologist [53]. Machine learning platforms geared toward echocardiography have been previously developed and tested [54], and may significantly aid clinicians with establishing timely diagnoses based on echocardiographic data. Early studies on artificial intelligence through neural networks with echocardiographic datasets demonstrated high sensitivity and specificity in prognostication [55]. Binder et al. in 1999 applied ANN to segment echocardiographic images into either blood or tissue regions with good interrater agreement when compared to manual interpretation by two separate investigators [56]. This was even demonstrated in poor image quality [56]. Image acquisition has been made easier with the introduction of AI to guide users in limited echocardiography. This will facilitate immediate interrogation of cardiac structures and function. AI models can be expected to expand echocardiographic interpretation using unsupervised machine learning models to extract information that may be used in assessment of myocardial textural characterization [57]. The FDA granted clearance for implementation of a machine learning algorithm for use in heart failure clinical practice. EchoGo Heart Failure, in collaboration with Mayo Clinic, uses AI to diagnose heart failure preserved ejection fraction (HFpEF) using a single apical four-chamber view on echocardiogram with greater than 90% accuracy [58].

Another example is HeartModel A.I. which uses AI segmentation algorithms and 3D echocardiography to measure cardiac volumes and function, which has been validated in prior studies [59]. Another example involves CNN-based algorithmic tools, which have been tested and are able to accurately segment the left ventricle, predict ejection fraction, and classify patients with heart failure with reduced ejection fraction [60,61]. Machine learning may help with further evaluation of left ventricular pressure changes through heart sounds [44]. Cardiac MRI (CMR) is a non-invasive imagine modality that produces high-quality images with soft tissue differentiation without exposure to ionizing radiation. Texture analysis of myocardium can be performed with high accuracy with the assistance of machine learning algorithms for the diagnosis of cardiomyopathy and predict risk of deterioration [62]. Such models are particularly useful to clinicians practicing in heart failure and transplantation cardiology.

Shade et al. demonstrated the use of machine learning using MRI-positron emission tomography fusion to assess the arrhythmogenic propensity of the remodeled substrate in cardiac sarcoid incorporating fibrosis infiltration and inflammation [63]. This resulted in the creation of Computational Heart and Artificial Intelligence (CHAI) Risk Predictor for patients with cardiac sarcoidosis. In a small cohort of 45 patients, the supervised machine learning was able to achieve sensitivity of 60%, specificity of 72%, and area under the receiver operating characteristic curve (AUROC) was 0.754. This model was able to outperform clinical metrics in predicting spontaneous cardiac death in cardiac sarcoidosis patients [63]. In terms of risk stratification, prediction of mortality [55], predicting adherence to medications [64], predicting responders to CRT [65], and predicting recurrent hospitalizations [66,67], AI algorithms have been developed and validated for patients with heart failure [7].

There is also scope for AI such as ChatGPT for patients with heart transplants or on advanced therapies, such as in the setting of post heart transplant management guidance. Prior models have attempted to target questions of detection of graph rejection and provide guidance on immunosuppression dosing [68–70]. An ANN-based model developed by Medved et al. was used to predict waitlist mortality, post-transplant survival, and similar heart allocation processes, particularly of use to clinicians [71]. The model was trained on both donor and recipient data and was able to predict, with significant accuracy, waitlist and post-transplant mortality, AUROC 89% and AUROC 66%, respectively. This demonstrated ANN use in heart allocation compared to conventional models. The ability of AI to utilize nonlinear interactions provides this novel approaches in predicting transplant waitlist mortality [72]. Lisboa et al. demonstrated similar accuracy using an interpretable model based on a model with fewer dimensions compared to deep learning models [73]. Interpretable models, such as generative additive models (GAMs), prioritize interpretability while maintaining accuracy. Similar to the convenience of ChatGPT, clinicians can stratify patients confidently using complex artificial intelligence [73]. Certain studies have also developed models to predict cyclosporin and tacrolimus levels, while incorporating medication history, and the patient's individual hepatic and renal function status, to guide medical therapy in this subset of patients [74,75].

Finally, there is a growing niche for post mechanical support outcome prediction and medication guidance and patients on advanced mechanical circulatory support therapies [76]. Growing AI technology such as ChatGPT can further extend this with potential utility in following up response to therapy for these patients in the outpatient setting, particularly useful for both patients and providers. Newer algorithms such as variational autoencoders (VAEs) have the potential to aid clinicians in prompter diagnosis, similar to transformer models. VAEs can assist in the generation of high-quality medical images and fill in missing parts of either damaged or partial echocardiographic images [58]. Similar to all fields of artificial intelligence, the performance of these complex computational algorithms is dependent on diverse, high-quality datasets and, in particular, labeled echocardiographic and cardiac MRI images.

3.4. Interventional Cardiology and Cardiovascular Imaging

Within the realm of interventional cardiology and cardiovascular imaging, machine learning and artificial intelligence have numerous clinician-facing applications including the potential to improve image construction, image interpretation, and data analysis [77,78]. Prior studies have shown that deep learning technology has the capability of precisely recognizing dissection, calcification, thrombus, and diameter of stenosis based on coronary angiography images, with high recall rates [79]. Du et al. demonstrated how a neural network can be used to label angiogram coronary arteries into 20 segments with high recognition accuracy and sensitivity (98% and 85%, respectively) similar to a SYNTAX (Synergy Between Percutaneous Coronary Intervention With Taxus and Cardiac Surgery) score [79]. A SYNTAX score is used to grade complexity of CAD and guide decision-making between PCI and coronary artery bypass graft (CABG). Notably, this study used a single center for training and testing. The lack of external validation potentially limits the generalizability of AI [80]. Additional studies have demonstrated high accuracy and high specificity of machine learning-based interpretation of coronary angiograms, as well as the utility of machine learning-based algorithms for segmenting intravascular ultrasound images, with excellent agreement with a human clinician expert in terms of calculating lumen area and plaque burden [81,82].

Radiomics is a process where a large number of quantitative image features are extracted for supervised machine learning models for data-characterization. This allows data mining and statistical classifiers to determine relevant features of an image for diagnosing abnormalities. Generative adversarial networks (GAN) use deep learning-based generative algorithms to solve generation and transformation problems in image processing [62]. An example of radiomic textural analysis, performed by Neisius et al., is its ability to differentiate hypertrophic cardiomyopathy from hypertensive heart disease on cardiovascular magnetic resonance images with an accuracy of 85.5% [62]. Coronary CT angiography (CCTA) is a useful diagnostic tool for screening and diagnosing coronary heart disease; however, it is limited by its examination quality, accuracy of reporting, and prognosis analysis. AI has demonstrated how it may optimize CCTA through radiation dose reduction without affecting image quality, reduce image noise and motion artifact, perform automatic segmentation, perform risk stratification through coronary artery calcium (CAC) assessment, and analyze coronary plaque and severity of stenosis [83], with all of these practical applications improving clinician efficiency and aiding with the diagnostic process. Wolterink et al. first trained a supervised machine learning system in 2014 to distinguish between true coronary calcifications and other candidate calcifications [84]. It demonstrated strong correlation to expert review and reduced processing time by more than a third [9]. AI can further improve risk assessment in CCTA by including the perivascular fat attenuation index [62]. Neural networks may also be applied to CMR for fully automated segmentation of heart chambers. These are often applied to myocardial infarction diagnosis in chronic settings and cardiac function [62].

Valvular heart disease is another frequently encountered pathology in structural heart disease cardiology. AI algorithms and machine learning-based models have been previously shown to accurately measure aortic annulus dimensions via cardiac computed tomography images [85,86]. Studies have also investigated similar parameters for measuring mitral annulus areas, with good correlation with manual measurements [87]. Overall, implementation of AI algorithms and ChatGPT within the realm of interventional cardiology can improve clinical diagnosis by applying algorithms to ECGs and non-invasive emerging modalities such as echocardiography and cardiac CT. This can also facilitate the appropriateness and prognostication of coronary or valvular interventions and play a role in prognosticating mortality and major adverse cardiovascular events [7,78]. Similarly, an interventionalist could use AI models to analyze angiographic images in real time to calculate SYNTAX scores and offer suggestions or interpretations [80].

4. Future Direction for Applications of Artificial Intelligence and ChatGPT in Cardiovascular Medicine

With ongoing advancements in the field, ChatGPT and other AI technologies hold great promise for advancing patient care, enhancing research, and improving diagnostics in the field of cardiovascular medicine. Future directions for areas of improvement and development encompass enhancing diagnostic capabilities, personalizing medicine, predictive analytics and risk stratification, remote monitoring and telemedicine, clinical decision support, and medical research in the field. Leveraging the utility of large language models, machine learning and artificial intelligence can help gain further efficiency in this field.

AI and ChatGPT can continue to evolve as powerful diagnostic tools through the ability of analyzing vast amounts of data ("big data"), and aid with both accurate and early detection of cardiovascular disease. Growth in AI is dependent on datasets on which to train their models. A push towards open and large datasets can help improve neural networks and language models. This also offers a point for external validation for generalizability. As AI algorithms develop, they can be combined with patient-specific data to tailor personalized, individualized treatment plans for patients. ChatGPT may play a pivotal role in explaining such personalized treatment plans to patients through its capabilities of interacting in human-like ways through text outputs. Moreover, as these algorithms develop, patient data integration with wearable devices can facilitate risk stratification and allow ChatGPT to assist in conveying risk assessment results to patients and their providers in a timely manner. Integration of AI algorithm outputs into clinical decision support systems can also assist healthcare providers in real time, evidence based, decision-making for patients. In this regard, ChatGPT may be able to act as an interactive interface with decision support systems by providing explanations, answering questions, and offering insights into the underlying rationale of clinical decisions, supported by evidence. Lastly, research capabilities and drug development can potentially be accelerated in cardiology by utilizing AI algorithms for analysis of vast amounts of scientific literature in a short period of time. ChatGPT could assist with aspects such as literature review and their interpretation, highly enhancing researcher efficiency.

As research remains ongoing in this field, it is important to note that although there is significant potential, integration of AI into clinical practice warrants caution, adherence to regulatory standards, strict data privacy, and maintenance of human expertise and judgment of clinical data interpretation. The pitfalls of ChatGPT raise many questions, in particular, medical ethics [88]. AI applications require clear explanations of algorithmic decisions (explainable AI) so that human expertise and clinical judgement can be made with certainty. This must also not come at the cost of accuracy. Most algorithmic decisions through deep learning are often difficult to understand due to its "black box" nature. Future directions can lead to enhancing trust among users and adoption of AI [80].

5. Conclusions

There are numerous promising applications of ChatGPT and AI, which will likely improve efficiency in cardiovascular medicine healthcare practice. The utility of ChatGPT in this field comes with numerous benefits in areas such as diagnostic capabilities, personalized medicine, predictive analytics, risk stratification, remote monitoring, telemedicine, clinical decision support, and medical research. Nevertheless, there are limitations and issues surrounding data privacy, algorithm transparency, accountability, inaccuracy, and inadequacy of said algorithms and machine-based models. Integration of AI and ChatGPT into routine clinical practice in cardiovascular medicine warrants caution, adherence to regulatory standards, strict data privacy, and maintenance of human expertise and judgment of clinical data interpretation. Future directions for improvement and development encompass enhancing diagnostic capabilities, personalizing medicine, predictive analytics and risk stratification, remote monitoring and telemedicine, clinical decision support, and medical research in the field (Figure 3). Leveraging the utility of large language models, machine learning, and artificial intelligence can help gain further efficiency in this field

(Figure 4). Future studies are warranted to evaluate the practical applicability of AI models in a real-world setting, assess for reproducibility of results using larger samples, and to evaluate reliability. Overall, given several benefits and potential applications in cardiovascular medicine, pending further studies ChatGPT may serve to be an extremely valuable resource in cardiovascular medicine and its subspecialties.

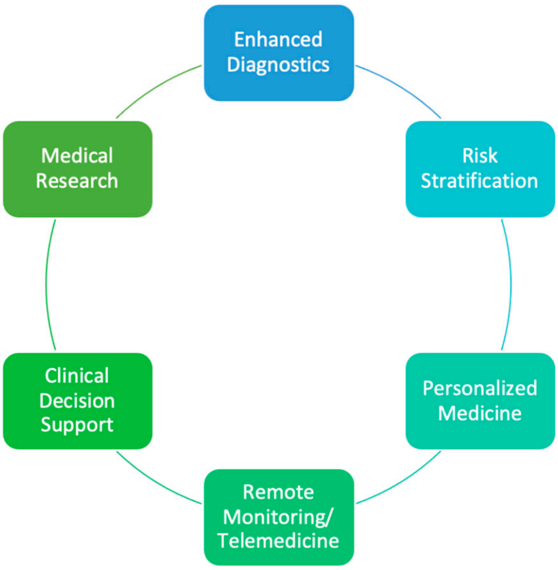

Figure 3. Potential areas of development and enhancement for ChatGPT in cardiovascular medicine.

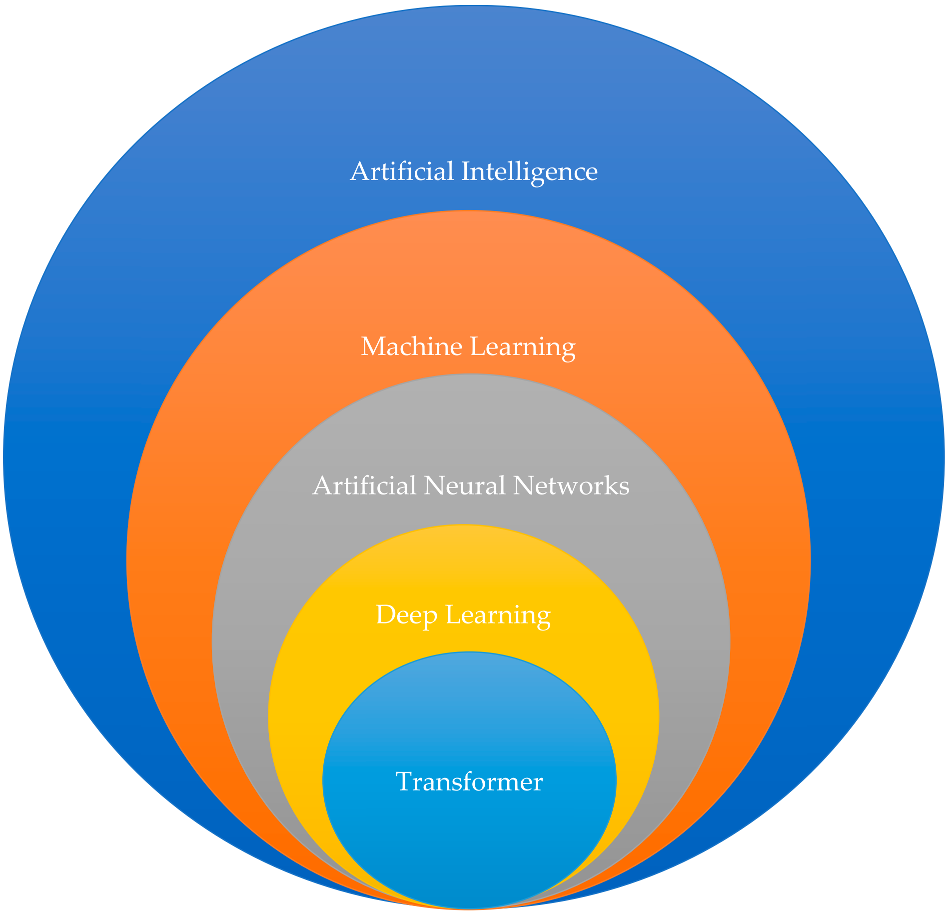

Figure 4. Basics of artificial general intelligence, machine learning, deep learning, and transformer.

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References

1. Sallam, M. ChatGPT Utility in Healthcare Education, Research, and Practice: Systematic Review on the Promising Perspectives and Valid Concerns. *Healthcare* **2023**, *11*, 887. [CrossRef]
2. Korteling, J.E.H.; van de Boer-Visschedijk, G.C.; Blankendaal, R.a.M.; Boonekamp, R.C.; Eikelboom, A.R. Human- versus Artificial Intelligence. *Front. Artif. Intell.* **2021**, *4*, 622364. [CrossRef] [PubMed]
3. Sarker, I.H. AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Comput. Sci.* **2022**, *3*, 158. [CrossRef] [PubMed]
4. OpenAI. OpenAI: Models GPT-3. Available online: https://beta.openai.com/docs/models (accessed on 9 May 2023).
5. Brown, T.B.; Mann, B.; Ryder, N.; Subbiah, M.; Kaplan, J.; Dhariwal, P.; Neelakantan, A.; Shyam, P.; Sastry, G.; Askell, A.; et al. Language Models are Few-Shot Learners. *arXiv* **2020**, arXiv:2005.14165. [CrossRef]
6. King, M.R.; ChatGPT. A Conversation on Artificial Intelligence, Chatbots, and Plagiarism in Higher Education. *Cell. Mol. Bioeng.* **2023**, *16*, 1–2. [CrossRef]
7. Haq, I.U.; Chhatwal, K.; Sanaka, K.; Xu, B. Artificial Intelligence in Cardiovascular Medicine: Current Insights and Future Prospects. *Vasc. Health Risk Manag.* **2022**, *18*, 517–528. [CrossRef]
8. Johnson, K.W.; Torres Soto, J.; Glicksberg, B.S.; Shameer, K.; Miotto, R.; Ali, M.; Ashley, E.; Dudley, J.T. Artificial Intelligence in Cardiology. *J. Am. Coll. Cardiol.* **2018**, *71*, 2668–2679. [CrossRef]
9. Lin, A.; Kolossváry, M.; Motwani, M.; Išgum, I.; Maurovich-Horvat, P.; Slomka, P.J.; Dey, D. Artificial Intelligence in Cardiovascular Imaging for Risk Stratification in Coronary Artery Disease. *Radiol. Cardiothorac. Imaging* **2021**, *3*, e200512. [CrossRef]
10. German, C.A.; Baum, S.J.; Ferdinand, K.C.; Gulati, M.; Polonsky, T.S.; Toth, P.P.; Shapiro, M.D. Defining preventive cardiology: A clinical practice statement from the American Society for Preventive Cardiology. *Am. J. Prev. Cardiol.* **2022**, *12*, 100432. [CrossRef] [PubMed]
11. Dawber, T.R.; Kannel, W.B.; Revotskie, N.; Stokes, J.; Kagan, A.; Gordon, T. Some Factors Associated with the Development of Coronary Heart Disease—Six Years' Follow-Up Experience in the Framingham Study. *Am. J. Public Health Nations Health* **1959**, *49*, 1349–1356. [CrossRef]
12. Kannel, W.B. Factors of Risk in the Development of Coronary Heart Disease—Six-Year Follow-Up Experience: The Framingham Study. *Ann. Intern. Med.* **1961**, *55*, 33. [CrossRef]
13. Kannel, W.B. Habitual level of physical activity and risk of coronary heart disease: The Framingham study. *Can. Med. Assoc. J.* **1967**, *96*, 811–812.
14. Kannel, W.B.; Lebauer, E.J.; Dawber, T.R.; Mcnamara, P.M. Relation of Body Weight to Development of Coronary Heart Disease: The Framingham Study. *Circulation* **1967**, *35*, 734–744. [CrossRef]
15. Kannel, W.B.; McGee, D.L. Diabetes and cardiovascular risk factors: The Framingham study. *Circulation* **1979**, *59*, 8–13. [CrossRef]
16. Sng, G.G.R.; Tung, J.Y.M.; Lim, D.Y.Z.; Bee, Y.M. Potential and Pitfalls of ChatGPT and Natural-Language Artificial Intelligence Models for Diabetes Education. *Diabetes Care* **2023**, *46*, e103–e105. [CrossRef]
17. Ciccarelli, M.; Giallauria, F.; Carrizzo, A.; Visco, V.; Silverio, A.; Cesaro, A.; Calabrò, P.; De Luca, N.; Mancusi, C.; Masarone, D.; et al. Artificial intelligence in cardiovascular prevention: New ways will open new doors. *J. Cardiovasc. Med.* **2023**, *24* (Suppl. S2), e106–e115. [CrossRef]
18. Liao, B.; Jia, X.; Zhang, T.; Sun, R. DHDIP: An interpretable model for hypertension and hyperlipidemia prediction based on EMR data. *Comput. Methods Programs Biomed.* **2022**, *226*, 107088. [CrossRef]
19. Elgendi, M.; Fletcher, R.; Liang, Y.; Howard, N.; Lovell, N.H.; Abbott, D.; Lim, K.; Ward, R. The use of photoplethysmography for assessing hypertension. *NPJ Digit. Med.* **2019**, *2*, 60. [CrossRef]
20. Tangri, N.; Ferguson, T.W. Artificial Intelligence in the Identification, Management, and Follow-Up of CKD. *Kidney360* **2022**, *3*, 554–556. [CrossRef]
21. Kabra, R.; Israni, S.; Vijay, B.; Baru, C.; Mendu, R.; Fellman, M.; Sridhar, A.; Mason, P.; Cheung, J.W.; DiBiase, L.; et al. Emerging role of artificial intelligence in cardiac electrophysiology. *Cardiovasc. Digit. Health J.* **2022**, *3*, 263–275. [CrossRef]
22. Lee, P.; Bubeck, S.; Petro, J. Benefits, Limits, and Risks of GPT-4 as an AI Chatbot for Medicine. *N. Engl. J. Med.* **2023**, *388*, 1233–1239. [CrossRef]
23. Kataoka, Y.; So, R. Benefits, Limits, and Risks of GPT-4 as an AI Chatbot for Medicine. *N. Engl. J. Med.* **2023**, *388*, 2399–2400. [CrossRef]
24. Dassen, W.R.M.; Mulleneers, R.; Smeets, J.; Den Dulk, K.; Cruz, F.; Brugada, P.; Wellens, H.J.J. Self-learning neural networks in electrocardiography. *J. Electrocardiol.* **1990**, *23*, 200–202. [CrossRef]

25. Dassen, W.R.M.; Mulleneers, R.G.A.; Dulk, K.D.; Smeets, J.R.L.M.; Cruz, F.; Penn, O.C.K.M.; Wellens, H.J.J. An Artificial Neural Network to Localize Atrioventricular Accessory Pathways in Patients Suffering from the Wolff-Parkinson-White Syndrome. *Pacing Clin. Electrophysiol.* **1990**, *13*, 1792–1796. [CrossRef]
26. January, C.T.; Wann, L.S.; Calkins, H.; Chen, L.Y.; Cigarroa, J.E.; Cleveland, J.C.; Ellinor, P.T.; Ezekowitz, M.D.; Field, M.E.; Furie, K.L.; et al. 2019 AHA/ACC/HRS Focused Update of the 2014 AHA/ACC/HRS Guideline for the Management of Patients with Atrial Fibrillation: A Report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines and the Heart Rhythm Society in Collaboration with the Society of Thoracic Surgeons. *Circulation* **2019**, *140*, e125–e151. [CrossRef]
27. Giudicessi, J.R.; Schram, M.; Bos, J.M.; Galloway, C.D.; Shreibati, J.B.; Johnson, P.W.; Carter, R.E.; Disrud, L.W.; Kleiman, R.; Attia, Z.I.; et al. Artificial Intelligence–Enabled Assessment of the Heart Rate Corrected QT Interval Using a Mobile Electrocardiogram Device. *Circulation* **2021**, *143*, 1274–1286. [CrossRef]
28. Hannun, A.Y.; Rajpurkar, P.; Haghpanahi, M.; Tison, G.H.; Bourn, C.; Turakhia, M.P.; Ng, A.Y. Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nat. Med.* **2019**, *25*, 65–69. [CrossRef]
29. Acharya, U.R.; Fujita, H.; Lih, O.S.; Hagiwara, Y.; Tan, J.H.; Adam, M. Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. *Inf. Sci.* **2017**, *405*, 81–90. [CrossRef]
30. Kashou, A.H.; Ko, W.-Y.; Attia, Z.I.; Cohen, M.S.; Friedman, P.A.; Noseworthy, P.A. A comprehensive artificial intelligence–enabled electrocardiogram interpretation program. *Cardiovasc. Digit. Health J.* **2020**, *1*, 62–70. [CrossRef]
31. Hughes, J.W.; Olgin, J.E.; Avram, R.; Abreau, S.A.; Sittler, T.; Radia, K.; Hsia, H.; Walters, T.; Lee, B.; Gonzalez, J.E.; et al. Performance of a Convolutional Neural Network and Explainability Technique for 12-Lead Electrocardiogram Interpretation. *JAMA Cardiol.* **2021**, *6*, 1285. [CrossRef]
32. Xiong, Z.; Stiles, M.; Zhao, J. Robust ECG Signal Classification for the Detection of Atrial Fibrillation Using Novel Neural Networks. In Proceedings of the 2017 Computing in Cardiology (CinC), Rennes, France, 24–27 September 2017. [CrossRef]
33. Attia, Z.I.; Noseworthy, P.A.; Lopez-Jimenez, F.; Asirvatham, S.J.; Deshmukh, A.J.; Gersh, B.J.; Carter, R.E.; Yao, X.; Rabinstein, A.A.; Erickson, B.J.; et al. An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: A retrospective analysis of outcome prediction. *Lancet* **2019**, *394*, 861–867. [CrossRef] [PubMed]
34. Tison, G.H.; Zhang, J.; Delling, F.N.; Deo, R.C. Automated and Interpretable Patient ECG Profiles for Disease Detection, Tracking, and Discovery. *Circ. Cardiovasc. Qual. Outcomes* **2019**, *12*, e005289. [CrossRef] [PubMed]
35. Grogan, M.; Lopez-Jimenez, F.; Cohen-Shelly, M.; Dispenzieri, A.; Attia, Z.I.; Abou Ezzedine, O.F.; Lin, G.; Kapa, S.; Borgeson, D.D.; Friedman, P.A.; et al. Artificial Intelligence–Enhanced Electrocardiogram for the Early Detection of Cardiac Amyloidosis. *Mayo Clin. Proc.* **2021**, *96*, 2768–2778. [CrossRef] [PubMed]
36. Siontis, K.C.; Liu, K.; Bos, J.M.; Attia, Z.I.; Cohen-Shelly, M.; Arruda-Olson, A.M.; Zanjirani Farahani, N.; Friedman, P.A.; Noseworthy, P.A.; Ackerman, M.J. Detection of hypertrophic cardiomyopathy by an artificial intelligence electrocardiogram in children and adolescents. *Int. J. Cardiol.* **2021**, *340*, 42–47. [CrossRef] [PubMed]
37. Cohen-Shelly, M.; Attia, Z.I.; Friedman, P.A.; Ito, S.; Essayagh, B.A.; Ko, W.-Y.; Murphree, D.H.; Michelena, H.I.; Enriquez-Sarano, M.; Carter, R.E.; et al. Electrocardiogram screening for aortic valve stenosis using artificial intelligence. *Eur. Heart J.* **2021**, *42*, 2885–2896. [CrossRef] [PubMed]
38. Attia, Z.I.; Kapa, S.; Dugan, J.; Pereira, N.; Noseworthy, P.A.; Jimenez, F.L.; Cruz, J.; Carter, R.E.; DeSimone, D.C.; Signorino, J.; et al. Rapid Exclusion of COVID Infection With the Artificial Intelligence Electrocardiogram. *Mayo Clin. Proc.* **2021**, *96*, 2081–2094. [CrossRef] [PubMed]
39. Bos, J.M.; Attia, Z.I.; Albert, D.E.; Noseworthy, P.A.; Friedman, P.A.; Ackerman, M.J. Use of Artificial Intelligence and Deep Neural Networks in Evaluation of Patients with Electrocardiographically Concealed Long QT Syndrome from the Surface 12-Lead Electrocardiogram. *JAMA Cardiol.* **2021**, *6*, 532. [CrossRef]
40. Perez, M.V.; Mahaffey, K.W.; Hedlin, H.; Rumsfeld, J.S.; Garcia, A.; Ferris, T.; Balasubramanian, V.; Russo, A.M.; Rajmane, A.; Cheung, L.; et al. Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation. *N. Engl. J. Med.* **2019**, *381*, 1909–1917. [CrossRef]
41. Pereira, T.; Tran, N.; Gadhoumi, K.; Pelter, M.M.; Do, D.H.; Lee, R.J.; Colorado, R.; Meisel, K.; Hu, X. Photoplethysmography based atrial fibrillation detection: A review. *NPJ Digit. Med.* **2020**, *3*, 3. [CrossRef]
42. Abdou, A.; Krishnan, S. Horizons in Single-Lead ECG Analysis From Devices to Data. *Front. Signal Process.* **2022**, *2*, 866047. [CrossRef]
43. Willcox, M.E.; Compton, S.J.; Bardy, G.H. Continuous ECG monitoring versus mobile telemetry: A comparison of arrhythmia diagnostics in human- versus algorithmic-dependent systems. *Heart Rhythm. O2* **2021**, *2*, 543–559. [CrossRef] [PubMed]
44. Westphal, P.; Luo, H.; Shahmohammadi, M.; Prinzen, F.W.; Delhaas, T.; Cornelussen, R.N. Machine learning-powered, device-embedded heart sound measurement can optimize AV delay in patients with CRT. *Heart Rhythm* **2023**, *20*, 1316–1324. [CrossRef] [PubMed]
45. Missel, R.; Gyawali, P.K.; Murkute, J.V.; Li, Z.; Zhou, S.; AbdelWahab, A.; Davis, J.; Warren, J.; Sapp, J.L.; Wang, L. A hybrid machine learning approach to localizing the origin of ventricular tachycardia using 12-lead electrocardiograms. *Comput. Biol. Med.* **2020**, *126*, 104013. [CrossRef] [PubMed]
46. Yu, J.; Wang, X.; Chen, X.; Guo, J. Automatic Premature Ventricular Contraction Detection Using Deep Metric Learning and KNN. *Biosensors* **2021**, *11*, 69. [CrossRef]

47. Liu, C.-M.; Chang, S.-L.; Chen, H.-H.; Chen, W.-S.; Lin, Y.-J.; Lo, L.-W.; Hu, Y.-F.; Chung, F.-P.; Chao, T.-F.; Tuan, T.-C.; et al. The Clinical Application of the Deep Learning Technique for Predicting Trigger Origins in Patients With Paroxysmal Atrial Fibrillation With Catheter Ablation. *Circ. Arrhythm. Electrophysiol.* **2020**, *13*, e008518. [CrossRef]
48. Lee, J.-H.; Kwon, O.-S.; Shim, J.; Lee, J.; Han, H.-J.; Yu, H.T.; Kim, T.-H.; Uhm, J.-S.; Joung, B.; Lee, M.-H.; et al. Left Atrial Wall Stress and the Long-Term Outcome of Catheter Ablation of Atrial Fibrillation: An Artificial Intelligence-Based Prediction of Atrial Wall Stress. *Front. Physiol.* **2021**, *12*, 686507. [CrossRef] [PubMed]
49. Zou, F.; Brahier, M.; Migliarese, F.; Ma, X.; Wu, C.; Taylor, A.; Sandfort, V.; Thomaides, A.; Vargas, J. B-PO03-076 a machine learning-derived recurrence risk model for atrial fibrillation after catheter ablation. *Heart Rhythm* **2021**, *18*, S219–S220. [CrossRef]
50. Schwartz, A.L.; Chorin, E.; Mann, T.; M., Y.L.; Hochstadt, A.; Margolis, G.; Viskin, S.; Banai, S.; Rosso, R. Reconstruction of the left atrium for atrial fibrillation ablation using the machine learning CARTO 3 m-FAM software. *J. Interv. Card. Electrophysiol.* **2022**, *64*, 39–47. [CrossRef]
51. Juhola, M.; Penttinen, K.; Joutsijoki, H.; Varpa, K.; Saarikoski, J.; Rasku, J.; Siirtola, H.; Iltanen, K.; Laurikkala, J.; Hyyrö, H. Signal analysis and classification methods for the calcium transient data of stem cell-derived cardiomyocytes. *Comput. Biol. Med.* **2015**, *61*, 1–7. [CrossRef]
52. Visco, V.; Radano, I.; Campanile, A.; Ravera, A.; Silverio, A.; Masarone, D.; Pacileo, G.; Correale, M.; Mazzeo, P.; Dattilo, G.; et al. Predictors of sacubitril/valsartan high dose tolerability in a real world population with HFrEF. *ESC Heart Fail.* **2022**, *9*, 2909–2917. [CrossRef]
53. McDonagh, T.A.; Metra, M.; Adamo, M.; Gardner, R.S.; Baumbach, A.; Böhm, M.; Burri, H.; Butler, J.; Čelutkienė, J.; Chioncel, O.; et al. 2021 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure. *Eur. Heart J.* **2021**, *42*, 3599–3726. [CrossRef]
54. Romiti, S.; Vinciguerra, M.; Saade, W.; Anso Cortajarena, I.; Greco, E. Artificial Intelligence (AI) and Cardiovascular Diseases: An Unexpected Alliance. *Cardiol. Res. Pract.* **2020**, *2020*, 4972346. [CrossRef]
55. Ortiz, J.; Ghefter, C.G.; Silva, C.E.; Sabbatini, R.M. One-year mortality prognosis in heart failure: A neural network approach based on echocardiographic data. *J. Am. Coll. Cardiol.* **1995**, *26*, 1586–1593. [CrossRef] [PubMed]
56. Binder, T.; Süssner, M.; Moertl, D.; Strohmer, T.; Baumgartner, H.; Maurer, G.; Porenta, G. Artificial neural networks and spatial temporal contour linking for automated endocardial contour detection on echocardiograms: A novel approach to determine left ventricular contractile function. *Ultrasound Med. Biol.* **1999**, *25*, 1069–1076. [CrossRef] [PubMed]
57. Yoon, Y.E.; Kim, S.; Chang, H.J. Artificial Intelligence and Echocardiography. *J. Cardiovasc. Imaging* **2021**, *29*, 193–204. [CrossRef] [PubMed]
58. Khan, M.S.; Arshad, M.S.; Greene, S.J.; Van Spall, H.G.C.; Pandey, A.; Vemulapalli, S.; Perakslis, E.; Butler, J. Artificial intelligence and heart failure: A state-of-the-art review. *Eur. J. Heart Fail.* **2023**, *25*, 1507–1525. [CrossRef]
59. Medvedofsky, D.; Mor-Avi, V.; Amzulescu, M.; Fernández-Golfín, C.; Hinojar, R.; Monaghan, M.J.; Otani, K.; Reiken, J.; Takeuchi, M.; Tsang, W.; et al. Three-dimensional echocardiographic quantification of the left-heart chambers using an automated adaptive analytics algorithm: Multicentre validation study. *Eur. Heart J. Cardiovasc. Imaging* **2018**, *19*, 47–58. [CrossRef]
60. Sun, J.; Qiu, Y.; Guo, H.; Hua, Y.; Shao, B.; Qiao, Y.; Guo, J.; Ding, H.; Zhang, Z.; Miao, L.; et al. A method to screen left ventricular dysfunction through ECG based on convolutional neural network. *J. Cardiovasc. Electrophysiol.* **2021**, *32*, 1095–1102. [CrossRef]
61. Ouyang, D.; He, B.; Ghorbani, A.; Yuan, N.; Ebinger, J.; Langlotz, C.P.; Heidenreich, P.A.; Harrington, R.A.; Liang, D.H.; Ashley, E.A.; et al. Video-based AI for beat-to-beat assessment of cardiac function. *Nature* **2020**, *580*, 252–256. [CrossRef]
62. Jiang, B.; Guo, N.; Ge, Y.; Zhang, L.; Oudkerk, M.; Xie, X. Development and application of artificial intelligence in cardiac imaging. *Br. J. Radiol.* **2020**, *93*, 20190812. [CrossRef]
63. Shade, J.K.; Prakosa, A.; Popescu, D.M.; Yu, R.; Okada, D.R.; Chrispin, J.; Trayanova, N.A. Predicting risk of sudden cardiac death in patients with cardiac sarcoidosis using multimodality imaging and personalized heart modeling in a multivariable classifier. *Sci. Adv.* **2021**, *7*, eabi8020. [CrossRef]
64. Son, Y.-J.; Kim, H.-G.; Kim, E.-H.; Choi, S.; Lee, S.-K. Application of Support Vector Machine for Prediction of Medication Adherence in Heart Failure Patients. *Healthc. Inform. Res.* **2010**, *16*, 253. [CrossRef]
65. Cikes, M.; Sanchez-Martinez, S.; Claggett, B.; Duchateau, N.; Piella, G.; Butakoff, C.; Pouleur, A.C.; Knappe, D.; Biering-Sørensen, T.; Kutyifa, V.; et al. Machine learning-based phenogrouping in heart failure to identify responders to cardiac resynchronization therapy. *Eur. J. Heart Fail.* **2019**, *21*, 74–85. [CrossRef]
66. Stehlik, J.; Schmalfuss, C.; Bozkurt, B.; Nativi-Nicolau, J.; Wohlfahrt, P.; Wegerich, S.; Rose, K.; Ray, R.; Schofield, R.; Deswal, A.; et al. Continuous Wearable Monitoring Analytics Predict Heart Failure Hospitalization: The LINK-HF Multicenter Study. *Circ. Heart Fail.* **2020**, *13*, e006513. [CrossRef]
67. Kang, Y.; McHugh, M.D.; Chittams, J.; Bowles, K.H. Utilizing Home Healthcare Electronic Health Records for Telehomecare Patients With Heart Failure: A Decision Tree Approach to Detect Associations With Rehospitalizations. *CIN Comput. Inform. Nurs.* **2016**, *34*, 175–182. [CrossRef]
68. Piening, B.D.; Dowdell, A.K.; Zhang, M.; Loza, B.-L.; Walls, D.; Gao, H.; Mohebnasab, M.; Li, Y.R.; Elftmann, E.; Wei, E.; et al. Whole transcriptome profiling of prospective endomyocardial biopsies reveals prognostic and diagnostic signatures of cardiac allograft rejection. *J. Heart Lung Transplant.* **2022**, *41*, 840–848. [CrossRef]

69. Peyster, E.G.; Arabyarmohammadi, S.; Janowczyk, A.; Azarianpour-Esfahani, S.; Sekulic, M.; Cassol, C.; Blower, L.; Parwani, A.; Lal, P.; Feldman, M.D.; et al. An automated computational image analysis pipeline for histological grading of cardiac allograft rejection. *Eur. Heart J.* **2021**, *42*, 2356–2369. [CrossRef]
70. Lipkova, J.; Chen, T.Y.; Lu, M.Y.; Chen, R.J.; Shady, M.; Williams, M.; Wang, J.; Noor, Z.; Mitchell, R.N.; Turan, M.; et al. Deep learning-enabled assessment of cardiac allograft rejection from endomyocardial biopsies. *Nat. Med.* **2022**, *28*, 575–582. [CrossRef] [PubMed]
71. Medved, D.; Ohlsson, M.; Höglund, P.; Andersson, B.; Nugues, P.; Nilsson, J. Improving prediction of heart transplantation outcome using deep learning techniques. *Sci. Rep.* **2018**, *8*, 3613. [CrossRef] [PubMed]
72. Gotlieb, N.; Azhie, A.; Sharma, D.; Spann, A.; Suo, N.-J.; Tran, J.; Orchanian-Cheff, A.; Wang, B.; Goldenberg, A.; Chassé, M.; et al. The promise of machine learning applications in solid organ transplantation. *NPJ Digit. Med.* **2022**, *5*, 89. [CrossRef] [PubMed]
73. Lisboa, P.J.G.; Jayabalan, M.; Ortega-Martorell, S.; Olier, I.; Medved, D.; Nilsson, J. Enhanced survival prediction using explainable artificial intelligence in heart transplantation. *Sci. Rep.* **2022**, *12*, 19525. [CrossRef]
74. Hoda, M.R.; Grimm, M.; Laufer, G. Prediction of Cyclosporine Blood Levels in Heart Transplantation Patients Using a Pharmacokinetic Model Identified by Evolutionary Algorithms. *J. Heart Lung Transplant.* **2005**, *24*, 1855–1862. [CrossRef]
75. Woillard, J.; Labriffe, M.; Debord, J.; Marquet, P. Tacrolimus Exposure Prediction Using Machine Learning. *Clin. Pharmacol. Ther.* **2021**, *110*, 361–369. [CrossRef]
76. Al-Ani, M.A.; Bai, C.; Hashky, A.; Parker, A.M.; Vilaro, J.R.; Aranda, J.M., Jr.; Shickel, B.; Rashidi, P.; Bihorac, A.; Ahmed, M.M.; et al. Artificial intelligence guidance of advanced heart failure therapies: A systematic scoping review. *Front. Cardiovasc. Med.* **2023**, *10*, 1127716. [CrossRef]
77. Henglin, M.; Stein, G.; Hushcha, P.V.; Snoek, J.; Wiltschko, A.B.; Cheng, S. Machine Learning Approaches in Cardiovascular Imaging. *Circ. Cardiovasc. Imaging* **2017**, *10*, e005614. [CrossRef]
78. Subhan, S.; Malik, J.; Haq, A.U.; Qadeer, M.S.; Zaidi, S.M.J.; Orooj, F.; Zaman, H.; Mehmoodi, A.; Majeedi, U. Role of Artificial Intelligence and Machine Learning in Interventional Cardiology. *Curr. Probl. Cardiol.* **2023**, *48*, 101698. [CrossRef] [PubMed]
79. Du, T.; Xie, L.; Liu, X. Intelligent recognition of coronary angiography by deep learning technology: A novel computer-aided diagnostic system. *J. Am. Coll. Cardiol.* **2018**, *72*, B98. [CrossRef]
80. Molenaar, M.A.; Selder, J.L.; Nicolas, J.; Claessen, B.E.; Mehran, R.; Bescós, J.O.; Schuuring, M.J.; Bouma, B.J.; Verouden, N.J.; Chamuleau, S.A.J. Current State and Future Perspectives of Artificial Intelligence for Automated Coronary Angiography Imaging Analysis in Patients with Ischemic Heart Disease. *Curr. Cardiol. Rep.* **2022**, *24*, 365–376. [CrossRef] [PubMed]
81. Ciusdel, C.; Turcea, A.; Puiu, A. An artificial intelligence based solution for fully auto- mated cardiac phase and end-diastolic frame detection on coronary angiographies. *J. Am. Coll. Cardiol.* **2018**, *72*, B96–B97. [CrossRef]
82. Molony, D.; Hosseini, H.; Samady, H. Deep IVUS: A machine learning framework for fully automatic IVUS segmentation. *J. Am. Coll. Cardiol.* **2018**, *72*, B1. [CrossRef]
83. Liao, J.; Huang, L.; Qu, M.; Chen, B.; Wang, G. Artificial Intelligence in Coronary CT Angiography: Current Status and Future Prospects. *Front. Cardiovasc. Med.* **2022**, *9*, 896366. [CrossRef] [PubMed]
84. Wolterink, J.M.; Leiner, T.; Takx, R.A.P.; Viergever, M.A.; Išgum, I. An automatic machine learning system for coronary calcium scoring in clinical non-contrast enhanced, ECG-triggered cardiac CT. Proceedings of SPIE: Medical Imaging 2014—Computer-Aided Diagnosis, San Diego, CA, USA, 15–20 February 2014; Aylward, S., Hadjiiski, L.M., Eds.; International Society for Optics and Photonics: Bellingham, WA, USA, 2014; Volume 9035, p. 90350. [CrossRef]
85. Mediratta, A.; Addetia, K.; Medvedofsky, D.; Schneider, R.J.; Kruse, E.; Shah, A.P.; Nathan, S.; Paul, J.D.; Blair, J.E.; Ota, T.; et al. 3D echocardiographic analysis of aortic annulus for transcatheter aortic valve replacement using novel aortic valve quantification software: Comparison with computed tomography. *Echocardiography* **2017**, *34*, 690–699. [CrossRef] [PubMed]
86. Guez, D.; Boroumand, G.; Ruggiero, N.J.; Mehrotra, P.; Halpern, E.J. Automated and Manual Measurements of the Aortic Annulus with ECG-Gated Cardiac CT Angiography Prior to Transcatheter Aortic Valve Replacement. *Acad. Radiol.* **2017**, *24*, 587–593. [CrossRef] [PubMed]
87. Kagiyama, N.; Toki, M.; Hara, M.; Fukuda, S.; Aritaka, S.; Miki, T.; Ohara, M.; Hayashida, A.; Hirohata, A.; Yamamoto, K.; et al. Efficacy and Accuracy of Novel Automated Mitral Valve Quantification: Three-Dimensional Transesophageal Echocardiographic Study. *Echocardiography* **2016**, *33*, 756–763. [CrossRef]
88. Baumgartner, C. The potential impact of ChatGPT in clinical and translational medicine. *Clin. Transl. Med.* **2023**, *13*, e1206. [CrossRef]